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AN EVALUATION OF PRECISION DAIRY FARMING TECHNOLOGY ADOPTION, PERCEPTION, EFFECTIVENESS, AND USE

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AN EVALUATION OF PRECISION DAIRY FARMING TECHNOLOGY ADOPTION, PERCEPTION, EFFECTIVENESS, AND USE

THESIS

A thesis submitted in partial fulfillment of the
requirements for the degree of Master of Science in the
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By

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ABSTRACT OF THESIS

AN EVALUATION OF PRECISION DAIRY FARMING TECHNOLOGY ADOPTION, EFFECTIVENESS, PERCEPTION, AND USE

Precision dairy farming technologies provide a variety of functions to dairy farmers. Little is known about dairy producer perception of these technologies. A study was performed to understand dairy producer perception of parameters monitored by precision dairy farming technologies. Calving has potential to be predicted using these same parameters and technologies. A second study was performed using two commercially marketed technologies in calving prediction. In order for these technologies to generate accurate and useful information for dairy farm use, they must accurately quantify these parameters. The final study evaluated the accuracy of five commercially marketed technologies in monitoring feeding, rumination, and lying behaviors.

KEYWORDS: precision dairy farming, precision dairy farming technologies, calving prediction, evaluated, accuracy

__________Matthew Borchers

___________ January 29, 2015

AN EVALUATION OF PRECISION DAIRY FARMING TECHNOLOGY ADOPTION, EFFECTIVENESS, PERCEPTION, AND USE

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FREQUENTLY USED ABBREVIATIONS

d = Day

Day0 = 24 Hours Immediately Before Calving

Day-1 = 48 Hours Before Calving

Day-2 = 72 Hours Before Calving

Day-3 = 96 Hours Before Calving

Day-4 = 120 Hours Before Calving

Day-5 = 144 Hours Before Calving

Day-6 = 170 Hours Before Calving

Day-7 = 194 Hours Before Calving

h = Hour

IACUC = Institutional Animal Care and Use Committee

kg = Kilogram

mL = Milliliter

NEL = Net Energy Lactation

CHAPTER ONE

REVIEW OF LITERATURE

PRECISION DAIRY FARMING TECHNOLOGIES IN DAIRY HERD MANAGEMENT

Precision dairy farming is defined as "the use of information and communication technologies for improved control of fine-scale animal and physical resource variability to optimize economic, social, and environmental dairy farm performance" (Eastwood et al., 2012). Precision dairy farming is a species-specific approach to precision livestock farming. Precision livestock systems have addressed animal growth, animal product output systems, endemic diseases, animal behavior, and the physical environment of a livestock building (Wathes et al., 2008).

Dairy producers implement precision technologies to improve individual animal management, group or pen management, whole-farm management, and overall farm production efficiency (Wathes et al., 2008). For dairy farmers, precision dairy farming technologies have the potential to remove subjectivity from decision-making processes, reducing the need for skilled and experienced labor in animal management. Technologies often reduce the need for specialized labor, or change its focus so more work can be accomplished by fewer laborers (Frost et al., 1997). Using technologies to monitor farm animals is useful as long as technologies continuously monitor parameters, reliably observe behaviors, and accurately describe behaviors with reliable algorithms (Berckmans, 2006). Improvements to work-routine efficiency can be made if technologies are as reliable as the labor replaced. Making improvements in work-routine efficiency reduces time required to complete a task, employee stress, and provides the operators time to focus on other areas (Schukken et al., 2008). This contrasts traditional dairy production systems where product quality depends almost entirely on the skill, experience, and subjective assessments of the individual producer or worker (Frost et al., 1997).

Management improvements ease public perception of animal agriculture. Dairy consumers have become increasingly concerned with food safety and quality, efficient and sustainable farming, animal health and well-being, and the impact of agriculture on the environment (Berckmans, 2006). Technology adoption can improve or maintain animal welfare on dairy farms and help to improve public perception by demonstrating the dairy community's commitment to developing welfare improvement strategies (Rutten et al., 2013). In addition to improving public perception of cattle welfare, technologies accurately monitor individual animals and farms, which can increase animal production efficiency and decrease the environmental impact of livestock production, thereby also improving public perception (Laca, 2009).

Precision Dairy Farming Technology Use

Technology use becomes important as dairy farmers refine their management practices with emphasis on efficiency (El-Osta and Morehart, 2000). Successful farms use and embrace modern manufacturing concepts and principles to improve their competitive position and increase efficiency and productivity (Boehlje and Schiek, 1998). In precision farming, technology adopters specialize production practices, and have lower input costs and higher profits (Daberkow and McBride, 1998). Furthermore, dairy producers with the lowest costs tend to be those implementing innovative management techniques and technologies (Short, 2004). Dairy farmers use many precision technologies to monitor many parameters pertaining to their cattle and operations. Parameters monitored by these technologies include daily milk yield, milk components, step number, temperature (in various places and forms on and within the cow), milk conductivity, automatic estrus detection monitors, and daily body weight measurements (Bewley, 2010). In addition to the parameters already monitored, many other parameters have also been proposed. Bewley (2010) proposed parameters such as jaw movements, ruminal pH, reticular contractions, heart rate, animal positioning and activity, vaginal mucus electrical resistance, feeding behavior, lying behavior, odor, glucose, acoustics, progesterone, individual milk components, color (as an indicator of cleanliness), infrared udder surface temperatures, and respiration rates. Technology manufacturers have since incorporated many of these parameters into their technologies.

Barriers to Adoption

Monitoring and control in livestock production is relatively undeveloped compared to most other industries, in spite of research showing higher production efficiency (Daberkow and McBride, 2003). Most monitored parameters are biological, and inherently variable and unpredictable (Frost et al., 1997). Ideal systems would provide continuous surveillance of the animal, automatically and accurately quantify the behavior of interest, and require minimal labor and maintenance (Senger, 1994). Technology performance and economic benefit also play a considerable role in technology decisions. Technology adoption has traditionally been higher in situations where profitability is evident and the extent of yield increase and cost reduction are evident (Daberkow and McBride, 1998; Russell and Bewley, 2013). Technological advances have been more readily adopted in situations where labor availability is low

(Rasmussen, 1962) or where labor alternatives are expensive (de Koning, 2011; Steeneveld et al., 2012).

A farmer must account for financial scale, demographic, and other considerations (Khanal et al., 2010). Dairy producers plan strategically for the long-term consequences of their decisions by mapping responses to a series of long-term occurrences (Boehlje and Schiek, 1998) allowing them to estimate financial impacts of management decisions. The decision to implement a precision dairy farming technology often represents a long-term decision and significant investment for a producer. With highly variable milk and feed prices, the impact of an unprofitable investment could be severely detrimental to a dairy farmer. Accordingly, investments are approached with caution.

Financial decisions is not always predictable, as advice and guidance is influenced by many factors in making management decisions. Trained professionals (i.e. veterinarians, nutritionists, consultants, extension specialists, etc.), family members, other dairy farmers, written publications, and even intuition are considered in the decision making process (Russell and Bewley, 2013).

In addition to apprehension in making costly financial decisions, producers must often select a specific technology to fit their needs. Producers have many choices in the type of precision dairy technology they implement. This is particularly difficult because many dairy farmers are simply unaware of the technologies currently available (Russell and Bewley, 2013). Available systems monitor animal activity, rumination, resting time, temperature, and many other events associated with animal well-being (Nebel, 2013). Although technologies are readily available, adoption has remained relatively low (Huirne et al., 1997; Gelb et al., 2001). In order to improve technology adoption, producer perception of these technologies will need to improve. Little is known about producers' parameter perception. Gathered information is often limited to technologies used in or around dairy parlors (Jago et al., 2013). Producers implementing technologies experience increased financial opportunity and understanding the process by which producers become aware of and adopt new technologies is of interest to the private sector, researchers, and policymakers alike (Pierce and Nowak, 1999; Daberkow and McBride, 2003). This contrasts the current trend in precision dairy farming where, despite being the end users, dairy farmers are typically excluded from technology development (Huirne et al., 1997), increasing the number of technologies not fulfilling an on-farm need, and lowering technology adoption.

In addition to not addressing on-farm needs, technology manufacturers select their marketing and education techniques primarily for dairies for which their products would be most beneficial (Daberkow and McBride, 2003), which may explain lower adoption rates. In the United States, dairy farms have been decreasing in number and increasing in size since the late 1970's, with existing herds expanding facilities, larger farms being constructed, and smaller farms leaving the industry (Hadley et al., 2002). The national share of milk produced on large dairy farms continues to increase (Khanal et al., 2010), and as farm size increases, the reliance on off-farm labor increases (Bewley et al., 2001). As a farmer transitions to off-farm labor reliance, management changes must be made. Affordable and available sources of labor then become larger concern for dairies as they grow.

Some of the most well-known and costly precision dairy farming technologies are automatic milking systems. Automatic milking systems were first implemented for the purpose of the reduction of labor costs in the Netherlands (Bijl et al., 2007). The adoption of these systems has been considerably higher in Europe than in the United States (De Koning, 2010). The difference between the adoption of such technologies and other precision dairy farming technologies may be explained by the difference in average employee wages. The average off-farm wage in the United States has been reported at $17.58 (MacDonald, 2007). In countries like the Netherlands, where the most automated milking systems are in use (De Koning, 2010), the average farm employee was paid $24.13 (Huijps et al., 2008). Because of the availability of inexpensive labor, dairy farmers in the United States may be less likely to incorporate precision dairy farming technologies into their management practices, and the same may be true for other countries with inexpensive labor. Labor is a concern commonly faced by dairy farmers across the world. In places where cheap labor is unavailable, technologies may decrease the need for specialized labor (Berckmans, 2006) and produce favorable profit margins. Wathes et al. (2008) predicted an increase in the number of European precision livestock management systems in response to decreased profit margins. In contrast, a survey of Kentucky dairy farmers by Russell and Bewley (2013), 23% of producers indicated that better alternatives existed or the task was easier to accomplish manually, than with technology. In the United States, 91% of herds have less than 200 milk cows (Short, 2004) and smaller dairies may have difficulty profiting from a technology investment (Hyde and Engel, 2002).

Demographics of Precision Dairy Farming Technology Adopters

Producer and farm demographics may be a factor influencing precision dairy farming technology adoption. Technology adoption is affected by age, education, farm size, full-time farming status, previous or concurrent implementation of other technologies, and computer literacy (Daberkow and McBride, 1998; Short, 2004; Khanal et al., 2010). Khanal et al. (2010) reported adopters of technology to be more educated (20.6%, adopters vs. 11.6%, non-adopters with college degrees), to have larger herd sizes (252 milking cattle, adopters vs. 56 milking cattle, non-adopters), and to produce more milk (7933 kg, adopters vs. 7394 kg, non-adopters). Khanal et al. (2010) and Daberkow and McBride (1998) reported technology adopters and non-adopters to be similar ages with adopters being slightly younger (49 adopters vs. 52 non-adopters). According to Russell and Bewley (2013), primary decision-maker characteristics influencing technology adoption include age, formal education level, and farm size. Other considerations also affect technology adoption. Considerations such as learning style, goals, business complexity, increased tenancy, risk perceptions, production type, nonfarm business ownership, production innovativeness, average information expenditures, and technology use by peers and other family members (Russell and Bewley, 2013). Risk perception is an influencer of the adoption-decision process. The adoption process depends on farmers' attitudes toward technology investment risk, willingness to try and learn from new production methods, and the outcome of delaying adoption (Marra et al., 2003).

CALVING PREDICTION

The time surrounding a calving event represents a difficult time for a dairy cow. The timeframe of the three weeks before calving to the three weeks after calving is referred to as the transition period in dairy cattle (Grummer, 1995). At this time, dairy cattle are most susceptible to disease and illness. Some diseases and illnesses affecting dairy cattle during the transition period are hypocalcaemia, hypomagnesaemia, ketosis, retained placenta, displaced abomasum, and laminitis. The effects of these diseases extend into the subsequent lactation, causing cow productivity reductions (Mulligan and Doherty, 2008). Having personnel on-hand at calving safeguards the cow and her calf.

Intensive management is especially essential at calving time. An evaluation of 666,341 calving records estimated the proportion of dystocia to be 28.6% in primiparous and 10.7% in multiparous cows (Meyer et al., 2001). Modern dairy cattle have traditionally been genetically selected for increased milk production and accordingly, less breeding emphasis was placed on other traits. This trend has potentially led to physiological and health problem increases experienced today (Mottram, 1997).

At calving time, the dairy cow and her calf are at risk for many reasons, but the most immediate problems encountered at calving time are perinatal mortality and dystocia (Mee, 2004). Perinatal mortality may be defined as "calf death before, during or within 48 h of calving, following a gestation period of at least 260 d, irrespective of the cause of death or the circumstances of the calving" (Mee, 1999). Around 60% of producers indicate that most calf mortalities occur at calving, and nearly 16% say they occur within one week of calving (Spicer et al., 1994). Calves that died within 48 h post-partum were 2.7 times more likely to have experienced a difficult birth requiring assistance (Johanson and Berger, 2003). Mee (2004) defined dystocia as, "calving difficulty resulting from prolonged spontaneous calving or prolonged or severe assisted extraction." Many maternal and calf-specific factors affect dystocia. In a model built by Johanson and Berger (2003) accounting for year, season, calf gender, perinatal mortality, parity, birth weight, and pelvic area, male calves increased the likelihood of dystocia by 25% versus female calves. Additionally, a 1 dm^2 increase in pelvic area is associated with an 11% decrease in dystocia incidence, while dystocia incidence increased 13% for every

1 kg increase in calf birth weight (Johanson and Berger, 2003). Holstein first-calf heifers have 4.7 times higher risk of dystocia than multiparous cows (Johanson and Berger, 2003). Primiparous cows more frequently need calving assistance (19%) than multiparous cows (11%; USDA, 2010). With skeletal growth continuing until around 5 years (Ragsdale, 1934) and a recommended age at first calving of 22 to 24 (Dairy, 2007), first-calf heifers have not reached their mature size at calving. Additionally, primiparous cattle are inexperienced with calving, potentially leading to differences in behavior (Houwing et al., 1990; Miedema et al., 2011a). This leads to increased stress and higher dystocia prevalence in primiparous dairy cattle (Wehrend et al., 2006).

To prevent and reduce the stress of calving events, a producer must recognize when a cow is in labor, move cows to appropriate pens in a timely manner, direct calving supervision, know when and how to intervene, and optimize calf and cow health following calving (Mee, 2004). Specialized calving pens allow producers to observe or assist parturient cows if necessary. Early cow movement into these pens is necessary because movement just before or following the appearance of the amniotic sac can extend the second stage of labor (Proudfoot et al., 2013). Responsible managers will take steps to prepare for calving events and be willing to ask for veterinary obstetrical assistance in a timely fashion. Taking these precautions improves animal production, health, and wellbeing (Mee, 2004).

Physical and Behavioral Changes Before Calving

The timing of calving events has traditionally been estimated from predicted calving dates from breeding dates and physical or behavioral cues assessed by dairy producers. Before calving, a dairy cow's udder will begin to "bag-up" or swell, her vulva will swell and become loose, and pelvic ligaments will begin to relax (Hulsen, 2006). The aforementioned observations serve as calving indicators, and require experience and nearly constant visual observation of a laboring cow to achieve an accurate guess at calving time. Additionally, these changes do not occur in every cow or in a timely manner. For example, in a study of beef cows, only 5.7 % of the animals had a completely developed udder with shiny teats filled with milk 8 h before parturition (Sendag et al., 2008). In a similar study, Hofmann et al. (2006) examined 105 suckler cows for vulva edematization for 168 h antepartum. All cows displayed some level of vulva edematization 168 h antepartum. This is indicative of this parameter being useful for a relative estimate of calving time, but still requires consistent monitoring prepartum. Using these observations, producers or their employees can estimate when a cow will calve, be able to group cattle accordingly, and provide assistance if necessary, but this will require labor commitment. This is done because providing assistance at this time will not only help to ensure a less stressful parturition event, but also to improve reproductive performance in the subsequent lactation (Bellows et al., 1988). While these methods are useful for predicating calving over a long period of time, indicators providing alerts over shorter time windows would be more useful.

Other behavior changes occur just before calving. Antepartum dairy cattle express decreased feed intake and rumination. Houwing et al. (1990) observed prepartum dairy cattle to decrease rumination from 46 to 10 min when rumination was viewed in 3 h time blocks, 12 h and 3 h, respectively before calving. Schirmann et al. (2013) also showed dairy cattle to decrease rumination by (mean ± SD) 63 ± 30 min per 24 h and feeding behavior by (mean ± SD) 66 ± 16 min per 24 h in the day before calving. Lying and standing behavior of periparturient cows also changes before calving. The number of transitions between standing and lying positions will increase in frequency for prepartum dairy cattle. The number of lying bouts increases (16.4 ± 4.8 bouts/d before calving vs. 24.2 ± 6.8 bouts/d at calving) and lying duration decreases (13.6 ± 1.8 h/d before calving vs. 12.6 ± 1.8 h/d on the day of calving) in prepartum dairy cattle (Miedema et al., 2011b). Huzzey et al. (2005) found standing bouts increased in the 24 h period before calving (11.7 ± 1.07 bouts/d pre-calving vs. 17.3 ± 1.08 bouts/d at calving; $P = 0.002$).

Cattle will begin walking more before calving (Jensen, 2012), potentially due to discomfort, and will seek isolation from other animals or the herd when possible (Lidfors et al., 1994; Proudfoot et al., 2014). The increase in walking and transitions between lying and standing increase restlessness (Owens et al., 1985; Huzzey et al., 2005; Jensen, 2012). During calving, dairy cattle experience uterine and abdominal contractions that may cause some discomfort and increase restlessness. Using walking behavior, and transitions between standing and lying to estimate restlessness could aid in determining when a calving onset. Dairy cattle increase the number of times the tail is raised before calving from 19.1 ± 7.6 times/d before calving, to 59.3 ± 24.9 times/d at calving (Miedema et al., 2011b). However, this may start as early as 15 d before calving, and as late as 7 h before calving (Berglund et al., 1987).

Producers have traditionally used many of these methods to determine calving time with varying degrees of success. Visual observation alone can be useful in determining calving time, but experience is needed to detect changes, and behavioral indicators can be missed if laborers infrequently monitor cattle prepartum (Dargatz et al., 2004). Additionally, methods differ from farm to farm, and these methods are often based on producer preference. These considerations outline the need for an objective approach to predicting calving time.

Methods of Predicting Calving

Several parameters have been identified to predict calving events. A technology predicting calving events days before actual calving events would allow for nutritional, grouping, or general management changes. Dry dairy cattle should transition from a diet of 1.25 Mcal/kg of NEL to a diet of 1.54 to 1.62 Mcal/kg of NEL, approximately 3 weeks before calving (NRC, 2001). A dairy producer can typically do this using breeding and predicted calving dates, but a technology predicting calving days before the event would allow a producer to meet specific cow nutritional needs. Additionally, a technology predicting calving over 24 h before the event would allow dairy producers to move cattle from close-up to calving pens. Moving cattle following the onset of parturition can prolong the second stage of labor (Proudfoot et al., 2013). Predicting calving before it begins, and moving the cow to a calving pen would reduce stress.

Parturition can be divided into three stages. The first stage of labor begins with cervical dilation and ends with the rupture of the chorioallantois upon entering the vagina (Senger, 1997). In the second stage of labor, the calf and fetal membranes may be visible. The second stage ends with the expulsion of the calf, when the third stage begins. The third and final stage ends with the expulsion of fetal membranes, ending the parturition process (Senger, 1997). Technologies predicting the onset of the second stage of calving would allow personnel to monitor calving progression following the rupture of fetal membranes; reducing stress and potential harm to the cow and calf at the time of the event. Before calving and at the end of pregnancy, circulating blood progesterone levels drop (Stabenfeldt et al., 1970). The decrease in plasma and blood progesterone levels has been outlined as potentially useful in the prediction of calving (Parker et al., 1988; Matsas et al., 1992). Matsas et al. (1992) observed an abrupt decrease in blood progesterone concentration from 2.31 + 0.15 ng/ml 48 h before calving to 0.59 + 0.06 ng/ml 24 h before calving (< 1.0 ng/ml on the day of calving).

