2018

ON-FARM UTILIZATION OF PRECISION DAIRY MONITORING: USEFULNESS, ACCURACY, AND AFFORDABILITY

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Digital Object Identifier: https://doi.org/10.13023/ETD.2018.081

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ON-FARM UTILIZATION OF PRECISION DAIRY MONITORING: USEFULNESS, ACCURACY, AND AFFORDABILITY

DISSERTATION

A dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy in the
College of Agriculture, Food and Environment
at the University of Kentucky

By
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Lexington, Kentucky

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2017

ABSTRACT OF DISSERTATION

ON-FARM UTILIZATION OF PRECISION DAIRY MONITORING: USEFULNESS, ACCURACY, AND AFFORDABILITY

Precision dairy monitoring is used to supplement or replace human observation of dairy cattle. This study examined the value dairy producers placed on disease alerts generated from a precision dairy monitoring technology. A secondary objective was calculating the accuracy of technology-generated disease alerts compared against observed disease events. A final objective was determining the economic viability of investing in a precision dairy monitoring technology for detecting estrus and diseases.

A year-long observational study was conducted on four Kentucky dairy farms. All lactating dairy cows were equipped with a neck and leg tri-axial accelerometer. Technologies measured eating time, lying time, standing time, walking time, and activity (steps) in 15-min sections throughout the day. A decrease of ≥ 30% or more from a cow's 10-d moving behavioral mean created an alert. Alerts were assessed by dairy producers for usefulness and by the author for accuracy. Finally, raw information was analyzed with three machine-learning techniques: random forest, least discriminate analyses, and principal component neural networks.

Through generalized linear mixed modeling analyses, dairy producers were found to utilize the alert list when ≤ 20 alerts occurred, when alerts occurred in cows' ≤ 60 d in lactation, and when alerts occurred during the week. The longer the system was in place, the less likely producers were to utilize alerts. This is likely because the alerts were not for a specific disease, but rather informed the dairy producer an issue might have occurred. The longer dairy producers were exposed to a technology, producers more easily decided which alerts were worth their attention.

Sensitivity, specificity, accuracy, and balanced accuracy were calculated for disease alerts that occurred and disease events that were reported. Sensitivity ranged from 12 to 48%, specificity from 91 to 96%, accuracy from 90 to 96%, and balanced accuracy from 50 to 59%. The high number of false positives correspond with the lack of usefulness producers reported. Machine learning techniques improved sensitivity (66 to 86%) and balanced accuracy (48 to 85%). Specificity (24 to 89%) and accuracy (70 to 86%) decreased with the machine learning techniques, but overall detection performance was improved. Precision dairy monitoring technologies have potential to detect behavior changes linked to disease events.

A partial budget was created based on the reproduction, production, and early lactation removal rate of an average cow in a herd. The cow results were expanded to a 1,000 cow herd for sensitivity analyses. Four analyses were run including increased milk production from early disease detection, increased estrus detection rate, decreased early lactation removal from early disease detection, and all changes in combination. Economic profitability was determined through net present value with a value ≥ $0 indicating a profitable investment. Each sensitivity analysis was conducted 10,000, with different numbers for key inputs randomly selected from a previously defined distribution. If either milk production or estrus detection were improved, net present value was ≥ 0 in 76 and 85% of the iterations. However, reduced early lactation removal never resulted in a value ≥ 0. Investing in precision dairy technology resulting in improved estrus detection rate and early disease detection was a positive economic decision in most iterations.

KEYWORDS: Precision Dairy Monitoring, Transition Cow Disease, Economics, Producer Use, Machine-learning

Elizabeth Eckelkamp

October 27, 2017___

ON-FARM UTILIZATION OF PRECISION DAIRY MONITORING: USEFULNESS, ACCURACY, AND AFFORDABILITY

By

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October 27, 2017

This manuscript is dedicated to the first two people to show me the world of dairy and life on a farm. Grandpa Bud and Grandmother Dorothy, thank you for always believing in me, inspiring me, and loving me. You are missed, every day.

ACKNOWLEDGEMENTS

How do you adequately thank all of the people that have made an impact on your life and have gotten you to where you are today? I would like to thank the person who has allowed me to pursue my dairy dreams. Thank you Jeffrey. You took a chance on a Louisiana girl whose only dairy experience was on the university farm, and you let me make a place for myself in the dairy world. Thank you from the bottom of my heart for teaching me more about cattle, farmers, and the world of extension. I would not be where I am today without you.

Secondly, I want to thank the love of my life, Logan Tolbert. Logan, you keep me going, all day every day. You feed me, you push me, you watch the animals, and through it all you keep me smiling. I cannot wait to marry you, you amazing man. You are the smartest, kindest, best man I know. I have been so blessed to have you in my life. You inspire me daily with your work ethic, your drive, and your passion. You have sacrificed so much for me to let me follow my dreams. I love you Logan, and I always will.

I want to thank my family. You have molded me into the person I am today. Thank you for showing me what hard work is, what it means to take care of your family, and how to be the person you want to be. Dad, because of you and Grandpa I have a passion for dairy. Thank you for raising me to shoot for the stars, and for telling me I could do anything I worked hard enough for. Mom, you showed me from the youngest age that women could make it in the workforce. You showed me what a woman could do if she put her mind to it, and you inspire me. Thank you for pushing me to go further,

even when I am not sure I can do it. Julia, I love you and I am so very proud of you. I cannot wait to see where life takes you.

Lee, you are closer to me than most people I know. You are such a big part of my life, and I love you so much. Thank you for listening to me, talking with me, laughing with me, and crying with me, usually all at the same time. I have been so blessed to have you in my life, and I plan on keeping you in it for a long time.

Kat, I love you so much. I am so proud of you and Kevin. You have made a wonderful life for yourselves in St. Louis, and given me the best present ever, my nephew Morgan. Thank you for always sticking up for me, even when I do not do it myself, and always saying the things I wish I could.

Stefani, you amaze me. North Carolina is lucky to have you. Thank you for listening to me, keeping me true to myself, and helping me keep going when I do not think I can. Tsai I-Ching, I miss you. Thank you for always being there for me. Di Liang, thank you for being there for me, helping me with modeling, and putting up with my incessant questions.

Gustavo Mazon, I am going to miss my new little brother. Jessica Ferrell, Melissa Cantor, Emily Rice, and Michele Jones, I just got one of you back and just found the other two. Thank you for letting me be a part of your lives. Jessica, you are going to be a beautiful bride, and I am so proud of you for finishing your master's. Melissa and Emily, you are both going to excel in graduate school. I cannot wait to see what the two of you do in the future. I am going to miss all of you. Michele, thanks for the nickname. I cannot wait to see what the dairy industry has in store for you.

I also want to thank my office mates, Derek Nolan and Karmella Dolecheck. Thank you guys, just thank you. I know I was a pain with all of my modeling questions, but without you I would not have made it through. You are both amazing scientists, and you are going to do such great things. Karmella, I hope you do not end up too far away, we started this whole thing together. It will be strange to not have you down the hallway or in the same office.

I also want to thank Matthew Borchers, Jenna Guinn, Barb Jones, Amanda Stone, Carissa Truman, Lori Grinter, Tanya French, Kevin Zhao, and Bettie Kawonga. In some way, all of you have touched my life, helped me be a better scientist, and kept me going. Thank you for all that you have done.

I would also like to thank my committee members Dr. Amanda Adams, Dr. Donna Amaral-Phillips, Dr. Roberta Dwyer, Dr. Tyler Mark, and Dr. Christina Petersson-Wolfe. Thank you for taking time out of your schedules to mentor me, encourage me, push me, and make me a better scientist. I look forward to working with you all in the future.

My biggest thank you is to the dairy farmers, county agents, and Kentucky Dairy Development Council agents who have inspired me, and fueled my desire to stay in the industry. Gail, Julie, and Taylor, thank you for letting me be a part of your dairy for my master's and PhD. Billy, Freddy, Bob, Angie, Richard, Stacy, Ona, and Jim, you are family. You really are. Thank you for opening your homes, your hearts, and your farms to me. You drive my desire to be an extension specialist. Because of you, I want to work with farmers for the rest of my life. Thank you so much.

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CHAPTER ONE

Review of literature

INTRODUCTION

The use of technology in the dairy industry has increased dramatically in the last 20 years (USDA, 2016). Precision dairy technology uses real-time monitoring of animals to supplement the “eyes and ears of the farmer” through behavior monitoring, milk yield, milk constituents, video analysis, temperature monitoring, or record analysis (Wathes et al., 2008, Hogeveen et al., 2010, Rutten et al., 2013). Precision dairy technology can aid in the detection of hypocalcemia, hyperketonemia, metritis, lameness, and mastitis. However, sensitivity and specificity must be improved for detection to be useful to dairy owners and managers (Hogeveen et al., 2010). Sensitivity and specificity are defined as the proportion of true positives and true negatives identified by a test (Altman and Bland, 1994). Technology needs to be sensitive enough to pick up most cases of a particular disease (true positives), but specific enough that cows without a particular disease are not also identified (false positives; Hogeveen et al., 2010). The technology must also be economically feasible and fit within the farm management style (Yule and Eastwood, 2012, Borchers and Bewley, 2015). Many technologies are available to dairy producers and researchers with the ability to detect estrus, illness, or calving (Dolecheck et al., 2016b, Stangaferro et al., 2016a, b, c, Borchers et al., 2017). However, research on producer perception, detection accuracy, and economic feasibility of on-farm daily application of health monitoring precision dairy technology is lacking.

TRANSITION COW DISEASES

The most unstable portion of a dairy cow's life is the three weeks before to the three weeks after parturition, the transition period. During the transition period, most cows experience reduced feed intake, negative energy balance, weight loss, hypocalcemia after calving, reduced immune function in the weeks around calving, and bacterial contamination of the uterus (LeBlanc, 2010). Negative energy balance occurs when a dairy cow cannot consume enough energy through her diet to offset the energy demands of biological processes, namely milk production (Adewuyi et al., 2005). Inability to consume enough energy and nutrients can lead to several clinical and subclinical diseases including hyperketonemia, hypocalcemia, retained placenta, and metritis. Infection during the transition period can seriously affect the remainder of the cow's lactation (decreased milk yield and impaired reproductive performance) and lead to other health issues (clinical advancement of subclinical diseases, endometritis, lameness, or mastitis throughout a lactation) or death (Oetzel, 2011, Giuliodori et al., 2013, Raboisson et al., 2015). Hyperketonemia, hypocalcemia, and metritis will be discussed in more detail below.

Hyperketonemia

Non-esterified fatty acids (**NEFA**) resulting from lipolysis are an alternative energy source to glucose. Non-esterified fatty acids can be used as a source of energy directly or exported to triacylglycerol (**TAG**) or very low-density lipopolysaccharides (**VLDL**). Once the liver metabolizes the TAG and oxidizes the VLDL, any remaining TAGs are stored in the liver. Acetyl CoA from fatty acid oxidation is also converted to ketone bodies in the liver (Adewuyi et al., 2005). Peripheral body tissues, the heart, and the brain can use ketone bodies as an energy source in place of glucose. If more ketone bodies are produced than can be used, ketones begin accumulating in the bloodstream. The presence of ketone bodies in milk, blood, or urine of cattle indicates severe negative energy balance, and at high enough levels cows suffer from hyperketonemia (Goff and Horst, 1997, Adewuyi et al., 2005).

Hyperketonemia is associated with negative energy balance, specifically the mobilization of body proteins and fats, measured indirectly through NEFA or directly through circulating ketone bodies: acetate, acetoacetate, and β-hydroxybutyrate (**BHBA;** Dye and Dougherty, 1956, Duffield, 2000, Ospina et al., 2010b). β-hydroxybutyrate has become a more standard identification of hyperketonemia and negative energy balance instead of acetate, acetoacetate, or NEFA (McArt et al., 2013, Ospina et al., 2013). Hyperketonemia, or ketosis, is a metabolic disorder subclinically or clinically affecting cattle in the weeks after parturition (Schulz et al., 2014).

Both subclinical and clinical hyperketonemia have been associated with decreased milk yield and increased risk for other fresh cow diseases (Duffield et al., 2009, McArt et al., 2012, Schulz et al., 2014). Hyperketonemia is more prevalent in multiparous (≥ 2 lactations) dairy cattle because of their increased milk production compared to primiparous (1 lactation) dairy cattle (Dye and Dougherty, 1956). Although hyperketonemia may be highly prevalent (1.8 to 55%; Duffield, 1998, McArt et al., 2011), it is rarely fatal (≤ 5% of all cases; Dye and Dougherty, 1956).

Up to 59% of fresh cows may experience subclinical hyperketonemia within the first 15 days following calving, although cases may extend two months into lactation (Duffield et al., 1998, Duffield, 2000, McArt et al., 2011). If left untreated, cows are at higher risk for other postpartum diseases including clinical hyperketonemia, displaced abomasum, and metritis (MacDonald and Bell, 1958, Duffield et al., 2009, Ospina et al., 2010a).

Subclinical hyperketonemia is often detected through the concentration of BHBA in the urine, blood, or milk (Duffield, 2000). The cutoff point for subclinical hyperketonemia has been reported from 1.0, 1.2, 1.4 and 2.0 mmol/L in the literature. Higher prevalence was associated with the lower values (Duffield, 2000). Cutoff thresholds have been based on anecdotal evidence (1.0 mmol/L; Whitaker et al., 1982), distribution (1.2 mmol/L; Nielen et al., 1994), additional disease risk (1.4 mmol/L; Duffield et al., 1998), and decreased milk yield (2.0 mmol/L; Duffield, 2000).

Clinical hyperketonemia may be experienced by 2 to 39% of fresh cows over a lactation period (Duffield, 2000, McArt et al., 2011). Clinical signs include decreased appetite (particularly of concentrate feeds), decreased milk yield, severe weight loss, hard dry feces, apparent blindness, and nervous signs (vigorous licking, turning in circles, etc.; Duffield, 2000, McArt et al., 2011). Subclinical and clinical hyperketonemia have been linked to increased occurrences of displaced abomasum, metritis, hypocalcemia, retained placenta, clinical and subclinical mastitis, and lameness (Raboisson et al., 2015).

Prevention of hyperketonemia has been explored through nutrition and management. In one study of 18 German Holstein cows, Schulz et al. (2014) reported that cows with a body condition score above 3.0 (1 to 5 point scale; 1 being emaciated and 5 being obese; Ferguson et al., 1994) were more likely to experience hyperketonemia (89%) than cows with a body condition score around 2.9 (11%). Feeding preventive feed additives pre- and post-parturition have also been explored. Sodium propionate, choline, and monensin have all been shown to reduce subclinical and clinical hyperketonemia incidence during the fresh period (Schultz, 1958, Duffield et al., 1998, Oelrichs et al., 2004). However, even with a well-managed nutritional program and the addition of feed additives, hyperketonemia was present in every herd.

Treatment of subclinical and clinical hyperketonemia is similar. To improve energy balance, a glucose substrate must be provided. The glucose substrate should stimulate gluconeogenesis and limit mobilization of body fat and muscle protein (Gordon et al., 2013). Substrates to provide glucose commonly used to treat hyperketonemia in dairy cattle include propylene glycol, glycerol, and sodium propionate (Geishauser et al., 2001). Dextrose, glucocorticoids, insulin, cyanocobalamin (vitamin B_{12}), and butophosphan have also been considered for hyperketonemia treatment, individually or in combination (Gordon et al., 2013).

Hyperketonemia costs depended on clinical and subclinical hyperketonemia incidence, treatment cost, milk price, and herd body condition (Duffield, 2000). If hyperketonemia was treated, the cost ranged from $52 to $375 per case (Duffield, 2000, Geishauser et al., 2001, McArt et al., 2015, Liang et al., 2017). McArt et al. (2015) divided the costs into component (pertaining directly to hyperketonemia; $119) and costs from increased metritis ($95) and displaced abomasum ($75) incidence. The cost of treatment was only 3% of the component hyperketonemia cost ($4). The largest component costs of hyperketonemia are the indirect costs of reduced reproductive performance (34%; $41) and future milk production (26%; $31). Lost milk production ranged from 44 to 328 kg/lactation (Duffield, 2000, Duffield et al., 2009). Liang et al. (2017) modeled a lower lost milk cost, $1.00 ± 0.65 per case (primiparous cows) and $6.67 ± 1.69 per case (multiparous cows), compared to $91.00 per case by Guard (2008).

Hypocalcemia

Hypocalcemia, or milk fever, is a disease commonly affecting high producing dairy cattle postpartum (Oetzel, 2011). Hypocalcemia presents with rapid decreases of blood calcium (**Ca**), occasionally decreased phosphates and magnesium, and increased blood sugar (Gibbons, 1956, Houe et al., 2000, Goff, 2008). The body's demand for Ca directly following parturition is increased from 15 to 20g Ca/d to 20 to 30g Ca/d (Oetzel, 2011). The cow cannot provide all the Ca for the increased demand from her diet. Supplemental Ca is pulled from dissolved Ca solution within the bone structure and osteoclastic activity on the bone collagen matrix (Oetzel, 2011). As Ca is used for milk production, the body lacks sufficient Ca to allow the nerve endings to efficiently trigger muscle movement resulting in muscle tremors, muscle weakness, and complete loss of muscle function (Blowey, 1999, Oetzel, 2011).

Usually, only multiparous cows are affected by hypocalcemia with a 9% increased risk with each following parity (Gibbons, 1956, Oetzel, 2011). For all cases, 75% occur within 24 h of parturition, 12% within 24 to 48 h, 6% during parturition, and 7% occur outside of parturition (nonparturient hypocalcemia; Oetzel, 2011).

Hypocalcemia can be diagnosed through blood serum Ca concentrations or through physical changes. The most notable physical change is the cow's inability to stand, commonly referred to as "going down" or "downer cows." Herd prevalence may vary (0 to 54% of cows), but downer cows will have a high mortality risk (60 to 67% of down cows; Houe et al., 2000, Goff, 2008). Since 2004, non-ambulatory cattle cannot be marketed and must be humanely euthanized if the cow does not recover (Becker, 2009).

Subclinical hypocalcemia is diagnosed through evaluation of blood Ca concentrations (Kimura et al., 2006, Goff, 2008). The cutoff values reported in the literature for diagnosing subclinical hypocalcemia vary from 7.5 mg/dL (Bigras-Poulin and Tremblay, 1998), 7.9 mg/dL (Massey et al., 1993), 8.0 mg/dL (Goff, 2008), and 8.4 to 9.2 mg/dL (Chapinal et al., 2011, Chapinal et al., 2012). The higher thresholds were identified through links to reduced milk yield and a higher incidence of hyperketonemia, metritis, and displaced abomasum. Subclinical hypocalcemia may cost \$125 to \$246 per case (Reinhardt et al., 2011, Liang et al., 2017), and cost a 100 cow herd \$2,437 annually (Oetzel and Eastridge, 2013). Costs were accrued through decreased dry matter intake, decreased milk production, decreased fertility, and increased risk of secondary diseases, such as hyperketonemia and displaced abomasum (Oetzel, 2011).

Clinical hypocalcemia is diagnosed through visual symptoms, including muscle weakness, collapse, and disorientation that can continue to unconsciousness (Houe et al., 2000, Goff, 2008). Clinical hypocalcemia affects 2 to 14% of dairy cows around parturition (Esslemont and Kossaibati, 1996, Oetzel, 2011). Clinical hypocalcemia can result in death (8% of cases), early culling (12% of cases), and decreased milk production in subsequent lactations (14% decrease from normal lactation; Oetzel, 2011).

Hypocalcemia may increase mastitis risk because of reduced muscle contractions for all muscles, including the teat sphincter, and an impaired immune response (Kimura et al., 2006). Clinical hypocalcemia cut-off points for each stage decreased as severity increases: 5.6 to 7.6 mg/dL (Stage I: standing with clinical signs), 3.4 to 6.4 mg/dL (Stage II: sternal recumbency with clinical signs), and 1.0 to 3.4 mg/dL (Stage III: lateral recumbency with clinical signs; Oetzel, 2011).

Treatment for subclinical and clinical hypocalcemia involves providing a Ca substrate. Veterinary and treatment costs were modeled at $85 ± 43 per case of hypocalcemia (Liang et al., 2017). Independent of calcium status, transition cow protocols may include an initial Ca treatment followed 12 to 24 h later with a secondary treatment. Cows with subclinical hypocalcemia or Stage I clinical hypocalcemia may be treated with an oral Ca supplement (bolus or oral gel; calcium chloride or calcium propionate) or a subcutaneous Ca injection (Oetzel, 2011). Cows with Stage II or III clinical hypocalcemia require intravenous Ca. Additional treatment with oral Ca supplements may be needed to prevent a relapse (Oetzel, 2011). Intravenous Ca injection is administered with 500 mL of 23% calcium gluconate substrate. The injection is administered slowly, to prevent the cow from going into shock (Oetzel, 2011). Decreasing milkings per d following treatment for hypocalcemia may also help prevent a relapse (Oetzel, 2011).

Uterine diseases

Metritis is a bacterial infection of the uterus, and a common illness in fresh cows (2 to 40% of fresh cows; Risco and Melendez, 2002, Sheldon and Dobson, 2004). Three different definitions of metritis have been established. Puerperal metritis indicates a cow with an enlarged uterus, fetid watery red-brown vaginal discharge, signs of systemic illness, and fever < 21 d after parturition. Clinical metritis indicates a cow with an enlarged uterus and fetid watery red-brown vaginal discharge without systemic signs < 21 d after parturition. Finally, clinical endometritis indicates cows with pus in vaginal discharge without systemic signs ≥ 21 d after parturition (Sheldon et al., 2006, Dubuc et al., 2010a, Giuliodori et al., 2013).

The primary factor leading to metritis is retained fetal membranes, or retained placenta, following parturition (Giuliodori et al., 2013). A retained placenta occurs when the fetal membranes (cotyledons) fail to detach from the uterine membranes (caruncles) within 24 h of parturition. Retained placenta affects 1.3 to 50.0% of all fresh cows, particularly those with hypocalcemia, dystocia, or twins (Bretzlaff et al., 1982, Esslemont and Kossaibati, 1996, Risco and Melendez, 2002). Roughly 20 to 88% of all retained placenta cases lead to moderate to severe metritis (Bretzlaff et al., 1982, Risco and Melendez, 2002). On average, a case of retained placenta costs $106 to $313 (Risco and Melendez, 2002, Liang et al., 2017). Additional factors contributing to metritis include dystocia, stillbirth, and negative energy balance (Giuliodori et al., 2013).

Metritis may occur in 15 to 24% of fresh cows (Esslemont and Kossaibati, 1996) with primiparous cows at 1.5 times greater risk than multiparous cows (Giuliodori et al., 2013). Severe metritis (i.e., puerperal) occurs in 18 to 40% of fresh cows with an average cost per metritis case of $106 to $161 (Markusfeld, 1987, Drillich et al., 2001, Risco and Melendez, 2002). Liang et al. (2017) modeled a metritis cost of $172 ± 48 for primiparous cows and $263 ± 56 for multiparous cows.

Cows with metritis experience reduced milk yield, decreased reproductive performance, and increased risk of culling (Sheldon and Dobson, 2004, Bell and Roberts, 2007, Wittrock et al., 2011, Giuliodori et al., 2013). Metritic multiparous cows produced less over a lactation than their healthy herd mates and decreased dry matter intake during the three weeks following parturition (Wittrock et al., 2011). Primiparous cows did not experience these reductions compared to healthy herd mates (Wittrock et al., 2011). In a study by Bell and Roberts (2007), culling and failure to conceive were associated with uterine infections. Conversely, Giuliodori et al. (2013) concluded only puerperal metritis negatively affected pregnancy rate and calving interval. Wittrock et al. (2011) suggested multiparous cows with metritis were culled because of a combination of illness and low milk production instead of impaired reproductive performance.

Natural resolution of metritis involves uterine involution or uterine contraction. Uterine involution and contraction occur naturally, and self-cure can occur (Giuliodori et al., 2013). Giuliodori et al. (2013) witnessed an 11% cure risk per d postpartum with clinically metritic cows having a 95% greater cure risk than puerperally metritic cows. When a corpus luteum is present, prostaglandin $F2_{\alpha}$ may be used to hasten uterine involution to clear the infection from the uterus (Sheldon and Dobson, 2004). Following parturition, oxytocin may be given to help the uterus contract and expel metritis (Blowey, 1999). Antibiotics may also be administered to clear bacterial infections, including ceftiofur (Risco and Hernandez, 2003, Giuliodori et al., 2013), oxytetracycline, and cephalosporins (Sheldon et al., 2004).

MASTITIS

The most costly disease in the dairy industry worldwide is inflammation of the mammary gland, more commonly known as mastitis (Jain, 1979, Bramley et al., 1996). According to the 2007 NAHMS survey (USDA), 94.9 ± 0.08% of U.S. dairy herds reported at least one case of clinical mastitis per year with 16.5 ± 0.05% of each herd affected yearly. In a study by Bar et al. (2007), if a cow experienced a single case of clinical mastitis her lactation yield remained below healthy herd mates in the current lactation ($P < 0.01$), and decreased by 1.2 kg/d below healthy herd mates in the subsequent lactation. If a cow experienced a single case of clinical mastitis, she would lose 253 kg of milk production within the first two mo after diagnosis. If a second or third case occurred, she would lose an additional 238 or 216 kg of milk production within the same period (Bar et al., 2007). In 2008, Bar et al. simulated the cost of clinical mastitis as $71 per cow per yr and $179 per case. Most of the cost was attributed to milk loss ($115), followed by treatment ($50), and increased mortality risk ($14; Bar et al., 2008). More recently, Liang et al. (2017) calculated the cost of the average clinical mastitis case as $326 ± 71 and $426 ± 80 per case in primiparous and multiparous cows, respectively.

Mastitis indicators can be found in milk composition, with the most readily recognized being somatic cell count (**SCC)**. Somatic cells contain epithelial cells and leukocytes (lymphocytes, macrophages, and neutrophils) whose purpose is to phagocytize and destroy microorganisms in the infected quarter (Bramley et al., 1996). An increased individual cow and bulk tank SCC (> 200,000 cells/mL) can be observed with the presence of mastitis. Increasing a cow's mean lactation SCC ≥ 100,000 cells/mL decreases milk production in an individual cow, ranging from 91 to 907 kg per year. Similarly, increasing bulk tank SCC ≥ 200,000 cells/mL corresponds to the percentage of quarters infected in a particular herd, and the resulting production loss (Bramley et al., 1996).

Destruction or neutralization of invading agents (or toxins produced by them) is the purpose of the inflammatory response that gives mastitis its name. However, the inflammation may also be caused by physical trauma or chemical irritation. Destruction of these intrusive organisms allows the mammary gland to return to its normal function. Intramammary infection in dairy cattle is caused by microbial invasion, often bacterial (Bramley et al., 1996). Bacterial agents enter the udder through the teat end and teat canal (Jain, 1979). These bacteria multiply in secretory tissue and create toxins that cause injury to the udder, such as *Escherichia coli* toxemia (Bramley et al., 1996, Blowey, 1999).

Two categories of mastitis have been identified: subclinical and clinical mastitis. Subclinical mastitis does not present physical signs in the udder or milk abnormalities but does lead to SCC changes. Subclinical mastitis is the most prevalent in dairy herds (40 subclinical mastitis cases for every clinical mastitis case), with decreased milk production attributing 67% of the cost per case (Hillerton, 1998, Ott, 1999). Additional costs include reduced milk quality, increased labor costs, increased culling, and veterinary and treatment costs (Ott, 1999). Clinical mastitis presents several physical changes including flakes, clots, watery appearance in the milk, and heat, sensitivity, swelling, and pain in the affected quarter (Jain, 1979, Bramley et al., 1996). In certain cases, such as acute or peracute mastitis, other systems of the cow may be affected and expressed through symptoms such as reduced rumen function, fever, dehydration, weakness, depression, loss of appetite, or a rapid pulse (Bramley et al., 1996).

Mastitis causing agents

Several causative agents have been linked to mastitis (Bramley et al., 1996). Pathogens are grouped into two broad categories: contagious and environmental. For all categories of mastitis, higher parity cows (≥ 4 lactations) are associated with increased infection rates (16.5, 20.5, 17.4, and 46.5% of clinical mastitis cases in the 1^{st}, 2^{nd}, 3^{rd}, and ≥ 4^{th} lactation, respectively; $P < 0.05$) and decreased cure rates (39.4, 31.6, 30.3, and 26.2% of clinical cases in 1^{st}, 2^{nd}, 3^{rd}, and ≥ 4^{th} lactation, respectively; $P < 0.05$; Deluyker et al., 1999).

Contagious pathogens are transferred from cow to cow by contact with infected quarters. Contagious pathogens can spread through contaminated milking machine inflations, the hands of milking personnel, or dirty udder towels. Predominant contagious pathogens include *Staphylococcus aureus*, *Streptococcus agalactiae*, and *Mycoplasma* species (Harmon, 1994, González and Wilson, 2003).

Staphylococcus aureus is an obligatory udder parasite, which means the majority of colonies reside within the udder (Jain, 1979). *Staphylococcus aureus* can inhabit teat and udder skin or infected milk, and spread through contact with contaminated materials (Jain, 1979, Fox et al., 1991). Antibiotic therapy has limited efficacy for treating *S. aureus* infections because bacteria penetrate infected quarter tissue (Jain, 1979). *Staphylococcus aureus* can survive inside neutrophils (Yancey et al., 1991, Mullarky et al., 2001), form micro-abscesses and induce fibrosis (Ziv and Storper, 1985, Sordillo et al., 1989, Erskine et al., 2003), form small-colony variants (L-forms; Owens and

Nickerson, 1989, Brouillette et al., 2004), and invade mammary epithelial cells (Lammers, 2000, Kerro Dogo et al., 2002). All these properties may decrease the effectiveness of antimicrobial treatment in cows (Barkema et al., 2006). *Staphylococcus aureus* has a low clinical-plus-bacteriological cure rate (18%) compared to other staphylococcal species (40%; Deluyker et al., 1999). Segregation or removal of infected cows from healthy animals in the herd may effectively reduce the spread of *S. aureus* (Jain, 1979, Barkema et al., 2006). *Staphylococcus aureus* can result in necrotic udder tissue and death in rare, severe cases (Fox and Gay, 1993, Green and Bradley, 2004).

Similar to *Staphylococcus aureus*, most *Streptococcus agalactiae* colonies also reside in the udder (Keefe, 1997, Zadoks et al., 2011). *Streptococcus agalactiae* also spreads during milking through contaminated milk, milker's gloves, milking equipment, or udder preparation towels (Fox and Gay, 1993, Keefe, 1997). *Streptococcus agalactiae* infections have been steadily declining, with only 2.6% of US dairy operations testing positive in bulk tank samples (USDA-APHIS, 2008). The decline is likely because unlike *Staphylococcus aureus*, *Streptococcus agalactiae* responds well to antibiotic therapy and can be eradicated from a herd (Jain, 1979).

Mycoplasma spp. are emerging contagious pathogens (Fox et al., 2003). Common *Mycoplasma* species known to cause mastitis include *M. bovis*, *M. bovigenitalium*, *M. californicum*, *M. canadense*, and *M. alkalenscens (Kirk et al., 1994).* Unlike *S. aureus* and *Strep. agalactiae*, *Mycoplasma spp.* are simple self-replicating organisms that attach to host cells to survive (Kirk et al., 1994). Similar (Kirk et al., 1994) to *S. aureus* and *Strep. agalactiae, Mycoplasma spp.* are spread during milking through contaminated milk, milker's gloves, milking equipment, or udder preparation towels (Kirk et al., 1994). *Mycoplasma* species can persist for long periods of time in manure and have been isolated from excretions associated with metritis in transition cows, respiratory and urogenital tracts, joints, and eyes (Jasper, 1980, Kirk et al., 1994). Effective treatments are still being sought for mastitis caused by *Mycoplasma species* (Jasper, 1980, Kirk et al., 1994).

Environmental pathogens are inherently present in the environment of the cow and infect the udder opportunistically or when present in high levels (Bramley et al., 1996, Bradley, 2002). Environmental pathogens are not adapted for survival within a host, and typically elicit an immune response and are quickly eliminated (Bradley, 2002). Environmental risk factors include bacteria level, pathogen nature, environmental condition, and cow exposure (Jain, 1979, Bramley et al., 1996, Breen et al., 2007). *Streptococcus uberis* and *S. dysgalactiae* are the most commonly cultured causative agents of environmental mastitis. These cause subclinical cases that will result in occasional flair ups of subacute or acute clinical mastitis (Bramley et al., 1996). Environmental streptococcal infection rate increased with increasing parity (0.009 to 0.0045 infections/cow-d from the 1^{st} to $\geq 6^{th}$ lactation, respectively; Smith et al., 1985). Coliforms encompass two commonly discussed mastitis pathogens: Klebsiella species (*Klebsiella pneumoniae* and *Klebsiella oxytocia*) and *Escherichia coli*. Additional coliform bacteria are *Enterobacter aerogenes, Citrobacter spp., Serratia spp.,* and *Proteus spp.* (Smith et al., 1985). Coliforms cause acute or peracute mastitis with occasional subclinical infections. Typically, coliforms cause no extensive damage or decrease in milk production. In some instances, endotoxemia from coliform mastitis may cause death within a few days (Jain, 1979).

Some pathogens do not fall into the contagious or environmental categories. These include coagulase-negative staphylococci (**CNS**), yeasts, molds, algae, *Bacillus* species, *Pseudomonas aeruginosa*, *Actinomyces pyogenes*, *Nocardia* species, and Mycobacteria species (Bramley et al., 1996). Coagulase-negative staphylococci are often referred to as opportunistic mastitis causing agents present on teat skin and in the teat canal (Bramley et al., 1996). However, CNS are becoming a more prominent mastitis-causing pathogen (Pitkälä et al., 2004, Olde Riekerink et al., 2008, Oliveira et al., 2013).

Precision Dairy Monitoring Technology

Precision livestock technologies' purpose is real-time monitoring of animals to enhance the "eyes and ears of the farmer" (Berckmans, 2015). Precision livestock farming manages a livestock production system according to "the principles and technology of process engineering" (Wathes et al., 2008). Originally developed in poultry and swine growing operations, precision livestock farming allows animals to be managed at the individual level. Individual management is especially important for high-value animals, such as sows and dairy cows (Wathes et al., 2008). Variables measured by technology can be related to several health, management, and production characteristics.

Technologies can be wearable, incorporated into the milking system, stand-alone, or part of the management software (Bewley et al., 2017). Technology evolution can be divided into four categories: 1) measurement (quantification), 2) interpretation of measurements (classification), 3) integration of interpretation with other information, and 4) decision support or creation (Rutten et al., 2013). Quantification simply tells the user what has occurred (i.e., the number of steps taken, kg of milk produced, h spent lying down) without drawing any conclusions. Quantification is the first step in technology development and is critical for the development of more sophisticated systems. Quantification can be used without further data management, allowing users to decide for themselves how the data should be interpreted. Without any other information, a dairy producer could make judgments about data (i.e., daily milk weights) and conclude check the cow, cull the cow, etc.

Interpretation of measurements uses the collected measurements to inform the user about the cows' current state (i.e., estrus, high electrical conductivity) and then the user can use that information to form a decision. An interpretation of this sort categorizes data based on the current information and a predetermined threshold. For example, high electrical conductivity does not definitively mean a cow has mastitis, but the electrical conductivity of the milk has risen above a predetermined threshold, so the producer or the milker is informed of that change (Hogeveen et al., 2010). Integration of the interpretation would mean the system combined the measured information with other information (i.e., herd records, weather data, additional cow measurements, or economic data) and provided a recommendation to the user or formulated a decision based on the recommendation (decision support or creation). For example, an activity monitor could be combined with a herd management software. An increased activity would not be shown to the dairy producer until after the voluntary waiting period had passed. At this point, the technology does not choose to breed the cow (formulating a decision) but in the future technology could potentially make those decisions.

Technology must provide actionable alerts, with a small number of false alarms (false positives). Too many alerts corresponding to no change, or an unimportant change, will cause the user to ignore system alerts completely (Hogeveen et al., 2013, Woodall and Montgomery, 2014). Sensitivity and specificity control the number of alerts corresponding to unimportant changes or changes without an explicit action (i.e., breed or treat the cow) and are calculated through changes in true positives, false positives, true negatives, and false negatives. For wearable precision dairy monitoring technologies (**PDM**), the test creating an alert was a change in behavior or combination of behaviors outside of "normal" behavior ranges (Fricke et al., 2014b, Dolecheck et al., 2016b, Stangaferro et al., 2016c, b, a). True positive (**TP**) refers to the number of cows correctly identified as having a status change (i.e., estrus, metabolic disease, mastitis, or metritis) by the technology. False positive (**FP**) refers to the number of cows incorrectly identified as having a status change when no change had occurred (i.e., not in estrus or ill). True negative (**TN**) refers to the number of cows correctly identified as not having a status change (i.e., not in estrus or ill). False negative (**FN**) refers to the number of cows incorrectly identified as not having a status change when a change had occurred (i.e., in estrus or ill).

Sensitivity refers to the proportion of true positives detected by a test (Altman and Bland, 1994). Sensitivity is the balance between true positives and false negatives calculated as Eq. 1.1 (Altman and Bland, 1994, Hogeveen et al., 2010).

$$\text{Sensitivity} = \frac{\text{TP}}{(\text{TP+FN})} \text{ x } 100 \qquad \text{Equation 1.1}$$

For example, a technology that correctly identified 8 out of 10 cows in estrus would have a sensitivity of 80%. Specificity refers to the proportion of true negatives detected by a test (Altman and Bland, 1994). Specificity is the balance between true negatives and false positives calculated as Eq. 1.2 (Altman and Bland, 1994, Hogeveen et al., 2010).

$$\text{Specificity} = \frac{\text{TN}}{(\text{TN+FP})} \times 100 \qquad \text{Equation 1.2}$$

For example, a technology that correctly identified 8 out of 10 cows not in estrus would have a specificity of 80%. Sensitivity and specificity are inversely related, so achieving a balance between them to identify most of the cows with a status change without identifying many cows without a status change can be difficult. Hogeveen et al. (2010) suggested mastitis alerts should have a ≥ 80% sensitivity and a ≥ 99% specificity within 48 h of an event. However, Leenarts et al. (2017) suggested the economic benefit of technology should govern sensitivity and specificity. A less sensitive technology (21.2 or 54.4%) may still be profitable if no additional investment is required (i.e., calving detection from an estrus detection technology; Leenarts et al., 2017).

Variables measured by PDM – activity, lying or standing time

Cow activity (steps) was the first behavior measured through precision technology (pedometers; Farris, 1954). Farris (1954) described a marked increase in steps/d corresponded to the onset of estrus. Since that time, more research has been conducted describing links to behaviors changes (activity, lying, or standing time) and disease (Marchesi, 2013). Accelerometers measure movement in three directions – up and down, side-to-side, and front to back – and provide more information than their predecessor, pedometers (Stone, 2017).

Lying is vital for dairy cattle health and well-being to the extent that lying is prioritized above eating and social contact (Munksgaard et al., 2005). A large portion of a dairy cow's d is spent lying down (10.5 to 11.0 h/d; Ito et al., 2009; Bewley et al., 2010;

Medrano-Galarza et al., 2012). Lying deviations from 10.5 to 11.0 h/d could be linked to distress or disease. Aubert (1999) suggested decreased activity and increased lying time were coping mechanisms for diseases, specifically those dealing with pathogenic causes. A temperature increase was required to clear animals of pathogen-induced infection. A 13% metabolic increase is required to raise internal temperature by 1°C, leaving less energy for other functions and leading to conservation of energy (i.e., lying instead of walking or standing; Aubert, 1999). Similarly, lying time decreased when cows' needed to expel heat (heat stress) from 10.9 to 7.9 h/d ($P < 0.01$; Cook et al., 2007).

Itle et al. (2015) monitored lying time pre- and post-parturition. Cows with hyperketonemia (BHBA ≥ 1.2 mmol/L) tended to stand longer in the week prepartum and d of calving than healthy counterparts (15.0 vs. 13.9 ± 0.5 h/d; $P = 0.06$). However, no changes in standing time occurred postpartum (Itle et al., 2015). Conversely, Stangaferro et al. (2016a) noted activity (neck activity, arbitrary units) decreased from -5 to 1 d (d relative to diagnosis) in cows with hyperketonemia and began to increase 2 d after diagnosis. Tsai (2017) noted decreased lying time (9.8 vs. 10.9 h/d; $P < 0.05$), activity (leg based; 3,137 ± 121 vs. 3,685 ± 73 steps/d; $P < 0.05$), and neck activity (359 ± 13 vs. 407 ± 16 arbitrary units; $P < 0.05$) in cows with hyperketonemia compared to healthy counterparts from 1 to 21 DIM. Liboreiro et al. (2015) and Edwards and Tozer (2004), also reported decreased activity in cows with hyperketonemia compared to healthy herd mates. Edwards and Tozer (2004) also noted an increase in activity over healthy herd mates in cows with a left displaced abomasum ($P < 0.01$; **LDA**), which can occur in combination with hyperketonemia. Hyperketonemia is a result of negative energy balance, and decreased activity could be attributed to energy savings similar to those seen with fever (Aubert, 1999, Tsai, 2017).

Jawor et al. (2012) noted cows with subclinical hypocalcemia stood longer the d before calving (2.6 h) and laid down longer (2.7 h) the d after calving. Tsai (2017) reported cows with hypocalcemia had longer lying times (9.4 vs. 8.2 ± 1 h/d; $P < 0.01$) and decreased activity (neck or leg activity) compared to cows without hypocalcemia from 1 to 21 DIM. Tsai (2017) suggested decreased activity and increased lying time were linked to energy conservation and impaired muscle function associated with calcium deficiency (Goff and Horst, 1997, Kimura et al., 2006, Oetzel, 2011).

Titler et al. (2013) reported similar changes in behavior, with metritic cows standing longer, walking less, and having less lying bouts 1 d before to 3 d after clinical diagnosis than healthy counterparts. Liboreiro et al. (2015) identified decreases in neck activity associated with retained placenta (444 ±11 vs. 466 ± 4 neck activity prepartum; 488 ± 14 vs. 539 ± 6 neck activity postpartum) and metritis (512 ± 11 vs. 539 ± 6 neck activity postpartum). Tsai (2017) also associated decreased activity with metritis (2,125 ± 1,215 vs. 2,689 ± 1,637 steps/d in cows with or without metritis, respectively) although no changes in lying time or neck activity were reported. Stangaferro et al. (2016c) noted a decreased neck activity for cows diagnosed with metritis, but the overall decrease varied. Stangaferro et al. (2016c) suggested more severe cases of metritis (systemic effects) would have a greater change in activity compared to less severe cases of metritis. Metritis can present with a fever (Sheldon and Dobson, 2004, Sheldon et al., 2006), which is normally present in severe cases of metritis. Decreased activity or walking could be related to energy saving associated with fever as described by Aubert (1999).

Variables measured by PDM – eating or rumination time

During the transition period, cows experience negative energy balance and high demand for calcium and other minerals. The diet of a dairy cow provides energy and calcium to prevent dairy cattle from depleting bodily energy and calcium stores. Monitoring eating time or rumination time could emphasize early issues and improve detection of diseases (Weary et al., 2009, Bewley, 2010).

Cows with hyperketonemia spent ≤ 28% time at the feed bunk compared to healthy herd mates (Goldhawk et al., 2009, Itle et al., 2015). Stangaferro et al. (2016a) reported decreased rumination -5 to 0 d before hyperketonemia or displaced abomasum detection. Liboreiro et al. (2015) found cows with hypocalcemia had lower rumination time on the d of calving or 3 d after parturition. Cows with hyperketonemia had increased rumination time on the d of parturition but decreased rumination time from 8 to 17 d postpartum. Tsai (2017) reported no differences in rumination time or eating time in cows with hypocalcemia or hyperketonemia from 1 to 21 DIM.

Cows with metritis consumed less feed, spend less time eating, and drank less than cows without metritis (Huzzey et al., 2007). Liboreiro et al. (2015) identified decreases in rumination time associated with stillbirth (478 ± 6 vs 417 ± 23 min/d rumination prepartum; 437 ± 5 vs. 386 ± 19 min/d rumination postpartum) and metritis (416 ± 10 vs. 441 ± 5 min/d rumination postpartum). Stangaferro et al. (2016c) reported cows with metritis ruminated less than healthy herd mates. Tsai (2017) found lower rumination time in cows with metritis, but no differences in time around the feed bunk or time spent eating.

Estrus detection

One of the more common uses of PDM is estrus detection. Conventional estrus detection involves many labor hours, patches to identify mounted cows, or hormones to synchronize estrous. Even with additional support, the mean yearly estrus detection rate is around 46.3% (DRMS, 2017). An ideal replacement would continuously surveil and identify cows, require little labor, and accurately predict when cows should be inseminated (Senger, 1994).

Precision dairy monitoring can improve estrus detection rate without synchronization hormones and reduce the labor hours spent watching cows. Instead, PDM measure changes in behavior or biology including lying time, activity (steps/d or neck and head movement), feeding time, rumination events, mounting events, and blood or milk progesterone levels (Senger, 1994, Saint-Dizier and Chastant-Maillard, 2012, Fricke et al., 2014a). True estrus detection with a PDM ranged from 74.2% to 89.2% (Liu and Spahr, 1993, Cavalieri et al., 2003, Roelofs et al., 2005, Dela Rue et al., 2014). Timed artificial insemination (**TAI**) and PDM were comparable on: probability of pregnancy to first artificial insemination, probability of pregnancy to repeat artificial insemination, or pregnancy loss (P = 0.81, 0.88, and 0.20, respectively; Dolecheck et al., 2016), conception risk (17.6 vs. 22.6%, 30.0 vs. 30.1%, and 39.4 vs. 38.1%; Galon, 2010, Neves et al., 2012, and Neves and LeBlanc, 2015, respectively), and pregnancy risk (15.9 vs. 14.6% and 18.0 vs. 17.3%; Neves et al., 2012 and Neves and LeBlanc, 2015, respectively).

Disease detection

A new avenue of wearable PDM is disease detection through behavior monitoring. Several papers have been published on assessing milk compositional changes to identify mastitis (Hogeveen et al., 2010), but less is known about early detection of disease through behavior monitoring. In a review by Rutten et al. (2013), the majority of work conducted on metabolic detection (69%) simply measured changes associated with a disease and did not classify a cow as healthy or having a particular disease. Of the 16 publications reported only two focused on behavioral measurements: rumination (Bar and Solomon, 2010) and activity (Edwards and Tozer, 2004, Rutten et al., 2013). Conversely, the majority of work conducted on mastitis detection (92%) was at the classification level (Rutten et al., 2013). However, the majority of sensors evaluated (29 out of 31 publications) involved nonattached sensors, with one publication evaluating a reticular bolus (Rutten et al., 2013).

Bar and Solomon (2010) associated rumination time decreases from 39 to 255 min/d with changes in diet, calving, heat stress, estrus, and mastitis. Clement et al. (2013) noted a specificity of 6.9 to 75.0% based on deviation from normal rumination time. Although this specificity may be too low for a sole disease detection method, rumination monitoring could give farmers an early disease indication (Clement et al., 2013). Decreases in activity (steps/d) and feed intake with changes in standing or lying time may also promote early intervention (Proudfoot and Huzzey, 2016).

Based on a decreased health index score (**HIS**; calculated by a proprietary algorithm), rumination and neck activity correctly identified displaced abomasum 3.0 d before clinical diagnosis (98% sensitivity), hyperketonemia 1.6 d before clinical diagnosis (91% sensitivity), indigestion 0.7 d before clinical diagnosis (89% sensitivity), or all metabolic and digestive diseases 2.1 d before clinical diagnosis (93% sensitivity; Stangaferro et al., 2016a). In a Stangaferro et al. (2016b) companion paper, HIS correctly identified clinical mastitis 0.5 d before diagnosis (58% sensitivity), with clinical cases caused by *E. coli* having the highest sensitivity (81%). Stangaferro et al. (2016b) surmised the severe inflammatory response to *E. coli* improved detection ability through modifying behavior. Stangaferro et al. (2016c) also noted HIS correctly identified metritis (clinical and puerperal) 1.2 d before diagnosis (55% sensitivity).

Tsai (2017) compared behavioral variables collected by 10 different PDM to predict hyperketonemia, hypocalcemia, metritis, or any combination of hyperketonemia, hypocalcemia, or metritis. Variables analyzed included: rumination time (min/d), eating time (min/d), time spent at feed bunk (min/d), times visited feed bunk (number/d), activity (steps/d or units/d), lying time (min/d), lying bouts (bouts/d), time not active (min/d), time active (min/d), high activity (min/d), reticulorumen temperature (°C), Tsai's alerts were created based on a particular variable either rising above the 10^{th} percentile value or below the 90^{th} percentile value. For example, the 10^{th} and 90^{th} percentile value for lying time was 315 and 711 min/d (AfiAct pedometer plus). Lying time increased in cows with hypocalcemia, so a hypocalcemia alert would be created when a cow's lying time was > 711 min/d. Conversely, lying time decreased in cows with hyperketonemia, so an alert would be created when a cow's lying time was < 315 min/d. If a technology measured multiple variables (lying, standing, activity, etc.), all significant variables were combined to create one alert threshold per technology. Tsai combined this detection method with a time window of -5 to 0 d before disease detection, similar to Stangaferro et al. (2016a; b; c). This approach was able to detect hyperketonemia (32 to 79% sensitivity; 68 to 94% specificity), hypocalcemia (31 to 79% sensitivity; 71 to 95% specificity), metritis (28 to 75% sensitivity; 76 to 85% specificity), and any combination of diseases (33 to 79% sensitivity; 79 to 96% specificity; Tsai, 2017). The lowest sensitivity occurred when hyperketonemia, hypocalcemia, and metritis were detected using changes in body weight (kg/d) or reticulorumen temperature (°C).

Technology validation

Technologies can provide behavior measurements, but technologies must be validated to verify behavior measurements. Van Erp-Van der Kooj et al. (2016) validated the ability of Nedap's (Nedap Livestock Management, the Netherlands) Smarttag Neck and Leg technology. Agreement was assessed between technology detection and visual or video observations of eating time (Smarttag Neck), ruminating time (Smarttag Neck), resting time (Smarttag Neck), lying time (Smarttag Leg), standing time (Smarttag Leg), walking time (Smarttag Leg), and stand-up count (Smarttag Leg). Concordance correlation analysis (**CCC**) between visual or video observations and Smarttag Neck or Leg measurements was high (0.70 to 0.90) or very high (0.90 to 1.00) for all variables except walking time (0.47; low correlation 0.30 to 0.50; Hinkle et al., 2003; Van Erp-Van der Koof et al., 2016).

Borchers et al. (2016) validated additional accelerometer technologies: AfiAct Pedometer Plus (lying time (h/d); Afimilk, Kibbutz Afikim, Israel), CowManager SensOor (rumination time (h/d); feeding time (h/d); Agis, Harmelen, the Netherlands), HOBO Data Logger (lying time (h/d); HOBO Pendant G Acceleration Data Logger, Onset Computer Corp., Pocasset, MA), CowAlert IceQube (lying time (h/d); IceRobotics Ltd., Edinburgh, Scotland), Smartbow (rumination time (h/d); Smartbow GmgH, Jutogasse, Austria), and Track A Cow (lying time (h/d); feeding time (h/d) based on location to feeding area; ENGS, Rosh Pina, Israel). Feeding behavior was highly correlated with visually recorded behavior (CCC = 0.82 and 0.79 for CowManager SensOor and Track A Cow, respectively). Rumination time was weakly correlated with SensOor (CCC = 0.59) and strongly correlated with Smartbow (CCC = 0.96). Lying behaviors were highly correlated with CowAlert IceQube, Track A Cow, and AfiAct Pedometer Plus (CCC > 0.99, respectively) and moderately correlated with HOBO Data Loggers (CCC > 0.81). Based on these studies, PDM accurately measured cow behaviors (Borchers et al., 2016, Van Erp-Van der Kooj et al., 2016).

Producer adoption

Technology has been demonstrated to detect estrus, metabolic disorders, and mastitis. However, technology adoption among dairy producers has been slower than expected (Huirne et al., 1997, Gelb et al., 2001). In 1993, Spahr stated that although technology reduced the amount or time of labor, work difficulty or drudgery, and improved cow performance and well-being, producers would not adopt it unless the benefits were obvious and technology was easy to learn and use. Currently, slow adoption of technology continues, even though technologies Spahr (1993) dreamed of are now a reality.

Technology adoption may remain slow, and continue to remain slow, because producers are not involved in technology development (Huirne et al., 1997, Wathes et al., 2008). This can result in technologies that do not answer an on-farm need, are difficult to understand and use, or are cost prohibitive (Huirne et al., 1997, Yule and Eastwood, 2012, Russell and Bewley, 2013, Borchers and Bewley, 2015). Since 1993, researchers have been asking the question “Why hasn’t technology been adopted yet?” When producers discuss what drives decision making, the answers have stayed fairly consistent: economic feasibility (Huirne et al., 1997, Russell and Bewley, 2013, Borchers and Bewley, 2015), animal care and well-being (Huirne et al., 1997, Russell and Bewley, 2013), human factors (quality of life, status, comparison to neighbors, etc.; Huirne et al., 1997, Russell and Bewley, 2013, Borchers and Bewley, 2015), and usability and technical support (Huirne et al., 1997, Borchers and Bewley, 2015).

Russell and Bewley (2013) examined what influenced limited technology adoption in Kentucky. Producers were unfamiliar with the available technology, perceived an undesirable cost-to-benefit ratio, and did not know what to do with the overload of technology information (Russell and Bewley, 2013). Hogeveen et al. (2013) noted this issue in automated milking systems (milking robots); only 3% of all generated mastitis alerts were checked. Producer reasons for not checking alerts were no flakes or clots on the filter (28% of alerts), cows were repeatedly on the list (10%), and no time to check cows (10%; Hogeveen et al., 2013).

Building on Russell and Bewley (2013), Borchers and Bewley (2015) assessed what influenced technology purchases, and which measurements producer’s found most useful. Producers wanted an affordable technology, with a good cost-to-benefit ratio (Borchers and Bewley, 2015). Producers also wanted a simple technology that was easy to understand with access to technology support (Borchers and Bewley, 2015). Producers should also consider how technology fits into their operation and what need it will fill

(Yule and Eastwood, 2012). Commonly measured parameters from already adopted technologies included daily milk yield (52%), cow activity (41%), mastitis (25%), and milk components (25%; n = 109 respondents; Borchers and Bewley, 2015). Producers, both with and without technology, valued mastitis detection (1 to 5 scale; 4.8 ± 0.5), standing estrus detection (4.7 ± 0.5), daily milk yield (4.7 ± 0.6), cow activity (4.6 ± 0.8), and temperature (4.3 ± 1.0). However, producers with technology valued milk yield above standing estrus, whereas producers without technology valued standing estrus above milk yield (Borchers and Bewley, 2015).

Moving forward, producers desired individualized technology information (Huirne et al., 1997). Producers' were more willing to adopt technologies providing familiar measurements, such as daily milk yield and cow activity (Borchers and Bewley, 2015). Providing familiar measurements backed by proven performance through research may decrease risk aversion over time (Huirne et al., 1997, Borchers and Bewley, 2015). Increased labor shortages may also drive technology adoption, as reliable and economical labor becomes scarcer (Borchers and Bewley, 2015). Overall, manufacturers must consider the needs and usefulness to the producer when developing and implementing technology (Wathes et al., 2008). More on-farm evaluations are needed to provide producers with more educated decisions and improved technology competition (Jago et al., 2013). Additionally, increased technical support and producer training may increase adoption rates in the future (Jago et al., 2013, Borchers and Bewley, 2015).

Precision Dairy Monitoring Technology Economic Investment

Animal health economics is described as providing a framework of "concepts, procedures, and data" to support decisions and optimize animal health management

(Dijkhuizen et al., 1991). A model must 1) depict financial losses of animal disease, 2) enhance decisions on an animal, herd, or population level, and 3) identify costs and benefits of disease prevention (Dijkhuizen et al., 1991). The three main inputs that must be considered are people, products, and resources (McInerney, 1987, Dijkhuizen et al., 1991). Disease modeling is complicated by unobvious or slight effects, housing and nutrition components, changes in effect over time and stage of life, and inter-related diseases (Ngategize and Kaneene, 1985, Dijkhuizen et al., 1991). However, reducing the number of health problems should improve herd production and increase farmer income (Dijkhuizen et al., 1991).

When considering investment economics of technology to improve animal health (improved or earlier detection, faster recovery time, reduced drug usage or cost, etc.), an investment cannot provide a return without replacing an older technology with more efficiency (Ward, 1990). El-Osta and Morehart (2000) stated “efficient dairy farmers have a better chance at staying competitive and financially solvent” during times of market volatility. Wathes et al. (2008) agreed efficiency drove technology adoption. According to Wathes et al. (2008), limited stockmen with slim profit margins drives the need to invest in computer-based process management. For disease, producers must spend time visually assessing or monitoring all cows within their herd. A technology must identify sick or injured cows at the same time or before farmers or staff to replace visual observation. Technical progress, farm characteristics, and farm scale must be accounted for to model these effects (van Asseldonk et al., 1999a). Because technology investment is somewhat irreversible, investment success influences future investments (van Asseldonk et al., 1999a). Therefore, careful consideration must be taken when investing in precision dairy monitoring technologies.

Investing in PDM for early disease detection has a unique problem. Farm personnel must determine a course of treatment with limited or less specific information than if clinical signs were present (Stangaferro et al., 2016a). Because of this, limited research has been conducted on early disease detection and intervention. One study conducted by Milner et al. (1997) explored early mastitis detection with electrical conductivity. Mastitis was detected 3.5 milkings (2 d) before clinical signs, required two fewer doses of antibiotic therapy (6 vs. 8), and resulted in 100% cure rate on eight cows (Milner et al., 1997). According to Milner et al. (1997), early detection reduced lost milk production, decreased the antibiotic withholding period, decreased antibiotic and labor use, and prevented long-term milk production depression. Applying these same improvements to fresh cow diseases could result in significant savings to a dairy producer (Bewley, 2010, Bewley et al., 2010a, b).

Bewley et al. (2010b) developed an investment tool accounting for the complexities of dairy cattle reproduction, production, and culling. Bewley's model was a dynamic, stochastic, mechanistic simulation of a dairy farm created in Microsoft Excel 2007 (Microsoft, Seattle, WA) with an @Risk 5.0 add-in (Palisade Corporation, Ithaca, NY) to allow key model inputs to be chosen from a distribution (2010b). Detailed modules were calculated within the model to account for: 1) the stochastic nature of price (milk price, feed price, etc.), 2) the stochastic price associated with disease, reproduction, revenues, and expenses, 3) herd demographics, 4) performance of an average (or typical) cow, 5) changes in body condition score, 6) changes in reproductive performance and reproduction state, 7) disease cost and incidence, 8) retention pay-off (optimum culling moment), 9) changes in culling decisions or time, and 10) investing in a PDM system across each mo of a cow's life across 10 yr (Bewley et al., 2010b). Bewley et al. (2010a) used this model to assess the economic feasibility of investing in an automated body condition scoring system. Bewley et al. (2010a) found that a 1,000-cow herd with normal body condition score ranges would only benefit from automated body condition score investment 36.1% of the time (positive net present value). Profitability was heavily related to willingness to feed multiple TMR's, current herd disease incidence, and current herd reproductive performance (Bewley et al., 2010a)

Dolecheck et al. (2016a) and Liang et al. (2017) created further tools from Bewley et al. (2010b) base model. Liang et al. (2017) created an updated predicted disease cost model using the typical cow simulation and disease simulations on a daily basis (Bewley et al. (2010b) monthly basis). Liang's model incorporated the retention pay-off costs of disease, veterinary, treatment, and labor costs, and discarded milk loss (Liang et al., 2017). The greatest contributors to disease were discarded milk, decreased milk production, and veterinary or treatment costs. Cost per clinical case (Mean ± SD primiparous; Mean ± SD multiparous) was calculated for mastitis ($325 ± 71; $426 ± 80), lameness ($185 ± 64; $333 ± 69), metritis ($172 ± 48; $263 ± 56), retained placenta ($150 ± 51; $313 ± 65), left-displaced abomasum ($432 ± 102; $639 ± 114), hyperketonemia ($77 ± 24; $181 ± 64), and hypocalcemia ($181 ± 64; $246 ± 52). Liang's model can help direct future investment decisions based on the overall cost associated with a disease.

Dolecheck et al. (2016a) created a model for investing in wearable automated estrus detection (**AED**) technologies. Dolecheck et al. (2016a) used the daily calculations described in Liang et al. (2017) with a PERT distribution (defined by minimum, maximum, and mean) to randomly sample values for conception rate, estrus detection rate, voluntary waiting period, age at first calving, semen cost, mature cow live weight, rolling herd average milk production, replacement price, feed price, milk price, yearly veterinary costs per cow, cull cow price, and DIM to assign an open cow as a reproductive cull. Retention pay-off was calculated to define a cost of days open from the stochastic model. Dolecheck et al. (2016a) created a user-friendly decision support partial budget with the information collected from the stochastic model. Dairy producers could input their current estrus detection rate and expected estrus detection rate from a PDM. The cost of the PDM, initial installation cost, and annual upkeep cost were considered as additional costs. The reduced cost of days open, semen, and labor were considered as revenues. Tag price and installation cost influenced NPV most, with increased costs decreasing NPV (Dolecheck et al., 2016a). Dolecheck et al. (2016a) assumed a 7-yr technology life and had a resulting payback period of 1.6 to 3.8 yr. Giordano (2015) suggested a five yr technology life was crucial to purchasing, in line with Dolecheck et al. (2016a) findings.

CONCLUSIONS

Transition cow diseases and mastitis make up a large portion of the diseases dairy producers must manage. Precision dairy technologies may help dairy producers monitor and manage diseases at or before the appearance of clinical symptoms. However, all analyses have been conducted retrospectively for transition cow disorders. Estrus detection technologies have promise for additional detection parameters, including calving, metabolic disorders, mastitis, and metritis.

CHAPTER TWO

Producer use of on-farm precision dairy technology generated disease alerts

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INTRODUCTION

Precision dairy management technologies (**PDM**) are real-time animal monitors to supplement the "eyes and ears of the farmer" and allow producers to manage on an individual cow basis (Wathes et al., 2008, Berckmans, 2015). Technologies can be wearable, incorporated into the milking system, stand-alone, or part of the herd management software (Bewley, 2010, Borchers and Bewley, 2015). Wearable technologies (leg, neck, or ear attached) have been validated to accurately characterize activity (steps/d), lying time, standing time, walking time, eating time, and rumination time (Borchers et al., 2016, Van Erp-Van der Kooj et al., 2016). Changes in behaviors have been linked to estrus (Farris, 1954, Fricke et al., 2014a, Dolecheck et al., 2016b), calving (Bar and Solomon, 2010, Borchers et al., 2017), and illness (Jawor et al., 2012, Itle et al., 2015, Liboreiro et al., 2015). By quantifying behavioral changes, PDM could predict or detect estrus, calving, or illness events. However, researchers and manufacturers can often lose sight of the end user: the dairy producer.

Precision dairy monitoring alerts correspond to a behavioral change that could be associated with estrus, calving, or illness. Woodall and Montgomery (2014) stated alerts must correspond to an actionable and vital status change. For instance, a PDM alert stating a cow is in estrus should correspond to a cow in estrus with a definite action – breed the cow. Users begin ignoring alerts if too many correspond with no visual or actionable change. For example, when an alert occurs and the cow is not in heat, no action should be taken (Woodall and Montgomery, 2014). Additionally, alerts that occur without an actionable change decrease the economic and efficiency advantages that should be provided to the producer (Wathes et al., 2008). Sensitivity and specificity are critical to providing actionable alerts to dairy producers. Sensitivity is defined as the proportion of true positives correctly identified by a test, in this case a, PDM alert (Altman and Bland, 1994). Conversely, specificity is defined as the proportion of true negatives correctly identified by a PDM alert (Altman and Bland, 1994).   Finding a balance between sensitivity and specificity ensures most cows with a condition (estrus, illness, or calving) are detected without detecting cows without a condition. Hogeveen et al. (2010) suggested mastitis alerts should have ≥ 80% sensitivity and 99% specificity within 48 h of a mastitis event. Similar suggestions have not been made for other disease events.

Since the 1990's, precision technologies have been used to detect estrus (Liu and Spahr, 1993, Spahr, 1993). Using precision technologies for illness detection occurred much more recently (Stangaferro et al., 2016a, b, c, Stone, 2017, Tsai, 2017). Most research has focused on mastitis or estrus detection (Rutten et al., 2013, Fricke et al., 2014a). In a review by Rutten et al. (2013), 31 publications reported technologies able to detect mastitis. Conversely, only 16 publications reported technologies to detect metabolic diseases (Rutten et al., 2013). Of those 16 publications, only two focused on behavioral measurements collected from wearable PDM: rumination (Bar and Solomon, 2010) and activity (Edwards and Tozer, 2004). Consequently, little research has been conducted on how producers use PDM alerts for daily farm management decisions.

A lack of PDM producer adoption has been attributed to high cost of technology, undesirable or unknown cost-to-benefit ratio, lack of technical support, and poor usability (Huirne et al., 1997, Russell and Bewley, 2013, Borchers and Bewley, 2015). Within usability, producers were overwhelmed by the vast information provided by systems and desired user-friendly technology and more training on technology implementation (Jago et al., 2013, Russell and Bewley, 2013, Borchers and Bewley, 2015). Hogeveen et al. (2013) witnessed the reality of information overload with an automated milking system. Producers were provided 421 mastitis alerts through the system, and producers only checked cows on 3% of the alerts (Hogeveen et al., 2013). More on-farm evaluations are needed to provide producers and manufacturers with more information-based decisions in technology adoption and creation (Wathes et al., 2008, Jago et al., 2013).

Long-term evaluation of PDM generated disease alerts is needed to identify how producers incorporate these systems into their management and how useful producers find them. The objective of this study was to quantify the usefulness dairy producers associated with PDM technology generated disease alerts. The hypotheses were 1) producer usefulness would decrease over time if un-actionable alerts were created, 2) usefulness would be higher for behaviors producers already associated with disease, and 3) usefulness would be higher in cows that producers were already monitoring, such as cows at higher risk for disease.