Additionally, maternal body temperatures begin to decrease 48 h before a calving event (Lammoglia et al., 1997; Aoki et al., 2005; Burfeind et al., 2011) and show potential for calving prediction. Burfeind et al. (2011) found vaginal temperatures to decrease from 39.5°C to 38.8°C, and indicated continuous temperature monitors to be more effective than manual temperature collection at quantifying body temperature changes. Approaches using blood progesterone and temperature for calving prediction often meet difficulty constantly monitoring these parameters. Manual blood progesterone or temperature collection presents labor difficulties and requires frequent animal handling. Methods exist to automatically collect milk progesterone (Herd Navigator, DeLaval International AB, Tumba, Sweden), but none currently exist for blood progesterone. In contrast, many commercial temperature monitors measure dairy cattle reticulorumen, skin, and vaginal temperature (DVM reticulorumen bolus, DVM Systems, LLC., Boulder, CO; MaGiiX reticulorumen bolus, MaGiiX Bolus Inc., Post Falls, ID; CowManager SensOor, Agis, Harmelen, Netherlands, Vel'Phone transvaginal bolus Medria, Châteaugiron, France). Few technologies have developed calving detection algorithms and incorporated them into their systems.

Predicting Calving Events Using Behavioral Monitors

Pedometers and accelerometers may have a future in calving prediction. Traditionally, these units have been used to characterize activity changes shown to increase around estrus events (Farris, 1954). These increases can identify cattle in estrus without observing a cow standing to be mounted (Kiddy, 1977). Precision dairy farming technologies have been used to characterize other behaviors and units exist accurately characterizing lying and standing behaviors (O'Driscoll et al., 2008), rumination (Schirmann et al., 2009), and feeding behavior (Bikker et al., 2014); often in combination with activity.

In timely calving assistance, dystocia is the primary concern. Using technologies to predict difficult calvings through behavioral changes may allow for special procedures or treatments to be implemented, reducing stress that may otherwise be caused by difficult calvings (Miedema et al., 2011a). The prediction of dystocia and need of obstetrical assistance intrinsically implies that personnel are present at calving events where assistance is most necessary. A technology quantifying the duration of a calving event could be useful in reducing dystocia effects, as the extended duration of parturition increases the occurrence of calving difficulties (Wehrend et al., 2006). Additionally, dystocia has been associated with decreased eating time and an increase in the number of standing bouts (Proudfoot et al., 2009).

Methods of calving prediction have previously been applied to data generated from existing behavioral monitors. Maltz and Antler (2007) described calving prediction methods using changes in daily step number, lying behavior, and number of times passing into a feeding area for 12 cows over 7 d. By combining changes in monitored behavioral parameters in the days before calving, Maltz and Antler (2007) achieved a sensitivity of 83.3% and a specificity of 95.2% in calving prediction methods.

Activity in Prepartum Dairy Cattle

Activity in dairy cattle can be described in two different ways when describing technologies mounted directly to the dairy cow. The first refers to the ability of a technology to quantify the number of steps an animal takes through the use of pedometers. Pedometers have been in use since the 1970's for tracking the activity of dairy cattle (Kiddy, 1977). Pedometers track cow step numbers, while an accelerometer measures the acceleration devices receive in proportion to freefall (MacKay, 2013). Behavioral quantification using accelerometers is comparatively newer than pedometer use; however, accelerometer use has increased in industries outside animal agriculture. In response, overall accelerometer production has increased for these industries and the dairy industry, leading to a greater availability and lower cost (MacKay, 2013). Accelerometers offer more potential uses than basic pedometers. This presents opportunities to monitor parameters other than activity. Accelerometers quantify movement from different points on an animal. The attachment point may change depending on the behavior of interest. The primary attachment points for accelerometers on a dairy cow are the ear, neck, front leg(s), back leg(s), and rump, but other areas have been used and proposed for additional uses (Rutten et al., 2013).

Lying and Standing Behavior in Prepartum Dairy Cattle

Direct visual, or video-recorded observations of dairy cattle have traditionally served to quantify lying and standing behavior. In these observations, lying bouts are instances where an animal's flank contacts the ground following transitions from standing to lying positions (Ledgerwood et al., 2010). Similarly, standing bouts occur following transition from lying positions to standing positions where all four limbs are fully extended and perpendicular to the ground (Ledgerwood et al., 2010). Lying or standing time is the time between either a lying or standing bout. While these methods serve as the gold standard for these behaviors, these approaches can be arduous and time consuming. With increasing use of accelerometers, technologies are often able to monitor these transitions and the amount of time in each standing or lying state.

Feeding Behavior in Prepartum Dairy Cattle

Feeding behavior provides an estimate of the amount cows are eating (Murphy, 1992; Nielsen, 1999) and refers to a collection of behaviors associated with feed consumption. Precision dairy farming technologies also provide estimates of this parameter. Parameters included in this category refer to the number of chewing behavior associated jaw movements (Beauchemin et al., 1989; Kononoff et al., 2002; Zehner et al., 2012), actual DMI, time at the feed bunk, or time spent near the feed bunk (Chapinal et al., 2007). Research has shown feeding time measured by technologies to be effective. Schirmann et al. (2013) showed dairy cattle to decrease feeding time by 66 ± 16 min/24h, 24h before calving and an ear-attached precision dairy farming technology produced this finding.

Rumination Behavior in Prepartum Dairy Cattle

Rumination has traditionally been recorded through visual observation (physical or video) or through chewing activity. More recently, the use of head movements, chewing activity, and microphones has become more standard in rumination monitoring. Technologies such as the HR Tag (SCR Engineers Ltd., Netanya, Israel) use a microphone to capture eructation and rumination sounds. Other technologies, such as the CowManager SensOor (Agis, Harmelen, Netherlands), quantify head movement associated with rumination events using accelerometers. Using these or similar technologies, rumination before calving can be quantified. Schirmann et al. (2013) used the HR Tag to observe periparturient cattle and found cattle spent 63 ± 30 min/24 h less time ruminating in the 24 h before calving.

Rumination may prove to be particularly useful because of its link to stress. A study of stressed Angus-Hereford cows with high cortisol levels (above 22 ng/mL) showed high negative correlation with decreased rumination ($r = -0.85$, $P < 0.01$). Because cortisol is released when an animal is stressed, an association between stress and rumination may exist (Bristow and Holmes, 2007). With increased cortisol levels (Lammoglia et al., 1997), and decreased rumination (Schirmann et al., 2009) in the 24 h before calving, a link between stress, cortisol, and rumination may exist at the time of calving. This link may implicate rumination as an important predictor of calving, and dystocial calvings in particular.

ESTABLISHING THE VALIDITY OF PRECISION DAIRY FARMING TECHNOLOGIES

For precision dairy farming technologies to be economically viable, they must accurately and easily describe physiological or behavioral parameters. Much of the work completed already has been in the classification of mastitis and estrus, and to a lesser extent, locomotion and metabolic health (Rutten et al., 2013).

Binary Classification in Precision Dairy Farming Technologies

Precision dairy farming technologies are evaluated using binary classification. In binary classification, events are compared against a gold standard, or when the event of interest actually happened. When evaluating precision dairy farming technologies, alerts generated by sensors are compared with the occurrence of the event of interest. These are often visual observations of these behaviors, which are treated as gold standards. How the technology performs against visual observations is often evaluated using these rules:

True Positives- Observations where an alert is generated and the event occurs

False Negatives- Observations where no alert is generated and the event occurs

False Positives- Observations where an alert is generated and the event does not occur

True Negatives- Observations where no alert is generated and the event does not occur

(Hogeveen et al., 2010)

Sensor performance evaluation involves the use of these basic classifications with the ideal system detecting events of interest and providing no false positives (type I error) or negatives (type II error) (Reneau, 1986). False positives cause problems for farmers because a treatment in response to type I error (if used for disease detection and diagnosis) implies the unnecessary treatment of a healthy animal. For type II errors, beneficial management actions may be withheld from animals in need if a technology fails to detect behaviors of interest (Burfeind et al., 2010). Calculations derived from the four event classifications provide values to evaluate technology performance. The sensitivity, specificity, positive predictive value, negative predictive value, and accuracy establish technology performance. These are calculated as follows:

Sensitivity = 100 * True Positives / (True Positives + False Negatives)

Specificity = 100 * True Negatives / (False Positives + True Negatives)

Positive Predictive Value = 100 * True Positives / (True Positives + False Positives)

Negative Predictive Value = 100 * True Negatives / (True Negatives + False Negatives)

Accuracy = 100 * True Positives + True Negatives / (True Positives + False Negatives + False Positives + True Negatives)

(Hogeveen et al., 2010)

The sensitivity and specificity of events are linked and a proper balance must be established between the two (Hogeveen et al., 2010). In order for technologies to be effectively implemented, they must accurately accomplish their tasks, and be as near 100% across all of the above categories. By many technology standards (mastitis detection), specificity greater than or equal to 99% and sensitivity greater than 80% is the acceptable minimum (ISO, 2007).

Validation in Precision Dairy Farming Technologies

Tools detecting physiological changes, behavioral changes, or general abnormalities early and accurately are useful to dairy farmers and researchers (Bikker et al., 2014). In behavioral monitoring, these tools can also be used to monitor dairy cattle without disturbing their natural behavioral patterns, giving more accurate indications of general animal welfare (Müller and Schrader, 2003). Specific animal behaviors are quantified and interpreted using company-specific algorithms (rules to follow during calculations) in alert creation. Software specific algorithms compare current animal behavior with a cow-specific reference point or period, creating alerts when established threshold levels are exceeded (Saint-Dizier and Chastant-Maillard, 2012). However, technologies must accurately quantify and describe behavioral data for algorithms to accurately create alerts for a producer.

Animals generate important process signals, and need to be measured directly and continuously (Wathes et al., 2008). Because of this, many measurements are generated from individual animals. Existing statistical methods in validation do not account for repeated measures being taken on the same animal over time (Chapinal et al., 2007; Schirmann et al., 2009; Bikker et al., 2014) and fail to account for the lack of independence among repeated measurements (Bland and Altman, 1994). Validation methods need to account for repeated measures taken from the same animals, as well as a lack of independence within subjects. In these instances, simple correlation coefficients are not appropriate (Bland and Altman, 1995a; b).

Rumination and Feeding Behavior

The automatic measurement of ruminants chewing and ruminating activity can enable the early detection of feeding deficiencies and assist in ration adjustments (Zehner et al., 2012). Rumination and feeding behavior have traditionally been monitored through visual observation in both research and farm settings; which is time consuming and especially impractical for dairy farmers. Additionally, while changes in behavior are useful in the detection of illness, they are subjective and open to individual interpretation (Weary et al., 2009). The alternative is the use of precision dairy farming technologies to constantly and objectively monitor these behaviors. In a study of cattle housed in a feedlot system, feeding time of sick animals was found to be 30% less than that of healthy animals when monitored using a radio frequency-based system (Sowell et al., 1998). Using Insentec Feeders (Insentec, Marknesse, the Netherlands), the feeding behavior of transition dairy cattle experiencing mild and severe uterine infection decreased relative to that of healthy animals (Huzzey et al., 2007).

Rumination and feeding behavior are similar in how they are quantified because both events are characterized using similar metrics. Specifically, chewing activity has been used in the quantification of both ruminating and feeding behavior through precision technology (Beauchemin et al., 1989; Kononoff et al., 2002; Zehner et al., 2012). The quantification of rumination behavior has been similar in performance between visual observation and precision technologies. Beauchemin et al. (1989) reported a correlation between rumination-based jaw movements monitored by visual observation and a logger recording chewing patterns of r = 0.91 to 0.98. Kononoff et al. (2002), found a difference of 42.9 min ± 12.0 ($P < 0.01$) per day between observed and electronically recorded rumination. They also noted visual observation overestimated eating and ruminating time due to difficulty recording exact event start and stop times. Neck-mounted technologies have also proven to be effective. A system evaluated by Schirmann et al. (2009) used a series of 3 trials comparing a system monitoring rumination through a microphone-equipped neck tag against visual observation (trial 1: r = 0.96, $R^2 = 0.93$, n = 15, $P < 0.001$; trial 2: r = 0.92, $R^2 = 0.86$, n = 36, $P < 0.001$; trial 3: r = 0.96, n = 60, $P < 0.001$). A newer approach in rumination quantification has been through the use of accelerometers. In a system quantifying rumination behavior through head movements, mean values of 42.6 ± 6.81 and 42.1 ± 6.94 ($P = 0.49$) were recorded for rumination recorded by sensor and visual observation, respectively (Bikker et al., 2014). Traditionally, rumination monitoring has been limited to research settings due to labor intensity and expense. The number of systems similar to those evaluated by Schirmann et al. (2009) and Bikker et al. (2014) has increased, and the potential to accurately monitor these parameters has grown.

Feeding behavior and rumination have been quantified using chewing activity (pressure and strain recorders) monitors (Beauchemin et al., 1989; Kononoff et al., 2002; Zehner et al., 2012). Beauchemin et al. (1989) and Zehner et al. (2012) evaluated similar technologies against visual or video observations, and technologies performed similarly for rumination quantification at r = 0.88 ($P > 0.05$) and $R^2 = 0.79$ ($P < 0.05$), respectively. Beauchemin et al. (1989) and Zehner et al. (2012) also evaluated feeding time using these same technologies and found agreement of r = 0.67 (P > 0.05) and R^2 = 0.77 (P < 0.05). In contrast, Kononoff et al. (2002) used a similar technology and found significant differences (*P* < 0.01) between observed rumination time (415.0 min) and recorded rumination time (372.1 min), but no significant differences (*P* = 0.09) between observed feeding time (246.9 min) and recorded feeding time (238.1 min). Technologies describing when cows approach feeding areas and eat have been highly correlated to visual methods (R^2 = 1.00, *P* < 0.01; Chapinal et al., 2007 and R^2 = 0.88, *P* < 0.01 DeVries et al., 2003). The aforementioned chewing activity (strain and pressure), and feeding behavior monitors are primarily used in research settings, but commercially available rumination and feeding behavior quantification methods have also been evaluated. Bikker et al. (2014) evaluated a technology monitoring rumination and feeding behavior through head movement and found a high correlation for rumination (r = 0.93; *P* < 0.01) and feeding time (r = 0.88; *P* < 0.01). Schirmann et al. (2009) evaluated a technology quantifying rumination sounds through a microphone and microprocessor and found a high correlation (r = 0.93, n = 51) between visual observations and the technology.

Because different feeding behavior definitions and gold standards exist technologies become difficult to compare. Technologies such as the Track a)))Cow System (ENGS, Hampshire, UK) monitor proximity to the feed bunk, and similar technologies can monitor a cow’s presence in the feeding area. Because these parameters do not specifically monitor feed intake, assessing the efficacy of feeding behavior recording becomes difficult. These technologies are typically used for health monitoring. Dairy cattle that are sick or ill spend less time eating, more time lying, and seek secluded or isolated areas (Proudfoot et al., 2014). While these technologies may not directly monitor feeding behavior, they may be as useful as those directly monitoring feed intake or chewing activity.

Lying and Standing Behavior

As compared to other parameters (e.g. rumination, activity, feeding behavior) measured by precision dairy farming technologies, standing and lying events are very definite when they occur and chance of error is smaller. As a result, the use of visual observation or video recording has served as the gold standard in much of the previous validation work evaluating these technologies. Accelerometers have served as the main recording device for these parameters, and commercially available and validated technologies include the Afi Pedometer Plus leg tag (afimilk, S.A.E. AFIKIM, Kibbutz Afikim, Israel; Mattachini et al., 2013), Rumiwatch Pedometer (GmbH, Switzerland; Kajava et al., 2014), and the IceQube activity monitor (IceRobotics, Scotland). Technologies other than these two exist for commercial use and many of which using accelerometers; however, most have yet to be validated and checked for accuracy.

Many technologies are intended for research use only. Validated technologies used primarily for research purposes include the HOBO Data Logger (HOBO Pendant G Acceleration Data Logger, Onset Computer Corporation, Pocasset, MA; Bonk et al., 2013; Mattachini et al., 2013a; Mattachini et al., 2013b), the Tinytag Plus (Tinytag Plus, Re-Ed volt, Gemini Dataloggers (UK) Ltd., Chichester, UK; O'Driscoll et al., 2008), the IceTag Activity Monitor (IceRobotics, Scotland); McGowan et al., 2007; Mattachini et al., 2013b) and several custom devices such as those used in Champion et al. (1997) using mercury tilt switches (RS Components Part No. 337-289).

Lying and standing behavior has traditionally been recorded through direct or indirect (video) visual observation; however, the evaluation of these behaviors using precision dairy farming technologies is less invasive to cattle (Müller and Schrader, 2003). Researchers have used different methods of validation, adding confusion as they are rarely equal. Additionally, methods other than visual observation have been used to establish technologies' validity. One such method is the use of technologies already validated compared to the performance of technologies not validated (Mattachini et al., 2013a; Mattachini et al., 2013b). In theory, this would remove potentially erroneous observations generated from human observers and make for easier data collection (Mattachini et al., 2013b). Mattachini et al. (2013b) achieved high levels of agreement using these methods to compare recorded lying behavior to video (IceTag and Video Observation, sensitivity = 0.997 ± < 0.001, specificity = 1.000 ± 0.000; HOBO Data Logger and Video Observation, sensitivity = 0.990 ± 0.004, specificity = 0.996 ± < 0.001; and IceTag and HOBO Data Loggers, sensitivity = 0.993 ± 0.001, specificity = 0.994 ± 0.002) and recorded standing behavior to video (IceTag and Video Observation, sensitivity = 0.969 ± 0.005, specificity = 0.951 ± 0.006; HOBO Data Logger and Video Observation, sensitivity = 0.996 ± < 0.001, specificity = 0.986 ± 0.008; and IceTag and HOBO Data Loggers, sensitivity = 0.961 ± 0.003, specificity = 0.991 ± 0.002). In contrast, researchers comparing performance between technologies showed differences when compared to visual observation on the same animals (Beauchemin et al., 1989). When evaluating technologies against other technologies, changes in technology accuracy occur when evaluated on different legs of the same cow, with the least accurate results being standing and lying data collected from sensors on the front legs (Müller and Schrader, 2003). Approaches evaluating technologies against other technologies should be approached with caution.

CONCLUSIONS

Precision dairy farming technologies perform many functions for dairy farmers, researchers, and manufacturers. These technologies aid producers in monitoring and caring for their animals without the need of experienced labor. Future work in this field, as a whole, will need to be sure technologies fulfill dairy farmer needs. Technology developers must consider producers in their current and future precision dairy farming technology marketing endeavors. Improving dairy farmer technology perception and establishing technology effectiveness will increase adoption likelihood and overall usefulness of these technologies. Barriers exist to precision dairy farming technology implementation and future research will need to establish the accuracy, economic payoff, and overall justifiability of these technologies

CHAPTER TWO

Producer assessment of precision dairy farming technologies adoption, pre-purchase considerations, and usefulness

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INTRODUCTION

Precision dairy farming has been defined as, “the use of information and communication technologies for improved control of fine-scale animal and physical resource variability to optimize economic, social, and environmental dairy farm performance” (Eastwood et al., 2012). Parameters monitored by these technologies include daily milk yield, milk components, step number, temperature (in various places and forms on and within the cow), milk conductivity, automatic estrus detection monitors, and daily body weight measurements (Bewley, 2010). In addition to the parameters already monitored, many other parameters have also been proposed. Proposed parameters include jaw movements, ruminal pH, reticular contractions, heart rate, animal positioning and activity, vaginal mucus electrical resistance, feeding behavior, lying behavior, odor, glucose, acoustics, progesterone, individual milk components, color (as an indicator of cleanliness), infrared udder surface temperatures, and respiration rates (Bewley, 2010). Through the use of precision dairy farming technologies, producers strive to improve farm performance. Technology use becomes important as dairy farmers refine their management practices with emphasis on farm efficiency (El-Osta and Morehart, 2000).

The decision to purchase and implement a precision dairy technology represents a significant investment for a producer, who often faces the challenge of choosing a technology that will serve their needs for several years. Dairy producers tend to plan for the long-term consequences of their decisions, mapping responses to a series of long-term occurrences (Boehlje and Schiek, 1998). In making decisions, a farmer must account for many different factors, like financial scale, demographic, and other considerations (Khanal et al., 2010).