MATERIALS AND METHODS

Data were collected from four cooperating Kentucky dairy farms from October 5, 2015 to October 30, 2016. Each farm was visited twice weekly for a total of 104 visits. All farms, herds, and producers were assigned an identifying number (1 to 4, respectively) that will be used from this point forward. Producers on farm 1, 2, 3, and 4 enrolled 373, 250, 365, and 386 cows in the study, respectively, from October 5, 2015 to October 30, 2016. Producer 1 enrolled 197 primiparous and 176 multiparous cows; producer 2 enrolled 162 primiparous and 88 multiparous cows; producer 3 enrolled 207 primiparous and 158 multiparous cows; producer 4 enrolled 201 primiparous and 185 multiparous cows. Herd 1 was comprised of Holsteins (n = 373); herd 2 was comprised of Holsteins (n = 223), Jerseys (n = 1), Brown Swiss (n = 10), and cross-bred cattle (n = 4); herd 3 was comprised of Holsteins (n = 210), Brown Swiss (n = 2), and cross-bred cattle (n = 116); herd 4 was comprised of Holsteins (n = 298) and cross-bred cattle (n = 61). Cows within farms 1, 2, 3, and 4 produced 39 ± 10, 36 ± 11, 37 ± 10, and 33 ± 10 kg/cow/d on DHI test day, respectively.

Six months before the start of the study, the entire lactating herd for each farm was equipped with a tri-axial accelerometer (attached to a right or left rear leg (70 x 40 x 72 mm, 108 g) with a thermoplastic polyurethane Nedap leg strap) measuring activity (steps/d) and lying time (min/d), and a tri-axial accelerometer attached around the neck (142 x 80 x 45 mm, 290 g) with a fully adjustable collar measuring eating time (min/d; CowWatch; Alta Genetics Inc., Watertown, WI manufactured by Nedap Livestock Management, the Netherlands). Any new cows without technologies entering the lactating herd had tags attached at or around calving. The tags sent their respective information to a wireless reader (located in the holding pen with a 1,000 m wireless radius) every 15 min as the number of seconds a behavior occurred (lying or eating time) or the number of steps taken within that 15-min interval. If the reader was out of range of the tags, data was stored for 24 h within the tag and each 15-min interval the tag attempted to connect with the reader again. Once a connection was established, all stored data was transferred to the reader.

Producers interested in purchasing a new precision dairy technology system were approached in October 2014. Four producers agreed to purchase the technology, participate in the study, and evaluate daily technology-generated herd health reports. Through the company's management software, a web-based system interface was made available to all producers on the study. The daily technology-generated health report was found by selecting the "Health and management" list (Figure 2.1). The list consisted of changes in eating, lying, or activity (steps/d) behavior according to a predetermined threshold set by the company. An alert was generated based on each variable individually, with a maximum of three alerts occurring for a cow in a d. Each cow was only listed once on the list, with each variable listed to the right of the cow number.

Producer 4 housed lactating cows in freestalls with mattresses and sawdust as the primary housing facility, producers 2 and 3 housed lactating cows in a combination of deep-bedded sawdust freestalls and compost bedded pack barns, and producer 1 housed lactating cows in compost bedded pack barns. All herds on the study were enrolled in DHI. Producer 3 fed a TMR once daily, with producers 1, 2, and 4 feeding a TMR twice daily. All cows were cooled by fans in the barn, feed alley, and holding pens when the temperature ≥ 21°C (Kiser et al., 2016, personal communication). Cows were milked 3x throughout the study at 0400, 1100, and 1800 on Farms 1, 2, and 3. On Farm 4, cows > 30 DIM were milked 2x, with cows 3 to 30 DIM milked 4x. On Farm 4, cows 3 to 30 DIM were milked at the start of the morning and evening milking, and again at the end of the morning and evening milking. Compost bedded pack barns were tilled 2 to 3 times per day depending on milking frequency and bedding was added when producers deemed appropriate. Bedding was added to freestalls at least weekly. No farms had headlocks. All handling of cows and attachment of technologies was conducted in handling chutes for Farms 1, 3, and 4. A palpation rail was used for whole herd technology attachment on Farm 2. A handling chute was used for cow handling and additional technology attachment after the initial whole herd technology attachment on Farm 2.

Two male and two female family members ran Farm 1. Farm 1 had two farm employees to assist with milking and the remaining farm tasks were completed by the family. One male family member ran Farm 2 almost entirely. Producer 2 also managed six chicken houses holding 24,000 birds each. Farm 2 had three full-time farm employees and one part-time farm employee for both the dairy and the chicken houses. Two male family members ran Farm 3 with three full-time farm employees. Two male and one female family member ran Farm 4. Farm 4 had four full-time farm employees.

Data collection

Performance records from DHI were collected with the permission of participating producers including bred/heat dates, DIM, parity, and amount of lactating animals in the herd. Producers were provided a HOBO U23 Series Pro v2 Logger (Onset, Cape Cod, MA) to collect barn temperature and humidity data. The HOBO was placed near the center of the primary housing barn above the height easily reached by cows and out of the direct airflow of fans. The HOBO was taken down on Tuesday of every week, and the lead author collected the data then restored the HOBO to the barn.

Herd behavior alert report. A technology-generated health report was created daily for every farm. Alert creation was proprietary and based on a percentage decrease from a cow's 10-d mean behavior. The default setting from the company used throughout the study was a decrease ≥ 30% from a cow's previous 10-d mean total daily activity (steps/d), lying time, or eating time. Until a full 10 d of data were collected on a cow, no alerts were created. The web-based interface presented alerts in the "Health and management" list as cow, DIM, group, eating attention, lying attention, and steps attention. Only cows with ≥ 1 attention were shown on the list. On May 11, 2016 a software update occurred for all farms. From October 5, 2015 to May 11, 2016 (**version 1**; Figure 2.1a), values were listed as "value (- %)" indicating the previous days' total eating, lying, or steps and the associated decrease from a cow's 10-d mean. Values in blue indicated no alert, whereas values in red indicated an eating, lying, or step alert. From May 11, 2016 to October 31, 2016 (**version 2**; Figure 2.1b) values were depicted as a horizontal bar, with a vertical line within the bar indicating a cow's 10-d mean. The amount of the bar filled (left to right) indicated the previous day's total eating or lying time. Blue bars indicated no alert, whereas red bars indicated an eating or lying alert. Steps/d were not shown after May 11, 2016, unless an alert was created. If an alert was created, "Decreased step count" appeared to the right of lying time in red. Although alert creation remained the same, cows that were identified as "in estrus" were not included on the "Health and management" list after May 11, 2016. Before May 11, 2016, cows could appear in the "Heat detection" and the "Health and management" lists. Cows in estrus experience a significant increase in activity which could correspond with decreased lying or eating time (Farris, 1954, Hurnik et al., 1975). After May 11, 2016, cows identified as in estrus were only shown on the "Heat detection" list even if a corresponding decrease in lying or eating time occurred. Producers were asked to provide feedback on each cow-alert that occurred on the list each day as explained in the next section. A cow-alert could contain a single change in activity, lying time, or eating time and any combination of the single changes.

Alert categorization and herd health. Producers recorded how they used cow-alerts generated by behavior changes according to Table 2.1 and Figure 2.2 (adapted from Hogeveen et al., 2013). Producers had the option to categorize alerts within an online Google form (Figure 2.3). Only one producer used the online Google form. Three producers printed off the daily health and management list and manually wrote the category (shorthand as A, B, or C) and the reason for categorization (shorthand 1 to 9) corresponding to the same set-up as the Google form. Producers were asked to select only one category and one reason the producer chose the category per cow-alert (Table 2.1 and Figure 2.2). A sample decision tree is provided in Figure 2.2. When a cow-alert occurred, a producer would either provide information on how the alert was used (**Evaluated**) or would not (**NotEvaluated**). Alerts producers evaluated could fall into 3 overall categories: cow visually checked because of the alert (**CowCheck**), the cow-alert behavior change was considered to be real, but the cow was not visually checked because of the alert (**NoAction**), or the cow-alert behavior change was not considered to be real (**AlertDoubted**).

Alerts categorized as CowCheck (cow visually checked because of the alert) were further divided into 5 reasons the producer chose the category: 1) cow was visually sick and treated, 2) cow was visually sick and not treated, 3) cow was not visually sick and treated, 4) cow was not visually sick and not treated, or 5) producer wrote in Other or selected "Other." Occasionally, producers provided written in responses for "Other" that included pen changes, calving, and estrus.

Alerts categorized as NoAction (cow-alert behavior change was considered to be real, but the cow was not visually checked because of the alert) were further divided into 9 reasons the producer chose the category: 1) the behavioral change from a cow's normal behavior did not worry the producer, 2) the cow underwent a pen change or dry-off, 3) the cow underwent a veterinary or pregnancy check or hoof trimming, 4) too many cows were currently being treated, 5) the cow had already been designated as a cull cow, 6) the cow was repeatedly on the alert list, 7) the cow was in estrus, 8) the producer had no time to visually check the cows, or 9) the producer wrote in Other or selected "Other." Occasionally, producers provided written in responses for "Other" that included estrus, weather changes, and feed changes.

Alerts categorized as AlertDoubted (cow-alert behavior change was not considered to be real) were further divided into 9 reasons the producer chose the category: 1) the alert was not believed to represent a real behavioral change, 2) the cow underwent a pen change or dry-off, 3) the cow underwent a veterinary or pregnancy check or hoof trimming, 4) the cow had been previously checked and was not ill, 5) the ear or neck tag was defective, removed, or lost, 6) the cow was repeatedly on the alert list, 7) the cow was in estrus, 8) the producer had no time to visually check the cows, or

9) the producer wrote in Other or selected “Other.” Occasionally, producers provided written in responses for “Other” that included estrus, weather changes, and feed changes.

Producers were asked to only select one overall category and one reason for selecting that category. If multiple reasons were selected (i.e., veterinary check and other) the reason providing the most information was selected (i.e., veterinary check). The similarities between reasons for NoAction and AlertDoubted were included to keep producers from choosing one reason and categorizing alerts based on the reason. Choosing an overall category (CowCheck, NoAction, or AlertDoubted) captured how the producer perceived that cow-alert’s usefulness, then allowed them to select why the cow-alert was categorized as CowCheck, NoAction, or AlertDoubted. The same family member from each farm categorized alerts during the study.

Statistical analyses

Data cleaning. Dairy producers only evaluated lactating dairy cows, so the data set was limited to lactating cows. Of the 1,197 cows in all herds with recorded disease events or disease alerts, 26 cows were removed from the dataset because some tags were assigned to incorrect cows, leaving 1,171 cows in the dataset. Dairy producers identified eleven cows as having incorrect tag information and an additional fifteen cows were identified as having incorrect tag information by bred or heat date. Bred and heat dates from the herd management software were compared to increases in activity (steps/d) over a cow’s 10-d mean activity on -1 to 1 d around a bred or heat date. If no increase in activity occurred during that period, the tag was determined to be on the wrong cow and the cow was removed from the data set.

The FREQ procedure of SAS 9.4 (SAS Institute, Inc., Cary, NC) with a Chi-square analysis was used to assess category and reason distribution across and within herds. Alert categorization reasons (5 to 9) were condensed to three main reasons per category. Reasons that accounted for ≤ 10% of cow-alert categorizations within CowCheck, NoAction, or AlertDoubted were combined with similar variables to improve odds-ratio calculation (Table 2.1). Within CowCheck, reasons were condensed to 1) **Sick** (visually sick and treated or visually sick and not treated), 2) **NotSick** (not visually sick and treated or not visually sick and not treated), and 3) **Other** (producer wrote in another response). Within NoAction, reasons were condensed to 1) **ChangeOk** (the behavioral change from normal behavior did not concern the producer), 2) **OutsideInfluence** (cow underwent a pen change, dry-off, veterinary or pregnancy check, or hoof trim), 3) **Other** (too many cows currently being treated, cow would be culled, cow repeatedly on the list, cow was in estrus, producer had no time to visually check cows, or producer wrote in a different response). Within AlertDoubted, reasons were condensed to 1) **ChangeDoubted** (the alert was not considered to represent a real behavior change), 2) **OutsideInfluence** (cow underwent a pen change, dry-off, veterinary or pregnancy check, or hoof trim), and 3) **Other** (cow previously checked and not ill, tag defective, removed, lost, cow was repeatedly on the list, cow was in estrus, producer had no time to visually check cows, or producer wrote in a different response). When analyses within CowCheck, NoAction, or AlertDoubted were conducted, the data set was reduced to include only alerts categorized as CowCheck, NoAction, or AlertDoubted, respectively. Associated cow numbers are given as (n = X) throughout the text.

Univariate analyses. A univariate analysis was conducted to test individual effects on alert categorization. Significant univariate effects ($P < 0.05$) were included in a multivariate model as fixed effects (Table 2.2). Fixed effects tested individually were software version, day group, lactation stage, parity, alerts/d, behavior type, and heat stress. Software version was either version 1 (pre-May 11, 2016) or version 2 (post-May 11, 2016). Day group was either weekday (Monday to Friday) or weekend (Saturday to Sunday). Lactation stage was either fresh (0 to 29 DIM), early (30 to 100 DIM), or post-peak (>100 DIM). Parity group was either 1st lactation, 2nd lactation, or $\geq$ 3rd lactation. Alerts/d were either $\leq$ 20 alerts/d or > 20 alerts/d. Alerts/d were divided based on the default number the Health and management list displayed (20 cow-alerts). Multiple pages had to be viewed or the default number of alerts showing had to be changed from 20 to 30, 50, or 100 to view $\geq$ 20 cow-alerts in a day. Behavior type triggering alerts was either eating time, lying time, activity, or any combination of eating, lying, and activity. Heat stress was either present ($\geq$ 68 maximum daily temperature humidity index) or absent (< 68 maximum daily temperature humidity index). Temperature humidity index (**THI**) was calculated using Eq. 2.1 (NOAA, 1976).

$$\text{THI} = \text{temperature (°F)} - (0.55 - (0.55 * \text{relative humidity}/100)) * (\text{temperature (°F)} - 58.8) \qquad \text{Equation 2.1}$$

A generalized linear mixed model (GLIMMIX procedure; SAS 9.4) with binary distribution and logit link was used to test fixed effects on the probability of a cow-alert being categorized as Evaluated (producer provided use information) or NotEvaluated (producer provided no use information). The model contained 24,012 observations on 1,171 cows across four farms. The random effect of clustering by cow within farm was included in the model. Repeated measures of cow within farm over the study was also included in the model.

A generalized linear mixed model with multinomial distribution and generalized logit link was used to test fixed effects on the probability of a cow-alert being categorized as CowCheck, NoAction, or AlertDoubted. The model contained 15,130 observations on 1,121 cows across four farms. The random effect of clustering by cow within farm was included in the model. Repeated measures of cow within farm over the study was also included in the model.

A generalized linear mixed model with multinomial distribution and generalized logit link was used to test fixed effects on the probability of a cow-alert being categorized as Sick, NotSick, or Other within the CowCheck category. The model contained 5,034 observations on 753 cows across four farms. The random effect of clustering by cow within farm was included in the model. Repeated measures of cow within farm over the study was also included in the model.

A generalized linear mixed model with multinomial distribution and generalized logit link was used to test fixed effects on the probability of a cow-alert being categorized as ChangeOk, OutsideInfluence, or Other within the NoAction category. The model contained 8,093 observations on 1,050 cows across four farms. The random effect of clustering by cow within farm was included in the model. Repeated measures of cow within farm over the study was also included in the model.

A generalized linear mixed model with multinomial distribution and generalized logit link was used to test fixed effects on the probability of a cow-alert being categorized as ChangeDoubted, OutsideInfluence, or Other within the AlertDoubted category. The model contained 2,003 observations on 560 cows across four farms. The random effect of clustering by cow within farm was included in the model. Repeated measures of cow within farm over the study was also included in the model.

Multivariate analysis – any feedback. A generalized linear mixed multivariate analysis was conducted to determine the effects of significant univariate variables in combination on alert categorization (GLIMMIX procedure SAS 9.4). A generalized linear mixed model with binary distribution and logit link was used to test fixed effects on alert categorization as Evaluated (producer provided use information) or NotEvaluated (producer provided no use information). Fixed effects were software version, day group, lactation stage, heat stress, alerts/d, and behavior type. The model contained 24,012 observations on 1,171 cows across four farms. The random effect of clustering by cow within farm was included in the model. Repeated measures of cow within farm over the study was also included in the model. Odds ratios (**OR**) were calculated comparing Evaluated alerts against alerts that were NotEvaluated for each fixed effect. Odds ratios with a 95% confidence interval including the null value (OR = 1) were not reported.

Multivariate analysis – evaluated alert categorization. A generalized linear mixed multivariate analysis was conducted to determine the effects of significant univariate variables in combination on alert categorization (GLIMMIX procedure SAS 9.4). A generalized linear mixed model with multinomial distribution and generalized logit link was used to test fixed effects on alert categorization as CowCheck (cow visually checked because of the alert), NoAction (cow-alert behavior change was considered to be real, but the cow was not visually checked because of the alert), or AlertDoubted (the cow-alert behavior change was not considered to be real). Fixed effects were software version, lactation stage, heat stress, alerts/d, and behavior type. The model contained 15,130 observations on 1,121 cows across four farms. The random effect of clustering by cow within farm was included in the model. Repeated measures of cow within farm over the study was also included in the model. Odds ratios were calculated comparing CowCheck against NoAction, CowCheck against AlertDoubted, and NoAction against AlertDoubted for each fixed effect. Odds ratios with a 95% confidence interval including the null value (OR = 1) were not reported.

Multivariate analysis – reasons for categorization: CowCheck. A generalized linear mixed multivariate analysis was conducted to determine the effects of significant univariate variables in combination on why alerts were categorized as CowCheck (GLIMMIX procedure SAS 9.4). A generalized linear mixed model with multinomial distribution and generalized logit link was used to test fixed effects to compare Sick (cow visually sick), NotSick (cow not visually sick), and Other (producer wrote in another response) as reasons for categorizing cow-alerts as CowCheck. Fixed effects were day group, lactation stage, alerts/d, and behavior type. The model contained 5,034 observations on 753 cows across four farms. The random effect of clustering by cow within farm was included in the model. Repeated measures of cow within farm over the study was also included in the model. Odds ratios were calculated comparing NotSick against Sick, Sick against Other, and NotSick against Other for each fixed effect. Odds ratios with a 95% confidence interval including the null value (OR = 1) were not reported.

Multivariate analysis – reasons for categorization: NoAction. A generalized linear mixed multivariate analysis was conducted to determine the effects of significant univariate variables in combination on why alerts were categorized as NoAction (GLIMMIX procedure SAS 9.4). A generalized linear mixed model with multinomial distribution and generalized logit link was used to test fixed effects to compare ChangeOk (the behavioral change from normal behavior did not worry the producer), OutsideInfluence (cow underwent a pen change, dry-off, veterinary or pregnancy check, or hoof trim), and Other (too many cows currently being treated, cow will be culled, cow repeatedly on the list, cow was in estrus, producer had no time to visually check cows, or producer wrote in a different response) as reasons for categorizing cow-alerts as NoCheck. Fixed effects were software version, day group, lactation stage, heat stress, alerts/d, and behavior type. The model contained 8,093 observations on 1,050 cows across four farms. The random effect of clustering by cow within farm was included in the model. Repeated measures of cow within farm over the study was also included in the model. Odds ratios were calculated comparing ChangeOk against OutsideInfluence, ChangeOk against Other, and OutsideInfluence against Other for each fixed effect. Odds ratios with a 95% confidence interval including the null value (OR = 1) were not reported.

Multivariate analysis – reasons for categorization: AlertDoubted. A generalized linear mixed multivariate analysis was conducted to determine the effects of significant univariate variables in combination on why alerts were categorized as AlertDoubted (GLIMMIX procedure SAS 9.4). A generalized linear mixed model with multinomial distribution and generalized logit link was used to test fixed effects to compare ChangeDoubted (the alert was not considered to represent a real behavior change), OutsideInfluence (cow underwent a pen change, dry-off, veterinary or pregnancy check, or hoof trim), and Other (cow previously checked and not ill, tag defective, removed, lost, cow was repeatedly on the list, cow was in estrus, producer had no time to visually check cows, or producer wrote in a different response) as reasons for categorizing cow-alerts as NoBelief. Fixed effects were software version, day group, lactation stage, heat stress, alerts/d, and behavior type. The model contained 2,003 observations on 560 cows across four farms. The random effect of clustering by cow within farm was included in the model. Repeated measures of cow within farm over the study was also included in the model. Odds ratios were calculated comparing OutsideInfluence against ChangeDoubted, OutsideInfluence against Other, and ChangeDoubted against Other for each fixed effect. Odds ratios with a 95% confidence interval including the null value (OR = 1) were not reported.

RESULTS

Overall, 24,012 cow-alerts were generated from 1,171 cows. Herds 1, 2, 3, and 4 included 217 ± 23, 137 ± 17, 202 ± 14, and 230 ± 14 lactating cows over the study period, respectively. Of the 24,012 cow-alerts, producers provided feedback on 15,130 cow-alerts (63%). Cow-alerts were caused by decreased eating time (n = 9,543), lying time (n = 9,777), activity (n = 1,590), or a combination of behaviors (n = 3,102). Across herds, producers provided feedback on 48 to 80% of the total cow-alerts (Table 2.3). Across herds, disease alerts were evaluated as CowCheck (2 to 45%), NoAction (17 to 45%), AlertDoubted (1 to 20%), and not evaluated (19 to 52%; Table 2.3).

Alert categorization

Software version. Software version was defined as 1 (pre-May 11, 2016; Figure 2.1a) or 2 (post-May 11, 2016; Figure 2.1b). Version influenced categorization and reason for categorization ($P < 0.01$) in all univariate models except reasons for categorizing cow-alerts as CowCheck ($P = 0.11$; Table 2.2). The longer the technology was used, the more likely producers were to not evaluate alerts (Table 2.4, OR = 1.40, 1.24 to 1.57 95% CI). The alerts that were evaluated in version 2 had an increased likelihood of being categorized as CowCheck (OR = 1.24, 1.01 to 1.52 95% CI), and were less likely to be categorized as AlertDoubted (OR = 2.90, 2.26 to 3.71 95% CI; Table 2.5). Although alerts were more likely to be assigned to CowCheck in version 2, no change in distribution within CowCheck occurred (Table 2.2).

Within NoAction, producers were more likely to categorize alerts as OutsideInfluence in version 1 (Table 2.7) than as ChangeOk or Other. Within AlertDoubted, producers were more likely to categorize alerts as OutsideInfluence in version 2 (Table 2.8) than as ChangeDoubted or Other. Within AlertDoubted, producers were more likely to categorize alerts as Other in version 1 (Table 2.8) than OutsideInfluence or ChangeDoubted.

Day group. Day group was divided into weekday (Mon to Fri) or weekend (Sat and Sun). Day group influenced categorization and reason for categorization in all univariate models ($P < 0.01$; Table 2.2) except categorization between CowCheck, NoAction, and AlertDoubted ($P = 0.06$; Table 2.2). Producers were more likely to evaluate alerts on weekdays (OR = 1.59, 1.45 to 1.74 95% CI; Table 2.4). Day group also affected distributions within CowCheck, NoAction, or AlertDoubted categorization ($P < 0.01$; Table 2.2). Within CowCheck, producers were more likely to categorize alerts as Sick on weekdays (OR = 1.53, 1.19 to 1.97 95% CI; Table 2.6). Within NoAction, producers were more likely to categorize alerts as ChangeOk instead of Other on weekends (OR = 1.28, 1.07 to 1.52 95% CI; Table 2.7). Within AlertDoubted, producers were more likely to categorize alerts as OutsideInfluence or ChangeDoubted instead of Other on weekends (OR = 1.67 and 4.14, respectively; Table 2.8).

Lactation stage. Lactation stage was divided into fresh (≤ 30 DIM), early (31 to 99 DIM) or post-peak (≥ 100 DIM) lactation. Lactation stage influenced categorization and reason for categorization in all univariate models ($P \leq 0.04$; Table 2.2). Producers were more likely to evaluate fresh and early lactation cows than post-peak lactation cows (OR = 1.15 and 1.30, respectively; Table 2.4). However, lactation stage did not affect CowCheck, NoAction, or AlertDoubted categorization, or reason for categorizing cow-alerts as CowCheck ($P = 0.08$ and 0.07, respectively).

Producers were more likely to categorize alerts as ChangeOk instead of OutsideInfluence in early or post-peak lactation instead of fresh lactation (OR = 2.20 and 3.58, respectively; Table 2.7). Alerts were more likely to be categorized as ChangeOk and OutsideInfluence instead of Other in fresh lactation instead of early or post-peak lactation (Table 2.7). Within AlertDoubted, alerts in fresh lactation cows were more likely to be categorized as OutsideInfluence instead of ChangeDoubted, OutsideInfluence instead of Other, and ChangeDoubted instead of Other compared to early and post-peak lactation cows (Table 2.8).

Alerts/d. Total cow disease alerts that occurred per day were divided into ≤ 20 (low) and > 20 (high) alerts/d. Twenty alerts corresponded to the number of alerts shown as the default on the Health and management list. Alerts/d influenced categorization and reason for categorization in all univariate models ($P < 0.01$; Table 2.2). Producers were more likely to evaluate alerts when ≤ 20 alerts/d occurred (OR = 1.92, 1.78 to 2.07 95%

CI; Table 2.4). When ≤ 20 alerts/d were on the list, producers were more likely to categorize alerts as CowCheck instead of NoAction (OR = 1.43, 1.26 to 1.63 95% CI; Table 2.5). Conversely, producers were more likely to categorize alerts as NoAction instead of AlertDoubted when > 20 alerts/d were on the list (OR = 1.65, 1.41 to 1.93; Table 2.5).

Within CowCheck when > 20 alerts/d occurred, producers were more likely to categorize alerts as Sick or NotSick instead of Other (OR = 2.01 and 2.55, respectively; Table 2.6). Within NoAction when ≤ 20 alerts occurred, producers classified alerts as ChangeOk instead of OutsideInfluence (OR = 2.37, 1.98 to 2.85 95% CI; Table 2.7), ChangeOk instead of Other (OR = 5.66, 4.84 to 6.61 95% CI; Table 2.7), and OutsideInfluence instead of Other (OR = 2.50, 2.06 to 3.04 95% CI; Table 2.7). Within AlertDoubted when ≤ 20 alerts occurred, producers categorized alerts as OutsideInfluence instead of Other (OR = 2.01, 1.28 to 3.16 95% CI; Table 2.8) and ChangeDoubted instead of Other (OR = 3.47, 2.03 to 5.92 95% CI; Table 2.8).

Behavior alerted. Behavior alerted referred to eating, lying, or activity and any 2 or 3-way combination of the behaviors that decreased below the predetermined threshold and triggered an alert to be created on the Health and management list. Behavior alerted influenced categorization and reason for categorization in all univariate models ($P < 0.01$; Table 2.2). Producers were more likely to evaluate eating over lying alerts, combinations over lying alerts, and activity over combination, eating, and lying alerts (Table 2.4).

When CowCheck and NoAction were compared, producers were more likely to visually check eating over combination, lying, or activity alerts (OR = 1.77, 11.28, and 6.24, respectively), combination over lying or activity alerts (OR = 6.39 and 3.53, respectively), and activity over lying (OR = 1.81; Table 2.5). When CowCheck and AlertDoubted were compared, producers were more likely to visually check eating over combination, lying, or activity alerts (OR = 2.30, 4.65, and 3.93, respectively) and eating over lying and activity alerts (OR = 4.65 and 3.93, respectively; Table 2.5). When NoAction and AlertDoubted were compared, producers were more likely to believe behavioral changes caused by lying over combination, eating, and activity (OR = 2.81, 2.56, and 1.53, respectively) and activity over combination and eating alerts (OR = 1.84 and 1.67, respectively; Table 2.5).

Within CowCheck, alerts categorized NotSick increased over Sick in eating over combination alerts (OR = 2.16), lying over combination and eating (OR = 5.66 and 2.62), and activity over combination, eating, and lying alerts (OR = 12.37, 5.74, and 2.19, respectively). Producers were more likely to categorize cow-alerts as Sick instead of Other in eating and combination alerts over activity alerts (OR = 4.38 and 3.68, respectively). Producers were more likely to categorize cow-alerts as NotSick instead of Other in eating, lying, and activity alerts over combination alerts (OR = 2.60, 4.24, and 3.63, respectively; Table 2.6).

Within NoAction, ChangeOk alerts were more likely to be eating over combination alerts (OR = 1.61), lying over combination, eating, and activity alerts (OR = 3.31, 2.06, and 1.58, respectively), and activity over combination alerts (OR = 3.31) instead of OutsideInfluence. ChangeOk alerts were more likely to be lying over combination or eating alerts (OR = 1.69 and 1.53, respectively) and activity over combination, eating, or lying alerts (OR = 3.44, 3.12, and 2.04, respectively) instead of Other. OutsideInfluence alerts were more likely to be combination over eating or lying alerts (OR = 1.42 and 2.19, respectively), eating over lying alerts (OR = 1.54), and activity over eating or lying alerts (OR = 2.23 and 3.43, respectively; Table 2.7) instead of Other.

Within AlertDoubted, OutsideInfluence alerts were more likely to be combination over eating alerts (OR = 7.88), lying over eating alerts (OR = 5.12), and activity over combination, eating, or lying alerts (OR = 3.31, 26.13, and 5.11, respectively) instead of ChangeDoubted. OutsideInfluence alerts were more likely to be combination over eating or lying alerts (OR = 3.66 and 4.44, respectively) and activity over eating or lying alerts (OR = 7.69 and 9.32, respectively) instead of Other. ChangeDoubted alerts were more likely to be combination or eating over lying alerts (OR = 3.20 and 5.90, respectively; Table 2.8) instead of Other.

Parity and heat stress. Parity was grouped as 1^{st}, 2^{nd}, and $\geq 3^{rd}$ lactation. Heat stress was grouped as temperature humidity index ≥ 68 or < 68. Parity group influenced categorization and reason for categorization in all univariate models except distribution of evaluated or not evaluated alerts ($P = 0.84$; Table 2.2). However, parity was not a significant influencer in any multivariate model. Heat stress influenced categorization and reason for categorization in all univariate models except distribution with CowCheck ($P = 0.16$; Table 2.2). Heat stress was only a significant influencer within NoAction and AlertDoubted models. Within NoAction, alerts were more likely to be categorized as ChangeOk instead of OutsideInfluence or Other when THI was ≥ 68 (OR = 1.45 and 5.66, respectively; Table 2.7). Within AlertDoubted, alerts were more likely to be categorized as OutsideInfluence instead of ChangeDoubted when THI was < 68 (OR = 2.44; Table 2.8).

DISCUSSION

Stangaferro et al. (2016a; b; c) and Tsai (2017) identified the potential for detecting mastitis, metritis, and metabolic disorders with PDM. In many instances, disease detection can occur days before human visual detection (Stangaferro et al., 2016a, b, c). However, little is known about how dairy producers use disease alerts in daily management. Hogeveen et al. (2013) monitored a snapshot of mastitis alerts created by an automated milking system, finding only 3% of the 421 alerts were checked by producers. The researchers checked cows based on 421 mastitis alerts and producers visually checked cows for 15 of the mastitis alerts (Hogeveen et al., 2013). Within our study, producers explained how they used alerts more often (63%; 15,130 out of 24,012), but only 21% of alerts (5,034 out of 24,012) were actively checked by dairy producers. Hogeveen et al. (2013) stated producers missed 74% of the clinical mastitis cases found by the researchers because of mastitis alerts (10 out of 39 mastitis cases found). A disease alert system is only as beneficial as the producers find it, and the producers in Hogeveen et al. (2013) and our study found a small percentage of alerts usable. Within our study, a popular response was ChangeOk (behavior change from normal did not worry the producer). Similarly, the most popular reason for not visually checking a cow for mastitis was no flakes or clots were found on the filter (28% of responses; Hogeveen et al., 2013). Admittedly, producers missed a large portion of mastitis events (74%) in Hogeveen et al. (2013) study, but in our study a low disease detection sensitivity (proportion of true positives) was associated with eating, lying, and activity (steps/d) alerts (31 ± 4 to 42 ± 3 sensitivity; Eckelkamp et al., 2017). The low sensitivity in our study coupled with the producer categorization of alerts as NoAction indicated too many alerts without a clear action or health-related issue were occurring.

Within our study, alert usefulness varied by the producer. Some producers rarely visually checked cows based on alerts (Farm 1; Table 2.3), whereas others preferred to check most of the cows (Farm 4; Table 2.3). Differences in usefulness did not necessarily mean the system performed differently on these farms. Hogeveen et al. (2013) reported similar differences with one producer checking an automatically generated mastitis alert list 10 times per d routinely and another checking the list 2 to 3 times per wk. Producer management style could also have influenced producer opinion. Farm 3 and 4 relied heavily on non-family labor to conduct daily tasks, allowing owners to spend time evaluating cow-alert lists and visually assessing cows. Farm 1 and 2 had limited non-family labor, relying instead on family labor to run the farm. Reliance on family labor limited the daily time owners could spend evaluating alerts and checking cows because they were busy with other on-farm tasks.

Producers on Farm 1 had the lowest number of alerts categorized as CowCheck (2%; Table 2.3). An elevated feed wagon was used to feed fresh cows on Farm 1. The feed wagon design (slanted head entrances) would press against the neck collar and prevent the tri-axial accelerometer from registering head movement, resulting in eating attentions for all cows in that pen. Over time, the alerts on cows within that pen were categorized as NoAction and written in as “fresh cows.” Including producers in technology development could help pinpoint issues like this before farm implementation and improve end-user technology confidence (Wathes et al., 2008).