As precision dairy farming technologies have evolved and advanced, new parameters and ways of monitoring have been created. As a result, dairy farmers encounter many choices in the type of precision dairy farming technology they may implement and many dairy farmers are simply unaware of the technologies currently available to them (Russell and Bewley, 2013). Systems are available for monitoring animal activity, rumination, resting time, temperature, and many other events associated with animal well-being (Nebel, 2013) but little is understood concerning producer technology adoption, perception of individual technologies, or opinion of the parameters they measure. Entrepreneurs implementing technologies drive the opportunity and increased productivity associated with technological change, and understanding the process by which entrepreneurs become aware of and adopt new technologies is of interest to the private sector, researchers, and policymakers (Pierce and Nowak, 1999; Daberkow and McBride, 2003). This contrasts the current trend in precision dairy farming where, despite being the end users, dairy farmers are typically excluded from technology development (Huirne et al., 1997) and as a result, technology adoption remains relatively low (Huirne et al., 1997; Gelb et al., 2001).The objectives of this study were to identify the parameters currently measured on farms, find the considerations a farmer takes when selecting precision dairy farming technologies, and determine the parameters perceived by producers as most useful.

MATERIALS AND METHODS

In March 2013, an 8-question survey was created through SurveyMonkey (SurveyMonkey, Inc. Palo Alto, CA). A test survey was made and links were sent to extension specialists and producers (n = 5). Appropriate revisions were made based on test sample respondent feedback regarding survey content and organization. Following revision, the survey was made accessible to the general public for 2 months (Appendix 2.1). Dairy producers were identified as the target audience of this survey, with no conditions being specified for respondents to be eligible to complete the survey. The survey was sent to potential respondents through uniform resource locator (**URL**) links distributed by email, internet publications, and magazines. Electronic methods of URL distribution were the preferred medium of distribution because respondents had the ability to click on the actual URL, taking them directly to the survey. Respondents seeing the URL in print had to copy the address and enter it directly into their web browser to access the survey, so the electronic method was thought to be easier for the respondent. The survey consisted of 7 close-ended questions, and 1 open-ended question in which respondents could express their thoughts, suggestions, and opinions. Responses to the open-ended question were not included in analysis.

Respondents were asked to disclose the country and state or province where their farm was located, their age, their current herd size (including dry cows), and their role on the farm. Age and farm role were presented to respondents in categories, while country and state or province and herd size required users to input values. Age categories were pre-defined at: < 30, 30 to 40, 41 to 50, 51 to 60, and > 60. Five options for on-farm role were provided to respondents: (1) owner, co-owner, or partner (2) president or vice president (3) manager, supervisor, or herdsman (4) general employee, or (5) other. Depending on country of origin, each respondent was placed into a United States or other countries category. Additionally, respondents were asked to identify the parameters currently measured on their farm by precision dairy farming technologies from a predetermined list (Table 2.1). Parameters from the predetermined list were generated from previous literature, producer input, and from the input of extension specialists. Parameters used to determine the general health of the mammary system were combined into the mastitis option within this survey as they were considered potentially confusing. One option within the list allowed farmers to answer “not applicable” if they did not currently use technologies on their farm. Depending on the answer to this question, producers were sorted into one of two categories: (1) producers using technologies or (2) producers not using technologies.

A Likert (1932) Scale was used to assign numerical values to the responses of the final two questions. Producers were asked to rank the considerations made in deciding to purchase precision dairy farming technologies from a predetermined list (Table 2.2) and each ranking was assigned a numerical value with: 1 = unimportant, 2 = of little importance, 3 = moderately important, 4 = somewhat important, and 5 = important. Producers were also asked to classify parameters, based on usefulness, from the same list used in the technology adoption question (Table 2.3). Each ranking was assigned a numerical value with: 1 = Not useful, 2 = Of little usefulness, 3 = Moderately useful, 4 = Somewhat useful, 5 = Useful.

Statistical Methods

Statistical analyses were conducted on completed surveys using SAS Version 9.3 (SAS Institute Inc., Cary, NC). Median herd size (lactating and dry) was calculated using the MEANS procedure. Least-squares means were calculated using the GLM procedure across age, herd size, country, and technology usage categories, on ranked parameter usefulness and pre-purchase considerations. Categorical variables described age, herd size, country categories, and whether producers used or did not use technologies. Accordingly, Chi-square analyses were performed using the FREQ procedure to compare differences in producer age, herd size, and country categories across all parameters currently measured on respondents' farms.

RESULTS AND DISCUSSION

One objective of this survey was to increase response numbers by decreasing survey length, as a smaller survey may increase the total number of responses (Deutskens et al., 2004). Following survey closure, 43 of the 152 surveys collected were removed due to incompletion or error. Surveys were considered incomplete or erroneous if more than 75% of questions were left unanswered, or the role on-farm was anything other someone directly employed on-farm. Incomplete and erroneous responses were removed from the sample. In data analyses, 109 complete responses were used.

Producer categories, generated based on respondents' role on the farm, were (1) owner, co-owner, or partner; 72.5% (2) president or vice president; 1.8% (3) manager, supervisor, or herdsman; 23.9% (4) and general employee; 1.8%. An "other" category was provided and respondents were asked to specify their role. Surveys with responses in the "other" category were removed because none were on-farm employees. Because of the high amount of respondents being in the first category, role on the farm was not considered as an explanatory factor in further analyses. Producers from nine countries responded to the survey. Respondent countries included Australia, Canada, India, Iran, Israel, Mexico, New Zealand, the United Kingdom, and the United States (Other countries; n = 19 vs. United States; n = 90). Producer ages were: < 30 (17.4%), 30 to 40 (28.4%), 41 to 50 (25.7%), 51 to 60 (20.2%), > 60 (8.3%). Producer age results are indicative of a sample that is younger than expected, with most dairy producers in the United States being between 45 and 54 (Vilsack and Clark, 2014). Median herd size was 230 cows (lactating and dry). Herd size categories were generated based on quartile and are as follows: < 110 (26.6%), 111 to 230 (24.8%), 231 to 573 (23.9%), > 574 (24.8%). In a report by NAHMS (2007), herds were categorized as small with fewer than 100 animals, medium with sizes between 100 and 499 animals, and large with 500 or more animals. The findings of the current study were in congruence with the 2007 NAHMS report and the 2012 Census of Agriculture.

Technology Adoption

Results of parameters currently measured by precision dairy farming technologies on dairy farms are presented in Table 2.1. Producers were able to select multiple parameters because several technologies can monitor multiple parameters. Additionally, the potential exists for producers to have more than one technology. Producer responses indicated that the most commonly measured parameters by already adopted technologies were: daily milk yield (52.3%), cow activity (41.3%), not applicable (31.2%), and mastitis (25.7%). The least used technologies were rumen pH (0.9%), respiration rate (1.8%), methane emissions (1.8%), body condition score (2.8%), and heart rate (3.7%). Results were consistent with the age of individual parameters and producers' the ability to monitor them. Cow activity is one of the oldest parameters used in dairy cattle monitoring and was first described by Farris (1954). In addition, parameters such as milk yield and SCC, although not automatic, have been available to producers through the National Dairy Herd Information Association (Verona, WI, United States) and other similar organizations for many years. Due to producer familiarity with these parameters and those similar to them, perception and use may be higher, especially when compared to the newer parameters with which producers are less likely to be familiar.

Criteria Considered in Purchasing Decisions

Results of criteria considered in purchasing precision dairy farming technologies on dairy farms are presented in Table 2.2. When asked to rank criteria on importance when making purchasing decisions regarding precision dairy farming technologies, producers indicated benefit to cost ratio as most important (4.57 ± 0.66), followed by total investment cost (4.28 ± 0.83), simplicity and ease of use (4.26 ± 0.75), proven performance through independent research (4.24 ± 0.75), and availability of local support (4.12 ± 0.95; Table 2.2). Similar results were observed by Russell and Bewley (2013) in a study of Kentucky dairy producers, where producers indicated an undesirable cost to benefit ratio, lack of perceived economic value, difficulty or complexity of use, and poor technical support or training, as influential on technology adoption. Producers found all considerations in this question to be important for evaluating precision dairy farming technology purchases, as all of the criteria ranked above 4 when the maximum selectable value was 5.

Parameter Usefulness

The perceived usefulness of individual technologies by producers is presented in Table 2.3. These results were generated from a question asking respondents to rank a predetermined list of parameters on perceived usefulness (where 5 is most useful). Producers indicated the most useful parameters to be: mastitis (mean ± SD; 4.77 ± 0.47), standing estrus (4.75 ± 0.55), daily milk yield (4.72 ± 0.62), cow activity (4.60 ± 0.83), and temperature (4.31 ± 1.04). Producers indicated body weight (3.26 ± 1.20), body condition score (3.26 ± 1.15), heart rate (3.07 ± 1.15), animal position and location (2.75 ± 1.26), and methane emissions (2.20 ± 1.16) to be the least useful.

Producer interest may not be in congruence with biological meaningfulness for many parameters. One such parameter was body condition score. Regular assessment of the amount of body fat mobilized during early lactation and restored during mid and late lactation by dairy cows can aid in adjusting the feeding strategy to meet actual requirements of dairy cows more closely (Gallo et al., 1996). Such a technology may prove useful for producers, but producer perception of it in this survey was relatively poor. One reason for the findings in this survey could be the lack of commercially available systems scoring body condition and other parameters. Methods have been described with which to automatically monitor body condition score by Coffey et al. (2003) and Bewley et al. (2008), but no technologies monitoring this parameter are commercially available at this time. Another reason for this trend may be the perception of body condition scoring as a whole. The commitment of skilled labor to undertake routine manual body condition score assessment is not always possible (Roche et al., 2009), which may lead to producers perceiving this parameter negatively. The combination of poor perception and lack of commercially available systems may be the reason for multiple poorly perceived parameters in the current study.

Producers indicated the automatic detection of standing estrus to be one of the most useful parameters. One explanation for the highly perceived usefulness of this parameter is that it could be confused with other parameters often associated with estrus detection, such as cow activity. Another explanation is that producers are more familiar with visual estrus detection techniques and may be more likely to perceive a technology that does this automatically as very useful. Methods of monitoring mounting events have been described (Senger, 1994), but few commercially available technologies monitor tangible standing estrus or mounting events, especially when compared to cow activity.

Statistical Comparisons

Chi-square analyses compared age, herd size, and country categories across the parameters currently monitored on dairy farms. Country of farm location yielded significant differences across technology adoption categories, with technologies monitoring animal position and location, body weight, cow activity, daily milk yields, lying and standing time, mastitis, milk components, rumen activity, and rumination all being higher and differing significantly between use in other countries and the United States (Table 2.4). While the current study did not consider robotic milkers specifically, robotic milkers monitor or have the potential to monitor many of the parameters listed in this survey. Adoption of automated milking systems has been higher in other countries, with more than 90% of the world's automated milking systems being located in northwestern Europe (de Koning, 2011). The increase in European technology adoption may be explained through pricing quota system. Foreign farmers may value technology more if they have labor constraints, have high input costs, or their pricing system dictates a milk production limit. The desire to increase milk production per cow while decreasing input costs is one of many reasons European dairy farmers adopt technologies (de Koning, 2011; Steeneveld et al., 2012). Bergevoet et al. (2004) found that farmers under the quota system perceive having a modern and highly productive farm as being the highest consideration to their businesses. As a result of valuing technology use, producers from other countries may be more likely to implement precision technologies due to the increased emphasis on efficiency and modernization.

Least-squares means were calculated on producer pre-purchase considerations and parameter usefulness across age, herd size, and region categories, with no significant results being found ($P \geq 0.05$); however, technology adopters and technology non-adopters differed in pre-purchase consideration importance and perceived parameter usefulness. Availability of local support was more important to producers already using technologies (4.25 ± 0.11) than those that were not (3.82 ± 0.16; $P = 0.03$; Table 2.5). Russell and Bewley (2013) established that producers value adequate technical support and training and that this was important in their decision making. The findings of the current study are in correspondence with this, while also adding that producers currently using technologies may be familiar with the problems, questions, and troubleshooting associated with technology implementation. These experiences may lead producers already using technologies to place more value on technical support when purchasing technologies.

Respondent perception of parameter usefulness also differed across technology use categories (Table 2.6). Milk yield was considered more useful by producers currently using technologies (4.83 ± 0.07) than those not using technologies (4.50 ± 0.10; $P = 0.01$), and standing estrus was perceived to be significantly less useful by producers using technologies (4.68 ± 0.06) versus those not using technologies (4.91 ± 0.09; $P = 0.04$). Both categories of producer regarded these parameters to be relatively useful because both producer categories ranked milk yield and standing estrus above 4. The automated measuring of milk yield can be used to identify sick animals in dairy herds (Deluyker et al., 1991; Mottram, 1997) or identify low producing cows for culling (Bascom and Young, 1998). Producers already using this technology may see the increased benefit of monitoring this parameter in their herds. Automated measures of cow activity can identify cattle in estrus without the necessity of observing an event where a cow stands to be mounted (Farris, 1954; Kiddy, 1977). Producers currently using technology may be familiar with this knowledge and as a result, perceive standing estrus as being less important.

Potential Bias

Responses in this study may not be representative of all dairy producers in the United States or in other countries around the world. Bias may be present in this survey and the means by which this survey was distributed may be to blame. Email, electronic publication, and written publications served as the medium of distribution for this survey, so only producers receiving the aforementioned materials would have access to the survey. Producers using email and electronic publications to gather and interpret information regarding their farm may have been more likely to access this web-based survey. Farmers not utilizing these methods would be less likely to receive the survey, or access it from a link provided in a written publication. As a consequence, the sample may not have been completely representative of the entire population of dairy producers; however, producers not using technology or computers would be less likely to implement these technologies (Daberkow and McBride, 1998). The sample of producers in this study may be more representative of the population of producers willing and able to implement technologies, but further research may be necessary to definitively corroborate the findings of this study. Results of the current study show the potential for mounting monitors to be highly utilized by producers. Precision dairy farming must be successfully demonstrated at a commercial scale if farmers are to have confidence in the manufacturers (Wathes et al., 2008). Perhaps after manufacturers identify parameters on which dairy farmers need educated, or parameters that producers value the most, manufacturers can more effectively market these technologies.

CONCLUSIONS

Technologies monitoring milking performance, reproductive performance, and udder health were the most widely used among current parameters; however, many farmers did not use technologies and could provide potential areas for manufacturers to expand their marketing and sales. Perception of parameter usefulness was highest for technologies monitoring mastitis, estrus, and milk yield parameters. Additionally, producers find factors associated with return on investment, total investment, and technology performance as the most important pre-purchase considerations when deciding whether to implement a technology. Producers currently using technologies value the availability of local support more than those not using technologies, meaning dairy farmers using technologies may be more familiar with the requirements of implementing a technology. Technology adoption was higher on dairy farms outside of the United States and technology adoption in the United States is one potential area of expansion for foreign and domestic technology manufacturers. The information in this study may allow technology manufacturers to better educate producers, market technologies, and develop parameters that are more useful to producers.

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Table 2.1. Results from a producer-based survey showing percentages of surveyed producers using technologies to measure various parameters[1]

Parameter	Respondent percentage (n = 109)
Daily milk yield	52.3%
Cow activity	41.3%
Not applicable[2]	31.2%
Mastitis[3]	25.7%
Milk components (e.g. fat, protein, and SCC)	24.8%
Standing estrus	21.1%
Feeding behavior	12.8%
Temperature	12.8%
Body weight	11.0%
Rumination	10.1%
Rumen activity	9.2%
Animal position and location	8.3%
Lying and standing behavior	8.3%
Jaw movement and chewing activity	7.3%
Hoof health	6.4%
Lameness	4.6%
Heart rate	3.7%
Body condition score	2.8%
Methane emissions	1.8%
Respiration rate	1.8%
Rumen pH	0.9%

[1]Parameters were presented to respondents in a predetermined list.

[2]Respondents replying “not applicable,” were those not currently utilizing precision dairy farming technologies on their farm.

[3]Parameters associated with mastitis detection were combined due to the highly technical and variable nature of these parameters.

Table 2.2. Results from a producer-based survey indicating the importance of criteria for evaluating precision dairy technology purchases[1]

Item	Response %					Responses (n)	LSMean ± SD
	Unimportant	Of little importance	Moderately important	Somewhat important	Important		
Benefit to cost ratio	0.9%	4.6%	11.9%	46.8%	35.8%	108	4.57 ± 0.66
Total investment cost	1.9%	2.8%	15.7%	45.4%	34.3%	109	4.28 ± 0.83
Simplicity and ease of use	1.9%	0.0%	7.5%	53.3%	37.4%	109	4.26 ± 0.75
Proven performance through independent research	0.9%	1.8%	12.8%	36.7%	47.7%	107	4.24 ± 0.75
Availability of local support	1.8%	3.7%	17.4%	34.9%	42.2%	109	4.12 ± 0.95
Compatibility with existing dairy practices and systems	0.9%	0.0%	3.7%	31.5%	63.9%	109	4.12 ± 0.86
Time involved using the technology	0.9%	0.9%	10.1%	47.7%	40.4%	108	4.07 ± 0.88

[1]Values calculated by assigning the following values to response categories: Unimportant: 1, Of little importance: 2, Moderately important: 3, Somewhat important: 4, Important: 5.

Table 2.3. Results from a producer-based survey indicating the usefulness of potential and current parameters measured by precision dairy technologies[1]

Parameter	Response %					Responses (n)	LSMean ± SD
	Not useful	Of little usefulness	Moderately useful	Somewhat useful	Useful		
Mastitis[2]	0.0%	0.0%	1.9%	19.4%	78.7%	108	4.77 ± 0.47
Standing estrus	0.0%	0.9%	2.8%	16.5%	79.8%	109	4.75 ± 0.55
Daily milk yield	0.0%	0.9%	6.4%	11.9%	80.7%	109	4.72 ± 0.62
Cow activity	1.8%	1.8%	5.5%	16.5%	74.3%	109	4.60 ± 0.83
Temperature	3.8%	2.8%	11.3%	22.6%	59.4%	106	4.31 ± 1.04
Feeding behavior	0.9%	0.0%	15.7%	35.2%	48.1%	108	4.30 ± 0.80
Milk components (e.g. fat, protein, and SCC)	0.9%	4.6%	13.8%	27.5%	53.2%	109	4.28 ± 0.93
Lameness	0.0%	4.6%	17.4%	26.6%	51.4%	109	4.25 ± 0.90
Rumination	3.8%	3.8%	18.9%	28.3%	45.3%	106	4.08 ± 1.07
Hoof health	0.9%	3.7%	19.4%	39.8%	36.1%	108	4.06 ± 0.89
Rumen activity	4.6%	3.7%	24.1%	27.8%	39.8%	108	3.94 ± 1.10
Lying and standing behavior	2.8%	8.3%	25.7%	33.9%	29.4%	109	3.79 ± 1.05
Rumen pH	5.5%	11.0%	26.6%	29.4%	27.5%	109	3.62 ± 1.16
Jaw movement and chewing activity	4.6%	13.0%	25.9%	29.6%	26.9%	108	3.61 ± 1.15
Respiration rate	7.5%	13.2%	29.2%	32.1%	17.9%	106	3.40 ± 1.15
Body weight	8.3%	18.5%	30.6%	24.1%	18.5%	108	3.26 ± 1.20
Body condition score	9.2%	12.8%	36.7%	25.7%	15.6%	109	3.26 ± 1.15
Heart rate	11.2%	16.8%	38.3%	21.5%	12.1%	107	3.07 ± 1.15
Animal position and location	19.3%	23.9%	31.2%	13.8%	11.9%	109	2.75 ± 1.26
Methane emissions	34.3%	30.6%	20.4%	10.2%	4.6%	108	2.20 ± 1.16

[1]Values calculated by assigning the following values to response categories: Not useful: 1, Of little usefulness: 2, Moderately useful: 3, Useful: 4, Very useful: 5.

[2]Parameters associated with mastitis detection were combined due to the highly technical and variable nature of these parameters.

Table 2.4. Differences between parameters currently measured by producers' precision dairy farming technologies in different countries determined using chi-square analysis after a producer-based survey

Parameter	Other countries (n = 19)	United States (n = 90)	χ^2-value	P-value
Not applicable	15.8%	34.4%	2.5	0.11
Animal position and location	21.1%	5.6%	5.0	0.03
Body condition score	5.3%	2.2%	0.5	0.46
Body weight	42.1%	4.4%	22.7	< 0.01
Cow activity	78.9%	33.3%	13.5	< 0.01
Daily milk yield	84.2%	45.6%	9.4	< 0.01
Feeding behavior	26.3%	10.0%	3.7	0.05
Heart rate	10.5%	2.2%	3.1	0.08
Hoof health	5.3%	6.7%	0.1	0.82
Jaw movement and chewing activity	15.8%	5.6%	2.4	0.12
Lameness	10.5%	3.3%	1.9	0.17
Lying and standing behavior	26.3%	4.4%	9.9	< 0.01
Mastitis[1]	63.2%	17.8%	16.9	< 0.01
Methane emissions	5.3%	1.1%	1.5	0.22
Milk components (e.g. fat, protein, and SCC)	47.4%	20.0%	6.3	0.01
Respiration rate	0.0%	2.2%	0.4	0.51
Rumen activity	26.3%	5.6%	8.1	< 0.01
Rumen pH	0.0%	1.1%	0.2	0.64
Rumination	26.3%	6.7%	6.7	< 0.01
Standing estrus	31.6%	18.9%	1.5	0.22
Temperature	15.8%	12.2%	0.2	0.67

[1]Parameters associated with mastitis detection were combined due to the highly technical and variable nature of these parameters.

Table 2.5. Results from a producer-based survey indicating least-squares means and standard deviations of technology pre-purchase consideration importance in producer precision dairy farming technology use[1]

Item	Producers using technologies (n = 75)	Producers not using technologies (n = 34)	P-value
Benefit to cost ratio	4.57 ± 0.08	4.59 ± 0.11	0.88
Availability of local support	4.25 ± 0.11	3.82 ± 0.16	0.03
Total investment cost	4.24 ± 0.10	4.38 ± 0.14	0.41
Simplicity and ease of use	4.24 ± 0.09	4.29 ± 0.13	0.73
Proven performance through independent research	4.22 ± 0.09	4.29 ± 0.13	0.63
Time involved using the technology	4.15 ± 0.10	3.91 ± 0.15	0.20
Compatibility with existing dairy practices and systems	4.12 ± 0.10	4.12 ± 0.15	0.99

[1]Values calculated by assigning the following values to response categories: Unimportant: 1, Of little importance: 2, Moderately important: 3, Somewhat important: 4, Important: 5.

Table 2.6. Results from a producer-based survey indicating least-squares means and standard deviations for perceived parameter importance in producer precision dairy farming technology use[1]

Parameter	Producers using technologies (n = 75)	Producers not using technologies (n = 34)	P-value
Animal position and location	2.87 ± 0.14	2.50 ± 0.21	0.16
Body condition score	3.19 ± 0.13	3.41 ± 0.20	0.35
Body weight	3.23 ± 0.14	3.23 ± 0.21	0.71
Cow activity	4.61 ± 0.10	4.56 ± 0.14	0.75
Daily milk yield	4.83 ± 0.07	4.50 ± 0.10	0.01
Feeding behavior	4.28 ± 0.09	4.32 ± 0.14	0.81
Heart rate	3.08 ± 0.13	3.03 ± 0.20	0.83
Hoof health	4.04 ± 0.10	4.12 ± 0.15	0.68
Jaw movement and chewing activity	3.70 ± 0.13	3.41 ± 0.20	0.22
Lameness	4.23 ± 0.10	4.29 ± 0.16	0.72
Lying and standing behavior	3.72 ± 0.12	3.94 ± 0.18	0.31
Mastitis[2]	4.77 ± 0.05	4.76 ± 0.08	0.95
Methane emissions	2.34 ± 0.13	1.91 ± 0.20	0.08
Milk components (e.g. fat, protein, and SCC)	4.33 ± 0.11	4.15 ± 0.16	0.33
Respiration rate	3.44 ± 0.14	3.29 ± 0.20	0.53
Rumen activity	3.96 ± 0.13	3.91 ± 0.19	0.83
Rumen pH	3.71 ± 0.13	3.44 ± 0.20	0.27
Rumination	4.21 ± 0.12	3.79 ± 0.18	0.06
Standing estrus	4.68 ± 0.06	4.91 ± 0.09	0.04
Temperature	4.34 ± 0.12	4.24 ± 0.18	0.65

[1]Values calculated by assigning the following values to response categories: Not useful: 1, Of little usefulness: 2, Moderately useful: 3, Useful: 4, Very useful: 5.

[2]Parameters associated with mastitis detection were combined due to the highly technical and variable nature of these parameters.

CHAPTER THREE

Predicting impending calving using automatic measures of activity and rumination in dairy cattle

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INTRODUCTION

A smooth transition into the milking herd helps to ensure a productive subsequent lactation. Calving time may be the most stressful point in the transition period. Perinatal mortality and dystocia are the biggest parturition concerns (Mee, 2004). An evaluation of 666,341 calvings records estimated the proportion of dystocia to be 28.6% in primiparous and 10.7% in multiparous cows (Meyer et al., 2001). In the US, 19% of primiparous and 11% of multiparous cows experienced mild to severe dystocia at calving (USDA, 2010). Providing calving assistance may reduce parturition stress and improve reproductive performance in the subsequent lactation (Bellows et al., 1988). Eight percent of calvings in the United States resulted in calf perinatal mortality, with 31% of primiparous and 21% of multiparous being provided calving assistance (USDA, 2010). To prevent and reduce parturition stress, a producer must estimate when cows will calve, move cows to appropriate pens in a timely manner, monitor calving, know when and how to intervene, and maintain calf and cow health following calving (Mee, 2004).

Breeding dates and physical or behavioral cues have traditionally estimated calving time. Before calving, a dairy cow’s udder will begin to develop, the vulva will swell and loosen, and pelvic ligaments will relax (Hulsen, 2006). Using visual indicators, producers can estimate calving time, move cows as necessary, and provide necessary assistance. Early cow movement into maternity pens is necessary because movement just before or following the appearance of the amniotic sac can extend the second stage of labor (Proudfoot et al., 2013). Specialized calving pens allow producers to observe or aid parturient cows if necessary. Visually observing calving indicators requires experienced laborers and nearly constant visual observation to achieve accurate calving time estimation. Cows laboring beyond 70 min past amniotic sac appearance are at increased risk for dystocia (Schuenemann et al., 2011). During daylight hours, 52.8% of US dairy operations wait longer than 3 h between preparturient cattle inspections and this number increases to 81.3% during nighttime hours (USDA, 2010). The same behavioral and physiological changes do not occur for every cow or in a timely manner (Hofmann et al., 2006; Sendag et al., 2008). Although visual inspection methods are useful for relative calving time estimates, constant calving monitors would be useful.

Precision dairy farming technologies are an alternative to visual monitoring. Precision dairy farming is defined as, "the use of information and communication technologies for improved control of fine-scale animal and physical resource variability to optimize economic, social, and environmental dairy farm performance" (Eastwood et al., 2012). Some precision technologies have already been used in calving prediction. Continuous monitors of maternal body temperatures have been shown to decrease 48 h before a calving event (Lammoglia et al., 1997), from 39.5°C to 38.8°C (Burfeind et al., 2011). Commercially marketed temperature monitors measure dairy cattle reticulorumen temperature (DVM reticulorumen bolus, DVM Systems, LLC., Boulder, CO; MaGiiX reticulorumen bolus, MaGiiX Bolus Inc., Post Falls, ID), skin temperature (CowManager SensOor, Agis, Harmelen, Netherlands), and vaginal temperature (Vel'Phone transvaginal bolus Medria, Châteaugiron, France). Several of these technologies perform calving prediction, but unbiased accuracy evaluation is still needed.

Vaginally inserted technologies expelled at the beginning of the second stage of labor, have also quantified calving events with relative accuracy. These technologies are commonly expelled when fetal membranes rupture, the amniotic sac enters the birth canal, or when the calf enters the birth canal. Sensors then create an alert that can be sent to producers. Palombi et al. (2013) described a system correctly identifying all of over 592 calvings, with 68.9% of fetuses being presented within (mean ± SD) 15 ± 5 min of the alarm. Pedometers and accelerometers have previously been adapted for dairy cattle use (Farris, 1954; Kiddy, 1977). Traditionally, these units have been used to characterize activity changes shown to increase around estrus events (Farris, 1954) and can be used in estrus detection (Kiddy, 1977). Several behavioral monitoring technologies also manage cow and herd health (Rutten et al., 2013; Van Hertem et al., 2013). Technologies quantifying behavioral changes may be an alternative for calving detection. Prepartum dairy cattle decrease feeding and ruminating behaviors (Huzzey et al., 2005; Schirmann et al., 2013). Using precision dairy technologies, Schirmann et al. (2013) showed preparturient dairy cattle decrease rumination by 63 ± 30 min/24 h and feeding behavior by 66 ± 16 min/24 h on the day before calving. Prepartum dairy cow lying and standing behavior also changes (Huzzey et al., 2005; Miedema et al., 2011b; Jensen, 2012), with lying bout frequency increasing (16.4 ± 4.8 bouts/d before calving vs. 24.2 ± 6.8 bouts/d at calving) and lying duration decreasing (13.6 ± 1.8 h/d before calving vs. 12.6 ± 1.8 h/d on the day of calving; Miedema et al., 2011). Standing bouts increased before calving from 11.7 ± 1.07 bouts/d before calving to 17.3 ± 1.08 bouts/d ($P < 0.01$) on the day of calving (Huzzey et al., 2005). Many of the behavioral changes around calving have the potential or already have been used in calving prediction. Adding calving time prediction to existing behavioral monitors would provide additional technology uses without necessity of additional measurements. This could increase producer technology usefulness and perception, potentially influencing technology adoption decisions (Borchers and Bewley, 2014).

The objective of this study was to quantify lying behavior, activity, and rumination before calving and establish methods for detecting and predicting calving events using these parameters individually or in combination.

MATERIALS AND METHODS

Data collection for 20 primiparous and 37 multiparous prepartum Holstein dairy cattle occurred from September 13, 2011 through May 16, 2013 at the University of Kentucky Coldstream Dairy (IACUC Protocol Number: 2010-0776). Prepartum cattle were housed in a 9.15 x 21.34 m straw bedded-pack with constant access to 3.64 hectares of pasture. A total mixed ration was delivered once daily. Behavior was quantified using two commercially available technologies. Technologies were fitted to each cow before the previous lactation and data were collected through cow dry periods. The HR Tag (SCR Engineers, Ltd., Israel) was used to automatically collect neck activity and rumination data in 2 h time increments using a 3-axis accelerometer and a microphone with microprocessor, respectively. The IceQube (IceRobotics, Ltd., Scotland) collected number of steps, time spent lying, number of lying bouts, and total motion data in 15 min time blocks using a 3-axis accelerometer. Data from both technologies were summed by day and 2 h time blocks for analyses. One month of prepartum behavioral data were used in analyses because all cows had been moved to the dry pen by this time.

On the day of calving, farm staff recorded each cow’s identification number, calving date, calving time, and parity. Cows visually recognized as laboring with visual fetal membranes or feet protruding from their vulva, were sorted into the bedded pack area until calving. Need for assistance in the birthing process was assessed and provided by the farm manager. Because all bihourly blocks began on evenly numbered hours, calving times were adjusted to the previous complete bihourly time block before calving events. Calf expulsion time was used to retrospectively generate the cow-specific number of hours before calving, similar to the methods of Schirmann et al. (2013) where cows were compared by the number of hours before their individual calving events.

Statistical analysis

Least-squares means of neck activity, rumination, and lying behavior parameters by both 2 h time block and day (for 21 d) were calculated using the MIXED procedure of SAS. Daily data for step number and total motion, and bihourly data for neck activity, total motion, and step were transformed using a natural logarithm. This was performed to meet normal distribution assumptions and was assessed through visual inspections of residual frequency distributions. Prepartum cows with incomplete data sets, or providing influential outliers, were removed from the study. The remaining dairy cattle (15 primiparous and 31 multiparous; n = 46) were used in further analysis.

Parameter daily least-squares means were calculated with parity (primiparous or multiparous) and day before calving serving as fixed effects; and cow serving as a repeated subject for all parameters. Days were described as the 24 h immediately before calving (**Day0**), 48 h before calving, (**Day-1**), 72 h before calving **(Day-2**), 96 h before calving (**Day-3**), 120 h before calving (**Day-4**), 144 h before calving (**Day-5**), 170 h before calving (**Day-6**), and 194 h before calving (**Day-7**). Significance was defined at $P < 0.05$. Bihourly least-squares means' fixed effects included parity (primiparous or multiparous), time block (12:00 AM to 11:59 PM by 2 h blocks), and hour before calving. Cow served as a repeated subject. All two-way interactions were tested and non-significant ($P \geq 0.05$) interactions were removed using backwards stepwise elimination. All main effects were included in final models regardless of significance. Residuals plots were used to verify favorable variance distributions and to detect possible influential data outliers for each parameter.

Algorithm Development

Machine-learning techniques were applied to the data sets to predict calving. The three machine learning techniques used for calving prediction were random forest, linear discriminant analysis, and neural network analysis. The random forest method is based on decision tree classification methods and develops a group of tree-structured classifications algorithm. Each tree contributes an opinion of how the data should be classified (Breiman, 2001; Bishop, 2006; Shahinfar et al., 2014). Linear discriminant analysis is similar to analysis of variance and regression methods, but uses a categorical dependent variable, and several continuous independent variables (McLachlan, 2004; Wetcher-Hendricks, 2011). Neural networks imitate the structure and function of the human brain, simulating human intelligence, leaning independently and quickly, adapting continuously, and applying inductive reasoning to process knowledge (Zahedi, 1991; Krieter et al., 2006). In animal sciences, neural networks are the most frequently used machine learning method (Shahinfar et al., 2014).

Machine-learning techniques were applied to 21 d of prepartum behavioral data before calving events (n = 46). For calving prediction, the outcome variable was if the cow calved on that day (0, calved or 1, did not calve). Parity and all available behavioral parameters monitored by the IceQube, HR Tag and standing behavior (inverse of lying behavior) were used to predict calving events alone or combined. Eighty percent of data were used as "training" set to train the algorithm, while the remaining 20% data were used to evaluate the performance of the algorithms. A 4-fold, leave-one-out cross-validation method, including 10 analyses per series, was also performed for each machine learning method to tune the algorithm in the training phase. Trained algorithms were used to predict calving events using the testing dataset in the testing phase. True positives (correctly predicted calving day), false positives (incorrectly predicted calving day), true negatives (no alert and not calving day), and false negatives (no alert and calving day) were compiled and the sensitivity, specificity, positive predictive value, and negative predictive values were calculated to evaluate the performance of different machine learning techniques and technology. All analyses were constructed and implemented using <caret> package in R version 3.1.0 (R Foundation for Statistical Computing, Vienna, Austria).

RESULTS AND DISCUSSION

Daily and bihourly behavioral changes are presented in Figure 3.1 and Figure 3.2, respectively. Two-way interactions by time of day and cow parity were significant ($P <$ 0.05) for neck activity, rumination, lying time, and total motion mixed models (Figure 3.3). Parity has been shown to affect behavioral patterns (Wehrend et al., 2006; Jensen, 2012), and similar results were shown in the current study.

Time spent ruminating was significantly lower on the day of calving compared to the 7 d before. From 10 h to 6 h before calving, rumination decreased from 20.8 ± 2.7 min/2 h time block, to 8.9 ± 2.7 min/2 h time block; a decrease of nearly 57% over 4 h. Schirmann et al. (2013) observed similar results with a 63 ± 30 min/24 h difference between the day of calving and a 2 d average rumination baseline value.

Lying bouts increased significantly on the day of calving compared to the day before calving. Lying bouts also increased between 12 h before calving and 2 h before calving, from 1.3 ± 0.2 bouts/2 h to 2.4 ± 0.2 bouts/2 h. The 2 h block just before calving significantly increased in the number of bouts compared to the 4 h before calving (3.0 ±

0.2 bouts 0 h vs. 1.8 ± 0.2 bouts 4 h). Over this same period Jensen (2012) showed bouts per hour to increase from 0.83 bouts/h 12 h before calving, to 2.79 bouts/h 2 h before calving. Miedema et al. (2011b) showed lying bout frequency to increase between a randomly selected control from the dry period and the calving period (16.4 ± 4.8 vs. 24.2 ± 6.8 bouts/24 h) and similar results were observed by Jensen (2012) and Huzzey et al. (2005).

In addition to an increase in the number of lying bouts, lying time decreased gradually over several days. Jensen (2012) showed a gradual decrease in the number of daily minutes lying from 998 min/d, 4 d before calving, to 970 min/d, 2 d before calving. A significant decrease in lying time occurred the day before calving. This finding is counterintuitive to the findings of bihourly least-squares means in the current study. As calving time approached, minutes lying became variable between subsequent bihourly blocks (Figure 3.2d.). In an hourly analysis by (Jensen, 2012) minutes spent lying per hour on the day of calving increased from 12 h before calving (31.4 min) to 2 h before calving (42.8 min), but daily data decreased. The changes between 2 h blocks and the total magnitude of this decrease in lying time decreases may negate the increase observed in the final 12 h before calving. When viewed in combination with rumination time, a decrease in both lying time and rumination occurs 6 h before calving. As lying time increases leading into calving events, rumination increased. Schirmann et al. (2012) previously found an association between lying time and rumination with cows ruminating more when lying. This suggests a link between rumination and lying time may exist.

Comparisons between daily and bihourly data indicate many activity parameters (neck activity, step number, and total motion) differ in the hours before parturition, but these were not significant. Differences in activity have previously been found in prepartum dairy cattle. Miedema et al. (2011b) found walking duration increased from randomly selected control periods during the dry period to the calving period (21.0 ± 7.4 vs. 31.5 ± 13.1 min; $P < 0.01$) and Jensen (2012) observed an increase in activity beginning 6 h before calving ($F_{11,209} = 5.46$; $P < 0.001$). While these events may show large variation between hour blocks, they were consistently non-significant. Daily data summation offsets variation between 2 h blocks, making behavioral changes non-significant.

Changes in daily time blocks were significant for several parameters (rumination, lying bouts, lying time). Daily time blocks significantly differed on the day of calving for lying bouts and rumination, but lying time decreased gradually during the days before calving. More frequent preparturient cattle inspection is best (Dargatz et al., 2004) and smaller time blocks would produce more valuable and productive alerts for producers.

Machine-learning Analyses

Calving prediction performance by technology and data analysis technique is shown in Table 3.1. Machine-learning techniques performed best when parameters from the HR Tag and IceQube were combined. The most ideal calving prediction results were obtained in the combined parameter neural network analysis with a sensitivity of 100.0%, a specificity of 96.5%, a positive predictive value of 60.0%, and a negative predictive value of 100.0%. Positive predictive values were far below specificity values, indicating a high number of false positives. These findings can be attributed to the large number of days potentially serving as false positives or true negatives. The number of true negatives generated offset the false positives in specificity calculation. This was apparent in the calculation of the positive predictive value where the small number of true positives was not able to offset the number of false positives, leading to a low negative predictive value.

Parameter combinations in calving prediction have previously been applied to data generated from existing behavioral monitors. Maltz and Antler (2007) described calving prediction methods using changes in daily step number, lying behavior, and number of times passing into a feeding area for 12 cows over 7 d. Their method achieved a sensitivity of 83.3% and a specificity of 95.2%. When considered alone, the HR Tag produced a lower sensitivity or specificity than their method (random forest: sensitivity = 55.6%, specificity = 91.8%; linear discriminant analysis: sensitivity = 77.8%, specificity = 88.8%; neural network: sensitivity = 44.4%, specificity = 95.3%), but the IceQube and a combination of the two technologies exceeded the findings of Maltz and Antler (2007).