System. The longer the system was in place, the less likely dairy producers were to give feedback on alerts (comparing evaluated to not evaluated alerts). According to the producers participating in this study, lack of feedback could indicate they were too busy, the system was not functioning correctly (lightning storms, lack of internet connection), or they were overloaded with alerts (≥ 100 alerts/d on the list; Kiser et al., 2016, personal communication) . Producers consistently provided cow-alert feedback (CowCheck, NoAction, or AlertDoubted) at least weekly over the study. Three producers provided feedback at least weekly over the study, with one producer giving feedback at least weekly until September 2016. Producer 3 had a family tragedy and was not present on the farm from September to November 2016. Producers may have been more willing to check alerts when the system was still novel. Decreased evaluations over time could have been linked to novelty wearing off or increased producer comfort with the system (knowing what was or was not linked to a disease event). Our results also suggested producers failed to evaluate the alerts they deemed unimportant. The likelihood of alerts categorized as CowCheck (cow visually checked because of the alert) or NoAction (cow-alert behavior change considered to be real, but the cow was not visually checked because of the alert) increased the longer the system was in place (Table 2.5). Woodall and Montgomery (2014) suggested too many alerts or alerts without a critical change (i.e. sickness) caused users to ignore alerts, in-line with our study findings.

Producers were more likely to attribute behavioral changes to outside influences (pen changes, dry-offs, estrus events, veterinary examinations, etc.) the longer the system was in place (Tables 2.7 and 2.8). Increased understanding of the system and logical connections to management effects were probably identified by producers over time. Including dairy producers in technology creation, or alert generation strategies, could help decrease the number of unnecessary alerts created by a system (Huirne et al., 1997, Wathes et al., 2008). Incorporating management software could also improve alert generation (Borchers and Bewley, 2015). If producers were able to enter pen changes, dry-offs, or scheduled events (pregnancy checks, hoof trimmings, etc.), technology companies could modify governing algorithms or alert thresholds based on the additional information. Although producers can recognize the changes in behavior occurred because of outside influences, potential disease alerts attributed to those changes could result in decreased producer confidence in disease alerts as it did in the current study.

Day group. Day group played a crucial role in evaluations. Producers were more likely to evaluate alerts, check alerts, and identify cows as sick during the workweek. Producers had less labor available on the weekends (personal communication) and were more likely to devote time to family (personal communication) than during the workweek. Conversely, Hogeveen et al. (2013) stated 7 AMS producers in the Netherlands did not change how often they checked a mastitis alert list between weekends and weekdays. However, Hogeveen et al. (2013) administered a questionnaire to gather how producers used mastitis alerts, followed up with five site visits. Tracking changes in how the alerts were used over time could have provided results similar to our study. Showing only urgent or high priority alerts (fresh cows, mastitis, or calving alerts) on weekends could improve producer use of disease alerts.

Lactation stage. Producers were more likely to evaluate alerts on cows in the fresh period or early lactation than cows in later lactation (Table 2.4). Cows are at the highest disease risk during the transition period, three wk pre- and three wk post-parturition (LeBlanc, 2010). Borchers and Bewley (2015) suggested producers were more likely to use measurements they were more familiar with (steps/d and milk weights). The same could be true for which cow-alerts producers placed a priority on. Producers may have increased alert evaluation during the fresh period and early lactation because of increased concern during that stage of a cow's life.

An increased likelihood of coding alerts as ChangeOk in fresh cows instead of Other was also seen. When talking with the producers, an idea was proposed. The alerts monitored eating time, lying time, and steps/d, and the possibility existed for changes in one variable to alter another. The producers noted fresh cows with lying time alerts (decreased lying time) could correspond to increases in eating time. Many alerts were coded ChangeOk because of this, with producers viewing this situation as a positive change indicative of cows improving postpartum (Kiser et al., 2016, personal communication). Huzzey et al. (2005) noted eating frequency increased postpartum (9.8 vs. 11.1 ± 0.5 meals/d pre and postpartum, respectively; $P = 0.09$) with standing time increasing postpartum (12.3 vs. 13.4 ± 0.3 h/d pre and postpartum, respectively; $P = 0.02$).

One limitation of the current alert creation strategy was increased behaviors did not create disease alerts. Theoretically, if a cow increased lying time, eating time and activity would decrease, creating an alert. However, the behavior volatility around calving could have made establishing a baseline difficult. Huzzey et al. (2005) reported inconsistency within and across herds pre- and postpartum for feeding and drinking behavior with standing time only increasing at the time of calving. With the behavioral volatility around calving, potentially providing different lists for different stages of lactation could improve producer use of disease alerts. Setting higher thresholds (above the ≥ 30% decrease set in our study) for later lactation cows could decrease the number of unused alerts, and enable producers to more closely focus on high risk cows.

Alerts/d. Similarly, ≤ 20 alerts/d on the health and management list improved the likelihood of producers evaluating alerts and visually checking alerts. Having a small number of alerts was more manageable to examine both on and off the computer screen. To view more than 20 alerts, producers had to either view multiple pages, or alter the number of alerts viewed at a single time. Increasing the number of alerts that can be viewed at a single time could improve alert use. Hogeveen et al. (2013) stated producers spent a maximum of 10 min looking at a mastitis alert list. However, Hogeveen's producers saw between 6 and 30 udder health alerts per d. Minimizing data noise from pen changes or scheduled events could help restrict alerts to health-specific behavioral changes and decrease the number of alerts per d and the time needed to evaluate alerts. Adopting these changes could encompass Woodall and Montgomery (2014), Wathes et al. (2008), and Russell and Bewley (2013) findings that producers desire actionable, individualized alerts, instead of information overload.

Additionally, producers could have associated a high number of alerts with increase false positives – an alert was created and the cow was healthy. Many studies have emphasized the importance of limiting false positives and negatives (sensitivity and specificity) with behavior generated alerts (Huzzey et al., 2005, Hogeveen et al., 2010, Fricke et al., 2014a, Borchers et al., 2017). In a companion study, the sensitivity ranged from 18 ± 3 to 29 ± 4% for the eating, lying, and activity alerts generated compared against disease events (any disease event: 24 ± 3%; hyperketonemia: 29 ± 4%; hypocalcemia: 29 ± 3%; metritis: 18 ± 3%; Eckelkamp et al., 2017). The results of the current study and the companion study indicated the producers had good reason to not evaluate alert lists with > 20 alerts/d.

Behavior alerted. Behavioral changes that created alerts affected at least one category within all groups. One of the most informative results was producers were more likely to evaluate eating or activity alerts instead of lying alerts. The high number of lying alerts (n = 9,777) compared to activity alerts (n = 1,590) further emphasizes the importance producers placed on activity alerts. Although lying time biologically is vital for dairy cow health (Munksgaard et al., 2005, Ito et al., 2009, Ito et al., 2010), producers did not consider decreased lying time as actionable as decreased eating time or activity. Borchers and Bewley (2015) noted producers were more willing to adopt technologies providing familiar measurements, particularly activity and milk yield. Dairy cattle activity monitoring (steps/d) has been available since the 1950s (Farris, 1954) with pedometers. Increased familiarity with activity could have influenced producers' preference for activity alerts. Huirne et al. (1997) and Borchers and Bewley (2015) suggested technologies with proven performance on familiar measurements were more likely to be adopted by dairy producers. Over time, lying time could become more readily accepted by dairy producers.

Producers were also more likely to categorize cows as visually ill in combination with eating alerts. In a companion study, eating time was a major influencer for random forests, principal component analysis neural networks, and least discriminate analyses techniques identifying diseases from behavioral patterns (Eckelkamp et al., 2017).

Edwards and Tozer (2004), Clement et al. (2013), Stangaferro et al. (2016a; b; c), and Tsai (2017) all reported detection of health disorders based on rumination and activity. Producers may have seen decreased activity and eating time as more actionable than decreased lying time. In the future, focusing on individual health behaviors or behavior combinations with strong links to diseases could improve alert usefulness and disease identification.

Further discussion

A technology must fit within the farm management style and fill a need before it can be considered a good investment (Yule and Eastwood, 2012). Although our study took place in the first year of adoption, producers showed a willingness to learn and to provide insight into how first-time users viewed technology-generated disease alerts. Our study showed producers placed a higher priority on eating or activity alerts, in fresh or early lactation cows, within the typical workweek, and when ≤ 20 alerts were on the alert list. Producers were more willing to evaluate high-risk cows (fresh or early lactation), especially when eating time and activity decreased. Borchers and Bewley (2015) suggested producers more readily adopted familiar measurements. The same could be suggested for measurements on cows already being observed. Willingness to evaluate alerts was likely because producers already visually monitored fresh and early lactation cows for eating and activity, and were willing to believe the system was accurately monitoring them also.

CONCLUSIONS

Precision dairy technology has many potential uses, but more work is needed to improve health detection alerts. Although producers indicated most of the alerts represented a real behavioral change (55%), 37% of alerts were not evaluated and producers only visually followed-up on 21% of the alerts. Behavioral disease alerts must be improved and respond to an actionable change for producers to use them. Producers were more likely to utilize eating or activity alerts, alerts in fresh or early lactation cows, during the workweek, and when ≤ 20 alerts were on the list. Incorporating herd management software, creating disease alert lists and managing alerts by stage of lactation, and focusing on behaviors producers' already find useful could improve alert utilization in the future.

ACKNOWLEDGEMENTS

The authors would like to thank the cooperating Kentucky farmers who made this study possible. We would also like to thank AltaGenetics for their financial support of this study, and Nedap for their technical support of this study. We also wish to thank Eric Roemmele for his time and statistical expertise. Finally, thank you to Davi Hutchins, Shaila Winston, Cerina Holcomb, Siobhan Gavigan, Kevin Zhoa, Amanda Lee, Gustavo Mazon, Matthew Borchers, Jenna Klefot, Karmella Dolecheck, Derek Nolan, Bettie Kawanga, Tsai I-Ching, Leen Leenaerts, Michele Jones, Carissa Truman, Lori Grinter, Emily Rice, Melissa Cornett, Tanya France, and Anna Hawkins for their assistance with laboratory analysis, data entry, and editing.

Table 2.1. Categorization guide provided to dairy producers for evaluation of cow-alerts generated through a change in activity (steps/d), lying time (h/d), or eating time (h/d) collected by wearing precision dairy technologies.

Abbreviation	Category	Subcategory	Alerts[1]	% total
CowCheck	Alert believed to represent a real behavioral change and cow visually checked		5,034[2]	21.0[2]
Sick		Cow visually sick and treated	532[3]	10.6[3]
Sick		Cow visually sick and not treated	35[3]	0.7[3]
NotSick		Cow not visually sick and treated	10[3]	0.2[3]
NotSick		Cow not visually sick and not treated	4,355[3]	86.5[3]
Other		Producer wrote in a different response	102[3]	2.0[3]
NoAction	Alert believed to represent a real behavioral change and cow not visually checked		8,093[2]	33.7[2]
ChangeOk		Behavioral change from normal did not worry producer	3,750[4]	46.3[4]
OutsideInfluence		Cow underwent a pen change or dry-off	1,078[4]	13.3[4]
OutsideInfluence		Cow underwent a veterinary or pregnancy check, or hoof trimming	431[4]	5.3[4]
Other		Too many cows currently being treated	0[4]	0.0[4]
Other		Cow will be culled	23[4]	0.3[4]
Other		Cow is repeatedly on the cow-alert list	22[4]	0.3[4]
Other		Cow is in estrus	675[4]	8.3[4]
Other		Producer had no time to visually check cow	123[4]	1.5[4]
Other		Producer wrote in a different response	1,991[4]	24.6[4]
AlertDoubted	Alert is not believed to represent a real behavioral change and cow not visually checked		2,003[2]	8.3[2]
ChangeDoubted		Alert was not considered to represent a real behavior change	495[5]	24.7[5]
OutsideInfluence		Cow underwent a pen change or dry-off	796[5]	39.7[5]
OutsideInfluence		Cow underwent a veterinary or pregnancy check, or hoof trimming	66[5]	3.3[5]
Other		Cow was previously checked and not visually ill	35[5]	1.7[5]
Other		Tag was defective, removed, or lost	2[5]	0.1[5]
Other		Cow is repeatedly on the cow-alert list	50[5]	2.5[5]
Other		Cow is in estrus	360[5]	18.0[5]
Other		Producer had no time to visually check cow	42[5]	2.1[5]
Other		Producer wrote in a different response	157[5]	7.8[5]

Table 2.1. (cont.)

[1]Alerts that were not categorized (NotEvaluated) accounted for 8,882 cow-alerts (37.0%) of 24,012 technology generated disease alerts.
[2]Number of alerts and percentages referred to the percentage of the total amount of technology generated disease alerts (n = 24,012).
[3]Number of alerts and percentages referred to the technology generated disease alerts categorized as CowCheck (cow visually checked because of the alert; n = 5,034).
[4]Number of alerts and percentages referred to the technology generated disease alerts categorized as NoAction (the cow-alert behavior change was considered to be real, but the cow was not visually checked because of the alert; n = 8,093).
[5]Number of alerts and percentages referred to the technology generated disease alerts categorized as AlertDoubted (the cow-alert behavior change was not considered to be real; n = 2,003).

Table 2.2. Univariate categorical influencers of producer categorization of cow-alerts generated by wearable precision dairy technologies from October 2015 to October 2016 assessed with the GLIMMIX procedure of SAS 9.4. Only influencers with $P < 0.05$ were included in a multivariate GLIMMIX procedure.

Producer categorization	Influencer	*P*-value
Evaluated[1] to NotEvaluated[2]		
	Software version[3]	< 0.01
	Day group[4]	< 0.01
	Lactation stage[5]	< 0.01
	Parity group[6]	0.84
	Heat stress[7]	< 0.01
	Alerts/d[8]	< 0.01
	Behavior alerted[9]	< 0.01
CowCheck[10], NoAction[11], or AlertDoubted[12]		
	Software version[3]	< 0.01
	Day group[4]	< 0.06
	Lactation stage[5]	< 0.01
	Parity group[6]	< 0.01
	Heat stress[7]	< 0.01
	Alerts/d[8]	< 0.01
	Behavior alerted[9]	< 0.01
Within CowCheck[13]		
	Software version[3]	0.11
	Day group[4]	< 0.01
	Lactation stage[5]	0.04
	Parity group[6]	0.04
	Heat stress[7]	0.16
	Alerts/d[8]	< 0.01
	Behavior alerted[9]	< 0.01
Within NoAction[14]		
	Software version[3]	< 0.01
	Day group[4]	< 0.01
	Lactation stage[5]	< 0.01
	Parity group[6]	< 0.01
	Heat stress[7]	< 0.01
	Alerts/d[8]	< 0.01
	Behavior alerted[9]	< 0.01
Within AlertDoubted[15]		
	Software version[3]	< 0.01
	Day group[4]	< 0.01
	Lactation stage[5]	< 0.01
	Parity group[6]	< 0.01
	Heat stress[7]	< 0.01
	Alerts/d[8]	< 0.01
	Behavior alerted[9]	< 0.01

Table 2.2. (cont.)

[1]Evaluated indicated cow-alerts that occurred and producer feedback was given. Evaluated cow-alerts were categorized as CowCheck, NoAction, and ChangeDoubted.
[2]NotEvaluated indicated cow-alerts that occurred, but no producer feedback was given.
[3]Software version was grouped as version 1 (pre-May 2016) or 2 (post-May 2016). The software was updated on May 11, 2016 to a visually different interface and cows in estrus were not included on the Health and management list.
[4]Day group was a weekday (Monday to Friday) or weekend (Saturday to Sunday).
[5]Lactation stage was grouped as fresh (≤ 30 DIM), early (31 to 99 DIM) or post-peak (≥ 100 DIM) lactation.
[6]Parity group was 1^{st}, 2^{nd}, and ≥ 3^{rd} lactation.
[7]Heat stress was grouped as temperature humidity index ≥ 68 or < 68.
[8]Alerts/d were grouped as ≤ 20 cow-alerts on the list per day or high > 20 cow-alerts on the list per day. Twenty cow-alerts corresponded to the default number displayed on the Health and management list.
[9]Behavior alerted referred to eating time, lying time, or activity (steps/d) and any 2 or 3-way combination of the behaviors that decreased below the predetermined threshold and triggered an alert to be created on the Health and management list.
[10]CowCheck indicated the cow was visually checked because of the alert.
[11]NoAction indicated the cow-alert behavior change was considered to be real, but the cow was not visually checked because of the alert.
[12]AlertDoubted indicated the cow-alert behavior change was not considered to be real.
[13]Within the alert category CowCheck, Sick indicated a cow was visually sick, NotSick indicated a cow was not visually sick, and Other indicated the producer wrote in their own response. Common responses included calving, pen change, and estrus (Table 2.1 and Figure 2.2).
[14]Within the alert category NoAction, ChangeOk indicated the behavioral change from normal did not worry the producer; OutsideInfluence indicated the behavioral change was attributed to a pen change, dry-off, veterinary or pregnancy check, or hoof trimming; Other indicated the producer wrote in their own response. Common responses included estrus, weather changes, and the producer had no time to visually assess cows (Table 2.1 and Figure 2.2).
[15]Within the alert category AlertDoubted, ChangeDoubted indicated the alert was not considered to represent a real behavior change; OutsideInfluence indicated the behavioral change was attributed to management change including: pen change, dry-off, veterinary or pregnancy check, or hoof trimming; Other indicated the producer wrote in their own response. Common responses included cow repeatedly on the list, weather changes, and the producer had no time to visually assess cows (Table 2.1 and Figure 2.2).

Table 2.3. Categorization distribution of cow-alerts generated by wearable precision dairy technologies within and across farms[1].

Category	Farm 1[1]			Farm 2[1]			Farm 3[1]			Farm 4[1]			All farms		
	Cow-alerts (#; %[2,3])			Cow-alerts (#; %[2,3])			Cow-alerts (#; %[2,2])			Cow-alerts (#; %[2,3])			Cow-alerts (#; %[2,3])		
Total cow-alerts[4]	6,537			5,394			5,579			6,499			24,012		
Total evaluated[5]	3,168	48%		3,352	62%		4,506	80%		4,104	63%		15,130	63%	
CowCheck[6]	103	2%	3%	393	7%	12%	1,588	28%	35%	2,950	45%	72%	5,034	21%	33%
NoAction[7]	2,776	42%	88%	2,430	45%	72%	1,772	32%	39%	1,115	17%	27%	8,093	34%	54%
AlertDoubted[8]	289	4%	9%	529	10%	16%	1,146	20%	25%	39	1%	1%	2,003	8%	13%
NotEvaluated[9]	3,369	52%		2,043	38%		1,075	19%		2,395	37%		8,882	37%	

[1]Farm 1, 2, 3, and 4 included 217 ± 23, 137 ± 17, 202 ±14, and 230 ± 14 lactating cows, respectively, from October 5, 2015 to October 30, 2016.
[2]First percentage refers to the percent of total alerts generated (Total cow-alerts).
[3]Second percentage refers to the percent of total cow-alerts evaluated (Total evaluated).
[4]Total cow-alerts included all cow-alerts generated by a -30% decrease in lying time, eating time, or step count from a 10-day moving mean regardless of producer evaluation of cow-alert.
[5]Total evaluated included all cow-alerts categorized as CowCheck, NoAction, and AlertDoubted.
[6]CowCheck indicated the cow was visually checked because of the alert.
[7]NoAction indicated the cow-alert behavior change was considered to be real, but the cow was not visually checked because of the alert.
[8]AlertDoubted indicated the cow-alert behavior change was not considered to be real.
[9]NotEvaluated indicated alerts that occurred, but no producer feedback was given.

Table 2.4. Odds ratios and 95% confidence intervals[1] for system[2], day group[3], lactation stage[4,5], alerts/d[6], and behavior alerted[7] effects of dairy producer alert evaluation[8] from the GLIMMIX procedure of SAS 9.4. Cow-alerts were generated for a change in activity (steps/d), lying time (h/d), or eating time (h/d) collected by wearable precision dairy technologies from October 5, 2015 to October 30, 2016.

Categorization and Risk factor	Reference Group	Odds ratio (OR)	95% CI[1] (OR)	*P*-value
Evaluated[8] to NotEvaluated[9] cow-alerts				
Version 1[2]	Version 2[2]	1.40	1.24 to 1.57	< 0.01
Weekday[3]	Weekend[3]	1.59	1.45 to 1.74	< 0.01
Fresh lactation[4]	Post-peak lactation[4]	1.15	1.02 to 1.31	< 0.01
Early lactation[4]	Post-peak lactation[4]	1.30	1.15 to 1.46	< 0.01
≤ 20 alerts/d[6]	> 20 alerts/d[6]	1.92	1.78 to 2.07	< 0.01
Combination[7]	Lying[7]	1.14	1.01 to 1.29	< 0.01
Eating[7]	Lying[7]	1.09	1.00 to 1.18	<0.01
Activity[7]	Combination[7]	1.27	1.06 to 1.51	< 0.01
Activity[7]	Eating[7]	1.33	1.13 to 1.56	< 0.01
Activity[7]	Lying[7]	1.45	1.23 to 1.70	< 0.01

[1]Confidence intervals (CI) overlapping the null value (OR = 1) were not included in the table.
[2]Software version was grouped as version 1 (pre-May 2016) or 2 (post-May 2016). The software was updated on May 11, 2016 to a visually different interface and cows in estrus were not included on the Health and management list.
[3]Day group was a weekday (Monday to Friday) or weekend (Saturday to Sunday).
[4]Lactation stage was grouped as fresh (≤ 30 DIM), early (31 to 99 DIM) or post-peak (≥ 100 DIM) lactation.
[5]Heat stress was grouped as temperature humidity index ≥ 68 or < 68. Heat stress was not a significant influencer of evaluating or not evaluating cow-alerts ($P = 0.71$).
[6]Alerts/d were grouped as ≤ 20 cow-alerts on the list per day or high > 20 cow-alerts on the list per day. Twenty cow-alerts corresponded to the default number displayed on the Health and management list.
[7]Behavior alerted referred to eating time, lying time, or activity (steps/d) and any 2 or 3-way combination (Combination) of the behaviors that decreased below the predetermined threshold and triggered an alert to be created on the Health and management list.

Table 2.4. (cont.)

[8]Evaluated indicated cow-alerts that occurred and producer feedback was given. Evaluated cow-alerts were categorized as CowCheck (cow visually checked because of the alert), NoAction (the cow-alert behavior change was considered to be real, but the cow was not visually checked because of the alert), and AlertDoubted (the cow-alert behavior change was not considered to be real).
[9]NotEvaluated indicated cow-alerts that occurred, but no producer feedback was given.

Table 2.5. Odds ratios and 95% confidence intervals[1] for system[2,3,4,5], alerts/d[6], and behavior alerted[7] effects on dairy producer alert evaluation[8,9,10] from the GLIMMIX procedure of SAS 9.4. Cow-alerts were generated for a change in activity (steps/d), lying time (h/d), or eating time (h/d) collected by wearable precision dairy technologies from October 5, 2015 to October 30, 2016.

Categorization and Risk factor	Reference Group	Odds ratio (OR)	95% CI[1] (OR)	*P*-value
CowCheck[8] vs. NoAction[9]				
Version 2[2]	Version 1[2]	1.24	1.01 to 1.52	< 0.01
≤ 20 alerts/d[6]	> 20 alerts/d[6]	1.43	1.26 to 1.63	< 0.01
Eating[7]	Combination[7]	1.77	1.40 to 2.23	< 0.01
Combination[7]	Lying[7]	6.39	4.84 to 8.42	< 0.01
Combination[7]	Activity[7]	3.53	2.53 to 4.92	< 0.01
Eating[7]	Activity[7]	6.24	4.42 to 8.79	< 0.01
Activity[7]	Lying[7]	1.81	1.39 to 2.35	< 0.01
Eating[7]	Lying[7]	11.28	8.54 to 14.90	< 0.01
CowCheck[8] vs. AlertDoubted[10]				
Version 2[2]	Version 1[2]	2.90	2.26 to 3.71	< 0.01
Eating[7]	Combination[7]	2.02	1.58 to 2.59	< 0.01
Combination[7]	Lying[7]	2.30	1.75 to 3.02	< 0.01
Combination[7]	Activity[7]	1.93	1.35 to 2.77	< 0.01
Eating[7]	Activity[7]	3.93	2.68 to 5.76	< 0.01
Eating[7]	Lying[7]	4.65	3.53 to 6.13	< 0.01
NoAction[9] vs. AlertDoubted[10]				
Version 2[2]	Version 1[2]	2.43	1.97 to 2.99	< 0.01
> 20 alerts/d[6]	≤ 20 alerts/d[6]	1.65	1.41 to 1.93	< 0.01
Lying[7]	Combination[7]	2.81	2.28 to 3.46	< 0.01
Activity[7]	Combination[7]	1.84	1.33 to 2.54	< 0.01
Activity[7]	Eating[7]	1.67	1.24 to 2.26	< 0.01
Lying[7]	Activity[7]	1.53	1.14 to 2.06	< 0.01
Lying[7]	Eating[7]	2.56	2.19 to 2.99	< 0.01

Table 2.5. (cont.)

[1]Confidence intervals (CI) overlapping the null value (OR = 1) were not included in the table.
[2]Software version was grouped as version 1 (pre-May 2016) or 2 (post-May 2016). The software was updated on May 11, 2016 to a visually different interface and cows in estrus were not included on the Health and management list.
[3]Lactation stage was grouped as fresh (≤ 30 DIM), early (31 to 99 DIM) or post-peak (≥ 100 DIM) lactation. Stage of lactation was not a significant influencer of CowCheck, NoAction, or AlertDoubted ($P = 0.08$).
[4]Parity group was 1st, 2nd, and ≥ 3rd lactation. Parity was not a significant influencer of CowCheck, NoAction, or AlertDoubted ($P = 0.26$).
[5]Heat stress was grouped as temperature humidity index ≥ 68 or < 68. Heat stress was not a significant influencer of CowCheck, NoAction, or AlertDoubted ($P = 0.97$).
[6]Alerts/d were grouped as ≤ 20 cow-alerts on the list per day or high > 20 cow-alerts on the list per day. Twenty cow-alerts corresponded to the default number displayed on the Health and management list.
[7]Behavior alerted referred to eating time, lying time, or activity (steps/d) and any 2 or 3-way combination of the behaviors that decreased below the predetermined threshold and triggered an alert to be created on the Health and management list.
[8]CowCheck indicated the cow was visually checked because of the alert.
[9]NoAction indicated the cow-alert behavior change was considered to be real, but the cow was not visually checked because of the alert.
[10]AlertDoubted indicated the cow-alert behavior change was not considered to be real.

Table 2.6. Odds ratios and 95% confidence intervals[1] for day group[2,3,4], alerts/d[5], and behavior alerted[6] effects on dairy producer alert evaluation within cow-alerts believed to represent a real behavioral change and cow visually checked based on the alert[7,8,9] from the GLIMMIX procedure of SAS 9.4. Cow-alerts were generated for a change in activity (steps/d), lying time (h/d), or eating time (h/d) collected by wearable precision dairy technologies from October 5, 2015 to October 30, 2016.

Categorization and Risk factor		Reference Group	Odds ratio (OR)	95% CI[1] (OR)	*P*-value
NotSick[7] vs.Sick[8]					
	Weekend[2]	Weekday[2]	1.53	1.19 to 1.97	< 0.01
	Eating[6]	Combination[6]	2.16	1.47 to 3.16	< 0.01
	Lying[6]	Combination[6]	5.66	3.31 to 9.65	< 0.01
	Lying[6]	Eating[6]	2.62	1.70 to 4.04	< 0.01
	Activity[6]	Combination[6]	12.37	5.98 to 25.59	< 0.01
	Activity[6]	Eating[6]	5.74	2.78 to 11.85	< 0.01
	Activity[6]	Lying[6]	2.19	1.01 to 4.74	< 0.01
Sick[8] vs. Other[9]					
	> 20 alerts/d[5]	≤ 20 alerts/d[5]	2.01	1.09 to 3.70	< 0.01
	Combination[6]	Activity[6]	3.68	1.30 to 10.42	< 0.01
	Eating[6]	Activity[6]	4.38	1.53 to 12.61	< 0.01
NotSick[7] vs. Other[9]					
	> 20 alerts/d[5]	≤ 20 alerts/d[6]	2.55	1.43 to 4.54	< 0.01
	Eating[6]	Combination[6]	2.60	1.38 to 4.91	< 0.01
	Lying[6]	Combination[6]	4.24	1.98 to 9.07	< 0.01
	Activity[6]	Combination[6]	3.63	1.47 to 8.99	< 0.01

[1]Confidence intervals (CI) overlapping the null value (OR = 1) were not included in the table.
[2]Day group was a weekday (Monday to Friday) or weekend (Saturday to Sunday).
[3]Lactation stage was grouped as fresh (≤ 30 DIM), early (31 to 99 DIM) or post-peak (≥ 100 DIM) lactation. Lactation stage was not a significant influencer of NotSick, Sick, or Other ($P = 0.07$).
[4]Parity group was 1st, 2nd, and ≥ 3rd lactation. Parity group was not a significant influencer of NotSick, Sick, or Other ($P = 0.09$).

Table 2.6. (cont.)

[5]Alerts/d were grouped as ≤ 20 cow-alerts on the list per day or high > 20 cow-alerts on the list per day. Twenty cow-alerts corresponded to the default number displayed on the Health and management list.
[6]Behavior alerted referred to eating time, lying time, or activity (steps/d) and any 2 or 3-way combination of the behaviors that decreased below the predetermined threshold and triggered an alert to be created on the Health and management list.
[7]NotSick indicated within the cow-alert category CowCheck (cow visually checked because of the alert) a cow was not visually sick (Table 2.1 and Figure 2.2).
[8]Sick indicated that within the cow-alert category CowCheck a cow was visually sick (Table 2.1 and Figure 2.2).
[9]Other indicated within the cow-alert category CowCheck the producers wrote in their own response. Common responses included calving, pen change, and estrus (Table 2.1 and Figure 2.2).

Table 2.7. Odds-ratios and 95% confidence intervals[1] for system[2], day group[3], lactation stage[4,5], heat stress[6], alerts/d[7] and behavior alerted[8] effects on dairy producer alert evaluation within cow-alerts believed to represent a real behavioral change and cow not visually checked based on the alert[9,10,11] from the GLIMMIX procedure of SAS 9.4. Cow-alerts were generated for a change in activity (steps/d), lying time (h/d), or eating time (h/d) collected by wearable precision dairy technologies from October 5, 2015 to October 30, 2016.

Categorization and Risk factor		Reference Group	Odds ratio (OR)	95% CI[1] (OR)	*P*-value
ChangeOk[9] vs. OutsideInfluence[10]					
	Version 2[2]	Version 1[2]	1.55	1.14 to 2.11	< 0.01
	Early lactation[4]	Fresh lactation[4]	2.20	1.64 to 2.94	< 0.01
	Post-peak lactation[4]	Fresh lactation[4]	3.58	2.72 to 4.74	< 0.01
	Post-peak lactation[4]	Early lactation[4]	1.62	1.25 to 2.13	< 0.01
	THI $\geq$ 68[6]	THI < 68[6]	1.45	1.12 to 1.89	< 0.01
	$\leq$ 20 alerts/d[7]	> 20 alerts/d[7]	2.37	1.98 to 2.85	< 0.01
	Eating[7]	Combination[8]	1.61	1.19 to 2.17	< 0.01
	Lying[8]	Combination[8]	3.31	2.45 to 4.48	< 0.01
	Activity[8]	Combination[8]	2.09	1.38 to 3.16	< 0.01
	Lying[8]	Eating[8]	2.06	1.62 to 2.61	< 0.01
	Lying[8]	Activity[8]	1.58	1.10 to 2.28	< 0.01
ChangeOk[9] vs. Other[11]					
	Weekend[3]	Weekday[3]	1.28	1.07 to 1.52	0.02
	Fresh lactation[4]	Early lactation[4]	3.27	2.44 to 4.37	< 0.01
	Fresh lactation[4]	Post-peak lactation[4]	2.80	2.14 to 3.67	< 0.01
	THI $\geq$ 68[6]	THI < 68[6]	1.56	1.24 to 1.95	< 0.01
	$\leq$ 20 alerts/d[7]	> 20 alerts/d[7]	5.66	4.84 to 6.61	< 0.01
	Lying[8]	Combination[8]	1.69	1.24 to 2.30	< 0.01
	Lying[8]	Eating[8]	1.53	1.21 to 1.94	< 0.01
	Activity[8]	Combination[8]	3.44	2.16 to 5.50	< 0.01
	Activity[8]	Eating[8]	3.12	2.03 to 4.81	< 0.01
	Activity[8]	Lying[8]	2.04	1.37 to 3.02	< 0.01

Table 2.7. (cont.)

Categorization and Risk factor	Reference Group	Odds ratio (OR)	95% CI[1] (OR)	*P*-value
OutsideInfluence[10] vs. Other[11]				
Version 1[2]	Version 2[2]	1.76	1.27 to 2.43	< 0.01
Fresh period[4]	Early lactation[4]	9.46	6.93 to 12.92	< 0.01
Fresh period[4]	Post-peak lactation[4]	11.45	8.44 to 15.54	< 0.01
≤ 20 alerts/d[7]	> 20 alerts/d[7]	2.50	2.06 to 3.04	< 0.01
Combination[8]	Eating[8]	1.42	1.06 to 1.91	< 0.01
Combination[8]	Lying[8]	2.19	1.59 to 3.03	< 0.01
Eating[8]	Lying[8]	1.54	1.19 to 1.99	< 0.01
Activity[8]	Eating[8]	2.23	1.41 to 3.52	< 0.01
Activity[8]	Lying[8]	3.43	2.15 to 5.48	< 0.01

[1]Confidence intervals (CI) overlapping the null value (OR = 1) were not included in the table.