While results are promising, few technologies monitor rumination, lying behavior, and activity in combination. Measuring both rumination and lying time using one technology is difficult. A two-technology calving prediction approach, similar to the current study's methods, may be more useful in calving prediction. In the absence of a two technology calving prediction approach, results indicate ankle-mounted accelerometers characterizing activity and lying behavior as viable alternatives. The IceQube sensor effectively predicted calvings in the random forest analysis with a sensitivity of 88.9%, a specificity of 98.2%, a positive predictive value of 72.7%, and a negative predictive value of 99.4%. For future machine-learning calving prediction techniques, in the absence of activity, lying and standing behavior, and rumination parameters in combination, technologies similar to the IceQube may be the best option in behavior-based calving prediction

Most machine-learning research has been applied for mastitis and estrus detection (Firk et al., 2003; Cavero et al., 2008; Sun et al., 2010). To the knowledge of the authors, no known technologies use machine-learning techniques in alert creation. Machine-learning techniques have difficulty performing in commercial settings as they must be "taught" using existing data. Using data to teach these techniques could lead to more accurate and farm-specific event prediction for not only calving prediction, but health and estrus detection as well. Future work will need to establish machine-learning technique validity in a commercial setting for alert improvement. Another important change technologies would have to make in order to use machine-learning methods is automatic data transfer. In this study, handheld readers were required to collect data, which prevents constant data interpretation. However, newer versions of these technologies constantly collect data.

Bihourly Prediction Methods Discussion

Bihourly prediction methods would be preferable over daily methods for calving prediction, but this was not used in the current study. The machine learning techniques used in this study compared 21 d of data to predict the day of calving. A similar analysis using bihourly data would need to compare 264 hourly periods to predict calving, which was not feasible using the current methods.

A bihourly analysis would also encounter issues with sensitivity and specificity. This is because sensitivity and specificity are inversely related and if an alert threshold is increased or decreased to make a respectively more specific or sensitive test, the specificity and sensitivity will proportionally and inversely change (Hogeveen et al., 2010). Larger specificity values have traditionally been more valued in estrus and health detection using precision dairy farming technologies (ISO, 2007; Hogeveen et al., 2010;

Rutten et al., 2013); however, this may not be as useful in calving prediction. False negatives in calving prediction would be instances where systems do not detect actual calving events. The consequences of missed calving events could be extremely detrimental (stillbirth, dead cow, etc.). Accordingly, more emphasis on increasing the percentage of correctly predicted calving events would be of benefit. In animal illness detection false positives (type I errors) can cause financial losses through unnecessary treatment (Burfeind et al., 2010). The same is true for calving detection, but this loss would be in the form of labor needed to physically check on potentially laboring animals. Alternatively, a false negative (type II error) leaves sick animals untreated because they are not detected (Burfeind et al., 2010). In calving prediction, the potential losses associated with missed calving may outweigh losses associated with false alerts and future prediction methods should weigh this consideration.

Calving alerts generated from shorter time frames may have potential to reduce disease incidence and stress in parturient cows. Calving alerts providing more preparation time before calving would be especially beneficial. Moving cows before the appearance of the amniotic sac (Proudfoot et al., 2013) and allowing them to occupy secluded areas (Proudfoot et al., 2014) would place less stress on parturient cows. Additionally, high producing and lame dairy cattle supplemented with calcium at calving have experienced a reduction in hypocalcemia incidence (Oetzel and Miller, 2012). Supplementing calcium to these cows after calving alerts and before calving, may allow for further disease incidence reductions. Labor pain reduction may be another benefit of timely calving alerts. Treating parturient dairy cattle with NSAIDs during the calving process has been theorized to help alleviate labor pain (Newby et al., 2013).

Dystocia is a major calving concern (Mee, 2004) and dystocial calving prediction may be possible. Proudfoot et al. (2009) showed cows experiencing dystocia to be more restless 24 h before calving than eutocial cows. Including calving ease evaluations in future machine learning techniques may allow models to discern between dystocial and eutocial calvings. Farm staff did not record accurate calving ease indications in this study, so they were not included in machine learning analyses. Additionally, 46 calvings were used in the final machine learning analyses and only a fraction of these would experience dystocia. Machine learning techniques will need enough calving data from cows experiencing dystocia to obtain potential for accurate prediction. More research is required to determine if cows experiencing dystocia can be identified using precision dairy farming technologies.

CONCLUSIONS

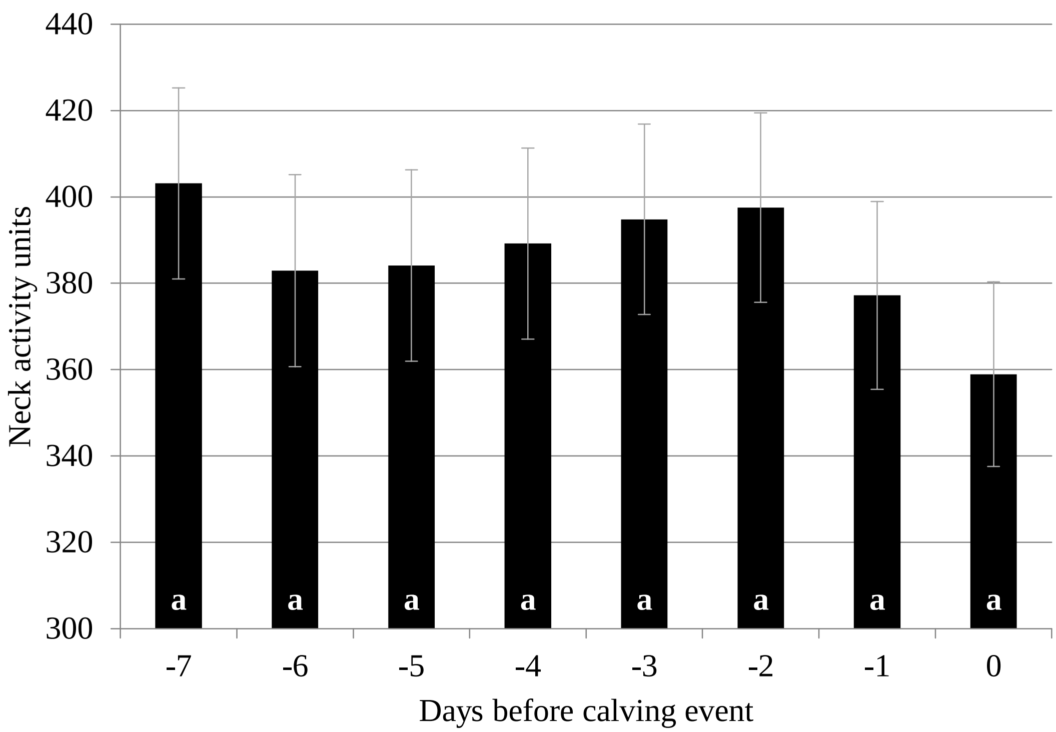
Behavior-based prepartum dairy cattle monitoring can provide additional uses for automated technologies already used to generate health and estrus alerts. Lying and rumination behavior differed most by day relative to calving and the application of these and activity parameters to machine learning techniques provided promising calving prediction results from daily data. In absence of rumination behavior, lying time and lying bout data could accurately predict calving events using random forest, machine-learning techniques. To maximize calving prediction alert usefulness, future studies will need to focus on shortening data reporting timeframes to provide more timely calving alerts.

ACKNOWLEDGEMENTS

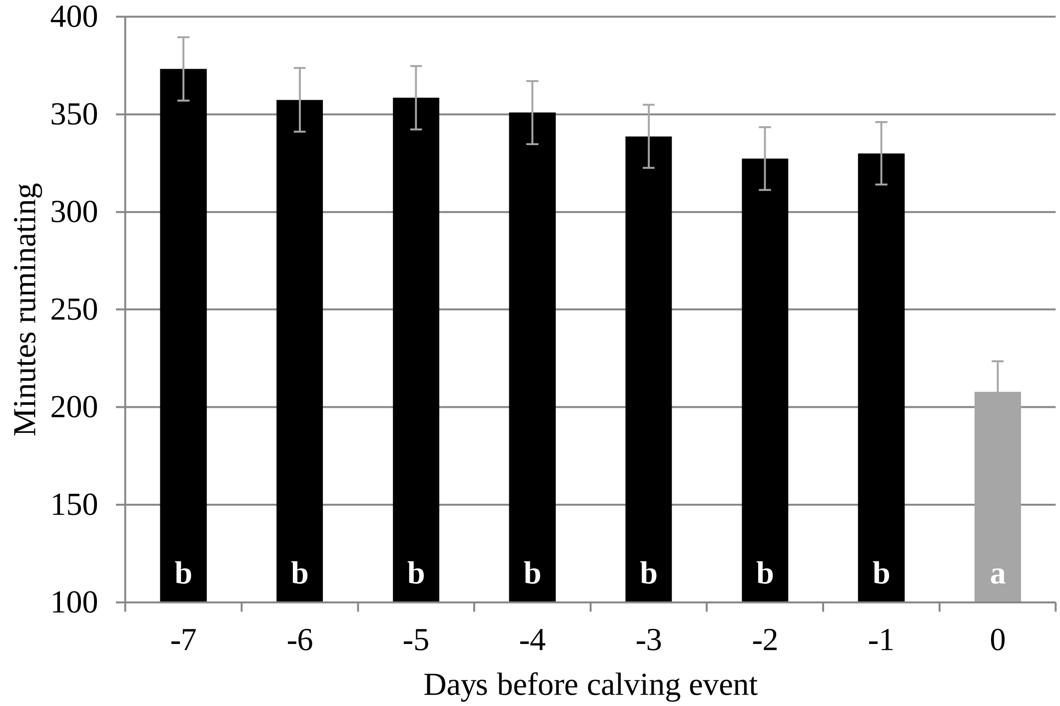
The authors would like to thank Joey Clark, Denise Ray, and the UK Coldstream Dairy Staff for collecting calving data.

Figure 3.1. Results of a study examining **a)** neck activity (measured by the HR Tag; SCR Engineers, Ltd., Israel, **b)** rumination (measured by the HR Tag), **c)** natural logarithm of step number (measured by the IceQube sensor; IceRobotics, Ltd., Scotland), **d)** total motion units (measured by the IceQube), **e)** total hours lying (measured by the IceQube sensor), and **f)** lying bouts (measured by the IceQube sensor) in least-squares means by day before calving in prepartum dairy cattle (n = 46 calvings).[1]

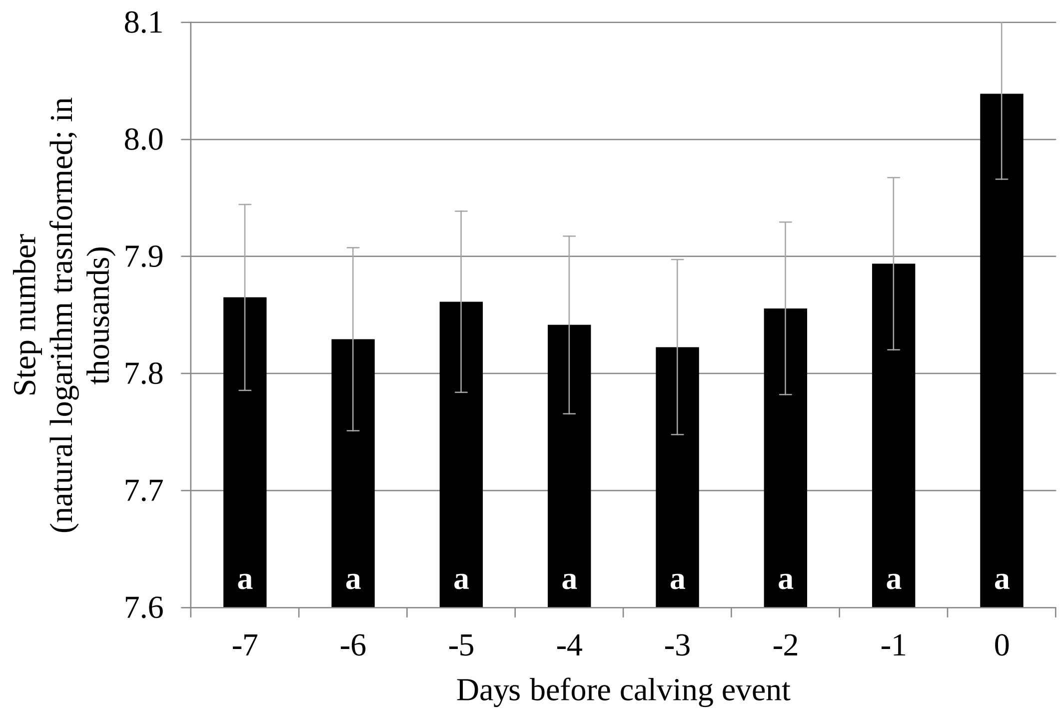
a)



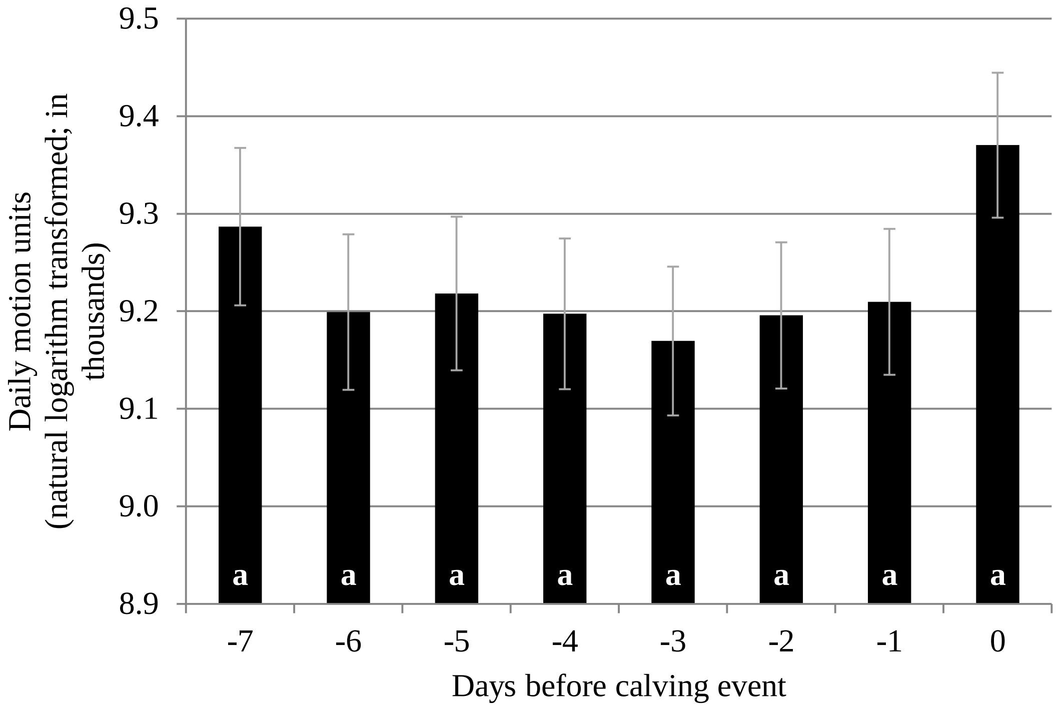
b)


400
350
300
250
200
150
100
Minutes ruminating
b
b
b
b
b
b
b
a
-7
-6
-5
-4
-3
-2
-1
0
Days before calving event

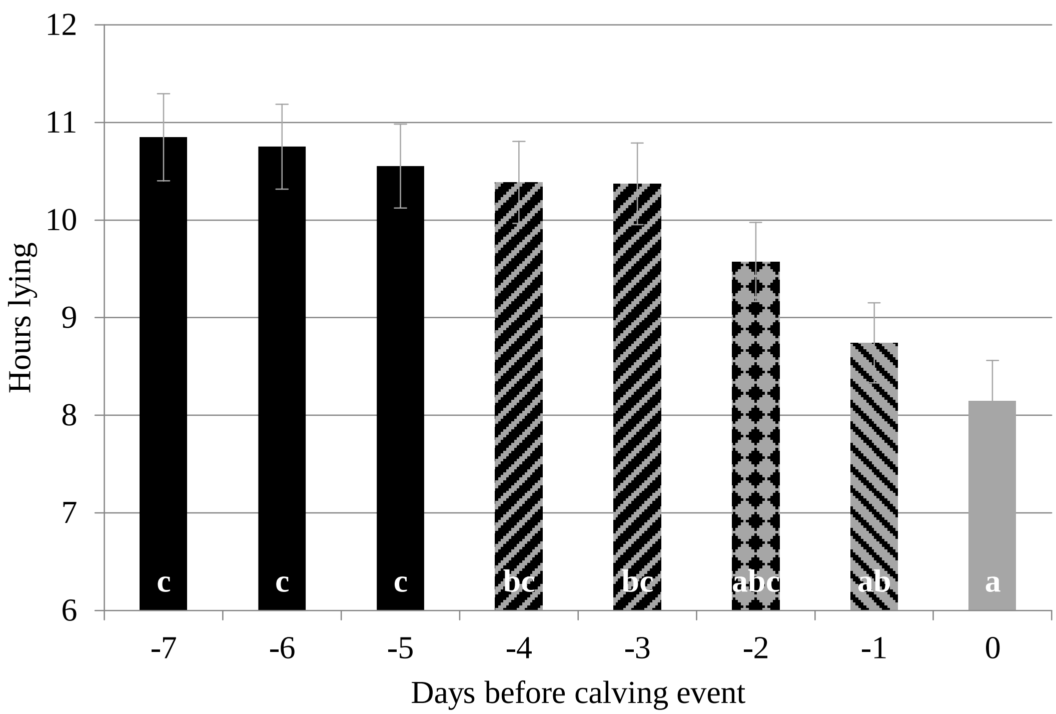
c)


8.1
8.0
7.9
7.8
7.7
7.6
Step number
(natural logarithm trasnformed; in thousands)
a
a
a
a
a
a
a
a
-7
-6
-5
-4
-3
-2
-1
0
Days before calving event

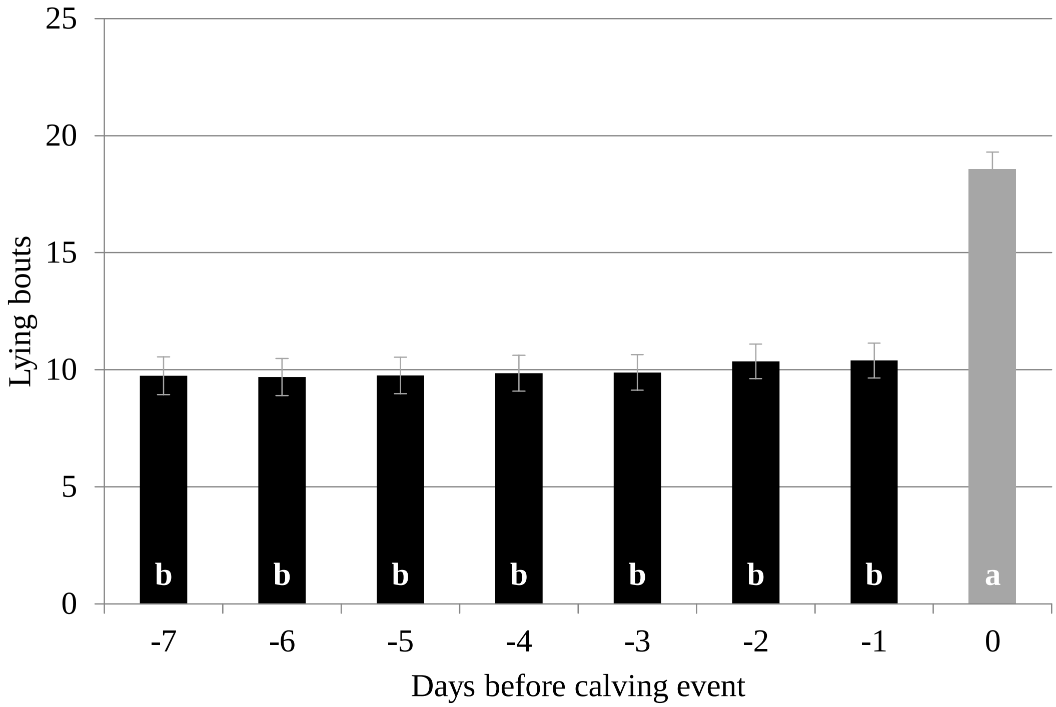
d)


9.5
9.4
9.3
9.2
9.1
9.0
8.9
Daily motion units
(natural logarithm transformed; in thousands)
a
a
a
a
a
a
a
a
-7
-6
-5
-4
-3
-2
-1
0
Days before calving event

e)


12
11
10
9
8
7
6
Hours lying
c
c
c
bc
bc
abc
ab
a
-7
-6
-5
-4
-3
-2
-1
0
Days before calving event

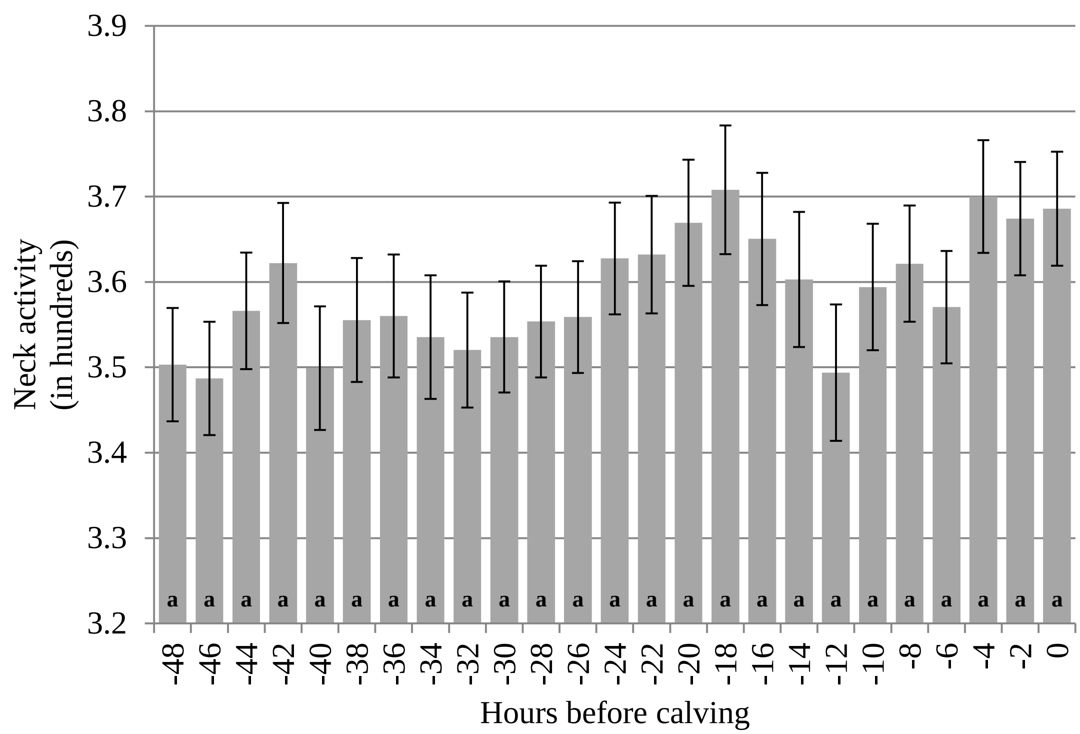
f)



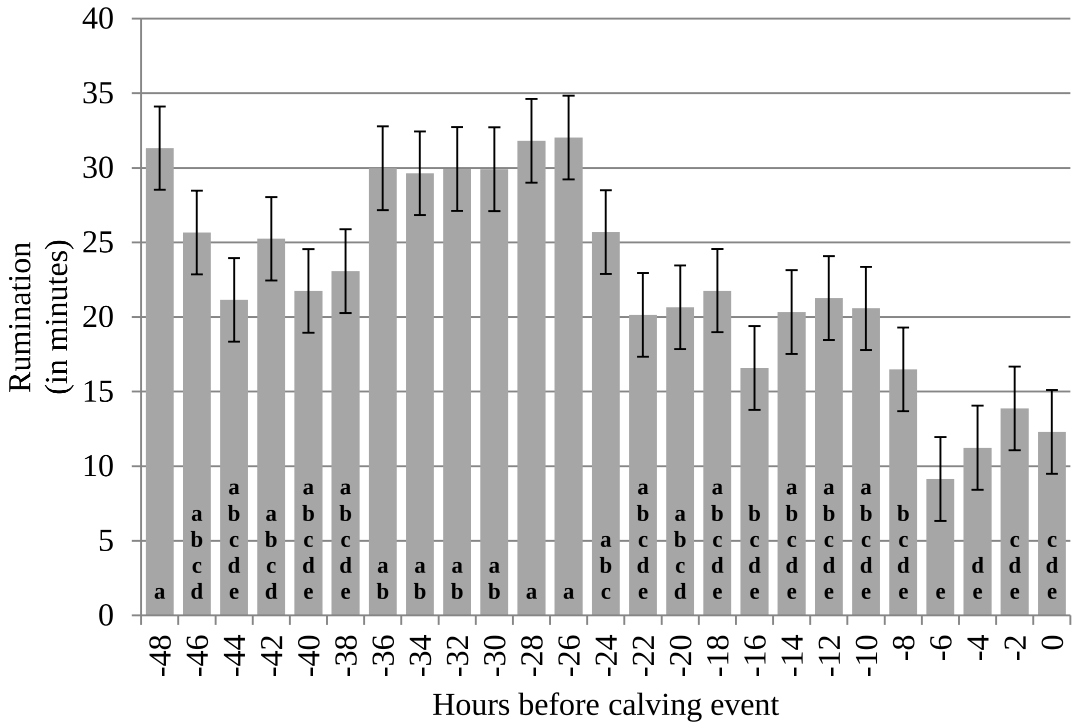
[1]Columns displaying differing letters are significantly different ($P < 0.05$).

Figure 3.2. Results of a study examining least-squares means of **a)** natural logarithm of activity (measured by the HR Tag; SCR Engineers, Ltd., Israel), **b)** rumination (measured by the HR Tag), **c)** natural logarithm of step number (measured by the IceQube sensor; IceRobotics, Ltd., Scotland), **d)** natural logarithm of total motion units (measured by the IceQube), **e)** total hours spent lying (measured by the IceQube sensor), and **f)** lying bouts (measured by the IceQube sensor) by hour before calving events in prepartum dairy cattle (n = 46 calvings).[1]

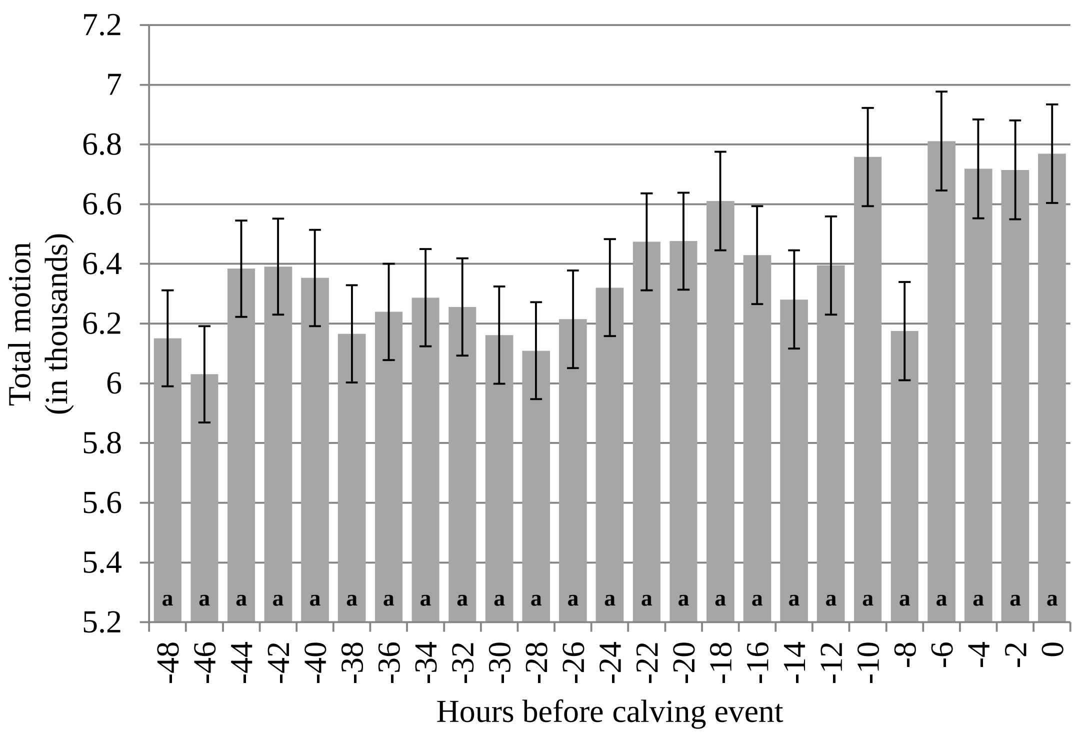
a)



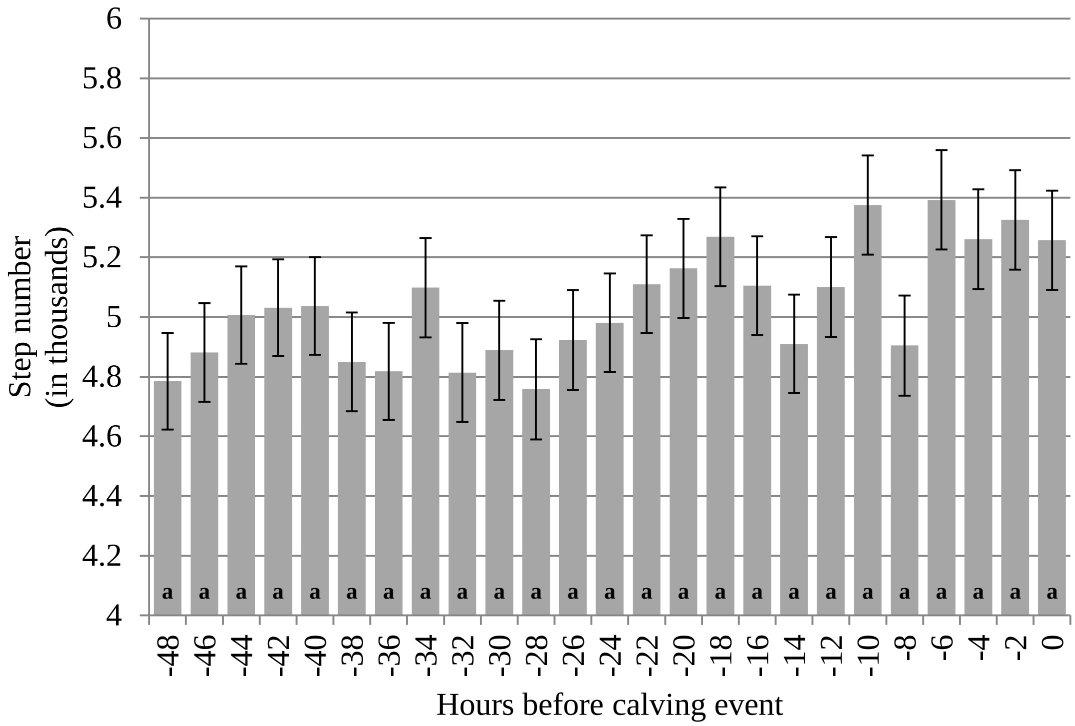
b)


Rumination
(in minutes)
Hours before calving event
40
35
30
25
20
15
10
5
0
-48
-46
-44
-42
-40
-38
-36
-34
-32
-30
-28
-26
-24
-22
-20
-18
-16
-14
-12
-10
-8
-6
-4
-2
0

c)

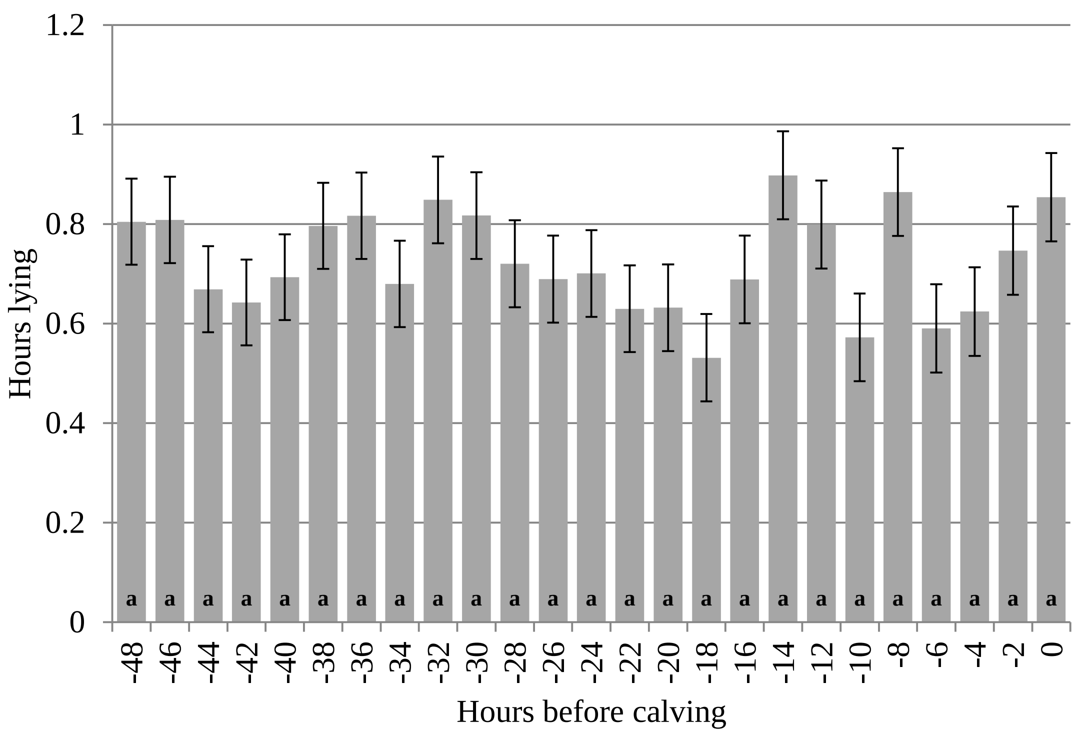

Total motion
(in thousands)
Hours before calving event
7.2
7
6.8
6.6
6.4
6.2
6
5.8
5.6
5.4
5.2
-48
-46
-44
-42
-40
-38
-36
-34
-32
-30
-28
-26
-24
-22
-20
-18
-16
-14
-12
-10
-8
-6
-4
-2
0

d)



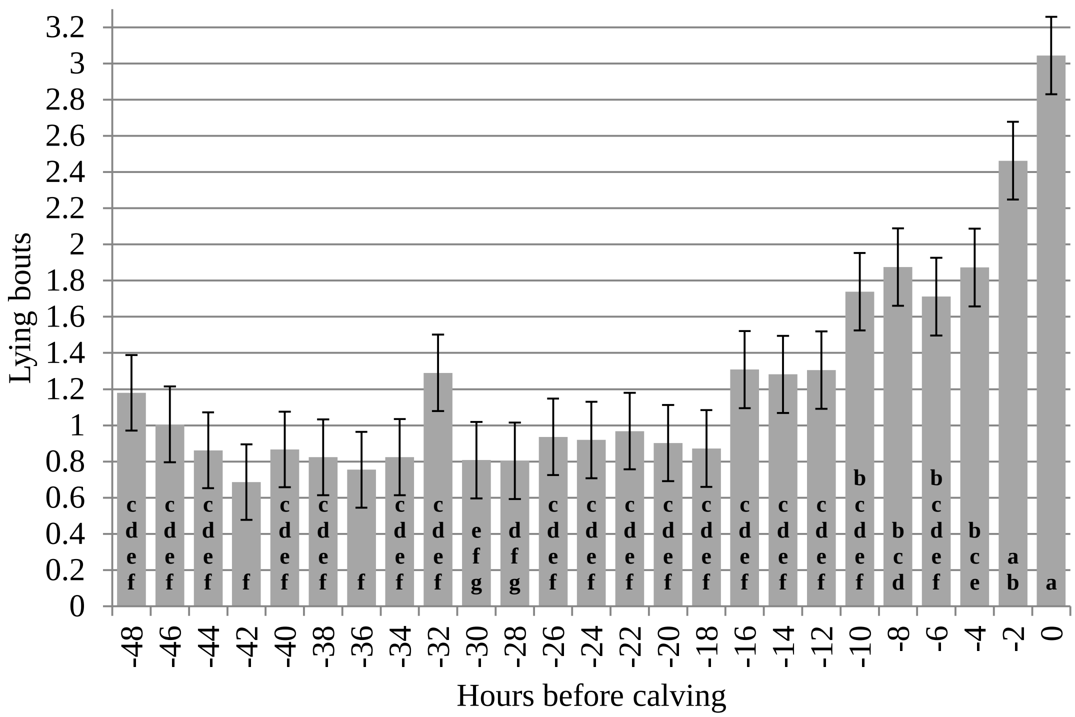
Step number
(in thousands)
6
5.8
5.6
5.4
5.2
5
4.8
4.6
4.4
4.2
4
a a a a a a a a a a a a a a a a a a a a a a a a a
-48 -46 -44 -42 -40 -38 -36 -34 -32 -30 -28 -26 -24 -22 -20 -18 -16 -14 -12 -10 -8 -6 -4 -2 0
Hours before calving event

e)



Hours lying
1.2
1
0.8
0.6
0.4
0.2
0
a a a a a a a a a a a a a a a a a a a a a a a a a
-48 -46 -44 -42 -40 -38 -36 -34 -32 -30 -28 -26 -24 -22 -20 -18 -16 -14 -12 -10 -8 -6 -4 -2 0
Hours before calving

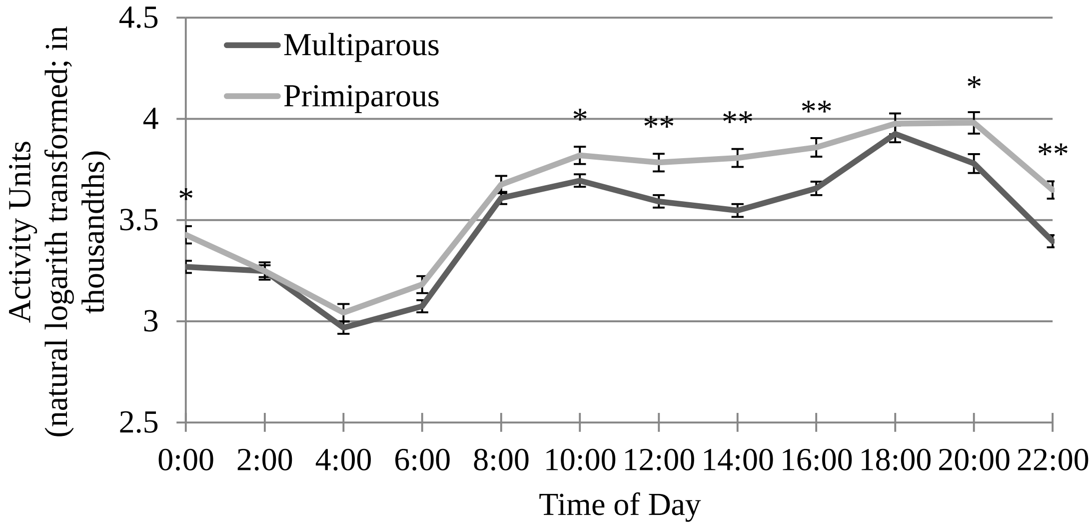
f)



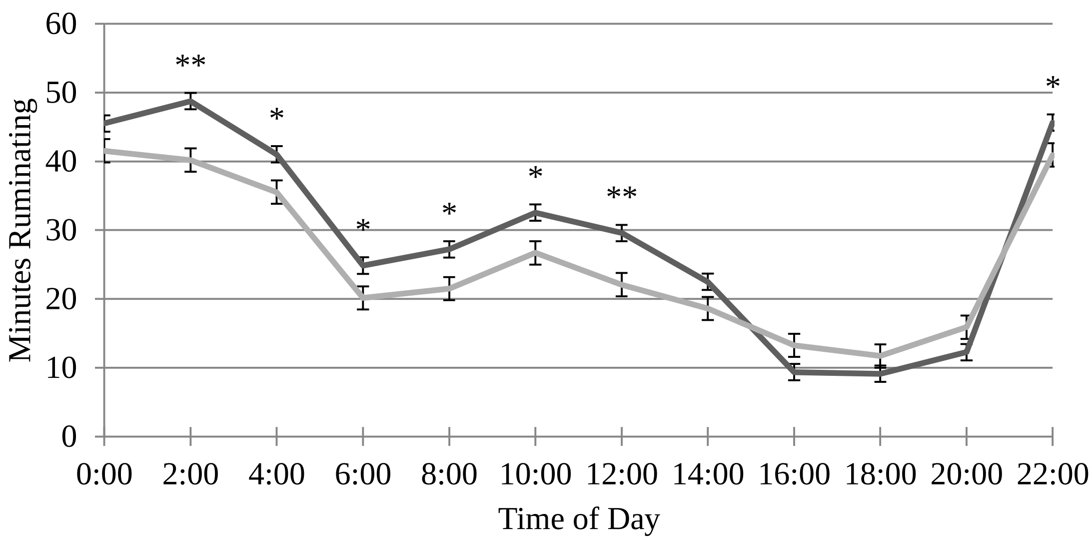
[1]Columns displaying different letters are significantly different ($P < 0.05$).