[2]Software version was grouped as version 1 (pre-May 2016) or 2 (post-May 2016). The software was updated on May 11, 2016 to a visually different interface and cows in estrus were not included on the Health and management list.

[3]Day group was a weekday (Monday to Friday) or weekend (Saturday to Sunday).

[4]Lactation stage was grouped as fresh (≤ 30 DIM), early (31 to 99 DIM) or post-peak (≥ 100 DIM) lactation.

[5]Parity group was 1st, 2nd, and ≥ 3rd lactation. Parity group was not a significant influencer of ChangeOk, OutsideInfluence, or Other (P = 0.61).

[6]Heat stress was grouped as temperature humidity index ≥ 68 or < 68.

[7]Alerts/d were grouped as ≤ 20 cow-alerts on the list per day or high > 20 cow-alerts on the list per day. Twenty cow-alerts corresponded to the default number displayed on the Health and management list.

[8]Behavior alerted referred to eating time, lying time, or activity (steps/d) and any 2 or 3-way combination of the behaviors that decreased below the predetermined threshold and triggered an alert to be created on the Health and management list.

[9]ChangeOk indicated within the cow-alert category NoAction (the cow-alert behavior change was considered to be real, but the cow was not visually checked because of the alert) that the behavioral change from normal did not worry the producer (Table 2.1 and Figure 2.2).

[10]OutsideInfluence indicated within the cow-alert category NoAction the behavioral change was attributed to a pen change, dry-off, veterinary or pregnancy check, or hoof trimming (Table 2.1 and Figure 2.2).

[11]Other indicated that within the cow-alert category NoAction the producers wrote in their own response. Common responses included estrus, weather changes, and the producer had no time to visually assess cows (Table 2.1 and Figure 2.2).

Table 2.8. Odds ratios and 95% confidence intervals[1] for system[2], day group[3], lactation stage[4,5], heat stress[6], alerts/d[7], and behavior alerted[8] effects on dairy producer alert evaluation within cow-alerts not believed to represent a real behavioral change and cow not visually checked based on the alert[9,10,11] from the GLIMMIX procedure of SAS 9.4. Cow-alerts were generated for a change in activity (steps/d), lying time (h/d), or eating time (h/d) collected by wearable precision dairy technologies from October 5, 2015 to October 30, 2016.

Categorization and Risk factor	Reference Group	Odds ratio (OR)	95% CI[1] (OR)	*P*-value
OutsideInfluence[9] vs. ChangeDoubted[10]				
Version 2[2]	Version 1[2]	14.67	6.36 to 33.83	< 0.01
Fresh lactation[4]	Early lactation[4]	10.16	4.15 to 24.89	< 0.01
Fresh lactation[4]	Post-peak lactation[4]	7.59	3.12 to 18.41	< 0.01
THI < 68[6]	THI ≥ 68[6]	2.44	1.28 to 4.66	0.01
Combination[8]	Eating[8]	7.88	4.06 to 15.31	< 0.01
Lying[8]	Eating[8]	5.12	2.77 to 9.44	< 0.01
Activity[8]	Combination[8]	3.31	1.07 to 10.26	< 0.01
Activity[8]	Eating[8]	26.13	8.84 to 77.20	< 0.01
Activity[8]	Lying[8]	5.11	1.74 to 14.95	< 0.01
OutsideInfluence[9] vs. Other[11]				
Version 2[2]	Version 1[2]	32.99	14.26 to 76.29	< 0.01
Weekend[3]	Weekday[3]	1.67	1.14 to 2.43	< 0.01
Fresh lactation[4]	Early lactation[4]	22.60	8.95 to 57.05	< 0.01
Fresh lactation[4]	Post-peak lactation[4]	28.46	12.73 to 63.62	< 0.01
≤ 20 alerts/d[7]	> 20 alerts/d[7]	2.01	1.28 to 3.16	< 0.01
Combination[8]	Eating[8]	3.66	1.88 to 7.11	< 0.01
Combination[8]	Lying[8]	4.44	2.32 to 8.48	< 0.01
Activity[8]	Eating[8]	7.69	3.04 to 19.45	< 0.01
Activity[8]	Lying[8]	9.32	3.87 to 22.49	< 0.01
ChangeDoubted[10] vs. Other[11]				
Version 2[2]	Version 1[2]	5.65	2.09 to 15.29	< 0.01

Table 2.8. (cont.)

Categorization and Risk factor		Reference Group	Odds ratio (OR)	95% CI[1] (OR)	*P*-value
ChangeDoubted[10] vs. Other[11]					
	Weekend[3]	Weekday[3]	4.14	2.58 to 6.65	< 0.01
	Fresh lactation[4]	Early lactation[4]	3.22	1.29 to 8.08	< 0.01
	Fresh lactation[4]	Post-peak lactation[4]	5.92	2.30 to 15.21	< 0.01
	≤ 20 alerts/d[7]	> 20 alerts/d[7]	3.47	2.03 to 5.92	< 0.01
	Combination[8]	Lying[8]	3.20	1.28 to 7.99	< 0.01
	Eating[8]	Lying[8]	5.90	3.08 to 11.28	< 0.01

[1]Confidence intervals (CI) overlapping the null value (OR = 1) were not included in the table.

[2] Software version was grouped as version 1 (pre-May 2016) or 2 (post-May 2016). The software was updated on May 11, 2016 to a visually different interface and cows in estrus were not included on the Health and management list.

[3]Day group was a weekday (Monday to Friday) or weekend (Saturday to Sunday).

[4]Lactation stage was grouped as fresh (≤ 30 DIM), early (31 to 99 DIM) or post-peak (≥ 100 DIM) lactation.

[5]Parity group was 1st, 2nd, and ≥ 3rd lactation. Parity group was not a significant influencer of OutsideInfluence, ChangeDoubted, or Other (P = 0.29).

[5]Heat stress was grouped as temperature humidity index ≥ 68 or < 68.

[6]Alerts/d were grouped as ≤ 20 cow-alerts on the list per day or high > 20 cow-alerts on the list per day. Twenty cow-alerts corresponded to the default number displayed on the Health and management list.

[7]Behavior alerted referred to eating time, lying time, or activity (steps/d) and any 2 or 3-way combination of the behaviors that decreased below the predetermined threshold and triggered an alert to be created on the Health and management list.

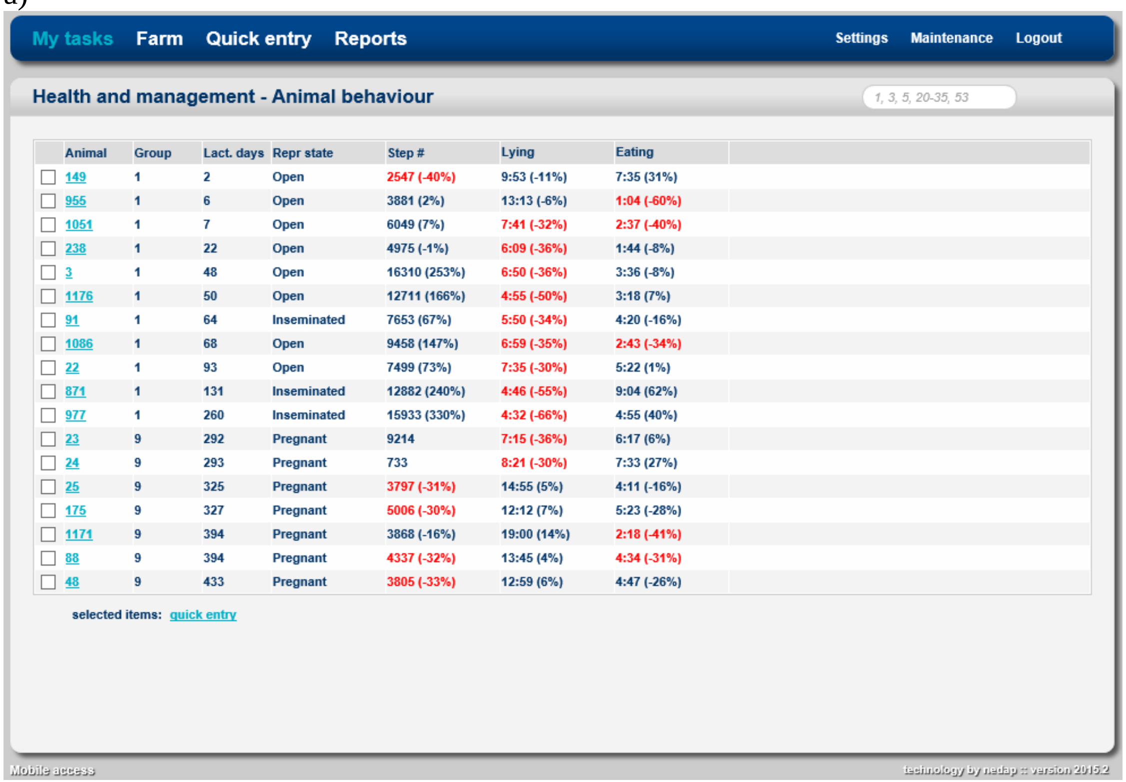
[8]ChangeDoubted indicated within the cow-alert category AlertDoubted (the cow-alert behavior change was not considered to be real) that the alert was not considered to represent a real behavior change (Table 2.1 and Figure 2.2).

[9]OutsideInfluence indicated within the cow-alert category AlertDoubted the behavioral change was attributed to a pen change, dry-off, veterinary or pregnancy check, or hoof trimming (Table 2.1 and Figure 2.2).

[10]Other indicated that within the cow-alert category AlertDoubted the producers wrote in their own response. Common responses included cow repeatedly on the list, weather changes, and the producer had no time to visually assess cows (Table 2.1 and Figure 2.2).

Figure 2.1. Health and management alert list created at midnight EST (Farm 4) or CST (Farm 1, 2, 3) for eating, lying, or activity behavior changes ≥ 30% from a cow's previous 10-d moving mean evaluated by dairy producers from October 5, 2015 to May 11, 2016 (a) and May 11, 2016 to October 31, 2016 (b). The physical appearance[1] of the list changed on May 11, 2016 (a to b), but behavior alert creation and producer evaluation remained the same from October 5, 2015 to October 31, 2016.

a)



Animal	Group	Lact. days	Repr state	Step #	Lying	Eating
149	1	2	Open	2547 (-40%)	9:53 (-11%)	7:35 (31%)
955	1	6	Open	3881 (2%)	13:13 (-6%)	1:04 (-60%)
1051	1	7	Open	6049 (7%)	7:41 (-32%)	2:37 (-40%)
238	1	22	Open	4975 (-1%)	6:09 (-36%)	1:44 (-8%)
3	1	48	Open	16310 (253%)	6:50 (-36%)	3:36 (-8%)
1176	1	50	Open	12711 (166%)	4:55 (-50%)	3:18 (7%)
91	1	64	Inseminated	7653 (67%)	5:50 (-34%)	4:20 (-16%)
1086	1	68	Open	9458 (147%)	6:59 (-35%)	2:43 (-34%)
22	1	93	Open	7499 (73%)	7:35 (-30%)	5:22 (1%)
871	1	131	Inseminated	12882 (240%)	4:46 (-55%)	9:04 (62%)
977	1	260	Inseminated	15933 (330%)	4:32 (-66%)	4:55 (40%)
23	9	292	Pregnant	9214	7:15 (-36%)	6:17 (6%)
24	9	293	Pregnant	733	8:21 (-30%)	7:33 (27%)
25	9	325	Pregnant	3797 (-31%)	14:55 (5%)	4:11 (-16%)
175	9	327	Pregnant	5006 (-30%)	12:12 (7%)	5:23 (-28%)
1171	9	394	Pregnant	3868 (-16%)	19:00 (14%)	2:18 (-41%)
88	9	394	Pregnant	4337 (-32%)	13:45 (4%)	4:34 (-31%)
48	9	433	Pregnant	3805 (-33%)	12:59 (6%)	4:47 (-26%)

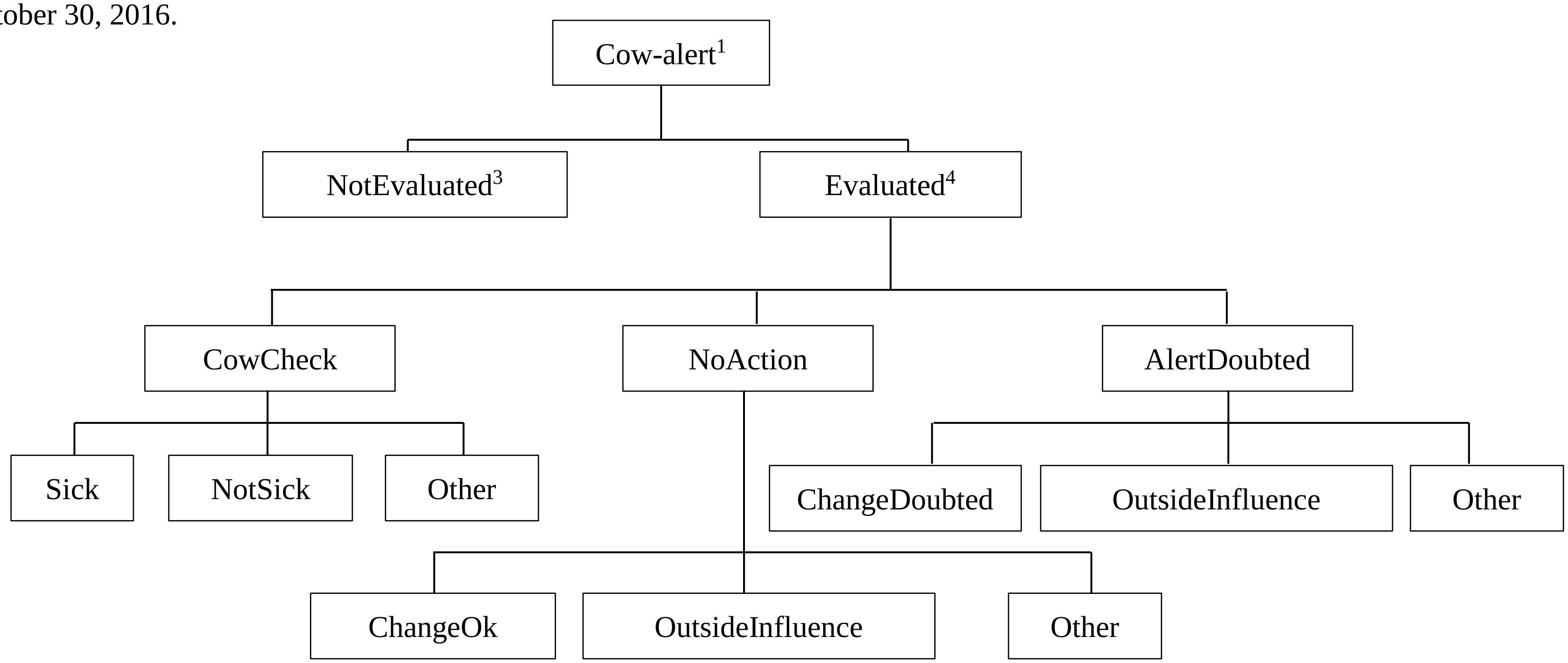
Figure 2.1. (cont.)

b)

Animal	Group	Lact. days	Eating time (0 6 12 18 24)	Lying time (0 6 12 18 24)	Standup #	
249	3. Pack Barn	7			13	
935	1. High Group	98			10	
175	4. Treated	169			16	Decreased step count
275	1. High Group	183			13	
260	2. Low Group	205			13	
169	2. Low Group	230			9	
59	4. Treated	256			9	Decreased step count
250	4. Treated	277			7	Decreased step count
293	2. Low Group	301			11	
285	2. Low Group	581			8	

[1]Physical appearance of the health and management list changed only for eating time, lying time, and activity (step #) alerts. Alert values were depicted with a horizontal bar instead of values in red (alert) or blue (no alert). Activity alerts were not depicted as a horizontal bar but indicated with "Decreased step count" in red.

Figure 2.2. Decision tree for producer evaluation of technology generated behavior alerts[1,2]. Cow-alerts were generated for a change in activity (steps/d), lying time (h/d), or eating time (h/d) collected by wearable precision dairy technologies from October 5, 2015 to October 30, 2016.



[1]Cow alerts were generated when a cow's lying time, eating time, activity (steps/d), or any combination decreased -30% or more from her 10-d moving average.
[2]Reference Table 2.1 for a full explanation of cow alert categorization.
[3]NotEvaluated indicated cow alerts that occurred, but no producer feedback was given.
[4]Evaluated included cow alerts that occurred and producer feedback was given. Evaluated cow alerts were categorized as CowCheck (cow visually checked because of the alert), NoAction (the cow alert behavior change was considered to be real, but the cow was not visually checked because of the alert), and AlertDoubted (the cow alert behavior change was not considered to be real).

Figure 2.3. Google document made available to dairy producers for evaluation of health and management list behavior alerts according to Table 2.1 and Figure 2.2. Farm 3 chose to use the Google form and Farm 1, 2, and 4 chose to print off the health and management list and record their categorization with shorthand (category A, B, or C and subcategory 1 to 9).

Dairy Study - Farm 1

Please fill out this form for all the animals listed under: Health and management - Animal behavior on the Nedap main screen. Please only select the action taken based on the alerts, sections are exclusive to a choice so something in each section should not need to be selected.

* Required

Cow ID *

Date *

Date the alert OCCURRED

mm/dd/yyyy

Initials *

Initials of person filling out the form

Value Alerted *

Please select all alerts that occurred for the animal on the date specified

- Step#
- Lying Time
- Eating Time
- No Alert, but animal visually ill

A **Alert Accepted and Animal Checked**

If the alert is considered TRUE AND the cow is checked for visual problems

1. Animal visually sick and treated
2. Animal visually sick and NOT treated
3. Animal NOT visually and treated
4. Animal NOT visually sick and NOT treated
5. Other:

Figure 2.3 (cont.)

B **Alert Accepted and Animal NOT Checked**

If the alert is considered TRUE BUT the cow is NOT checked for visual problems

1 ☐ Change from normal not alarming
2 ☐ Animal is repeatedly on alert list
3 ☐ Too many animals currently being treated
4 ☐ Animal will be culled
5 ☐ Animal underwent a pen change/dry off
6 ☐ Animal underwent a veterinary check/hoof trimming/pregnancy check
7 ☐ Animal is in heat
8 ☐ No time
9 ☐ Other: ________

C **Alert Rejected and animal NOT Checked**

If the alert is considered FALSE and the cow is NOT checked for visual problems

1 ☐ Animal repeatedly on alert list
2 ☐ Tag defective/removed/lost
3 ☐ Animal previously checked and not visually ill
4 ☐ Animal underwent a pen change/dry off
5 ☐ Animal underwent a veterinary check/hoof trimming/pregnancy check
6 ☐ Animal is in heat
7 ☐ Alert is not believed to be true
8 ☐ No time
9 ☐ Other: ________

Submit

Never submit passwords through Google Forms.

CHAPTER THREE

Precision dairy technology-generated disease alert accuracy and disease prediction with machine-learning techniques

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INTRODUCTION

Health disorders throughout lactation affect a large portion of cows within a herd, detrimentally impacting health, performance, welfare, and farm profitability. Hyperketonemia, hypocalcemia, metritis, and other diseases cause losses in production (Oetzel, 2011, McArt et al., 2015, Liang et al., 2017), increased risk of additional diseases, culling, or death (Goff, 2008, Chapinal et al., 2011, Raboisson et al., 2015), impaired reproductive performance (LeBlanc et al., 2002, Chapinal et al., 2012), and increased treatment costs (Milner et al., 1997, Duffield, 2000, McArt et al., 2014). Early detection could prevent disease progression, improve response to treatment, and reduce treatment costs (Milner et al., 1997, Stangaferro et al., 2016a).

Precision dairy management (**PDM**) technologies are real-time monitors to supplement the "eyes and ears of the farmer" and allow producers to manage on an individual cow basis (Wathes et al., 2008, Berckmans, 2015). Wearable PDM technologies (leg, neck, or ear attached) have been validated to accurately characterize leg activity (steps/d), neck activity (arbitrary units), lying time, standing time, walking time, eating time, and rumination time (Borchers et al., 2016, Van Erp-Van der Kooj et al., 2016). Wearable PDM technologies have been used for estrus (Galon, 2010, Neves and LeBlanc, 2015, Dolecheck et al., 2016b), disease (Edwards and Tozer, 2004, Liboreiro et al., 2015, Stangaferro et al., 2016a, b, c), and calving (Maltz and Antler, 2007, Ouellet et al., 2016, Borchers et al., 2017) detection through behavioral changes. However, few studies have assessed wearable PDM technology generated alerts for disease detection (Liboreiro et al., 2015, Stangaferro et al., 2016a, b, c).

Disease alerts must occur in conjunction with disease events to be useful to dairy producers (Woodall and Montgomery, 2014). Sensitivity and specificity are evaluations of how often a test (disease alert) coincides with an event, in this case, a disease. True positive (**TP**) refers to the number of cows correctly identified as having a status change (alert + illness). False positive (**FP**) refers to the number of cows incorrectly identified as having a status change when no change occurred (alert + healthy). True negative (**TN**) refers to the number of cows correctly identified as not having a status change (no alert + healthy). False negative (**FN**) refers to the number of cows incorrectly identified as not having a status change when a change has occurred (no alert + illness). Sensitivity is the proportion of true positives detected by a PDM (TP / (TP + FN) *100), whereas specificity is the proportion of true negatives detected by a PDM (TN / (TN + FP) * 100; Altman and Bland, 1994). Hogeveen et al. (2010) suggested automated milking system mastitis alerts should have ≥ 80% sensitivity and ≥ 99% specificity within 48h of an event. However, Leenarts et al. (2017) suggested a less sensitive technology (21 or 54%) could still be profitable if no additional investment was required (i.e., calving detection or disease detection from an estrus detection technology).

Several studies have been conducted using commercially available wearable PDM to detect or predict disease. Activity (steps/d or neck activity; Edwards and Tozer, 2005, Liboreiro et al., 2015, Stangaferro et al., 2016a, b, c), rumination time (Bar and Solomon 2010, Clement et al., 2013, Liboreiro et al., 2015, Stangaferro et al., 2016a, b, c,), eating and lying time (Tsai, 2017), and movement (Titler et al., 2013, Tsai, 2017) have been discussed as potential predictors for disease detection. Decreased rumination and eating time has been associated with hyperketonemia, displaced abomasum, mastitis, metritis, and stillbirth (Huzzey et al., 2007, Liboreiro et al., 2015, Stangaferro et al., 2016a, b, c, Tsai, 2017). Decreased activity (neck, steps/d, walking time) and changes in lying and standing time have been associated with hyperketonemia, hypocalcemia, displaced abomasum, mastitis, metritis, and retained placenta (Jawor et al., 2012, Titler et al., 2013, Liboreiro et al., 2015, Tsai, 2017).

Precision dairy technologies that monitor daily changes in eating time, lying time, standing time, walking time, and activity (steps/d) have potential to detect diseases throughout a lactation. However, the sensitivity and specificity of disease detection with PDM has not been well documented (Clement et al., 2013, Stangaferro et al., 2016a, b, c, Tsai, 2017). More information is needed on the ability of these PDM to predict or coincide with a disease event. The objectives of this study were to 1) identify the sensitivity, specificity, accuracy, and balanced accuracy of disease detection available with two commercially available technologies, 2) determine the disease prediction efficacy of the technologies separately using machine-learning techniques, and 3) determine the disease prediction efficacy of both technologies with previous lactation information using machine-learning techniques. The study hypotheses were 1) technology generated disease alerts would detect disease events over lactation, 2) individual technology machine-learning techniques would improve detection accuracy over the technology generated disease alerts, and 3) combining behavior changes with herd record information would provide the best detection accuracy.

MATERIALS AND METHODS

Data were collected from four cooperating Kentucky dairy farms from October 5, 2015 to October 30, 2016. Each farm was visited twice weekly for 104 visits and assigned an identifying number (1 to 4). Producers on farm 1, 2, 3, and 4 enrolled 373, 250, 365, and 386 cows in the study (n = 1,374 total cows enrolled), respectively, from October 5, 2015 to October 30, 2016. Producer 1 enrolled 197 primiparous and 176 multiparous cows; producer 2 enrolled 162 primiparous and 88 multiparous cows; producer 3 enrolled 207 primiparous and 158 multiparous cows; producer 4 enrolled 201 primiparous and 185 multiparous cows. Detailed herd and housing information can be found in Eckelkamp and Bewley (2017).

Six months before the start of the study, the entire lactating herd for each farm was equipped with a tri-axial accelerometer (attached to a right or left rear leg (70 x 40 x 72 mm, 108 g) with a thermoplastic polyurethane Nedap leg strap) measuring activity (steps/d) and lying, standing, and walking time (min/d), and a tri-axial accelerometer attached around the neck (142 x 80 x 45 mm, 290 g) with a fully adjustable collar measuring eating time (min/d; CowWatch; Alta Genetics Inc., Watertown, WI manufactured by Nedap Livestock Management, the Netherlands). Any cows without technologies entering the lactating herd had tags attached at or around calving. The tags sent their respective information to a wireless reader (located in the holding pen with a

1,000 m wireless radius) every 15 min as the number of seconds a behavior occurred (lying, walking, standing, or eating time) or the number of steps taken within that 15-min interval. If the reader was out of range of the tags, data was stored for 24 h within the tag and each 15-min interval the tag attempted to connect with the reader again. Once a connection was established, all stored data were transferred to the reader.

Producers interested in purchasing a new precision dairy technology system were approached in October 2014. Four producers agreed to purchase the technology, participate in the study, and evaluate daily technology-generated herd health reports. Through the company's management software, a web-based system interface was made available to all producers on the study. The daily technology-generated health report was found by selecting the "Health and management" list (Appendix I). The list consisted of changes in eating, lying, or activity (steps/d) behavior according to a predetermined threshold set by the company – a decrease of ≥ 30% from a cow's 10-d moving mean behavior. An alert was generated based on each variable individually, with a maximum of three alerts occurring for a cow in a d. Each cow was only listed once on the list, with each variable listed to the right of the cow number.

Data collection

Performance records from DHI were collected with the permission of participating producers including disease events, DIM, parity, number of lactating animals in the herd, and previous lactation milk yield, fat, protein, lactation length, average SCS, and actual calving interval. Producers were provided a HOBO U23 Series Pro v2 Logger (Onset, Cape Cod, MA) to collect barn temperature and humidity data. The HOBO was placed near the center of primary housing barn above the height easily reached by cows and out of the direct air flow of fans. The HOBO was taken down on Tuesday of every week, the lead author collected the data, and the HOBO was restored to the barn.

Herd health. Dairy producers and farm staff recorded observed clinical cases of disease (clinical mastitis, hypocalcemia, hyperketonemia, retained placenta, metritis, displaced abomasum, and lameness). Participating producers were provided a laminated identification sheet and a binder containing pre-printed recording sheets for mastitis (Figure 3.1) and other clinical diseases (Figure 3.2). Each sheet had a coding guide (all diseases sheet: MF = hypocalcemia, MET = metritis, LDA = left displaced abomasum, RDA = right displaced abomasum, LAME = lameness, RP = retained placenta, and KET = hyperketonemia; mastitis sheet: LF = left front quarter, RF = right front quarter, LR = left rear quarter, and RR = right rear quarter; severity score: 1 = abnormal milk but no swelling, 2 = abnormal milk with swelling, and 3 = abnormal milk with systemic signs; Hogan et al., 1989; Bramley et al., 1996), a column for date, cow number, event type, milking event occurred (mastitis only), quarter affected (mastitis only), severity score (mastitis only), treatment (Y/N), treatment type, and treatment length. Mastitis quarter and severity was not included in analyses but was recorded for culture reports delivered to dairy producers.

Examinations were conducted Tuesday and Friday of every week by the lead author on cows from 3 to 6 and from 7 to 10 DIM. Cows were either separated after milking or separated out of their pens by the lead author and farm staff or owners. Cows were confined in a chute area, and the lead author collected rectal temperature with a rectal probe attachment (M700 Thermometer; GLA Agricultural Electronics, San Luis

Obispo, CA). The lead author collected vaginal fluid with the MetriCheck device (MetriCheck; VetENT, New Zealand). The lead author collected blood from the coccygeal vein for later analysis with an 18-gauge 2.54 cm multi-sample needle and a 10cc vacutainer tube without additives (red top). A stainless-steel bucket was filled with warm water and Dermachlor 2% chlorhexidine solution (Henry Schein Animal Health, Dublin, OH) according to label directions. Clean paper towels were submerged in the solution, and the MetriCheck device remained in the solution when not in use. The rectal thermometer and MetriCheck were wiped clean between cows, and the rectum and vulva of each cow were cleaned with clean paper towels and the chlorhexidine solution before rectal or vaginal samples were taken. Cows with rectal temperatures > 39.3°C were classified with a fever. Fever was collected to provide producers with additional information not as a definitive sign of disease. Cows with pus or purulent discharge were considered to have metritis (≥ 2 on a 1 to 3 scale; Sterrett et al., 2014). The PrecisionXtra device (Abbot Laboratories, Chicago, IL) was used cow-side with 1 drop of blood from a red top tube to determine β-hydroxybutyrate concentrations (Iwersen et al., 2009). Cows with β-hydroxybutyrate concentrations ≥ 1.2 mmol/mL were considered to have subclinical hyperketonemia (Nielen et al., 1994). Tubes were kept in a cooler after collection. At the end of a data collection day, tubes were centrifuged at 3000 RPM for 20 min (CR4-12, Jouan Inc.). Serum was separated into 5 mL vials and stored in a refrigerator until calcium analysis at the University of Kentucky Veterinary Diagnostic Laboratory. The Calcium-Arsenazo assay (ACE Alera, Alfa Wassermann Diagnostic Technologies, LLC, West Caldwell NJ) was used to analyze serum Ca concentrations.

Cows with serum Ca concentrations ≤ 8.6 mg/dL were considered to have subclinical hypocalcemia (Oetzel 2014, personal communication).

Behavior collection and alerts. The neck and leg technologies used a tri-axial accelerometer to define changes in behavior. The technologies were validated for eating (neck tag only), lying (leg tag only), standing (leg tag only), walking (leg tag only), and activity (steps/d; leg tag only) characterization by Van Erp-Van der Kooj et al. (2016). Offloads from the Nedap Livestock Management – Dairy Management systems group (Nedap, Groenlo, The Netherlands) were received daily for all variables on all cows equipped with technologies in all herds.

A technology-generated health report was created daily for every farm. Alert creation was proprietary and based on a percentage decrease from a cow's 10-d mean behavior. The default setting from the company used throughout the study was a decrease ≥ 30% from a cow's previous 10-d mean total daily activity (steps/d), lying time, or eating time. Until a full 10 d of data were collected on a cow, no alerts were created. The web-based interface presented alerts in the "Health and management" list as cow, DIM, group, eating attention, lying attention, and steps attention (Figure 2.1; Eckelkamp and Bewley, 2017). Only cows with ≥ 1 attention were shown on the list. From October 5, 2015 to May 11, 2016, values were listed as "value (- %)" indicating the previous days total eating, lying, or steps and the associated decrease from a cow's 10-d mean. Values in blue indicated no alert, whereas values in red indicated an eating, lying, or step alert (Figure 2.1a; Eckelkamp and Bewley, 2017). From May 11, 2016 to October 31, 2016 values were depicted as a horizontal bar, with a vertical line within the bar indicating a cow's 10-d mean. The amount of the bar filled (left to right) indicated the previous day's total eating or lying time. Blue bars indicated no alert, whereas red bars indicated an eating or lying alert. Steps/d were not shown post-May 11, 2016 unless an alert was created. If an alert was created "Decreased step count" appeared to the right of lying time in red (Figure 2.1b; Eckelkamp and Bewley, 2017). Although alert creation remained the same, cows that were identified as "in estrus" were not included on the "Health and management" list after May 11, 2016. Before May 11, 2016, cows could appear in the "Heat detection" and the "Health and management" list. Cows in estrus experience a significant increase in activity which could correspond with decreased lying or eating time (Farris, 1954, Hurnik et al., 1975). After May 11, 2016, cows identified as in estrus were only shown on the "Heat detection" list even if a corresponding decrease in lying or eating time occurred. A cow-alert could contain a single change in activity, lying time, eating time, or any combination of the single changes. Daily, cow-alerts were recorded by the lead author for analyses of sensitivity, specificity, accuracy, and balanced accuracy.

Behavior data conversion. A daily offload was received from Nedap for eating time, lying time, standing time, walking time, and activity (steps/d) for every herd for the previous two wk period. Data were received as seconds of behavior (eating, lying, standing, and walking time) or steps (activity) that occurred in a 15-min period. Data were converted from Central European Summer Time to Central Standard Time (Farm 1, 2, and 4) or Eastern Standard Time (Farm 3) and summed to daily totals using MATLAB 7.14.0.739 (The MathWorks Inc., 2012, Natick, Massachusetts). Offloads from a 15-min period without data were recorded as "-1" by the system. If no action occurred and data was transferred, data was recorded as "0" by the system. If less than 92 15-min periods had actual data recorded (< 23h of data), that d was considered missing. The EXPAND procedure of SAS 9.4 (SAS Institute, Inc., Cary, NC) was used to calculate a 10-d moving mean of daily totals for eating, lying, standing, walking, and activity to mirror the alerts created by the system. Daily activity, eating, lying, standing, and walking time deviations from a 10-d moving mean were calculated to explore differences outside a ≥ 30% decrease in behavior on sensitivity, specificity, accuracy, and balanced accuracy. Daily differences were calculated as a percent of a 10-d moving mean of daily totals and could be positive or negative differences.

Analyses

The four herds provided data for 1,374 cows and 517,293 cow-days. Cow-days referred to the number of calendar days an individual cow had recorded behavior data from the technology. Exclusions were sequentially applied as follows:

1) Twenty-six cows with incorrect technology information were removed (n = 1,348 cows and n = 506,711 cow-days remaining in the data set). Eleven cows were identified by dairy producers as having incorrect tag information, fifteen cows were identified by bred or heat date. Bred and heat dates from the herd management software were compared to increases in activity (steps/d) over a cow's 10-d mean activity on -1 to 1 d around a bred or heat date. If no increase in activity occurred during that period, the tag was determined to be on the incorrect cow, and the cow was removed from the data set.
2) Data were confined within the start (October 5, 2015) and end (October 31, 2016) date of the project. Dry cow-days and days after a cow left the herd

were removed based on DHI records (n = 1,251 cows and 307,827 cow-days remaining in the data set).

3) Cows with ≤ 7 d total of technology data or no records for technology data were removed (n = 1,169 cows and 302,876 cow-days remaining in the data set).

4) Cow-days with no data recorded or with < 92 15-min periods (23 h) of recorded data were removed based on visually checking the data around calving or dry-off to remove d before the tag was attached or after the tag was removed (n = 1,168 cows and 296,824 cow-days remaining in the data set).

Statistical analysis

Within the data set, four disease scenarios were examined: 1) any disease event (n = 2,252 cow-days; **AllEvents**; hyperketonemia, hypocalcemia, retained placenta, metritis, displaced abomasum, lameness, mastitis, or other on d of disease detection), 2) hyperketonemia (n = 311 cow-days; hyperketonemia alone or with any other disease on d of disease detection), 3) hypocalcemia (n = 748 cow-days; hypocalcemia alone or with any other disease on d of disease detection), and 4) metritis (n = 505 cow-days; metritis alone or with any other disease on d of disease detection). Cow-days with recorded mastitis (n = 166 cow-days), lameness (n = 120 cow-days), retained placenta (n = 95 cow-days), displaced abomasum (n = 18 cow-days), or other disease (n = 66 cow-days) did not occur frequently enough to be included individually in analysis. Other diseases reported by producers included eye infection (n = 1 cow-day), pneumonia (n = 9 cow-days), sick (n = 55 cow-days), and uterine torsion (n = 1 cow-day). The first recorded incidence of a disease, whether by the farm staff or by the lead researcher, was considered the d of disease detection. Duplicate data was removed from the data sets.

Because the majority of diseases reported occurred during the transition period, analyses of behavior changes during that time was conducted. The MIXED procedure of SAS was used to quantify behavior changes (eating time, lying time, standing time, walking time, and activity) within the first 21 d of lactation based on the methodology of Tsai (2017). Analyses included events that occurred during the first 21 d of lactation for 1) cows with no record of disease (n = 451) and cows with any recorded disease event (n = 717), 2) cows with no recorded metritis (n = 785) and cows with metritis (n = 383), 3) cows with no recorded hyperketonemia (n = 937) and cows with subclinical or clinical hyperketonemia (n = 229 and n = 2, respectively), and 4) cows with no recorded hypocalcemia (n = 614) and cows with subclinical or clinical hypocalcemia (n = 539 and n = 15, respectively). Cows with hyperketonemia, metritis, or hypocalcemia could have had an individual disease or the disease of interest and another disease(s).

To quantify the efficacy of the wearable technologies to identify a cow with a disease, 11 lengths of time around a disease event (time-windows) were compared. Time-windows were created using the EXPAND procedure of SAS 9.4. Time-windows increased the length of time a disease event and a cow-alert could occur simultaneously. Time-windows were 1) the d of visual disease detection, 2) the d of and d after visual disease detection, 3) the d of and 2 d after visual disease detection, 4) the d of and 3 d after visual disease detection, 5) the d of and 4 d after visual disease detection, 6) the d of and 5 d after visual disease detection, 7) the d of and 6 d after visual disease detection, 8) the d before to the d after visual disease detection, 9) 2 d before to 2 d after visual disease detection, 10) 3 d before to 3 d after visual disease detection, and 11) 5 d before to 2 d after visual disease detection (adapted from Stangaferro et al., 2016a, b, c).

The FREQ procedure of SAS 9.4 was used to calculate the occurrence of true positives, true negatives, false positives, and false negatives. Sensitivity, specificity, accuracy, and balanced accuracy were calculated for each time-window. Sensitivity was calculated using Eq. 3.1, specificity using Eq. 3.2, accuracy using Eq. 3.3, and balanced accuracy using Eq. 3.4. Balanced accuracy was included to account for the imbalance between healthy cow-days and disease cow-days.

$$\text{Sensitivity} = \frac{\text{True positive}}{(\text{True positive+False negative})} \qquad \text{Equation 3.1}$$

$$\text{Specificity} = \frac{\text{True negative}}{(\text{True negative +False positive})} \qquad \text{Equation 3.2}$$

$$\text{Accuracy} = \frac{(\text{True positive+True negative})}{(\text{True positive+False positive+True negative+ False negative})} \qquad \text{Equation 3.3}$$

$$\text{Balanced accuracy} = \frac{\frac{\text{True positive}}{(\text{True positive+False positive})}+\frac{\text{True negative}}{(\text{True negative+False negative})}}{2} \qquad \text{Equation 3.4}$$

Odds-ratios and significance estimations were conducted using a logistic regression model. The generalized linear model (GENMOD procedure; SAS 9.4) with a binomial distribution was used to test fixed effects on the probability of a disease event occurring. The model contained 1,168 cows and 296,824 cow-days across four farms. The repeated effect of cow with an exchange correlation was included in the model. Fixed effects included previous lactation actual milk yield, previous lactation projected 305-d mature equivalent (**ME**) milk yield, previous lactation ECM, previous lactation actual fat %, previous lactation ME fat %, previous lactation actual protein %, previous lactation ME protein %, previous lactation mean SCS, previous lactation last test day SCS, previous lactation last test day SCC, previous lactation length; previous lactation days dry, previous lactation actual calving interval, daily maximum temperature humidity index, daily mean ambient temperature, or daily mean ambient humidity. Daily maximum temperature humidity index (**THI**) was calculated using Eq 3.5 (NOAA, 1976).

$$\text{THI} = \text{temperature (°F)} - (0.55 - (0.55 * \text{relative humidity}/100)) * (\text{temperature (°F)} - 58.8) \qquad \text{Equation 3.5}$$

Only variables with $P \leq 0.05$ were considered for inclusion in the machine-learning prediction models. Previous lactation ECM (P = 0.01), previous lactation mean SCS (P = 0.01), previous lactation length (P = 0.05), previous lactation actual calving interval (P = 0.03), and daily maximum THI (P = 0.04) were included in machine-learning models.

Prediction model development

Machine-learning techniques were applied to the data set to predict hyperketonemia, hypocalcemia, metritis, or AllEvents. The 3 machine-learning techniques used were previously described by Borchers et al. (2017). Briefly, linear discriminant analysis (**LDA**), random forest (**RF**), and principal component analysis neural network (**PCANNet**) were used. Linear discriminant analysis uses a categorical dependent variable and several continuous independent variables, similar to an ANOVA (McLachlan, 2004, Wetcher-Hendricks, 2011). The random forest method develops a group of decision-tree classification models. Each tree classifies the data independently. The forest then pulls from the individual classifications and classifiers, returning the most popular class (Breiman, 2001, Kamphuis et al., 2010, Shahinfar et al., 2014). Principal component analysis neural networks are a modification of the neural network. Neural networks simulate human intelligence by mimicking the function and structure of the human brain, continuously adapting, learning independently, and applying inductive reasoning (Zahedi, 1991, Krieter et al., 2006). Instead of the traditional neural network (Borchers et al., 2017), the PCANNet was used to improve classification over the traditional neural network by identifying and grouping similar variables through data reduction (Maćkiewicz and Ratajczak, 1993, Tantithamthavorn et al., 2016).

All analyses were constructed and executed used the lattice, caret, e1071, and randomForest packages in R (version 3.3.3; R Foundation for Statistical Computing, Vienna, Austria). Prediction models were developed with the intention of identifying each disease at or before diagnosis. Four time-windows were examined, 1) d of, 2) d before to d of disease detection, 3) 3 d before to d of disease detection, and 4) 5 d before to d of disease detection. To identify technology variable disease detection efficacy, 5 scenarios were run. Scenario 1 included daily eating and lying time, daily step count, and the daily difference in eating, lying, and steps from a 10-d moving mean as predictors for AllEvents, hyperketonemia, hypocalcemia, or metritis. Scenario 2 included daily eating time and daily eating difference from a 10-d moving mean as predictors for AllEvents, hyperketonemia, hypocalcemia, or metritis. Scenario 3 included daily lying, standing, and walking time, daily step count, and the daily difference in lying, standing, walking, and step count from a 10-d moving mean as predictors for AllEvents, hyperketonemia, hypocalcemia, and metritis. Scenario 4 included daily eating, lying, standing, and walking time, daily step count, and the daily difference in eating, lying, standing, walking, and step count from a 10-d moving mean as predictors for AllEvents, hyperketonemia, hypocalcemia, and metritis. Scenario 5 included daily eating, lying, standing, and walking time, daily step count, daily difference in eating, lying, standing, walking, and step count from a 10-d moving mean, previous lactation ECM, previous lactation mean SCS, previous lactation DIM, previous lactation actual calving interval, and daily maximum THI as predictors for AllEvents, hyperketonemia, hypocalcemia, and metritis. Separate LDA, RF, and PCANNet analyses were run for each combination of time-windows and predictors for a total of 240 prediction models (5 scenarios x 4 time-windows x 3 machine-learning techniques x 4 disease groups).

The data sets used for each model were prepared the same way. A data subset of 80% of the observations was used as a training set to generate the prediction models. Within the training set, 10-fold cross-validation with down-sampling was used. Cross-validation allowed the model to further divide the 80% into 10 segments. Each segment was then run through the training model, with each subsequent run improving the predictive power of the model. The remaining 20% was used as a testing set, evaluating the performance of the prediction created by the training set. The output calculated for each model included sensitivity, specificity, accuracy, and balanced accuracy.

RESULTS

Behavior variables: Activity, eating, lying, standing, and walking time

Overall, 827 cows out of 1,168 cows experienced a disease event over their lactation (Table 3.1). If a disease occurred during the first 21 DIM, cows were considered positive for that disease from 0 to 21 DIM. Cows were grouped as no disease (**ND -** no recorded diseases; n = 451 cows) or disease (**D –** recorded disease; n = 717 cows). Cows were further grouped as metritis (**Met+**: n = 383 cows with metritis; **Met-**: n = 785 cows without metritis), hyperketonemia (**Ket+**: n = 231 cows with hyperketonemia; **Ket-**: n = 937 cows without hyperketonemia), and hypocalcemia

(**Hyp+**: n = 554 cows with hypocalcemia; **Hyp-**: n = 614 cows without hypocalcemia). All behavior variables were changed by the presence of disease (Figures 3.3 to 3.6). Eating time, walking time, and activity remained below herd mates without a recorded disease throughout the first 21 DIM (LSM ± SE: 213 ± 1 vs. 243 ± 2 min/d eating, 46.9 ± 0.1 vs. 52.4 ± 0.3 min/d walking, and 4,100 ± 11 vs. 4,539 ± 26 steps/d for D and ND, P < 0.01 respectively; Figure 3.1a, d, e). Conversely, standing time remained similar between disease and no disease cows (806 ± 1 vs. 811 ± 3 min/d standing for D and ND, P = 0.10; Figure 3.1c) while lying time remained slightly elevated in D cows throughout the first 21 DIM (587 ± 1 vs. 577 ± 3 min/d lying for D and ND cows, P < 0.01; Figure 3.1c).

During the first 8 DIM, cows with metritis had lesser eating time (199 ± 5 vs. 217 ± 4 min/d in Met+ and Met- cows; P < 0.01; Figure 3.2a), greater lying time (627 ± 8 vs. 600 ± 7 min/d in Met+ and Met- cows; P < 0.01; Figure 3.2b), and lesser standing time (763 ± 8 vs. 787 ± 7 min/d in Met+ and Met- cows; P < 0.01; Figure 3.2c). From 8 to 21 DIM, eating, lying, and standing time were similar between Met+ and Met- cows (224 ± 5 vs. 221 ± 4 min/d eating, 570 ± 8 vs. 569 ± 7 min/d lying, and 826 ± 8 vs. 824 ± 6 min/d standing in Met+ and Met- cows, respectively; Figure 3.2a, b, c). However, walking time and activity remained lesser in cows that had experienced metritis from 1 to 21 DIM (45.9 vs. 49.0 ± 0.2 min/d walking and 4,023 ± 16 vs. 4,270 ± 13 steps/d for Met+ and Met- cows, P < 0.01 respectively; Figure 3.2d, e).

Cows that experienced hyperketonemia (BHBA ≥ 1.2 mmol/L) had marked elevation in lying time (615 ± 2 vs. 576 ± 1 min/d in Ket+ and Ket- cows; P < 0.01; Figure 3.3b) and a corresponding suppression in standing time (783 ± 2 vs. 814 ± 1 min/d in Ket+ and Ket- cows; *P* < 0.01; Figure 3.3c) throughout the first 21 DIM. Walking time and activity remained below Ket- in Ket+ cows from 2 to 21 DIM (42.2 ± 0.3 vs. 49.5 ± 0.2 min/d walking and 3,757 ± 20 vs. 4,298 ± 11 steps/d in Ket+ and Ket- cows, respectively; *P* < 0.01; Figure 3.3d, e). Eating time changed the least between Ket+ and Ket- cows (211 and 219 ± 1 in Ket+ and Ket- cows, respectively; *P* < 0.01; Figure 3.3a). Cows with and without hyperketonemia both experienced lesser eating time following parturition, with Ket+ cows spending less time eating from 6 to 11 DIM. From 11 to 21 DIM, Ket+ and Ket- cows spent similar time eating (221 ± 6 vs. 226 ± 3 min/d eating in Ket+ and Ket- cows).

Cows that experienced hypocalcemia (serum Ca ≤ 8.6 mg/dL) had lesser eating time throughout the first 21 DIM (211 vs. 227 ± 1 min/d eating Hyp+ and Hyp- cows, respectively; *P* < 0.01; Figure 3.4a). Lying time was greater while standing time was lesser until 12 DIM in Hyp+ cows compared to Hyp- cows (617 ± 7 vs. 588 ± 8 min/d lying and 775 ± 6 vs. 799 ± 8 min/d standing in Hyp+ cows and Hyp- cows, respectively; *P* < 0.01; Figure 3.4b, c). Walking time and activity remained suppressed below Hyp- cow levels in Hyp+ cows throughout the first 21 DIM (46.0 vs. 50 ± 0.2 min/d walking and 4,040 ± 13 vs. 4,358 ± 16 steps/d in Hyp+ and Hyp- cows, respectively; *P* < 0.01; Figure 3.4d, e).

Precision Dairy Monitoring technology-generated alerts

Depending on the time-window, 1,646 to 9,550 out of 296,824 cow-days had recorded disease events for 827 cows (Table 3.2). Over the study, the technologies generated 10,349 to 26,133 cow alerts, depending on the combination of alerts considered (Tables 3.3 to 3.7). This discrepancy was apparent throughout the models, with 91 to

97% specificity and 13 to 48% sensitivity for all system generated disease alerts (Table 3.3 to 3.7). Compared to the system default variables of eating, lying, and activity, decreased sensitivity was observed when all variables from the leg tag were considered (Table 3.6), when eating time was considered (Table 3.5), and when all variables were considered (Table 3.7). Improved sensitivity occurred when more than one variable was considered (eating time only: 25 ± 6% sensitivity). However, the greatest accuracy and balanced accuracy occurred when only eating alerts were considered (Table 3.5). Across diseases, sensitivity and specificity remained similar, except for metritis detection with only eating alerts (18 ± 3% sensitivity). The greatest sensitivity occurred for hyperketonemia on the day of disease detection when eating, lying, and activity alerts were considered (48% sensitivity, 92% specificity).

Sensitivity was highest on the day of disease detection (d 0; Table 3.13). Balanced accuracy was highest at the longer time-windows, particularly -5 to 2 d after disease detection. However, sensitivity, specificity, accuracy, and balanced accuracy were within < 1 to 4% across all time-windows within a disease (Tables 3.3 to 3.7). Across all time-windows, specificity, accuracy, and balanced accuracy remained similar (Table 3.13) with sensitivity causing the variability in accuracy and balanced accuracy.

Machine-learning analyses

Machine-learning techniques produce results and outputs unlike algorithm producing prediction models. Prediction performance for each variable group is shown in Tables 3.8 to 3.12. Overall, PCANNet had the best sensitivity across diseases and time-windows (Table 3.13; 82 to 84 ± 3), whereas the highest balanced accuracy occurred with the RF (Table 3.13; 79 ± 5 to 80 ± 6). The best prediction models for neck tag only alerts (eating time) were PCANNet, with random forest analysis being the better predictor for all other combinations. The best prediction models for all disease events (any event) were the PCANNet. Predicting specific diseases (hypocalcemia, hyperketonemia, and metritis) was best with the random forest analysis. Although an algorithm was not created, variables of importance could be calculated through R. Daily eating time was the most important variable for disease detection in every LDA and PCANNet model. In the RF models where daily eating time was the 2nd or 3rd most important variable, daily difference in eating time from a cow's 10-d mean was the most important variable for disease detection.

Sensitivity, specificity, accuracy, and balanced accuracy were similar between PCANNet, random forest, and linear discriminant analysis (79 ± 5% sensitivity, 74 ± 9% specificity, 80 ± 5% accuracy, and 77 ± 6% balanced accuracy). Neck tag measurements had a lower sensitivity compared to combinations of neck and leg tag measurements (Table 3.8; 75 ± 5 vs. 81 ± 4%). Leg tag measurements had similar sensitivity but lower specificity to combinations of neck and leg tag measurements (Table 3.10; 81 ± 4% sensitivity, 64 ± 12 vs. 78 ± 7% specificity). The best combination of sensitivity, specificity, accuracy, and balanced accuracy was achieved when neck, leg, and previous lactation information were combined (81 ± 4, 79 ± 6, 81 ± 4, and 80 ± 5% sensitivity, specificity, accuracy, and balanced accuracy, respectively; Table 3.12).

DISCUSSION

Behavior variables: Activity, eating, lying, standing, and walking time

Decreased activity was associated with ill, Met+, Ket+, and Hyp+ cows in our study. Similarly, Tsai (2017) reported decreased activity in cows with metritis (2,125 ±

1,215 vs. 2,689 ± 1,637 steps/d), hyperketonemia (3,137 ± 121 vs. 3,685 ± 72 steps/d), and hypocalcemia (2,490 vs. 2,856 ± 1,180 steps/d) from 1 to 21 DIM. Stangaferro et al., (2016a; b; c) noted decreased neck activity (au/d) -5 d to d of clinical diagnosis in cows with mastitis, metritis, or metabolic disorders (displaced abomasum, indigestion, hyperketonemia, or all). Liboreiro et al. (2015) also reported decreased neck activity (512 ± 11 vs. 539 ± 6 au/d) in cows with metritis compared to cows without metritis. In our study, walking time also decreased parallel to activity (Figure 3.3 to 3.7). Titler et al. (2013) recorded decreased walking time in cows that experienced metritis from 1 d before to 3 d after clinical diagnosis compared to healthy counterparts.

In our study, lying time was higher in Met+, Ket+, and Hyp+ with a corresponding lower standing time. Tsai (2017) also reported increased lying time in Ket+ and Hyp+ cows compared to Ket- and Hyp- cows, respectively. Although Itle et al. (2015) reported Ket+ cows had lower lying time compared to Ket- cows, Sepúlveda-Varas et al. (2014) noted cows that experienced multiple diseases had greater lying times than cows that experienced only one disease. Like Tsai (2017), most cows in our study that experienced disease experienced > 1 throughout their lactation (507 out of 844 cows). Herdt (1988) suggested increased lying time was an energy conservation response to disease. The need for energy conservation could have been exacerbated by the decreased eating time experienced by Met+, Ket+, and Hyp+ cows in our study.

Conversely, Tsai (2017) reported no difference in lying time in Met+ cows. Titler et al. (2013) reported longer standing times in Met+ compared to Met- cows, unlike Tsai (2017) or the current study. Decreased activity and increased lying time are energy conservation methods employed by many species (Aubert, 1999). Aubert (1999) suggested diseases, particularly those with a pathogenic cause, required animals to conserve energy to support a temperature increase. Metritis was the only disease of interest with a bacterial cause and had the shortest period of difference (1 to 8 DIM) compared to herd mates without metritis. Stangaferro et al. (2016c) reported high variability in activity and rumination responses in Met+ cows. Stangaferro et al. (2016c) attributed the variability in behavior response to the variability in metritis severity with more severe cases of metritis causing a greater behavior change. Our study did not have enough cases of metritis to break them out by severity score, but differing degrees of decrease could have occurred.

Eating time remained below herd mates without the disease of interest for any disease and hypocalcemia from 1 to 21 DIM. Metritis cows had decreased eating time from 1 to 8 DIM, with hyperketonemia cows having decreased eating time from 6 to 11 DIM. Huzzey et al. (2007) also reported decreased eating time and feed consumption in cows with metritis. Tsai (2017) also characterized eating time from 1 to 21 DIM. Unlike our study, Tsai (2017) noted no significant differences in eating time in cows with hypocalcemia, hyperketonemia, or metritis although numeric decreases in eating time occurred. Lack of significant difference between cows with or without hypocalcemia, hyperketonemia, or metritis could indicate not enough cows were included in Tsai (2017) study (n = 138 cows). More cows in Tsai (2017) could have yielded significant differences similar to Liboreiro et al., (2015), Stangaferro et al., (2016a; c), and our study.

Unlike metritis, hypocalcemia and hyperketonemia do not require an elevated temperature to eradicate a pathogen (Goff and Horst, 1997, DeGaris and Lean, 2008, Oetzel, 2011). Hyperketonemia is associated with negative energy balance, specifically mobilization of body fats to supplement cow maintenance and lactation requirements postpartum (Duffield, 2000, Ospina et al., 2010b). Similarly, hypocalcemia occurs when cows lack sufficient calcium to maintain muscle function (Houe et al., 2000, Goff, 2008, Oetzel, 2011). Decreased activity and increased lying time could serve as energy conserving methods for cows in negative energy balance. Tsai (2017) suggested muscle weakness and fatigue could contribute to decreased activity and increased lying time in cows with hypocalcemia.

Precision Dairy Monitoring technology-generated alerts

Overall, PDM-generated alerts had the highest sensitivity on d 0, the day of disease detection. Conversely, balanced accuracy was highest when -5 to 2 d or -3 to 3 d around a disease detection were considered. Balanced accuracy considers the balance between positives (true and false) and negatives (true and false). Accuracy divides TP and TN by TP, TN, FP, and FN. Accuracy can be artificially inflated if sensitivity or specificity is high. For instance, a 38% sensitivity in combination with a 93% specificity had an associated 92% accuracy. A 92% accuracy would imply a low number of false positives and negatives, which was not the case. Conversely, 38% sensitivity with 93% specificity had an associated 53% balanced accuracy, more precisely reflecting the number of false positives associated with that test (Table 3.3).

The longer time-windows (-5 to 2 or -3 to 3 d) had the most desirable balanced accuracy and specificity (lowest number of false positives – cows without disease but an alert created). Confounding effects with the days of data collection were unlikely, as examination days were set and had no influence on when disease alerts were generated.

Hogeveen et al. (2010) suggested a 48h time-window around an event was an acceptable alert window. However, Stangaferro et al., (2016a; b; c) used -5 to 2 d after clinical diagnosis to set their sensitivity. Widening the alert window could provide additional information to dairy producers, especially if days a suspected disease condition lasted were recorded. Stangaferro et al. (2016a) reported steady decreases in rumination time (min/d) from -5 to -1 d before hyperketonemia diagnosis and steady decreases in neck activity (arbitrary units/d) from -5 to 1 d around hyperketonemia diagnosis. Similarly, rumination time (min/d) and neck activity (arbitrary units/d) steadily decreased from -5 d to d of displaced abomasum diagnosis (Stangaferro et al., 2016a). Potentially identifying diseases earlier in the behavior decrease could prevent disease progression, improve treatment efficacy, reduce treatment cost, and prevent relapse (Milner et al., 1997, Stangaferro et al., 2016a). Conversely, rumination steadily increased from -5 to 5 d around metritis diagnosis, but was lower than healthy herd mates from -5 to 5 d around metritis diagnosis ($P < 0.01$; Stangaferro et al., 2016a). Comparing cows to herd mates at the same stage of lactation and themselves could improve alert detection instead of considering one or the other. A difficulty with behavioral changes is each disease affects behavior differently, and each cow responds differently also. In the future, utilizing behavior data in combination with other data (herd records, milk components, feed intake, etc.) could create a more robust, disease specific alert by accounting for more variability.

Within our study, mean (± SD) sensitivity (31 ± 7%) was lower than sensitivities reported by Stangaferro et al. (2016a; b; c; 55 to 98%) and well below the sensitivity suggested by Hogeveen et al., (2010; ≥ 80%). Low sensitivity coincided with low producer use of cow-alerts. In a companion study, Eckelkamp and Bewley (2017) reported producers followed-up 21% of cow-alerts with a visual examination. The remaining 79% were either not checked, ignored, or attributed to known herd changes. To address this issue, Wathes et al. (2008), Russell and Bewley (2013), and Woodall and Montgomery (2014) stressed the importance of actionable alerts, decreasing false positive alert creation, and reducing information overload.

The best sensitivity occurred when eating, lying, and activity alerts were considered together (Table 3.3 and 3.4). Similar performance was seen between the daily recorded eating, lying, and activity alerts and the calculated eating, lying, and activity alerts from the daily offloads (Table 3.3 and 3.4). This result indicated recorded and calculated alerts were similar, validating the calculations done to create alerts from raw data by the lead author. Similar results were expected from evaluating similar variables. Stangaferro et al. (2016a, c) noted a combination of an intake measurement (rumination) and mobility (neck activity) was able to identify cows with metritis and hyperketonemia. However, Stangaferro et al. (2016a, b) reported greater sensitivity for hyperketonemia and metritis compared to our study (22 to 38% compared to 91% sensitivity hyperketonemia; 18 to 31% compared to 55% sensitivity metritis). Although these variables are not identical, a combination of intake (eating instead of rumination time) and cow mobility (lying time and steps/d instead of neck activity) outperformed other behavior variable combinations in our study. The technology Stangaferro et al. (2016a; b; c) used had the advantage of providing rumination and neck activity within the same tag. Our study required two tags to provide eating time and activity (steps/d).

When eating alerts were considered individually, sensitivity decreased and specificity increased compared to eating, lying, and activity models. Metritis events, in particular, had poor sensitivity (18 ± 3%). When considering eating events, this finding could be expected. Cows with hypocalcemia or hyperketonemia often experience decreased feed intake (Duffield, 2000, Oetzel, 2011). Eating decreases may not be as severe or as noticeable within a cow. Stangaferro et al. (2016c) reported a decrease in rumination time in cows with metritis compared to herd mates, but rumination time within a cow still increased following calving. Conversely, cows diagnosed with hyperketonemia decreased in rumination time until the day of diagnosis (Stangaferro et al., 2016a).

When leg tag variables (lying, standing, walking, and activity) were considered together, sensitivity decreased, and specificity remained similar to eating, lying, and activity models. Activity (steps/d) or neck activity (arbitrary units) have been shown to change around disease events (Edwards and Tozer, 2004, Proudfoot and Huzzey, 2016), along with standing or lying time and walking time (Titler et al., 2013). Within our leg tag model, the highest sensitivity was seen for hyperketonemia on the day of disease detection. Stangaferro et al. (2016a) reported a steady decrease from -5 d to the day after disease diagnosis. However, the health index score Stangaferro et al. (2016a) relied on did not decrease until the day after disease diagnosis. Low sensitivities in our study could also indicate the detection threshold was set too low. This would allow steady decreases like those seen in hyperketonemia and clinical metritis to generate disease alerts, but also created alerts for sudden short changes such as pen movements (Stangaferro et al., 2016c, a, Eckelkamp and Bewley, 2017).

When all leg tag and neck tag variables (lying, standing, walking, activity, and eating) were considered together, sensitivity was slightly lower than the eating, lying, and activity model (33 ± 4 vs. 37 ± 5%) with similar specificity (91 vs. 92%). Our study indicated although sensitivity was low, eating, lying, and activity alerts could predict diseases. When used individually, eating time had more potential then lying, standing, walking, and activity alerts for predicting disease events.

Machine-learning prediction

Machine-learning techniques greatly improved sensitivity, specificity, accuracy, and balanced accuracy over PDM-generated alerts (Table 3.8 to Table 3.12). Sensitivity never fell below 67%, with specificity falling below 63% when all leg tag variables were considered (Table 3.10). Unlike the generated alerts, combinations of eating, lying, and activity had inferior predicting ability compared to all behavior variables, and all behavior variables with previous lactation information. Similarly, Vergara et al. (2014) noted when previous lactation milk production was included in a model, postpartum disease prediction improved. Nordlund and Cook (2004) also noted a decreased ME milk yield at first test compared to a cow's previous lactation could detect hyperketonemia, displaced abomasum, and digestive disorders.

Other disease predictions have been conducted by examining herd records (Nordlund and Cook, 2004, Vergara et al., 2014), behavioral changes (Stangaferro et al., 2016c, b, a), automated milk analysis (automatic milking systems; Kamphuis et al., 2010), and blood NEFA (Dubuc et al., 2010b, Ospina et al., 2010b) or BHBA (Ospina et al., 2010b, Chapinal et al., 2011). However, sensitivity and specificity were rarely as high in combination as our study. Specificity and sensitivity are inversely proportional, increasing the difficulty of identifying all true positive incidences without a high proportion of false positives. Kamphuis et al. (2010) noted this difficulty, even when using decision tree models with bagging or boosting, similar to our random forest technique (25 to 40% sensitivity with 99% specificity; 44 to 57% sensitivity with 97.9% specificity). Also unlike our study, Kamphuis et al. (2010) witnessed the greatest combination of sensitivity and specificity when -10 to 7 d after a clinical mastitis observation were considered. Within our study, the greatest combinations of sensitivity and specificity occurred within 24 h before a clinical disease event. If producers were provided with reliable disease-specific information, cows could experience improved treatment responses, decreased antibiotic or treatment administrations, and less impaired lactation yield (Milner et al., 1997).

Although the best prediction across generated or machine-learning alerts occurred with combinations of eating, lying, and activity behavior, two technologies were required to generate these results. A few technologies can measure a mixture of these behaviors, but most technologies do not measure all three or four (including walking time) in combination. For dairy producers, investing in two technologies for health detection would not be economically feasible (Borchers et al., 2017). Unlike Borchers et al. (2017), machine-learning techniques applied to technologies measuring eating time, or rumination and neck activity, could be the best option for behavior-based disease detection (Liboreiro et al., 2015, Stangaferro et al., 2016a, b, c).

CONCLUSIONS

Precision dairy monitoring technologies can efficiently track behavioral changes around hypocalcemia, metritis, hyperketonemia, and other diseases. However, technology generated disease alerts were not sensitive enough to be used as sole disease detection criteria. Applying machine-learning principles to the behavior data improved sensitivity, and the balance between sensitivity and specificity. A combination of eating and movement behaviors with additional herd information provided the highest sensitivity and specificity. However, eating time and the daily difference from a cow's 10-d moving mean have potential to be an effective predictor of disease. Future research should focus on applying machine-learning principles to behavioral data to create meaningful, actionable alerts for producers.

ACKNOWLEDGMENTS

The authors would like to thank the cooperating Kentucky farmers who made this study possible. We would also like to thank AltaGenetics for their financial support of this study, and Nedap for their technical support of this study. We also want to thank Eric Roemmele for his time and statistical expertise. Finally, thank you to Davi Hutchins, Shaila Winston, Cerina Holcomb, Siobhan Gavigan, Kevin Zhao, Amanda Lee, Gustavo Mazon, Matthew Borchers, Jenna Klefot, Karmella Dolecheck, Derek Nolan, Bettie Kawonga, Tsai I-Ching, Leen Leenaerts, Michele Jones, Carissa Truman, Lori Grinter, Emily Rice, Melissa Cornett, Tanya France, and Anna Hawkins for their assistance with laboratory analysis, data entry, and editing.

Table 3.1. Cows that experienced a disease event over a lactation (n = 1,168 total cows on study) monitored from October 5, 2015 to October 31, 2016.