Figure 3.3. Results showing two-way interactions of the time of day and parity (primiparous or multiparous) on the least-squares means of **a)** neck activity (measured by the HR Tag; SCR Engineers, Ltd., Israel, **b)** rumination (measured by the HR Tag), **c)** total motion units (measured by the IceQube), and **e)** total hours lying (measured by the IceQube sensor) in prepartum dairy cattle (n = 46 calvings).[1]

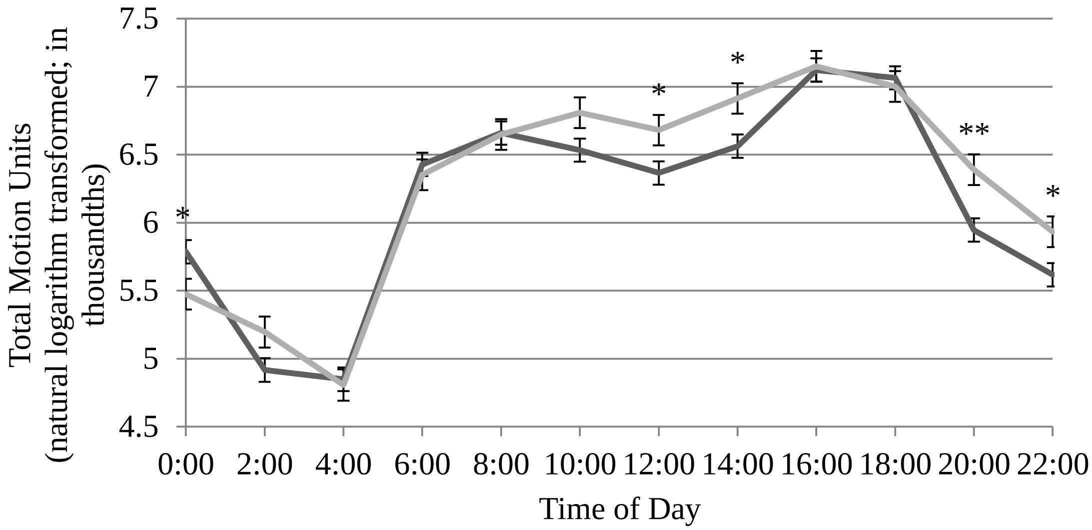
a)



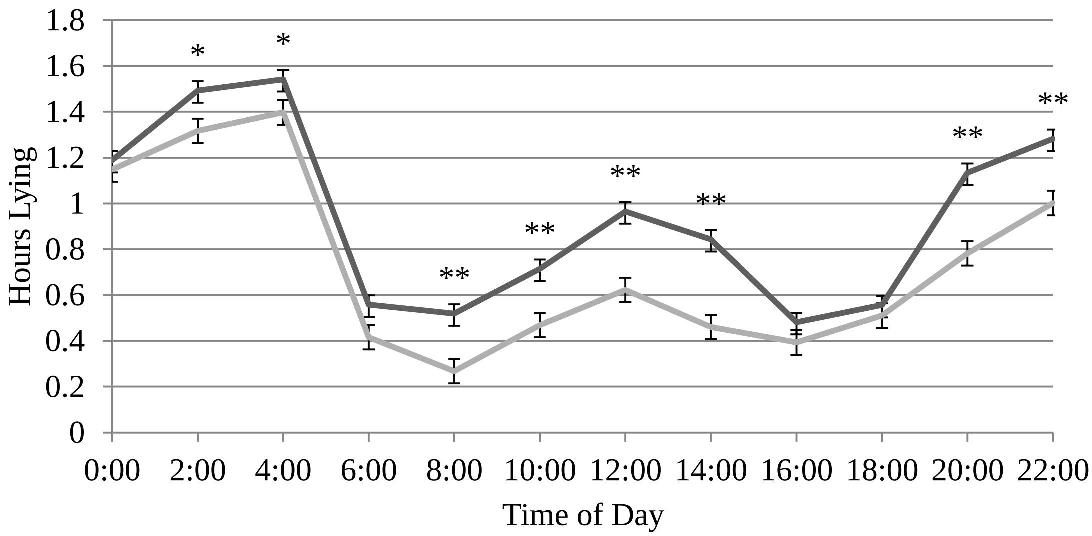
b)



c)



d)



*Denotes significance at *P < 0.05, **P < 0.01.

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Table 3.1. Results of machine-learning techniques applied to behavioral data from the HR Tag (SCR Engineers, Ltd., Israel; neck activity and rumination) and IceQube sensor (IceRobotics, Ltd., Scotland; lying bouts, lying time, standing time, step number, and total motion) for 21 d of daily prepartum behavioral data (n = 46).[1]

Analysis	Technology	Sensitivity	Specificity	Positive predictive value	Negative predictive value
Random forest	HR Tag	44.4%	95.3%	33.3%	97.0%
	IceQube	88.90	98.2%	72.7%	99.4%
	Combination[2]	88.9%	98.2%	72.7%	99.4%
Linear discriminant analysis	HR Tag	77.8%	88.8%	26.9%	98.7%
	IceQube	77.8%	98.2%	70.0%	98.8%
	Combination[2]	77.8%	97.6%	63.6%	98.8%
Neural network	HR Tag	55.6%	91.8%	26.3%	97.5%
	IceQube	88.9%	93.5%	42.1%	99.4%
	Combination[2]	100.0%	96.5%	60.0%	100.0%

[1]Sensitivity = TP / (TP + FN) x 100, specificity = TN / (TN + FP) x 100, positive predictive value = TP / (TP + FP) x 100, negative predictive value = TN / (TN + FN) x 100; where TP = true positive, TN = true negative, FP = false positive, and FN = false negative

[2]Parameters from both the HR Tag and the IceQube were used in combination analyses.

CHAPTER FOUR

A technical evaluation of rumination, feeding behavior, and lying behavior monitored by various precision dairy farming technologies

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INTRODUCTION

Dairy producers purchase precision dairy farming technologies to improve individual animal management, group or pen management, whole-farm management, and overall farm production efficiency (Wathes et al., 2008). Many precision dairy farming technologies classify udder, estrus, feet and leg, and metabolic health (Rutten et al., 2013). Technologies have the ability to monitor dairy cattle without disturbing their natural behavior, providing indications of animal welfare (Müller and Schrader, 2003). Additionally, technologies can reduce specialized labor needs, or change labor focus so fewer laborers accomplish more work (Frost et al., 1997). For precision dairy farming technologies to be viable management or labor alternatives, they must accurately and easily describe physiological or behavioral parameters.

One parameter that can be monitored by technologies is feeding behavior (González et al., 2008). Chewing and ruminating activity changes can also be used to monitor individual cow or herd health changes or to make ration adjustments (Zehner et al., 2012). Feeding behavior and rumination have traditionally been monitored through labor-intensive visual observation or video recording methods in both research and farm settings (Schirmann et al., 2009). Both methods are time consuming and impractical for dairy farmers. Additionally, tracking behavior using visual observation is subjective and open to observer interpretation (Weary et al., 2009). Monitoring rumination and feeding behavior with precision dairy farming technologies could remove observer subjectivity.

Feeding behavior and rumination have been quantified using chewing activity (pressure and strain recorders) monitors (Beauchemin et al., 1989; Kononoff et al., 2002; Zehner et al., 2012). Beauchemin et al. (1989) and Zehner et al. (2012) evaluated similar technologies using visual or video observations. These technologies performed similarly for rumination quantification and were shown to be effective. Beauchemin et al. (1989) and Zehner et al. (2012) also evaluated feeding time using these same technologies and found similar agreement with visual observation. In contrast, Kononoff et al. (2002) used a similar technology and found significant differences between observed rumination time and recorded rumination time, but no significant differences between observed feeding time and recorded feeding time. Technologies describing when cows approach feeding areas and eat have been highly correlated to visual methods (DeVries et al., 2003; Chapinal et al., 2007). Chewing activity (strain and pressure), and feeding behavior monitors are primarily used in research settings, but commercially available rumination and feeding behavior quantification methods have also been evaluated. Bikker et al. (2014) evaluated a technology monitoring rumination and feeding behavior through head movement and found a high correlation for rumination and feeding time. Schirmann et al. (2009) evaluated a technology quantifying rumination sounds through a microphone and microprocessor and found a high correlation between visual observations and the technology.

Time spent lying (Haley et al., 2000), and the laterality of lying behavior (Tucker et al., 2009) can indicate cow comfort, welfare, and health changes. Proudfoot et al. (2014) found sick or ill cattle spent more time lying apart from the herd. Lying behavior is another parameter that has been quantified using precision dairy farming technologies (McGowan et al., 2007; O'Driscoll et al., 2008; Ledgerwood et al., 2010). Compared to other parameters measured by precision dairy farming technologies (e.g. feeding behavior, rumination, and activity), standing and lying events are easily visually monitored. Monitoring these parameters using precision dairy farming technologies may be an alternative (Bonk et al., 2013).

Studies previously evaluating lying behavior have reported high correlations between technologies and visual or video monitoring. The HOBO Data Logger (HOBO Pendant G Acceleration Data Logger, Onset Computer Corporation, Pocasset, MA) showed a high level of agreement with video monitoring ($\kappa = 0.96$; O'Driscoll et al., 2008). The Afi Pedometer Plus (afimilk, S.A.E. AFIKIM, Kibbutz Afikim, Israel; Mattachini et al., 2013a) and the IceTag (IceRobotics Ltd, Edinburgh, Scotland; Mattachini et al., 2013b) technologies recording dairy cow lying behavior have shown high agreement with video monitoring. Similar methods quantifying behavior in sheep (Champion et al., 1997), goats (Zobel et al., 2014), and dairy calves (Bonk et al., 2013) have shown data loggers to effectively characterize lying and standing behavior in other species as well.

Behavioral recording methods have rarely been compared on the same animals over the same periods of time. The objective of the current study was to evaluate multiple technologies characterizing dairy cattle feeding, rumination, and lying behaviors against direct visual observations on the same cows.

MATERIALS AND METHODS

This study was conducted at the University of Kentucky Coldstream Dairy Research Farm under Institutional Animal Care and Use Committee protocol number 2014-1309. All cows were housed in two groups separated by a shared, raised feedbunk with a conveyer feed delivery system. A TMR ration containing corn silage, alfalfa silage, whole cottonseed, and grain mix was delivered 2X at 0530 and 1330. Cows were given unrestricted access to freestalls. One group of cows was provided sawdust-covered rubber-filled mattresses (PastureMat; Promat, Ontario, Canada). The other group of cows was provided sawdust-covered Dual Chamber Cow Waterbeds (Advanced Comfort Technology, Inc., Reedburg, WI). Grass seeded exercise lot access was permitted for 1 h per day at 10:00 AM, weather permitting. All other surfaces (freestall area, feedbunk alley, holding pen, and alleys) contained grooved concrete. Milking occurred twice daily at 04:30 and 15:30.

The study included primiparous (n = 24) and multiparous (n = 24) Holstein dairy cows averaging 223.4 ± 117.8 DIM and producing an average 29.22 ± 8.20 kg/d. Enrolled cattle were fitted with the following technologies: Afi Pedometer Plus (attached to left rear leg), CowManager SensOor (Agis, Harmelen, the Netherlands; attached to left ear), IceQube Sensor (IceRobotics Ltd, Edinburgh, Scotland; right rear leg), Smartbow (MKW electronics GmbH, Jutogasse, Austria; left ear), and Track a)) Cow(ENGS, Israel; right front leg). These tags were attached at or before transition into the milking herd. Further technology information is included in Table 4.1. HOBO Data Loggers were placed in watertight bags, wrapped in colored self-adhesive wrap, and attached to each cow's left rear leg (6 cm above the Afi Pedometer Plus) following evening milking the day before observation. HOBO Data Loggers recorded lying behavior using a triaxial accelerometer to collect relative position every minute. Previous studies have established HOBO Data Logger accuracy in 1 min periods (Ito et al., 2009).

Technologies were compared by data summation time blocks and parameters measured. The CowManager SenOor and Track a)) Cow systems monitored feeding behavior in minutes per hour block. The SensOor and Smartbow systems monitored rumination in minutes per hour block. Lying behavior was characterized by the Afi

Pedometer Plus system (variable time blocks generated from a handheld reader; minutes lying between readings), the HOBO Data Logger (3-dimensional position sample collected every minute), the IceQube sensor (minutes lying per 15 min time block), and the Track a)) Cow system (minutes lying per hour). Afi Pedometer Plus lying behavior data was downloaded using handheld readers because the available technology version could not constantly record and transmit data. Readings were collected at shift start, and approximately every 15 min following.

Parameters were compared to the results of direct visual observation. Observation shifts occurred following morning and evening milking as cows exited the milking parlor, in 2 h shifts. The study took place over 8 d. Each of the 48 enrolled cows was observed for 2 observation periods, on the same day, for a total of 4 h. Forty-two observers consisting of undergraduate and graduate students from the University of Kentucky. Six observers were assigned to each shift. Each observer was assigned to observe a different cow (six cows observed per shift). Fourteen observers contributed at least one observation shift and 28 observers contributed multiple observation shifts.

Data recording sheets and event classification instructions were sent to each observer before the beginning of their shift. Upon arrival at the dairy and before the beginning of their observational shift, observers were again shown how to properly classify and record behaviors. Videos were used to illustrate eating, rumination, and lying or standing events and observers were instructed on proper recording procedures. Observers were also instructed to disrupt cattle as little as possible.

Observers recorded the hour, minute, and second of start and stop times for rumination, feeding, and lying events using multi-function atomic watches (CASIO,

CASIO America, Inc., Dover, NJ). A time-synchronizing radio frequency synchronized watches to one another. The same time was used to synchronize computers equipped with each data logger's software. Start and stop times of each visually monitored behavior were compared against computer recorded times of each individual technology to determine technology classification accuracy. Cows lying for the entire observation period were encouraged to stand, similar to methods used by Bonk et al. (2013) to generate standing bouts. Cattle were also persuaded to enter the feeding area if eating events had not yet occurred.

Event Classification

Previous work involving feeding behavior characterized the behavior through jaw movements, licking movements, chewing behavior, or whether a cow crossed a threshold or gate to a predefined feeding area (Schirmann et al., 2009; Zehner et al., 2012; Bikker et al., 2014). A combination of these methods was used in this study because different methods of quantifying feeding behavior were used for each evaluated technology. A cow was considered to be eating if actively chewing, and standing near the feedbunk. If chewing stopped for longer than 5 seconds, cattle were recorded as having stopped eating. Rumination was quantified in similar methods to Schirmann et al. (2009), where rumination was defined as the point in time of regurgitation. Observers recorded events where regurgitated boluses reached the esophagus, entered the mouth, and were subsequently followed by the initiation of rhythmic chewing by the cow. Rumination events ended when rhythmic chewing ceased and the bolus was swallowed. Similar to the methods of Ledgerwood et al. (2010), transition from a standing position to a lying position defined lying events. Cattle were considered lying if the flank of the animal came in contact with a surface during transition from a standing position. Upon flank impact with the ground, time was recorded. Similar to Ledgerwood et al. (2010), a cow was classified as standing when a transition from a lying position to a standing position occurred and all four limbs were fully extended and perpendicular to the ground; at this point the time was recorded.

Data corresponding to study periods were collected, and analyzed in SAS version 9.3 (SAS Institute, Cary, NC). Two shifts of feeding behavior and three shifts of rumination behavior data were removed because of observation error. PROC CORR of SAS generated Pearson correlation coefficients for two analyses. A direct measures correlation analysis compared agreement between data loggers and visual observations. A repeated measures analysis established data independence and removed variation between and within subjects. Repeated measures analyses averaged subject logger and visual observation data to provide one observation per subject and established agreement between data loggers and visual observations (Bland and Altman, 1995a; b).

Because multiple observers were used to collect visual observations, a subset of observers served to establish the variability between observers. These observers collected data in the same methods as previously described. For both a morning and evening observation shift, the 4 observers collected data from a single cow. A different cow was used for the morning and evening observations shifts for a total of 4 h. Observers were instructed to stand out of sight of each other and to not talk to one another. PROC CORR generated Pearson correlation coefficients to establish interobserver variability.

RESULTS AND DISCUSSION

Interobserver Variability

Observations of four volunteers established interobserver variability (Table 4.2). A high level of agreement was found between observers for eating time ($r > 0.96$ across observers; $P < 0.01$) and lying time (r > 0.99 across all observers; $P < 0.01$). Rumination time was most variable between observers (r > 0.89 across all observers; $P < 0.01$), but was relatively high. The use of visual observation as a rumination gold standard has previously been questioned (Kononoff et al., 2002). Many observers in this study indicated rumination to be difficult to visually quantify, which may explain some observer rumination recording variation.

Feeding Behavior

Technologies recorded feeding behavior in minutes per hour time block and were evaluated against visual observations over the same time period. Sample size, mean number of units, and standard deviations can be found for all feeding behavior measures in Table 4.3. Hourly feeding behavior data for the CowManager SensOor (mean ± SD; 9.9 ± 6.7 min/h) and Track a)) Cow (7.7 ± 5.6 min/h) systems were compared against direct visual observation (14.1 ± 6.5 min/h).

A direct and repeated measures analysis between visual observation and data loggers recording feeding behaviors is shown in Table 4.4. Evaluation of feeding behavior data from the CowManager SensOor and direct visual observation using direct measures (not accounting for repeated measures) produced a high agreement level (r = 0.97; $P = 0.03$). In evaluation of time present at the feedbunk monitored by the Track a)) Cow system, a high level of agreement between actual feed intake time and number of minutes at the feedbunk was found (r = 0.91; $P = 0.09$). A comparison between the two technologies showed them to perform similarly with r = 0.91 ($P = 0.09$). For the repeated measures analysis, performance decreased in comparison to the direct measures analysis for the CowManager SensOor to visual observation (r = 0.91; $P = 0.09$), Track a)) Cow to visual observation (r = 0.88; P = 0.12) and for the CowManager SensOor to Track a)) Cow system (r = 0.83; P = 0.17).

Bikker et al. (2014) previously evaluated the CowManager SensOor, finding a moderately weaker correlation (r = 0.88; P < 0.01). Bikker et al. (2014) used visual observations by minute to compare behaviors. The current study quantified visual observations to the second to more accurately describe behavior. This may explain the greater correlation and lower significance levels.

To our knowledge, this is the first study to validate the Track a)) Cow system. A similar system that records a cow's proximity to the feedbunk was highly correlated to feeding behavior (r^2 = 0.98; P < 0.01; DeVries et al., 2003). In that study, eating event documentation occurred when cattle placed their heads under feed rails and over feed. A system evaluated by Chapinal et al. (2007) also showed greater correlation to visual observation (R^2 = 1.00; P < 0.01) than the current study, but this technology is primarily a research tool.

The direct (r = 0.91; P = 0.09) and repeated (r = 0.88; P = 0.12) measures in our study were lower, but the Track a)) Cow system recorded feeding events when cows approached the feedbunk by right front leg proximity. Requiring cows to stand perpendicularly to the feedbunk through headlock implementation may improve results.

Rumination

Technologies recorded rumination in minutes per hour time block and were evaluated against visual observations over the same time period. Sample size, mean number of units, and standard deviations can be found for all rumination behavior recording technologies in Table 4.5. Data for the Smartbow (35.0 ± 10.1 min/h) and

CowManager SensOor (26.6 ± 5.6 min/h) systems were compared to direct visual observations (20.1 ± 5.5 min/h) over all hourly periods.

A rumination behavior direct and repeated measures analysis between visual observation and data loggers is shown in Table 4.6. In the direct measures comparisons, the Smartbow system closely agreed with visual observations (r = 0.99; $P < 0.01$), as did the CowManager SensOor (r = 0.96; $P < 0.01$). The Smartbow and CowManager SensOor performed similarly when compared to each other (r = 0.94; $P = 0.06$). In a repeated measures analysis of the same data, the CowManager SensOor more closely matched visual observations (r = 0.44; $P = 0.56$) than the Smartbow system (r = -0.11; $P = 0.89$). The systems were weakly correlated when compared against each other (r = -0.28; $P = 0.72$).

In a previous evaluation of the CowManager SensOor, rumination was highly correlated to visual observation (r = 0.93; $P < 0.01$; Bikker et al., 2014). Direct measures correlation analysis indicated a similar level of performance. The repeated measures analyses indicate a lower agreement level. Rumination was the most difficult for observers to evaluate (r = 0.89, $P < 0.01$; interobserver variability) in the current study. Rumination monitor evaluation has traditionally been completed in tie stalls, small pens, or a similar controlled setting (Schirmann et al., 2009; Zehner et al., 2012; Bikker et al., 2014). The current study allowed cattle to express behaviors as they would in the general herd, potentially leading to misidentified rumination events. This would have a larger effect on the repeated measures analysis because visual observations and technology-generated data were averaged to obtain a single measurement per cow. Misidentified visual observation events could skew the mean values used in repeated measures analysis, generating weaker correlations.

Lying Behavior

The Afi Pedometer Plus, IceQube, and Track a)) Cow were all evaluated against visual observation and the HOBO Data Logger. Sample size, mean number of units, and standard deviations can be found for all lying behavior recording technologies and time blocks in Table 4.7. Lying behavior direct and repeated measures analyses between visual observation, the HOBO Data Loggers, and the various technologies is shown in Table 4.8.

The IceQube correlated highly with visual observations at r > 0.94 ($P < 0.01$) in both direct and repeated measures analyses. The IceTag (IceRobotics Ltd, Edinburgh, Scotland) was previously evaluated for accuracy (McGowan et al., 2007; Mattachini et al., 2013b) but this is primarily a research tool. The current study used the IceQube, which is the commercially marketed version of the IceTag. Mattachini et al. (2013b) found the IceTag to perform similarly to video observation with a sensitivity of 1.00 ± < 0.01, and a specificity of 1.00 ± < 0.01. IceQube performance in the current study was also compared to HOBO data logger performance on a 15 min basis (direct, r = 1.00; P < 0.01 and repeated, r = 0.94; P < 0.01). Mattachini et al. (2013b) found similar results between the HOBO Data Logger and IceTag with a sensitivity of 0.99 ± < 0.01 and a specificity of 0.99 ± < 0.01.

The Track a)) Cow system achieved high correlations with visual observation (r > 0.93; $P < 0.01$) in both the direct and repeated measures analyses. This was an unexpected result as previous studies have shown the front legs to be the least accurate in monitoring lying behavior (Müller and Schrader, 2003). Track a)) Cow on an hourly basis was highly correlated with HOBO Data Loggers (direct, $r = 1.00$; $P < 0.01$ and repeated, $r = 0.89$; $P = 0.11$). These results indicate lying behavior monitored on front and hind limbs to perform similarly.

Afi Pedometer Plus and visual observations were highly correlated ($r > 0.90$; $P < 0.01$), as were Afi Pedometer Plus and HOBO Data Logger observations ($r > 0.90$; $P < 0.01$). Although correlations were high, the Afi Pedometer Plus least agreed with visual observations and HOBO Data Loggers. The method (handheld reader) used to collect Afi Pedometer Plus lying behavior data may have influenced results. The Afi Pedometer Plus tag delays data generation to account for potentially erroneous data readings. Tags must remain in a lying or standing set for a period of time to register a lying or standing event (Mattachini et al., 2013a). Because of this, the tag tended to overestimate or underestimate lying time in comparison to visual observations and HOBO Data Logger readings. If the handheld reader collected lying behavior before data delays were complete, time lying or standing for those readings would be passed to subsequent time blocks, misrepresenting data. If data was continuously recorded, delayed data would have a lesser effect on results. Future studies will need to establish the Afi Pedometer Plus's accuracy using automatically collected lying and standing at regular intervals.

The HOBO Data Logger showed a high level of agreement in lying time between the IceQube, on a 15 min basis (direct, $r = 1.00$; $P < 0.01$ and repeated, $r = 0.94$; $P < 0.01$); Track a)) Cow on an hourly basis (direct, $r = 1.00$; $P < 0.01$ and repeated, $r = 0.89$; $P = 0.11$); and Afi system, in variable time periods (direct, $r = 0.93$; $P < 0.01$ and repeated, $r = 0.90$; $P < 0.01$). HOBO Data Loggers have previously been shown to accurately describe lying behavior in dairy cattle (Ledgerwood et al., 2010; Mattachini et al., 2013a; Mattachini et al., 2013b), dairy calves (Bonk et al., 2013) , and dairy goats (Zobel et al., 2014).Visual observations were previously found to be more similar to the Afi Pedometer Plus and IceTag than to the HOBO Data Logger (Mattachini et al., 2013a; Mattachini et al., 2013b). This could be for several reasons. HOBO Data Loggers are research tools and have differing sampling times. In this experiment, the HOBO Data Loggers sampled the device's 3-dimensional position every minute. Data analysis techniques assumed this position to remain constant for each minute. This could lead to variation in the number of minutes spent lying in comparison to technologies sampling more frequently. Previous methods have evaluated the HOBO Data Logger's performance over different sampling time frequencies (Ito et al., 2009; Ledgerwood et al., 2010; Mattachini et al., 2013b). Adjustments in sampling frequency may increase technology performance.

The data loggers used in the current study were able to accurately quantify feeding, rumination, and lying behaviors. Direct measures correlations resulted in greater agreement between technologies and visual observations than repeated measures in all comparisons. Direct measures may overestimate technology performance by not accounting for a lack of data independence. Commercially marketed technologies showed only slight differences in correlation with visual observations and that of HOBO Data Loggers (in lying time evaluation only). Comparing all data across the same time frame may provide more accurate technology comparisons, but this was not possible in the current study. Summation of technology and observation data into hour blocks would have allowed for all but the Afi Pedometer Plus (because of variable time blocks) to be compared. This was not performed because technology manufacturers describe technology-recorded behaviors in different time blocks. Manufacturers use the parameters measured by these technologies in the generation alerts describing events of interest (e.g. health and estrus). Technologies were evaluated to match behavioral use by algorithms for health and estrus alerts. Changing time blocks could misrepresent data used in algorithms, creating biased comparisons. Future research obtaining technology data in common time units directly from manufacturers would allow for a more accurate technology performance comparison.

CONCLUSIONS

To the knowledge of the authors, this is the first precision dairy farming technology validation study performed evaluating multiple parameters and technologies attached to the same cows. Commercially marketed technologies recording feeding behavior, rumination, and lying behavior performed similarly to one another when compared against visual observation over the same periods. Results of direct correlations for all observations produced results similar to previously completed validation work. Much of the previous work did not account for repeated measures collected on the same animals over time. Results of the current study accounting for repeated measures indicate direct correlations may overestimate technology performance.

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Table 4.1. Technology information for data loggers used in a study evaluating behavioral quantification performance.[1]

Technology	Cow location	Parameters measured	Internal technology	Units
Afi Pedometer Plus[2]	Left rear leg	Lying behavior	Triaxial accelerometer	min between readings[1]
CowManager SensOor	Left ear	Feeding behavior, rumination behavior	Triaxial accelerometer	min/h
HOBO Data Logger	Left rear leg (upper)	Lying behavior	Triaxial accelerometer	min/h
IceQube	Right rear leg	Lying behavior	Triaxial accelerometer	min/15 min
Smartbow	Right ear	Rumination behavior	Triaxial accelerometer	min/h
Track a)) Cow	Right front leg	Feeding behavior, lying behavior	Triaxial accelerometer	min/h

[1]Afi Pedometer Plus leg tag (afimilk, S.A.E. AFIKIM, Kibbutz Afikim, Israel), CowManager SensOor ear tag (Agis, Harmelen, the Netherlands), IceQube Sensor leg tag (IceRobotics Ltd, Edinburgh, Scotland), Smartbow ear tag (MKW electronics GmbH, Jutogasse, Austria), and Track a)) Cow leg tag (ENGS, Israel) and HOBO Data Loggers (HOBO Pendant G Acceleration Data Logger, Onset Computer Corporation, Pocasset, MA).

[2]Afi Pedometer Plus lying behavior data was downloaded using a handheld reader. Readings were collected at shift start, and around every 15 min following, until shift end.

Table 4.2. Results from a technology evaluation study indicating observer agreement by second (Pearson correlation coefficients) for visually observed dairy cow eating time, lying time, and rumination time for four observers.[1, 2]

Behavior	Observer #	Pearson correlation coefficients between observers			
		1	2	3	4
Eating	1		0.99	0.99	0.97
	2	0.99		0.99	0.96
	3	0.99	0.99		0.96
	4	0.97	0.96	0.96	
Lying	1		1.00	1.00	1.00
	2	1.00		1.00	1.00
	3	1.00	1.00		1.00
	4	1.00	1.00	1.00	
Rumination	1		0.88	0.95	0.92
	2	0.88		0.91	0.88
	3	0.95	0.91		0.95
	4	0.92	0.88	0.95	

[1]All Pearson Correlation Coefficients were evaluated for the probability of observing results under the null hypothesis that correlations were 0.

[2]$P < 0.01$ was observed for all correlations.

Table 4.3. Results from a technology evaluation study indicating hourly feeding behavior statistics for data loggers and visual observations in Holstein dairy cattle.[1]

Data recording method	Observations per cow (n = 46)	Mean time (min)	SD (min)
CowManager SensOor	4	9.9	6.7
Track a)) Cow	4	7.7	5.6
Observed	4	14.1	6.5

[1]CowManager SensOor ear tag (Agis, Harmelen, the Netherlands) and Track a)) Cow leg tag (ENGS, Israel).

Table 4.4. Results from a technology evaluation study indicating levels of agreement between hourly feeding behavior monitored by data loggers and visual observations in Holstein dairy cattle.[1, 2]

Technology	Observations per cow (n = 46)	Repeated measures correlation coefficients		Direct measures correlation coefficients	
		Observed Intake	Track a)) Cow	Observed Intake	Track a)) Cow
CowManager SensOor	4	0.91	0.83	0.91	0.91
Track a)) Cow	4	0.88		0.97*	

[1]CowManager SensOor ear tag (Agis, Harmelen, the Netherlands) and Track a)) Cow leg tag (ENGS, Israel).

[2]Correlation coefficients were performed accounting for repeated measures, or directly across all observations.

*-Denotes significance at $*P < 0.05$, $**P < 0.01$.

Table 4.5. Results from a technology evaluation study indicating hourly rumination behavior statistics for data loggers and visual observations in Holstein dairy cattle.[1]

Data recording method	Observations per cow (n = 46)	Mean time (min)	SD (min)
Smartbow	4	35.0	10.1
CowManager SensOor	4	26.6	5.6
Observed	4	20.1	5.5

[1]CowManager SensOor ear tag (Agis, Harmelen, the Netherlands) and Smartbow ear tag (MKW electronics GmbH, Jutogasse, Austria)

Table 4.6. Results from a technology evaluation study indicating levels of agreement between hourly rumination behaviors monitored by data loggers and visual observations in Holstein dairy cattle.[1, 2]

Technology	Observations Per Cow (n = 46)	Repeated Measures Pearson Correlation Coefficients		Direct Measures Correlation Coefficients	
		Observed	Smartbow	Observed	Smartbow
CowManager SensOor	4	0.44	-0.28	0.96*	0.94
Smartbow	4	-0.11		0.99**	

[1]CowManager SensOor ear tag (Agis, Harmelen, the Netherlands) and Smartbow ear tag (MKW electronics GmbH, Jutogasse, Austria)

[2]Correlation coefficients were performed accounting for repeated measures, or directly across all observations.

*-Denotes significance at *P < 0.05, **P < 0.01.

Table 4.7. Results from a technology evaluation study indicating data logger and visual observation statistics in Holstein dairy cattle.[1]

Time frame[2]	Data recording method	Observations per cow (n = 46)	Mean time (min)	SD (min)
Minute	HOBO Data Logger	162	0.5	0.3
	Observed	162	0.5	0.3
15 Minutes	IceQube	20	6.3	4.2
	HOBO Data Logger	20	6.7	4.2
	Observed	20	5.9	4.1
Hourly	Track a)) Cow	4	2223.0	953.0
	HOBO Data Logger	4	2182.0	973.3
	Observed	4	2057.0	1052.0
Variable[3]	Afi Pedometer Plus	9	6.7	2.8
	HOBO Data Logger	9	6.8	3.3
	Observed	9	6.2	2.9

[1]Afi Pedometer Plus leg tag (afimilk, S.A.E. AFIKIM, Kibbutz Afikim, Israel), IceQube Sensor leg tag (IceRobotics Ltd, Edinburgh, Scotland), and Track a)) Cow leg tag (ENGS, Israel) and HOBO Data Loggers (HOBO Pendant G Acceleration Data Logger, Onset Computer Corporation, Pocasset, MA).

[2]Observational data was summed in 1 minute, 15 minute, hourly, and variable time blocks to match technology data summation times.

[3]Data was collected using a handheld reader for the Afi Pedometer Plus system. Data was collected once approximately every 15 min.

Table 4.8: Results from a technology evaluation study indicating levels of agreement between data loggers, visual observations, and the HOBO Data Logger in Holstein dairy cattle.[1, 2]

Time frame[3]	Technology	Observations per cow (n = 46)	Repeated measures Pearson correlation coefficients		Direct measures Pearson correlation coefficients	
			HOBO	Observed	HOBO	Observed
Minute	HOBO	162		0.83**		0.98**
15 Minutes	IceQube	20	0.94**	0.94**	1.00**	0.99**
	HOBO	20		0.88**		0.99**
Hourly	Track a)) Cow	4	0.89	0.93	1.00**	0.99**
	HOBO	4		0.89		1.00**
Variable[4]	Afi Pedometer Plus	9	0.90**	0.90**	0.93**	0.97**
	HOBO	9		0.84**		0.99**

[1]Afi Pedometer Plus leg tag (afimilk, S.A.E. AFIKIM, Kibbutz Afikim, Israel), IceQube Sensor leg tag (IceRobotics Ltd, Edinburgh, Scotland), and Track a)) Cow leg tag (ENGS, Israel) and HOBO Data Loggers (HOBO Pendant G Acceleration Data Logger, Onset Computer Corporation, Pocasset, MA).

[2]Correlation coefficients were performed accounting for repeated measures, or directly across all observations.

[3]Observational data was summed in 1 min, 15 min, hourly, and variable time blocks to match technology data summation times.

[4]Data collected using a handheld reader for the Afi Pedometer Plus system. Data was collected once approximately every 15 min.

*Denotes significance at *P < 0.05, **P < 0.01.

APPENDIX

Figure A2.1. A producer survey to assess precision dairy farming technology adoption, considerations made pre-purchase, and usefulness

Hello!

If you are a dairy producer, whether or not you currently implement cow monitoring technologies on your farm, we would like to hear from you!

Are you interested in technology that could detect heats and foresee illnesses in your cows before you do?

Do you think there is room for some technological updates that could improve the efficiency of your farm?

Are you aware of monitoring technologies but don't quite know what's out there?

This survey could be of great benefit to dairy producers and the dairy industry. This survey is intended specifically for dairy producers and aims to gather data related to dairy farmers and their use of cow monitoring technologies, whether or not they currently use them.

The information collected from this survey will help researchers and industry representatives form an idea of the use of monitoring technologies, their perception by farmers, and what dairy farmers find most useful. The data will be collected and interpreted and the results will be used to more effectively adhere technologies to the needs of dairy farmers.

All responses to this survey are completely anonymous. No data collected from this survey will include names, nor can the identity of a survey taker be gained. Only your responses will be recorded.

Thank you,

Matthew Borchers and Jeffrey Bewley

Figure A2.1 cont.

1. In what country and state or province is your dairy farm, or the dairy farm on which you work?

Country

State or Province

2. What is your age? (only the person taking this survey)

- < 30
- 31-40
- 41-50
- 51-60
- > 60

3. What is the job title for your current position?

- Owner/Co-owner/Partner
- President/Vice President
- Manager/Supervisor/Herdsman
- Employee

Other (please specify)

4. How many adult cows do you have on your farm? (milking and dry)

Figure A2.1 cont.

***5. What automatic monitoring technologies do you currently have on your dairy? (If not applicable, select "Not applicable")**

- ☐ Not applicable
- ☐ Animal position/Location
- ☐ Body condition score
- ☐ Body weight
- ☐ Cow activity
- ☐ Cow cleanliness
- ☐ Daily milk yield
- ☐ Feeding behavior
- ☐ Fertility Hormones (e.g. Progesterone)
- ☐ Heart rate
- ☐ Hoof health
- ☐ Jaw movement/Chewing activity
- ☐ Lameness
- ☐ Lying/Standing behavior
- ☐ Mastitis
- ☐ Methane emissions
- ☐ Milk components (e.g. fat, protein, and SCC)
- ☐ Respiration rate
- ☐ Rumen activity
- ☐ Rumen pH
- ☐ Rumination
- ☐ Standing heat
- ☐ Temperature

Other (please specify)

Figure A2.1 cont.

6. Please rate the importance of the following criteria for evaluating technology purchases:

	Unimportant	Of Little Importance	Moderately Important	Important	Very Important
Availability of local support	○	○	○	○	○
Compatibility with existing dairy practices/systems	○	○	○	○	○
Benefit:cost ratio	○	○	○	○	○
Total investment cost	○	○	○	○	○
Proven performance through independent research	○	○	○	○	○
Simplicity and ease of use	○	○	○	○	○
Time involved using the technology	○	○	○	○	○

Other (please specify)

Figure A2.1 cont.

7. Please rate the potential usefulness of the following measures:

	Not Useful	Of Little Usefulness	Moderately Useful	Somewhat Useful	Useful
Animal position/Location	○	○	○	○	○
Body condition score	○	○	○	○	○
Body weight	○	○	○	○	○
Cow activity	○	○	○	○	○
Cow cleanliness	○	○	○	○	○
Daily milk yield	○	○	○	○	○
Feeding behavior	○	○	○	○	○
Fertility hormones (e.g. Progesterone)	○	○	○	○	○
Heart rate	○	○	○	○	○
Hoof health	○	○	○	○	○
Jaw movement/Chewing activity	○	○	○	○	○
Lameness	○	○	○	○	○
Lying/Standing behavior	○	○	○	○	○
Mastitis	○	○	○	○	○
Methane emissions	○	○	○	○	○
Milk components (e.g. fat, protein, and SCC)	○	○	○	○	○
Respiration rate	○	○	○	○	○
Rumen activity	○	○	○	○	○
Rumen pH	○	○	○	○	○
Rumination	○	○	○	○	○
Standing heat	○	○	○	○	○
Temperature	○	○	○	○	○

Other (please specify)

Figure A2.1 cont.

Thank you for taking the time to fill out this survey. Your participation is greatly appreciated!

8. Do you have any other suggestions, comments, or thoughts on the use of dairy cattle monitoring technologies?

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VITA

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Matthew started his Master’s at the University of Kentucky in January 2013. He studied under Dr. Jeffrey Bewley and focused on the uses of precision dairy farming technologies. His work has been presented at the 2013 Precision Dairy Conference in Rochester, MN and the 2014 Joint Annual ADSA-AMPA-ASAS-CSAS-WSASAS Meeting in Kansas City, MO.

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Scientific Abstracts:

Borchers, M.B. and J.M. Bewley. 2013. A producer assessment of precision dairy farming technology use, usefulness, and pre-purchase considerations. Precision Dairy 2013. Rochester, MN.

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