Disease event	Number of cows
Any disease event[1]	827
Hyperketonemia[2]	24
Hypocalcemia[3]	161
Metritis[4]	83
Other[5]	129
Hyperketonemia[2] and hypocalcemia[3]	57
Hyperketonemia[2] and metritis[4]	17
Hyperketonemia[2] and other[5]	4
Hypocalcemia[3] and metritis[4]	109
Hypocalcemia[3] and other[5]	50
Metritis[4] and other[5]	14
Hyperketonemia[2], hypocalcemia[3], and metritis[4]	66
Hyperketonemia[2], hypocalcemia[3], and other[5]	19
Hyperketonemia[2], metritis[4], and other[5]	2
Hypocalcemia[3], metritis[4], and other[5]	50
Hyperketonemia[2], hypocalcemia[3], metritis[4], and other[5]	42

[1]Any disease event referred to cows that experienced any disease event over their lactation.
[2]Hyperketonemia was defined as blood β-hydroxybutyrate ≥ 1.2 mmol/L when cows were examined between 3 and 7 DIM (n = 229 cows). Farm staff also recorded hyperketonemia if any clinical signs were present throughout lactation (n = 2 cows).
[3]Hypocalcemia was defined as serum Ca ≤ 8.6 mg/dL when cows were examined between 3 and 7 DIM (n = 539 cows). Farm staff also recorded hypocalcemia if any clinical signs were present throughout lactation (n = 15 cows).
[4]Metritis was defined as vaginal discharge score ≥ 2 (1 to 3 scale; Sterrett et al., 2014) when cows were examined between 3 and 7 DIM (n = 371 cows). Farm staff also recorded metritis if any clinical signs were present throughout lactation (n = 12 cows).
[5]Other referred to retained placenta (n = 35 cows), displaced abomasum (n = 15 cows), lameness (n = 73 cows), eye infection (n = 1 cow), pneumonia (n = 7 cows), uterine torsion (n = 1 cow), generic illness defined as “sick” by the producer (n = 55 cows), or mastitis (n = 121 cows) recorded by farm staff if any clinical signs were present throughout lactation.

Table 3.2. Cow-days with recorded disease events expanded across 14 time-windows[1,2] on 1,168 cows monitored from October 5, 2015 to October 31, 2016. Changes in disease event cow-days correspond to the expanded period when disease events and disease alerts were considered to be true positives.

Time-window	All[3]	Hyperketonemia[4]	Hypocalcemia[5]	Metritis[6]
0[1,2]	1,646	311	748	505
1[1]	3,254	662	1,501	1,007
2[1]	4,838	930	2,253	1,506
3[1]	6,242	1,209	2,948	1,958
4[1]	7,430	1,452	3,557	2,362
5[1]	8,608	1,694	4,167	2,766
6[1]	9,833	1,937	4,775	3,174
-1 to 1[1]	4,807	925	2,234	1,494
-2 to 2[1]	7,331	1,438	3,480	2,327
-3 to 3[1]	9,414	1,884	4,462	3,076
-5 to 2[1]	9,550	2,038	4,604	3,313
-1 to 0[2]	3,647	730	1,804	1,133
-3 to 0[2]	6,104	1,325	3,283	2,018
-5 to 0[2]	7,309	1,660	3,800	2,605

[1]Time-windows were calculated as d of (0), d of to 1 d after (1), d of to 2 d after (2), d of to 3 d after (3), d of to 4 d after (4), d of to 5 d after (5), d of to 6 d after (6), d before to d after (-1 to 1), 2 d before to 2 d after (-2 to 2), 3 d before to 3 d after (-3 to 3), and 5 d before to 2 d after (-5 to 2) disease detection by producer or lead author.
[2]Time-windows correspond to linear discriminant analysis, random forest, or principal component analysis neural network machine-learning prediction techniques on technology measured parameters, previous lactation information, and ambient temperature-humidity index. Time-windows were calculated as d of (0), d before to d of (-1 to 0), 3 d before to d of (-3 to 0), and 5 d before to d of (-5 to 0) disease detection by the producer or lead author.
[3]All disease events referred to cows that experienced any disease event over their lactation including hyperketonemia, hypocalcemia, metritis, lameness, mastitis, displaced abomasum, or retained placenta.
[4]Hyperketonemia was defined as blood β-hydroxybutyrate ≥ 1.2 mmol/L when cows were examined between 3 and 7 DIM. Farm staff also recorded hyperketonemia if any clinical signs were present throughout lactation.
[5]Hypocalcemia was defined as serum Ca ≤ 8.6 mg/dL when cows were examined between 3 and 7 DIM. Farm staff also recorded hypocalcemia if any clinical signs were present throughout lactation.
[6]Metritis was defined as vaginal discharge score ≥ 2 (1 to 3 scale; Sterrett et al., 2014) when cows were examined between 3 and 7 DIM. Farm staff also recorded metritis if any clinical signs were present throughout lactation.

Table 3.3. Sensitivity, specificity, accuracy, and balanced accuracy[1] of precision dairy monitoring technology generated alerts[2] for identifying any disease[3], hyperketonemia[4], hypocalcemia[5], or metritis[6]. Alerts based on activity (steps/d), eating time (min/d), and lying time (min/d) were created if that behavior decreased ≥ 30% from a cow's previous 10-d moving mean for each behavior. Eleven time-windows[7] were considered to determine true positives when disease alerts and events would overlap.

Disease	Time-window[7]	Sensitivity[1]	Specificity[1]	Accuracy[1]	Balanced accuracy[1]
All[3]					
	0	43	92	92	51
	1	40	92	92	52
	2	38	93	92	53
	3	36	93	91	54
	4	35	93	91	55
	5	33	93	91	55
	6	31	93	91	55
	-1 to 1	39	93	92	53
	-2 to 2	37	93	91	55
	-3 to 3	35	93	91	56
	-5 to 2	34	93	91	56
	Mean ± SD	36 ± 3	93 ± 0	91 ± 0	54 ± 1
Hyperketonemia[4]					
	0	48	92	92	50
	1	44	92	92	51
	2	43	92	92	51
	3	40	92	92	51
	4	39	92	92	51
	5	37	92	92	51
	6	35	92	92	51
	-1 to 1	43	92	92	51
	-2 to 2	43	92	92	51
	-3 to 3	41	92	92	51
	-5 to 2	44	92	92	52
	Mean ± SD	42 ± 3	92 ± 0	92 ± 0	51 ± 0
Hypocalcemia[5]					
	0	46	92	92	51
	1	43	92	92	51
	2	42	92	92	52
	3	40	92	92	52
	4	39	92	92	53
	5	37	92	92	53
	6	36	92	92	53
	-1 to 1	43	92	92	52
	-2 to 2	41	92	92	53
	-3 to 3	39	92	92	53
	-5 to 2	39	92	92	53
	Mean ± SD	40 ± 3	92 ± 0	92 ± 0	52 ± 1

Table 3.3. (cont.)

Disease	Time-window[7]	Sensitivity[1]	Specificity[1]	Accuracy[1]	Balanced accuracy[1]
Metritis[6]					
	0	38	92	92	50
	1	33	92	92	51
	2	31	92	92	51
	3	28	92	92	51
	4	27	92	92	51
	5	26	92	92	51
	6	25	92	91	51
	-1 to 1	34	92	92	51
	-2 to 2	33	92	92	52
	-3 to 3	32	92	92	52
	-5 to 2	35	92	92	52
	Mean ± SD	31 ± 4	92 ± 0	92 ± 0	51 ± 0

[1]Sensitivity, specificity, accuracy, and balanced accuracy were calculated from true positives, true negatives, false positives, and false negatives.
[2]Eating time, lying time, and activity (steps/d) alerts were generated when decreases of 30% or more from a 10-d moving mean occurred. Alerts were limited to ones identified by the system and presented to dairy producers on a daily basis (n = 23,737).
[3]All disease events referred to cow-days when any disease event occurred for the first time in a lactation including hyperketonemia, hypocalcemia, metritis, lameness, mastitis, displaced abomasum, retained placenta, or other disease identified by producers (Table 3.2).
[4]Hyperketonemia was defined as blood β-hydroxybutyrate ≥ 1.2 mmol/L when cows were examined between 3 and 7 DIM. Farm staff also recorded hyperketonemia if any clinical signs were present throughout lactation (Table 3.2).
[5]Hypocalcemia was defined as serum Ca ≤ 8.6 mg/dL when cows were examined between 3 and 7 DIM. Farm staff also recorded hypocalcemia if any clinical signs were present throughout lactation (Table 3.2).
[6]Metritis was defined as vaginal discharge score ≥ 2 (1 to 3 scale; Sterrett et al., 2014) when cows were examined between 3 and 7 DIM. Farm staff also recorded metritis if any clinical signs were present throughout lactation (Table 3.2).
[7]Time-windows were set around the d of disease detection (**DD**) by producers or lead author. Time-windows were 0 (d of DD), 1 (d of to 1 d after DD), 2 (d of to 2 d after DD), 3 (d of to 3 d after DD), 4 (d of to 4 d after DD), 5 (d of to 5 d after DD), 6 (d of to 6 d after DD), -1 to 1 (d before to d after DD), -2 to 2 (2 d before to 2 d after DD), -3 to 2 (3 d before to 3 d after DD), and -5 to 2 (5 d before to 2 d after DD).

Table 3.4. Sensitivity, specificity, accuracy, and balanced accuracy[1] of precision dairy monitoring technology generated alerts[2] for identifying any disease[3], hyperketonemia[4], hypocalcemia[5], or metritis[6]. Alerts based on activity (steps/d), eating time (min/d), and lying time (min/d) were created if that behavior decreased ≥ 30% from a cow's previous 10-d moving mean for each behavior. Eleven time-windows[7] were considered to determine true positives when disease alerts and events would overlap.

Disease	Time-window[7]	Sensitivity[1]	Specificity[1]	Accuracy[1]	Balanced accuracy[1]
All[3]					
	0	38	93	92	51
	1	37	93	92	52
	2	36	93	92	53
	3	34	93	92	54
	4	32	93	92	55
	5	31	93	91	55
	6	29	93	91	55
	-1 to 1	36	93	92	53
	-2 to 2	35	93	92	55
	-3 to 3	32	93	91	56
	-5 to 2	32	93	91	56
	Mean ± SD	34 ± 3	93 ± 0	92 ± 0	54 ± 1
Hyperketonemia[4]					
	0	45	93	93	50
	1	43	93	93	51
	2	43	93	93	51
	3	41	93	92	51
	4	39	93	92	51
	5	37	93	92	51
	6	34	93	92	51
	-1 to 1	44	93	93	51
	-2 to 2	43	93	92	51
	-3 to 3	41	93	92	52
	-5 to 2	43	93	92	52
	Mean ± SD	41 ± 3	93 ± 0	92 ± 0	51 ± 0
Hypocalcemia[5]					
	0	42	93	93	51
	1	42	93	92	51
	2	41	93	92	52
	3	39	93	92	52
	4	38	93	92	53
	5	36	93	92	53
	6	34	93	92	53
	-1 to 1	41	93	92	52
	-2 to 2	39	93	92	53
	-3 to 3	38	93	92	53
	-5 to 2	38	93	92	53
	Mean ± SD	39 ± 2	93 ± 0	92 ± 0	52 ± 1

Table 3.4. (cont.)

Disease	Time-window[7]	Sensitivity[1]	Specificity[1]	Accuracy[1]	Balanced accuracy[1]
Metritis[6]					
	0	33	93	93	50
	1	30	93	92	51
	2	29	93	92	51
	3	27	93	92	51
	4	25	93	92	51
	5	24	93	92	51
	6	23	93	92	51
	-1 to 1	32	93	92	51
	-2 to 2	31	93	92	51
	-3 to 3	30	93	92	52
	-5 to 2	33	93	92	52
	Mean ± SD	29 ± 3	93 ± 0	92 ± 0	51 ± 0

[1]Sensitivity, specificity, accuracy, and balanced accuracy were calculated from true positives, true negatives, false positives, and false negatives.

[2]Eating time, lying time, and activity (steps/d) alerts were calculated from raw data offloads when decreases of 30% or more from a 10-d moving mean occurred (n = 22,077).

[3]All disease events referred to cow-days when any disease event occurred for the first time in a lactation including hyperketonemia, hypocalcemia, metritis, lameness, mastitis, displaced abomasum, retained placenta, or other disease identified by producers (Table 3.2).

[4]Hyperketonemia was defined as blood β-hydroxybutyrate ≥ 1.2 mmol/L when cows were examined between 3 and 7 DIM. Farm staff also recorded hyperketonemia if any clinical signs were present throughout lactation (Table 3.2).

[5]Hypocalcemia was defined as serum Ca ≤ 8.6 mg/dL when cows were examined between 3 and 7 DIM. Farm staff also recorded hypocalcemia if any clinical signs were present throughout lactation (Table 3.2).

[6]Metritis was defined as vaginal discharge score ≥ 2 (1 to 3 scale; Sterrett et al., 2014) when cows were examined between 3 and 7 DIM. Farm staff also recorded metritis if any clinical signs were present throughout lactation (Table 3.2).

[7]Time-windows were set around the d of disease detection (**DD**) by producers or lead author. Time-windows were 0 (d of DD), 1 (d of to 1 d after DD), 2 (d of to 2 d after DD), 3 (d of to 3 d after DD), 4 (d of to 4 d after DD), 5 (d of to 5 d after DD), 6 (d of to 6 d after DD), -1 to 1 (d before to d after DD), -2 to 2 (2 d before to 2 d after DD), -3 to 2 (3 d before to 3 d after DD), and -5 to 2 (5 d before to 2 d after DD).

Table 3.5. Sensitivity, specificity, accuracy, and balanced accuracy[1] of precision dairy monitoring technology generated alerts[2] for identifying any disease[3], hyperketonemia[4], hypocalcemia[5], or metritis[6]. Alerts based on eating time (min/d) were created if that behavior decreased ≥ 30% from a cow's previous 10-d moving mean. Eleven time-windows[7] were considered to determine true positives when disease alerts and events would overlap.

Disease	Time-window[7]	Sensitivity[1]	Specificity[1]	Accuracy[1]	Balanced accuracy[1]
All[3]					
	0	29	97	96	52
	1	28	97	96	54
	2	26	97	96	55
	3	24	97	95	56
	4	22	97	95	57
	5	20	97	95	57
	6	19	97	94	57
	-1 to 1	27	97	96	56
	-2 to 2	24	97	95	58
	-3 to 3	22	97	95	59
	-5 to 2	22	97	95	59
	Mean ± SD	24 ± 3	97 ± 0	95 ± 0	56 ± 2
Hyperketonemia[4]					
	0	34	97	96	50
	1	32	97	96	51
	2	29	97	96	51
	3	28	97	96	51
	4	26	97	96	52
	5	24	97	96	52
	6	22	97	96	52
	-1 to 1	32	97	96	51
	-2 to 2	30	97	96	52
	-3 to 3	28	97	96	52
	-5 to 2	29	97	96	53
	Mean ± SD	29 ± 4	97 ± 0	96 ± 0	52 ± 1
Hypocalcemia[5]					
	0	34	97	96	51
	1	34	97	96	52
	2	32	97	96	53
	3	30	97	96	54
	4	27	97	96	54
	5	25	97	96	55
	6	23	97	96	55
	-1 to 1	32	97	96	53
	-2 to 2	29	97	96	54
	-3 to 3	27	97	96	55
	-5 to 2	27	97	96	55
	Mean ± SD	29 ± 3	97 ± 0	96 ± 0	54 ± 1

Table 3.5. (cont.)

Disease	Time-window[7]	Sensitivity[1]	Specificity[1]	Accuracy[1]	Balanced accuracy[1]
Metritis[6]					
	0	21	97	96	50
	1	19	97	96	51
	2	17	97	96	51
	3	16	97	96	51
	4	15	97	96	51
	5	13	97	96	51
	6	13	97	96	51
	-1 to 1	20	97	96	51
	-2 to 2	20	97	96	52
	-3 to 3	19	97	96	52
	-5 to 2	22	97	96	53
	Mean ± SD	18 ± 3	97 ± 0	96 ± 0	51 ± 1

[1]Sensitivity, specificity, accuracy, and balanced accuracy were calculated from true positives, true negatives, false positives, and false negatives.

[2]Eating time alerts were calculated from raw data offloads when decreases of 30% or more from a 10-d moving mean occurred (n = 10,349).

[3]All disease events referred to cow-days when any disease event occurred for the first time in a lactation including hyperketonemia, hypocalcemia, metritis, lameness, mastitis, displaced abomasum, retained placenta, or other disease identified by producers (Table 3.2).

[4]Hyperketonemia was defined as blood β-hydroxybutyrate ≥ 1.2 mmol/L when cows were examined between 3 and 7 DIM. Farm staff also recorded hyperketonemia if any clinical signs were present throughout lactation (Table 3.2).

[5]Hypocalcemia was defined as serum Ca ≤ 8.6 mg/dL when cows were examined between 3 and 7 DIM. Farm staff also recorded hypocalcemia if any clinical signs were present throughout lactation (Table 3.2).

[6]Metritis was defined as vaginal discharge score ≥ 2 (1 to 3 scale; Sterrett et al., 2014) when cows were examined between 3 and 7 DIM. Farm staff also recorded metritis if any clinical signs were present throughout lactation (Table 3.2).

[7]Time-windows were set around the d of disease detection (**DD**) by producers or lead author. Time-windows were 0 (d of DD), 1 (d of to 1 d after DD), 2 (d of to 2 d after DD), 3 (d of to 3 d after DD), 4 (d of to 4 d after DD), 5 (d of to 5 d after DD), 6 (d of to 6 d after DD), -1 to 1 (d before to d after DD), -2 to 2 (2 d before to 2 d after DD), -3 to 2 (3 d before to 3 d after DD), and -5 to 2 (5 d before to 2 d after DD).

Table 3.6. Sensitivity, specificity, accuracy, and balanced accuracy[1] of precision dairy monitoring technology generated alerts[2] for identifying any disease[3], hyperketonemia[4], hypocalcemia[5], or metritis[6]. Alerts based on activity (steps/d), standing (min/d), walking (min/d), or lying time (min/d) were created if that behavior decreased ≥ 30% from a cow's previous 10-d moving mean for each behavior. Eleven time-windows[7] were considered to determine true positives when disease alerts and events would overlap.

Disease	Time-window[7]	Sensitivity[1]	Specificity[1]	Accuracy[1]	Balanced accuracy[1]
All[3]					
	0	23	94	93	51
	1	22	94	93	51
	2	23	94	93	52
	3	22	94	92	53
	4	23	94	92	53
	5	22	94	92	54
	6	22	94	92	54
	-1 to 1	22	94	93	52
	-2 to 2	22	94	92	53
	-3 to 3	22	94	92	54
	-5 to 2	21	94	92	54
	Mean ± SD	22 ± 1	94 ± 0	92 ± 1	53 ± 1
Hyperketonemia[4]					
	0	30	93	93	50
	1	28	93	93	50
	2	30	94	93	51
	3	29	94	93	51
	4	29	94	93	51
	5	28	94	93	51
	6	27	94	93	51
	-1 to 1	27	94	93	51
	-2 to 2	29	94	93	51
	-3 to 3	28	94	93	51
	-5 to 2	28	94	93	51
	Mean ± SD	29 ± 1	94 ± 0	93 ± 0	51 ± 1
Hypocalcemia[5]					
	0	25	93	93	50
	1	22	94	93	51
	2	24	94	93	51
	3	23	94	93	51
	4	24	94	93	52
	5	24	94	93	52
	6	24	94	93	52
	-1 to 1	24	94	93	51
	-2 to 2	24	94	93	52
	-3 to 3	24	94	93	52
	-5 to 2	24	94	93	52
	Mean ± SD	24 ± 1	94 ± 0	93 ± 0	51 ± 0

Table 3.6. (cont.)

Disease	Time-window[7]	Sensitivity[1]	Specificity[1]	Accuracy[1]	Balanced accuracy[1]
Metritis[6]					
	0	25	93	93	50
	1	22	93	93	50
	2	22	94	93	51
	3	21	94	93	51
	4	21	94	93	51
	5	21	94	93	51
	6	20	94	93	51
	-1 to 1	22	94	93	51
	-2 to 2	23	94	93	51
	-3 to 3	22	94	93	51
	-5 to 2	23	94	93	51
	Mean ± SD	22 ± 1	94 ± 0	93 ± 0	51 ± 0

[1]Sensitivity, specificity, accuracy, and balanced accuracy were calculated from true positives, true negatives, false positives, and false negatives.
[2]Standing time, lying time, walking time, and activity (steps/d) alerts were calculated from raw data offloads when decreases of 30% or more from a 10-d moving mean occurred (n = 19,485).
[3]All disease events referred to cow-days when any disease event occurred for the first time in a lactation including hyperketonemia, hypocalcemia, metritis, lameness, mastitis, displaced abomasum, retained placenta, or other disease identified by producers (Table 3.2).
[4]Hyperketonemia was defined as blood β-hydroxybutyrate ≥ 1.2 mmol/L when cows were examined between 3 and 7 DIM. Farm staff also recorded hyperketonemia if any clinical signs were present throughout lactation (Table 3.2).
[5]Hypocalcemia was defined as serum Ca ≤ 8.6 mg/dL when cows were examined between 3 and 7 DIM. Farm staff also recorded hypocalcemia if any clinical signs were present throughout lactation (Table 3.2).
[6]Metritis was defined as vaginal discharge score ≥ 2 (1 to 3 scale; Sterrett et al., 2014) when cows were examined between 3 and 7 DIM. Farm staff also recorded metritis if any clinical signs were present throughout lactation (Table 3.2).
[7]Time-windows were set around the d of disease detection (**DD**) by producers or lead author. Time-windows were 0 (d of DD), 1 (d of to 1 d after DD), 2 (d of to 2 d after DD), 3 (d of to 3 d after DD), 4 (d of to 4 d after DD), 5 (d of to 5 d after DD), 6 (d of to 6 d after DD), -1 to 1 (d before to d after DD), -2 to 2 (2 d before to 2 d after DD), -3 to 2 (3 d before to 3 d after DD), and -5 to 2 (5 d before to 2 d after DD).

Table 3.7. Sensitivity, specificity, accuracy, and balanced accuracy[1] of precision dairy monitoring technology generated alerts[2] for identifying any disease[3], hyperketonemia[4], hypocalcemia[5], or metritis[6]. Alerts based on activity (steps/d), eating (min/d), standing (min/d), lying (min/d), and walking time (min/d) were created if that behavior decreased ≥ 30% from a cow's previous 10-d moving mean behavior. Eleven time-windows[7] were considered to determine true positives when disease alerts and events would overlap.

Disease	Time-window[7]	Sensitivity[1]	Specificity[1]	Accuracy[1]	Balanced accuracy[1]
All[3]					
	0	34	91	91	51
	1	34	91	91	52
	2	33	92	91	52
	3	31	92	90	53
	4	31	92	90	53
	5	30	92	90	54
	6	29	92	90	54
	-1 to 1	33	92	91	52
	-2 to 2	32	92	90	54
	-3 to 3	30	92	90	54
	-5 to 2	29	92	90	54
	Mean ± SD	31 ± 2	92 ± 0	90 ± 0	53 ± 1
Hyperketonemia[4]					
	0	38	91	91	50
	1	38	91	91	50
	2	39	91	91	51
	3	37	91	91	51
	4	37	91	91	51
	5	36	91	91	51
	6	34	91	91	51
	-1 to 1	39	91	91	51
	-2 to 2	39	91	91	51
	-3 to 3	38	91	91	51
	-5 to 2	39	91	91	51
	Mean ± SD	38 ± 2	91 ± 0	91 ± 0	51 ± 0
Hypocalcemia[5]					
	0	35	91	91	50
	1	36	91	91	51
	2	35	91	91	51
	3	34	91	91	52
	4	34	92	91	52
	5	34	92	91	52
	6	32	92	91	52
	-1 to 1	36	91	91	51
	-2 to 2	34	92	91	52
	-3 to 3	34	92	91	52
	-5 to 2	34	92	91	52
	Mean ± SD	34 ± 1	91 ± 0	91 ± 0	52 ± 1

Table 3.7. (cont.)

Disease	Time-window[3]	Sensitivity[1]	Specificity[1]	Accuracy[1]	Balanced accuracy[1]
Metritis[7]					
	0	32	91	91	50
	1	30	91	91	50
	2	29	91	91	51
	3	31	91	91	51
	4	27	91	91	51
	5	27	91	91	51
	6	26	91	91	51
	-1 to 1	30	91	91	51
	-2 to 2	30	91	91	51
	-3 to 3	29	91	91	51
	-5 to 2	31	91	91	52
	Mean ± SD	29 ± 2	91 ± 0	91 ± 0	51 ± 0

[1]Sensitivity, specificity, accuracy, and balanced accuracy were calculated from true positives, true negatives, false positives, and false negatives.
[2]Eating time, standing time, lying time, walking time, and activity (steps/d) alerts were calculated from raw data offloads when decreases of 30% or more from a 10-d moving mean occurred (n = 26,133).
[3]All disease events referred to cow-days when any disease event occurred for the first time in a lactation including hyperketonemia, hypocalcemia, metritis, lameness, mastitis, displaced abomasum, retained placenta, or other disease identified by producers (Table 3.2).
[4]Hyperketonemia was defined as blood β-hydroxybutyrate ≥ 1.2 mmol/L when cows were examined between 3 and 7 DIM. Farm staff also recorded hyperketonemia if any clinical signs were present throughout lactation (Table 3.2).
[5]Hypocalcemia was defined as serum Ca ≤ 8.6 mg/dL when cows were examined between 3 and 7 DIM. Farm staff also recorded hypocalcemia if any clinical signs were present throughout lactation (Table 3.2).
[6]Metritis was defined as vaginal discharge score ≥ 2 (1 to 3 scale; Sterrett et al., 2014) when cows were examined between 3 and 7 DIM. Farm staff also recorded metritis if any clinical signs were present throughout lactation (Table 3.2).
[7]Time-windows were set around the d of disease detection (**DD**) by producers or lead author. Time-windows were 0 (d of DD), 1 (d of to 1 d after DD), 2 (d of to 2 d after DD), 3 (d of to 3 d after DD), 4 (d of to 4 d after DD), 5 (d of to 5 d after DD), 6 (d of to 6 d after DD), -1 to 1 (d before to d after DD), -2 to 2 (2 d before to 2 d after DD), -3 to 2 (3 d before to 3 d after DD), and -5 to 2 (5 d before to 2 d after DD).

Table 3.8. Sensitivity, specificity, accuracy, and balanced accuracy[1] of precision dairy technology collected behaviors[2] for predicting any disease[3], hyperketonemia[4], hypocalcemia[5], or metritis[6]. Behaviors collected were activity (steps/d), eating (min/d), and lying time (min/d). Three machine-learning methods[7] and four time-windows[8] were considered to determine true positives when diseases were accurately predicted.

Disease	Time-window[8]	Sensitivity[1]	Specificity[1]	Accuracy[1]	Balanced accuracy[1]
All[3]					
LDA[7]					
	0	72	69	72	71
	-1 to 0	72	71	72	71
	-3 to 0	72	68	72	70
	-5 to 0	71	68	71	69
PCANNet[7]					
	0	84	70	84	77
	-1 to 0	83	76	83	80
	-3 to 0	83	72	83	78
	-5 to 0	82	71	82	77
RF[7]					
	0	80	75	80	78
	-1 to 0	81	77	81	79
	-3 to 0	81	75	81	78
	-5 to 0	79	75	79	77
Hyperketonemia[4]					
LDA[7]					
	0	73	69	73	71
	-1 to 0	73	72	73	72
	-3 to 0	71	68	71	70
	-5 to 0	70	68	70	69
PCANNet[7]					
	0	83	76	83	80
	-1 to 0	83	83	83	83
	-3 to 0	84	84	84	84
	-5 to 0	84	80	84	82
RF[7]					
	0	82	82	82	82
	-1 to 0	81	89	81	85
	-3 to 0	79	85	79	82
	-5 to 0	81	82	81	82
Hypocalcemia[5]					
LDA[7]					
	0	74	74	74	74
	-1 to 0	74	73	74	73
	-3 to 0	73	70	73	72
	-5 to 0	73	70	73	71

Table 3.8. (cont.)

Disease	Time-window[8]	Sensitivity[1]	Specificity[1]	Accuracy[1]	Balanced accuracy[1]
Hypocalcemia[5]					
PCANNet[7]					
	0	86	77	86	81
	-1 to 0	87	78	86	82
	-3 to 0	86	79	86	82
	-5 to 0	84	76	84	80
RF[7]					
	0	84	81	84	82
	-1 to 0	82	83	82	82
	-3 to 0	83	83	83	83
	-5 to 0	83	81	83	82
Metritis[6]					
LDA[7]					
	0	73	66	73	69
	-1 to 0	74	68	74	71
	-3 to 0	75	70	75	72
	-5 to 0	74	69	77	72
PCANNet[7]					
	0	81	73	81	77
	-1 to 0	84	76	84	80
	-3 to 0	85	81	85	83
	-5 to 0	85	79	85	82
RF[7]					
	0	80	80	80	80
	-1 to 0	82	81	82	82
	-3 to 0	83	81	83	82
	-5 to 0	82	84	82	83

[1]Sensitivity, specificity, accuracy, and balanced accuracy were calculated outputs from each machine-learning model based on true positives, true negatives, false positives, and false negatives.

[2]Daily eating time, lying time, activity (steps/d) and a calculated daily difference from an individual cow's 10-d moving mean for each behavior were included as explanatory variables for each machine-learning model (n = 1,168 cows and 296,824 cow-days).

[3]All disease events referred to cow-days when any disease event occurred for the first time in a lactation including hyperketonemia, hypocalcemia, metritis, lameness, mastitis, displaced abomasum, retained placenta, or other disease identified by producers (Table 3.2).

[4]Hyperketonemia was defined as blood β-hydroxybutyrate $\geq$ 1.2 mmol/L when cows were examined between 3 and 7 DIM. Farm staff also recorded hyperketonemia if any clinical signs were present throughout lactation (Table 3.2).

[5]Hypocalcemia was defined as serum Ca $\leq$ 8.6 mg/dL when cows were examined between 3 and 7 DIM. Farm staff also recorded hypocalcemia if any clinical signs were present throughout lactation (Table 3.2).

Table 3.8. (cont.)

[6]Metritis was defined as vaginal discharge score ≥ 2 (1 to 3 scale; Sterrett et al., 2014) when cows were examined between 3 and 7 DIM. Farm staff also recorded metritis if any clinical signs were present throughout lactation (Table 3.2).
[7]A least discriminant analysis (LDA), principle component analysis neural network (PCANNet), and a random forest (RF) technique were run on all data to identify patterns in the data and predict disease incidence within four time-windows.
[8]Time-windows were set around the d of disease detection (**DD**) by producers or lead author. Time-windows were 0 (d of DD), -1 to 0 (1 d before to d of DD), -3 to 0 (3 d before to d of DD), and -5 to 0 (5 d before to d of DD).

Table 3.9. Sensitivity, specificity, accuracy, and balanced accuracy[1] of precision dairy technology collected behavior[2] for predicting any disease[3], hyperketonemia[4], hypocalcemia[5], or metritis[6]. Behavior collected was eating time (min/d). Three machine-learning methods[7] and four time-windows[8] were considered to determine true positives when diseases were accurately predicted.

Disease	Time-window[8]	Sensitivity[1]	Specificity[1]	Accuracy[1]	Balanced accuracy[1]
All[3]					
LDA[7]					
	0	72	70	72	71
	-1 to 0	73	71	73	72
	-3 to 0	71	69	71	70
	-5 to 0	70	68	70	69
PCANNet[7]					
	0	81	67	81	74
	-1 to 0	80	73	80	77
	-3 to 0	80	69	80	74
	-5 to 0	79	69	78	74
RF[7]					
	0	71	69	71	70
	-1 to 0	70	72	70	71
	-3 to 0	69	67	69	68
	-5 to 0	67	67	67	67
Hyperketonemia[4]					
LDA[7]					
	0	71	65	71	68
	-1 to 0	71	67	71	69
	-3 to 0	69	69	69	69
	-5 to 0	70	66	70	68
PCANNet[7]					
	0	80	66	80	73
	-1 to 0	79	78	79	79
	-3 to 0	80	75	80	77
	-5 to 0	80	73	80	76
RF[7]					
	0	73	63	73	68
	-1 to 0	73	73	73	73
	-3 to 0	71	71	71	71
	-5 to 0	71	68	71	69
Hypocalcemia[5]					
LDA[7]					
	0	74	80	74	77
	-1 to 0	74	73	74	74
	-3 to 0	73	70	73	71
	-5 to 0	73	71	73	72

Table 3.9. (cont.)

Disease	Time-window[8]	Sensitivity[1]	Specificity[1]	Accuracy[1]	Balanced accuracy[1]
Hypocalcemia[5]					
PCANNet[7]					
	0	84	77	84	80
	-1 to 0	84	72	84	78
	-3 to 0	83	73	82	78
	-5 to 0	82	73	82	78
RF[7]					
	0	74	79	74	76
	-1 to 0	76	73	76	75
	-3 to 0	74	72	74	73
	-5 to 0	72	74	72	73
Metritis[6]					
LDA[7]					
	0	73	68	99	71
	-1 to 0	73	71	73	72
	-3 to 0	74	68	74	71
	-5 to 0	73	68	73	71
PCANNet[7]					
	0	76	71	76	74
	-1 to 0	80	76	80	78
	-3 to 0	82	74	82	78
	-5 to 0	83	74	82	78
RF[7]					
	0	72	66	72	69
	-1 to 0	72	74	72	73
	-3 to 0	73	74	73	74
	-5 to 0	73	73	73	73

[1]Sensitivity, specificity, accuracy, and balanced accuracy were calculated outputs from each machine-learning model based on true positives, true negatives, false positives, and false negatives.

[2]Daily eating time and a calculated daily difference from an individual cow's 10-d moving mean eating time were included as explanatory variables for each machine-learning model (n = 1,168 cows and 296,824 cow-days).

[3]All disease events referred to cow-days when any disease event occurred for the first time in a lactation including hyperketonemia, hypocalcemia, metritis, lameness, mastitis, displaced abomasum, retained placenta, or other disease identified by producers (Table 3.2).

[4]Hyperketonemia was defined as blood β-hydroxybutyrate ≥ 1.2 mmol/L when cows were examined between 3 and 7 DIM. Farm staff also recorded hyperketonemia if any clinical signs were present throughout lactation (Table 3.2).

[5]Hypocalcemia was defined as serum Ca ≤ 8.6 mg/dL when cows were examined between 3 and 7 DIM. Farm staff also recorded hypocalcemia if any clinical signs were present throughout lactation (Table 3.2).

Table 3.9. (cont.)

[6]Metritis was defined as vaginal discharge score ≥ 2 (1 to 3 scale; Sterrett et al., 2014) when cows were examined between 3 and 7 DIM. Farm staff also recorded metritis if any clinical signs were present throughout lactation (Table 3.2).
[7]A least discriminant analysis (LDA), principle component analysis neural network (PCANNet), and a random forest (RF) technique were run on all data to identify patterns in the data and predict disease incidence within four time-windows.
[8]Time-windows were set around the d of disease detection (**DD**) by producers or lead author. Time-windows were 0 (d of DD), -1 to 0 (1 d before to d of DD), -3 to 0 (3 d before to d of DD), and -5 to 0 (5 d before to d of DD).

Table 3.10. Sensitivity, specificity, accuracy, and balanced accuracy[1] of precision dairy technology collected behaviors[2] for predicting any disease[3], hyperketonemia[4], hypocalcemia[5], or metritis[6]. Behaviors collected were activity (steps/d), standing (min/d), lying (min/d), and walking time (min/d). Three machine-learning methods[7] and four time-windows[8] were considered to determine true positives when diseases were accurately predicted.

Disease	Time-window[8]	Sensitivity[1]	Specificity[1]	Accuracy[1]	Balanced accuracy[1]
All[3]					
LDA[7]					
	0	76	61	76	68
	-1 to 0	76	61	76	69
	-3 to 0	78	55	78	67
	-5 to 0	80	53	79	66
PCANNet[7]					
	0	86	49	86	68
	-1 to 0	88	50	87	69
	-3 to 0	89	42	88	66
	-5 to 0	88	42	87	65
RF[7]					
	0	76	72	76	74
	-1 to 0	78	72	77	75
	-3 to 0	78	71	78	75
	-5 to 0	78	69	78	72
Hyperketonemia[4]					
LDA[7]					
	0	78	71	78	75
	-1 to 0	74	78	74	76
	-3 to 0	75	72	75	74
	-5 to 0	75	68	75	72
PCANNet[7]					
	0	82	60	82	71
	-1 to 0	83	59	83	71
	-3 to 0	84	52	84	68
	-5 to 0	87	46	87	67
RF[7]					
	0	82	74	82	78
	-1 to 0	79	74	79	76
	-3 to 0	78	80	78	79
	-5 to 0	79	77	79	78
Hypocalcemia[5]					
LDA[7]					
	0	77	68	80	74
	-1 to 0	79	61	79	70
	-3 to 0	81	59	81	70
	-5 to 0	84	56	83	70

Table 3.10. (cont.)

Disease	Time-window[8]	Sensitivity[1]	Specificity[1]	Accuracy[1]	Balanced accuracy[1]
Hypocalcemia[5]					
PCANNet[7]					
	0	90	45	90	67
	-1 to 0	87	49	86	68
	-3 to 0	87	52	87	70
	-5 to 0	90	48	89	69
RF[7]					
	0	78	81	78	79
	-1 to 0	81	74	81	78
	-3 to 0	81	78	81	80
	-5 to 0	81	79	80	80
Metritis[6]					
LDA[7]					
	0	76	60	76	68
	-1 to 0	77	72	77	74
	-3 to 0	78	64	78	71
	-5 to 0	78	61	78	70
PCANNet[7]					
	0	83	64	83	74
	-1 to 0	83	60	83	72
	-3 to 0	86	58	85	72
	-5 to 0	89	50	88	69
RF[7]					
	0	80	79	80	80
	-1 to 0	81	81	81	81
	-3 to 0	81	75	81	78
	-5 to 0	81	77	81	79

[1]Sensitivity, specificity, accuracy, and balanced accuracy were calculated outputs from each machine-learning model based on true positives, true negatives, false positives, and false negatives.
[2]Daily lying time, standing time, walking time, activity (steps/d), and a calculated daily difference from an individual cow's 10-d moving mean for each behavior were included as explanatory variables for each machine-learning model (n = 1,168 cows and 296,824 cow-days).
[3]All disease events referred to cow-days when any disease event occurred for the first time in a lactation including hyperketonemia, hypocalcemia, metritis, lameness, mastitis, displaced abomasum, retained placenta, or other disease identified by producers (Table 3.2).
[4]Hyperketonemia was defined as blood β-hydroxybutyrate ≥ 1.2 mmol/L when cows were examined between 3 and 7 DIM. Farm staff also recorded hyperketonemia if any clinical signs were present throughout lactation (Table 3.2).
[5]Hypocalcemia was defined as serum Ca ≤ 8.6 mg/dL when cows were examined between 3 and 7 DIM. Farm staff also recorded hypocalcemia if any clinical signs were present throughout lactation (Table 3.2).
[6]Metritis was defined as vaginal discharge score ≥ 2 (1 to 3 scale; Sterrett et al., 2014) when cows were examined between 3 and 7 DIM. Farm staff also recorded metritis if any clinical signs were present throughout lactation (Table 3.2).

Table 3.10. (cont.)

[7]A least discriminant analysis (LDA), principle component analysis neural network (PCANNet), and a random forest (RF) technique were run on all data to identify patterns in the data and predict disease incidence within four time-windows.
[8]Time-windows were set around the d of disease detection (**DD**) by producers or lead author. Time-windows were 0 (d of DD), -1 to 0 (1 d before to d of DD), -3 to 0 (3 d before to d of DD), and -5 to 0 (5 d before to d of DD).

Table 3.11. Sensitivity, specificity, accuracy, and balanced accuracy[1] of precision dairy technology collected behaviors[2] for predicting any disease[3], hyperketonemia[4], hypocalcemia[5], or metritis[6]. Behaviors collected were activity (steps/d), eating (min/d), walking (min/d), standing (min/d), and lying time (min/d). Three machine-learning methods[7] and four time-windows[8] were considered to determine true positives when diseases were accurately predicted.

Disease	Time-window[8]	Sensitivity[1]	Specificity[1]	Accuracy[1]	Balanced accuracy[1]
All[3]					
LDA[7]					
	0	74	72	74	73
	-1 to 0	76	73	76	74
	-3 to 0	73	70	73	72
	-5 to 0	72	69	72	71
PCANNet[7]					
	0	80	73	80	77
	-1 to 0	84	75	84	80
	-3 to 0	83	73	83	78
	-5 to 0	83	70	83	76
RF[7]					
	0	82	74	82	78
	-1 to 0	83	78	83	80
	-3 to 0	82	77	82	80
	-5 to 0	81	74	81	78
Hyperketonemia[4]					
LDA[7]					
	0	80	84	80	82
	-1 to 0	78	82	78	80
	-3 to 0	77	72	77	75
	-5 to 0	76	67	76	72
PCANNet[7]					
	0	79	74	79	77
	-1 to 0	85	71	85	78
	-3 to 0	84	82	84	83
	-5 to 0	83	80	83	82
RF[7]					
	0	79	84	79	81
	-1 to 0	82	86	82	84
	-3 to 0	81	87	81	84
	-5 to 0	82	85	82	84
Hypocalcemia[5]					
LDA[7]					
	0	79	78	79	78
	-1 to 0	76	73	76	75
	-3 to 0	76	74	76	75
	-5 to 0	75	71	75	73

Table 3.11. (cont.)

Disease	Time-window[8]	Sensitivity[1]	Specificity[1]	Accuracy[1]	Balanced accuracy[1]
Hypocalcemia[5]					
PCANNet[7]					
	0	85	79	85	82
	-1 to 0	85	77	85	81
	-3 to 0	85	85	85	85
	-5 to 0	85	79	84	82
RF[7]					
	0	86	84	86	85
	-1 to 0	84	80	84	82
	-3 to 0	84	86	84	85
	-5 to 0	84	86	84	85
Metritis[6]					
LDA[7]					
	0	76	73	76	75
	-1 to 0	75	76	75	75
	-3 to 0	77	75	77	76
	-5 to 0	78	70	78	74
PCANNet[7]					
	0	80	82	80	81
	-1 to 0	83	81	83	82
	-3 to 0	86	81	86	84
	-5 to 0	85	80	85	83
RF[7]					
	0	81	87	81	84
	-1 to 0	83	87	83	85
	-3 to 0	84	87	84	85
	-5 to 0	84	85	84	85

[1]Sensitivity, specificity, accuracy, and balanced accuracy were calculated outputs from each machine-learning model based on true positives, true negatives, false positives, and false negatives.
[2]Daily eating time, lying time, standing time, walking time, activity (steps/d), and a calculated daily difference from an individual cow's 10-d moving mean for each behavior were included as explanatory variables for each machine-learning model (n = 1,168 cows and 296,824 cow-days).
[3]All disease events referred to cow-days when any disease event occurred for the first time in a lactation including hyperketonemia, hypocalcemia, metritis, lameness, mastitis, displaced abomasum, retained placenta, or other disease identified by producers (Table 3.2).
[4]Hyperketonemia was defined as blood β-hydroxybutyrate $\geq$ 1.2 mmol/L when cows were examined between 3 and 7 DIM. Farm staff also recorded hyperketonemia if any clinical signs were present throughout lactation (Table 3.2).
[5]Hypocalcemia was defined as serum Ca $\leq$ 8.6 mg/dL when cows were examined between 3 and 7 DIM. Farm staff also recorded hypocalcemia if any clinical signs were present throughout lactation (Table 3.2).
[6]Metritis was defined as vaginal discharge score $\geq$ 2 (1 to 3 scale; Sterrett et al., 2014) when cows were examined between 3 and 7 DIM. Farm staff also recorded metritis if any clinical signs were present throughout lactation (Table 3.2).

Table 3.11. (cont.)

[7]A least discriminant analysis (LDA), principle component analysis neural network (PCANNet), and a random forest (RF) technique were run on all data to identify patterns in the data and predict disease incidence within four time-windows.
[8]Time-windows were set around the d of disease detection (**DD**) by producers or lead author. Time-windows were 0 (d of DD), -1 to 0 (1 d before to d of DD), -3 to 0 (3 d before to d of DD), and -5 to 0 (5 d before to d of DD).

Table 3.12. Sensitivity, specificity, accuracy, and balanced accuracy[1] of precision dairy technology collected behaviors[2] with previous lactation information[3] and daily THI[4] for predicting any disease[5], hyperketonemia[6], hypocalcemia[7], or metritis[8]. Behaviors collected were activity (steps/d), eating (min/d), walking (min/d), standing (min/d), and lying time (min/d). Three machine-learning methods[9] and four time-windows[10] were considered to determine true positives when diseases were accurately predicted.

Disease	Time-window[10]	Sensitivity[1]	Specificity[1]	Accuracy[1]	Balanced accuracy[1]
All[5]					
LDA[9]					
	0	75	70	75	73
	-1 to 0	75	74	75	74
	-3 to 0	73	71	73	72
	-5 to 0	72	68	72	70
PCANNet[9]					
	0	80	71	80	75
	-1 to 0	81	74	81	78
	-3 to 0	81	74	81	77
	-5 to 0	82	72	82	77
RF[9]					
	0	82	75	82	79
	-1 to 0	84	81	84	82
	-3 to 0	84	80	84	82
	-5 to 0	83	78	83	81
Hyperketonemia[6]					
LDA[9]					
	0	81	87	81	84
	-1 to 0	79	82	79	80
	-3 to 0	79	77	79	78
	-5 to 0	77	72	77	75
PCANNet[9]					
	0	80	74	80	77
	-1 to 0	82	77	82	80
	-3 to 0	83	82	83	83
	-5 to 0	83	79	83	81
RF[9]					
	0	82	90	82	86
	-1 to 0	83	88	83	86
	-3 to 0	84	89	84	87
	-5 to 0	85	89	85	87
Hypocalcemia[7]					
LDA[9]					
	0	78	80	78	79
	-1 to 0	78	72	78	75
	-3 to 0	76	74	76	75
	-5 to 0	75	71	75	73

Table 3.12. (cont.)

Disease	Time-window[10]	Sensitivity[1]	Specificity[1]	Accuracy[1]	Balanced accuracy[1]
Hypocalcemia[7]					
PCANNet[9]					
	0	79	72	79	76
	-1 to 0	84	79	84	82
	-3 to 0	85	83	85	84
	-5 to 0	85	81	85	83
RF[9]					
	0	84	82	84	83
	-1 to 0	86	85	86	85
	-3 to 0	86	88	86	87
	-5 to 0	86	88	86	87
Metritis[8]					
LDA[9]					
	0	78	75	78	77
	-1 to 0	77	77	77	77
	-3 to 0	78	76	78	77
	-5 to 0	79	70	79	75
PCANNet[9]					
	0	75	75	75	75
	-1 to 0	84	83	84	83
	-3 to 0	84	83	84	83
	-5 to 0	85	83	85	84
RF[9]					
	0	82	91	82	86
	-1 to 0	85	86	85	85
	-3 to 0	85	88	85	86
	-5 to 0	85	87	85	85

[1]Sensitivity, specificity, accuracy, and balanced accuracy were calculated outputs from each machine-learning model based on true positives, true negatives, false positives, and false negatives.

[2]Daily eating time, lying time, standing time, walking time, activity (steps/d), and a calculated daily difference from an individual cow's 10-d moving mean for each behavior were included as explanatory variables for each machine-learning model (n = 1,168 cows and 296,824 cow-days).

[3]Previous lactation information included energy corrected milk, average somatic cell score, lactation length, and actual calving interval (Dairy Herd Information Association, DRMS, Raleigh, NC).

[4]Daily maximum temperature humidity index (THI) was calculated from daily barn ambient humidity and temperature according to NOAA (1976).

[5]All disease events referred to cow-days when any disease event occurred for the first time in a lactation including hyperketonemia, hypocalcemia, metritis, lameness, mastitis, displaced abomasum, retained placenta, or other disease identified by producers (Table 3.2).

[6]Hyperketonemia was defined as blood β-hydroxybutyrate ≥ 1.2 mmol/L when cows were examined between 3 and 7 DIM. Farm staff also recorded hyperketonemia if any clinical signs were present throughout lactation (Table 3.2).

Table 3.12 (cont.)

[7]Hypocalcemia was defined as serum Ca ≤ 8.6 mg/dL when cows were examined between 3 and 7 DIM. Farm staff also recorded hypocalcemia if any clinical signs were present throughout lactation (Table 3.2).
[8]Metritis was defined as vaginal discharge score ≥ 2 (1 to 3 scale; Sterrett et al., 2014) when cows were examined between 3 and 7 DIM. Farm staff also recorded metritis if any clinical signs were present throughout lactation (Table 3.2).
[9]A least discriminant analysis (LDA), principle component analysis neural network (PCANNet), and a random forest (RF) technique were run on all data to identify patterns in the data and predict disease incidence within four time-windows.
[10]Time-windows were set around the d of disease detection (**DD**) by producers or lead author. Time-windows were 0 (d of DD), -1 to 0 (1 d before to d of DD), -3 to 0 (3 d before to d of DD), and -5 to 0 (5 d before to d of DD).

Table 3.13. Detection[1] or prediction[2] performance[3] of precision dairy technology measured behaviors for all diseases, hyperketonemia, hypocalcemia, and metritis occurrence was done individually in Tables 3.3 to 3.12. An overview of detection and prediction performance is given here as a mean ± SD across all diseases and behavior combinations for each time-window[4,5].

Alert type	Time-window[4,5]	Sensitivity[3]	Specificity[3]	Accuracy[3]	Balanced accuracy[3]
Generated[1]					
	0[4]	35 ± 8	93 ± 2	93 ± 2	51 ± 0
	1[4]	33 ± 8	93 ± 2	93 ± 2	51 ± 1
	2[4]	32 ± 7	93 ± 2	93 ± 2	52 ± 1
	3[4]	31 ± 7	93 ± 2	93 ± 2	52 ± 2
	4[4]	30 ± 7	93 ± 2	93 ± 2	52 ± 2
	5[4]	28 ± 7	93 ± 2	93 ± 2	53 ± 2
	6[4]	27 ± 6	93 ± 2	92 ± 2	53 ± 2
	-1 to 1[4]	33 ± 7	93 ± 2	93 ± 2	52 ± 1
	-2 to 2[4]	32 ± 7	93 ± 2	93 ± 2	53 ± 2
	-3 to 3[4]	31 ± 7	93 ± 2	92 ± 2	53 ± 2
	-5 to 2[4]	31 ± 7	93 ± 2	92 ± 2	53 ± 2
Machine-learning					
LDA[2]					
	0[5]	76 ± 3	72 ± 7	77 ± 6	74 ± 5
	-1 to 0[5]	75 ± 2	72 ± 5	75 ± 2	74 ± 3
	-3 to 0[5]	75 ± 3	70 ± 5	75 ± 3	72 ± 3
	-5 to 0[5]	75 ± 4	67 ± 5	75 ± 4	71 ± 2
PCANNet[2]					
	0[5]	82 ± 3	70 ± 9	82 ± 3	76 ± 4
	-1 to 0[5]	83 ± 2	72 ± 10	83 ± 2	78 ± 5
	-3 to 0[5]	84 ± 2	73 ± 12	84 ± 2	78 ± 6
	-5 to 0[5]	84 ± 3	70 ± 13	84 ± 3	77 ± 6
RF[2]					
	0[5]	79 ± 4	78 ± 7	79 ± 4	79 ± 5
	-1 to 0[5]	80 ± 5	80 ± 6	80 ± 5	80 ± 5
	-3 to 0[5]	80 ± 5	80 ± 7	80 ± 5	80 ± 6
	-5 to 0[5]	80 ± 5	79 ± 7	80 ± 5	79 ± 6

[1]Generated referred to eating time, standing time, lying time, walking time, and activity (steps/d) alerts created when decreases of 30% or more from a 10-day moving mean were calculated either individually or in combination (Table 3.3 to 3.7).
[2]A least discriminant analysis (LDA), principle component analysis neural network (PCANNet), and a random forest (RF) technique were run on all data to identify patterns in the data and predict disease incidence within four time-windows (Table 3.8 to 3.12).
[3]Sensitivity, specificity, accuracy, and balanced accuracy were calculated from true positives, true negatives, false positives, and false negatives.

Table 3.13. (cont.)

[4]Time-windows correspond to eating, lying, standing, walking, or activity alerts generated from a neck or leg attached precision dairy monitoring technology (Table 3.3 to 3.7). Time-windows were were set around the d of disease detection (**DD**) by producers or lead author. Time-windows were 0 (d of DD), 1 (d of to 1 d after DD), 2 (d of to 2 d after DD), 3 (d of to 3 d after DD), 4 (d of to 4 d after DD), 5 (d of to 5 d after DD), 6 (d of to 6 d after DD), -1 to 1 (d before to d after DD), -2 to 2 (2 d before to 2 d after DD), -3 to 2 (3 d before to 3 d after DD), and -5 to 2 (5 d before to 2 d after DD).
[5]Time-windows correspond to linear discriminant analysis, random forest, or principal component analysis neural network machine-learning prediction techniques on technology measured parameters, previous lactation information, and ambient temperature-humidity index (Table 3.8 to 3.12). Time-windows were set around the d of disease detection (**DD**) by producers or lead author. Time-windows were 0 (d of DD), -1 to 0 (1 d before to d of DD), -3 to 0 (3 d before to d of DD), and -5 to 0 (5 d before to d of DD).

Figure 3.1. Mastitis recording sheet used by producers on Farm 1 to 4 from October 5, 2015 to October 31, 2016.

Mastitis Report Sheet

Farm ID: ___________________

Date	**Cow Number**	**Milking (1^{st}, 2^{nd}, 3^{rd} etc.)**	**Quarter Infected**	**Mastitis Severity Code**	**Treated (Yes/No)**	**Length of treatment (days)**	**Product treated with:**

Use a row for each case of mastitis. If more than 1 quarter is infected, repeat the information for the cow and the other quarter(s) infected in a new row. Please include non-antibiotic treatments as well, such as UdderComfort, oxytocin, etc. Quarters should be labeled as LF (left front), LR (left rear), RR (right rear), or RF (right front).

<u>Please use the following guide for severity score:</u>

1 – milk changes (clots, flakes, clear)
2 – milk changes plus udder changes (reddening, hardening, heat)
3 – systemic changes (depression, fever, dehydration, weakness, loss of appetite, or rapid pulse)

Figure 3.2. Clinical disease recording sheet used by producers on Farm 1 to 4 from October 5, 2015 to October 31, 2016.

Disease Incidence Report Sheet

Farm ID: __________________

Date	Cow Number	Disease Identified	Initials of Person who identified disease	Treated (Yes/No)	Length of treatment (days)	Product treated with:

Please use the following shorthand for disease identification:

LDA – left displaced abomasum
RDA – right displaced abomasum
MF – milk fever
KET – ketosis
RP – retained placenta
MET – metritis
LAME – animal visually identified as lame

Figure 3.3. LSMean ± SE eating time (a; min/d), lying time (b; min/d), standing time (c; min/d), walking time (d; min/d), and activity (e; steps/d) characterized by a precision dairy monitoring technology for cows without (n = 451; grey lines) or with (n = 717; black lines) any disease events[1,2] within the first 21 DIM on 1,168 cows observed across 4 farms from October 5, 2015 to October 31, 2016 calculated with the MIXED procedure of SAS 9.4 (Cary, NC). Statistically different LSMeans are represented as: ⁎ health status (no disease vs. disease); † DIM; ‡ health status x DIM.

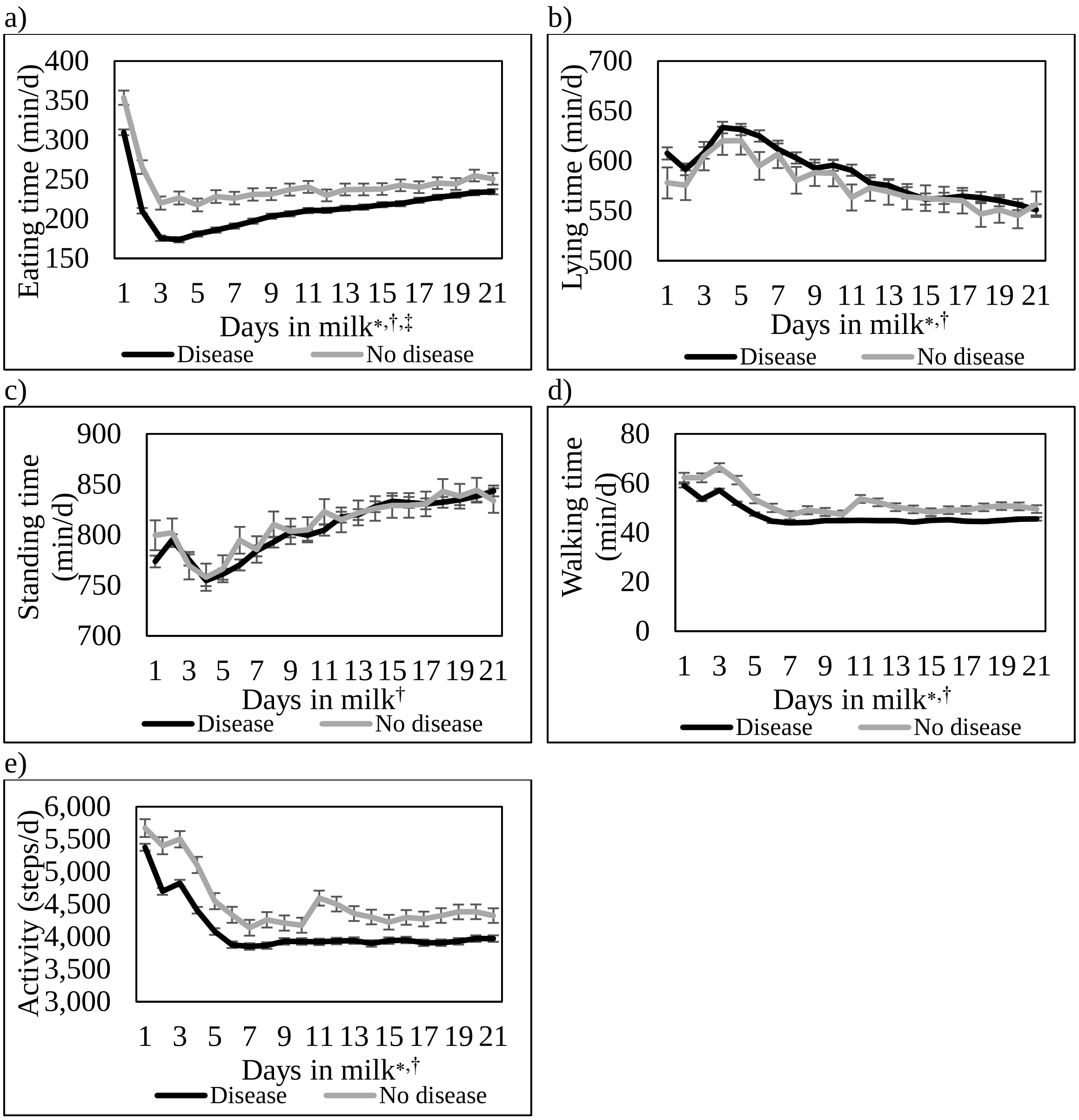

Figure 3.3. (cont.)

[1]Cows without any recorded disease events by the lead author or the farm owners and staff within the first 21 DIM per lactation were considered healthy (grey line).
[2]Cows with any recorded disease events (hyperketonemia, hypocalcemia, metritis, lameness, mastitis, retained placenta, pneumonia, displaced abomasum, or other disease event; Table 3.2) by the lead author or the farm owners and staff within the first 21 DIM per lactation were considered not healthy (black line).
[a)]Health status (no recorded disease events vs. recorded disease events), DIM, and the interaction of health status and DIM impacted eating behavior throughout the first 21 DIM ($P < 0.01$, respectively)
[b)]Health status and DIM impacted lying behavior throughout the first 21 DIM ($P < 0.01$, respectively).
[c)]Days in milk impacted standing behavior throughout the first 21 DIM ($P < 0.01$).
[d)]Health status and DIM impacted walking behavior throughout the first 21 DIM ($P < 0.01$, respectively).
[e)]Health status and DIM impacted activity behavior throughout the first 21 DIM ($P < 0.01$, respectively).

Figure 3.4. LSMean ± SE eating time (a; min/d), lying time (b; min/d), standing time (c; min/d), walking time (d; min/d), and activity (e; steps/d) characterized by a precision dairy monitoring technology for cows without (n = 785; grey lines) or with (n = 383; black lines) metritis events[1,2] within the first 21 DIM on 1,168 cows observed across 4 farms from October 5, 2015 to October 31, 2016 calculated with the MIXED procedure of SAS 9.4 (Cary, NC). Statistically different LSMeans are represented as: ∗ health status (metritis vs. none); † DIM; ‡ health status x DIM.

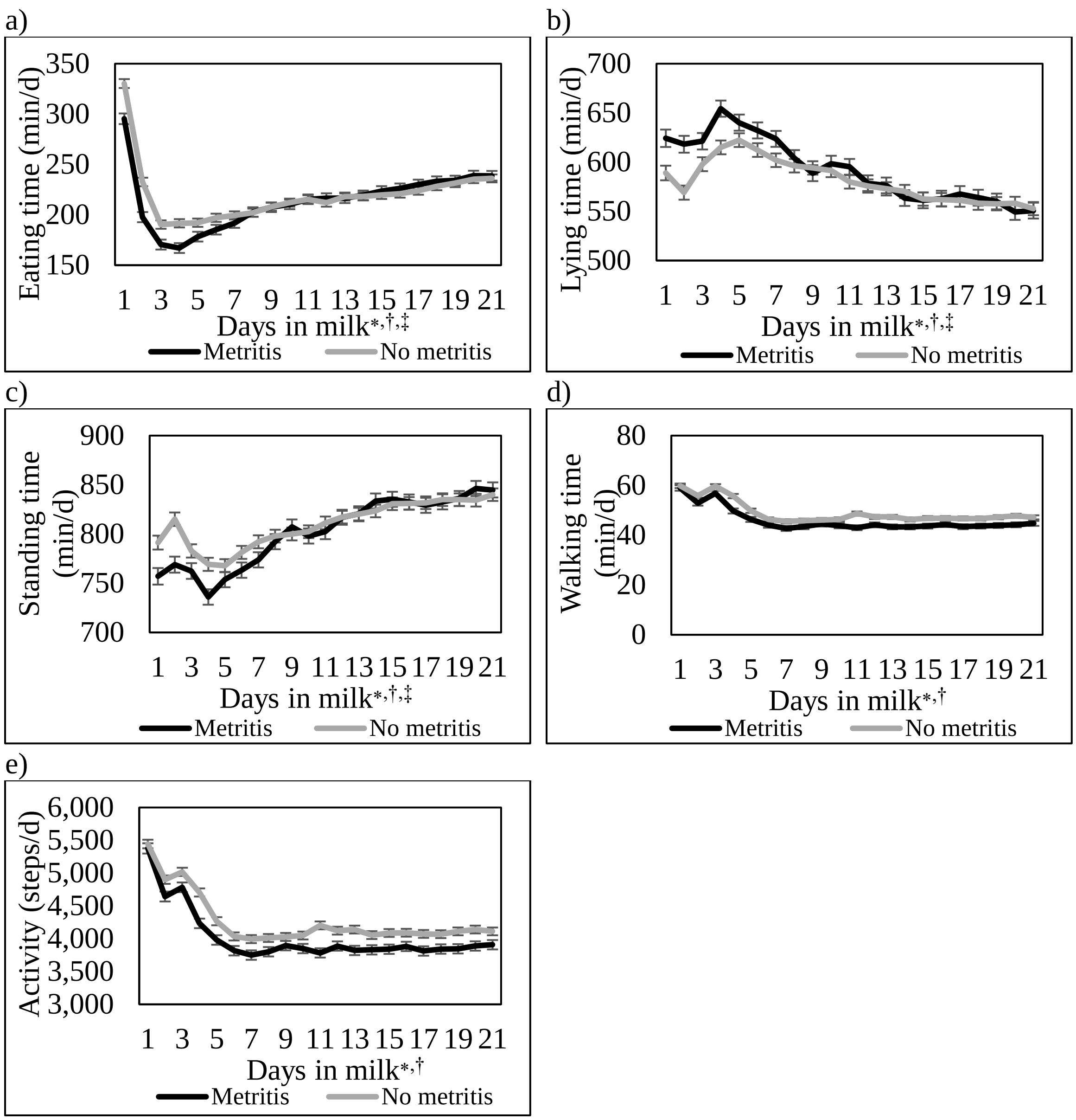

Figure 3.4. (cont.)

[1]Cows without any recorded metritis events by the lead author or the farm owners and staff within the first 21 DIM per lactation are depicted by the grey lines.
[2]Cows with any recorded metritis events (vaginal discharge score ≥ 2 on 1 to 3 scale described by Sterrett et al., 2014) by the lead author or the farm owners and staff within the first 21 DMI per lactation were considered to have metritis (black line).
[a)]Health status (no metritis events vs. recorded metritis events), DIM, and the interaction of health status and DIM impacted eating behavior throughout the first 21 DIM ($P < 0.01$, respectively)
[b)]Health status, DIM, and the interaction of health status and DIM impacted lying behavior throughout the first 21 DIM ($P < 0.01$, respectively).
[c)]Health status, DIM, and the interaction of health status and DIM impacted standing behavior throughout the first 21 DIM ($P < 0.01$, respectively).
[d)]Health status and DIM impacted walking behavior throughout the first 21 DIM ($P < 0.01$, respectively).
[e)]Health status and DIM impacted activity behavior throughout the first 21 DIM ($P < 0.01$, respectively).

Figure 3.5. LSMean ± SE eating time (a; min/d), lying time (b; min/d), standing time (c; min/d), walking time (d; min/d), and activity (e; steps/d) characterized by a precision dairy monitoring technology for cows without (n = 937; grey lines) or with (n = 231; black lines) hyperketonemia events[1,2] within the first 21 DIM on 1,168 cows observed across 4 farms from October 5, 2015 to October 31, 2016 calculated with the MIXED procedure of SAS 9.4 (Cary, NC). Statistically different LSMeans are represented as: ⁎ health status (hyperketonemia vs. none); † DIM; ‡ health status x DIM.

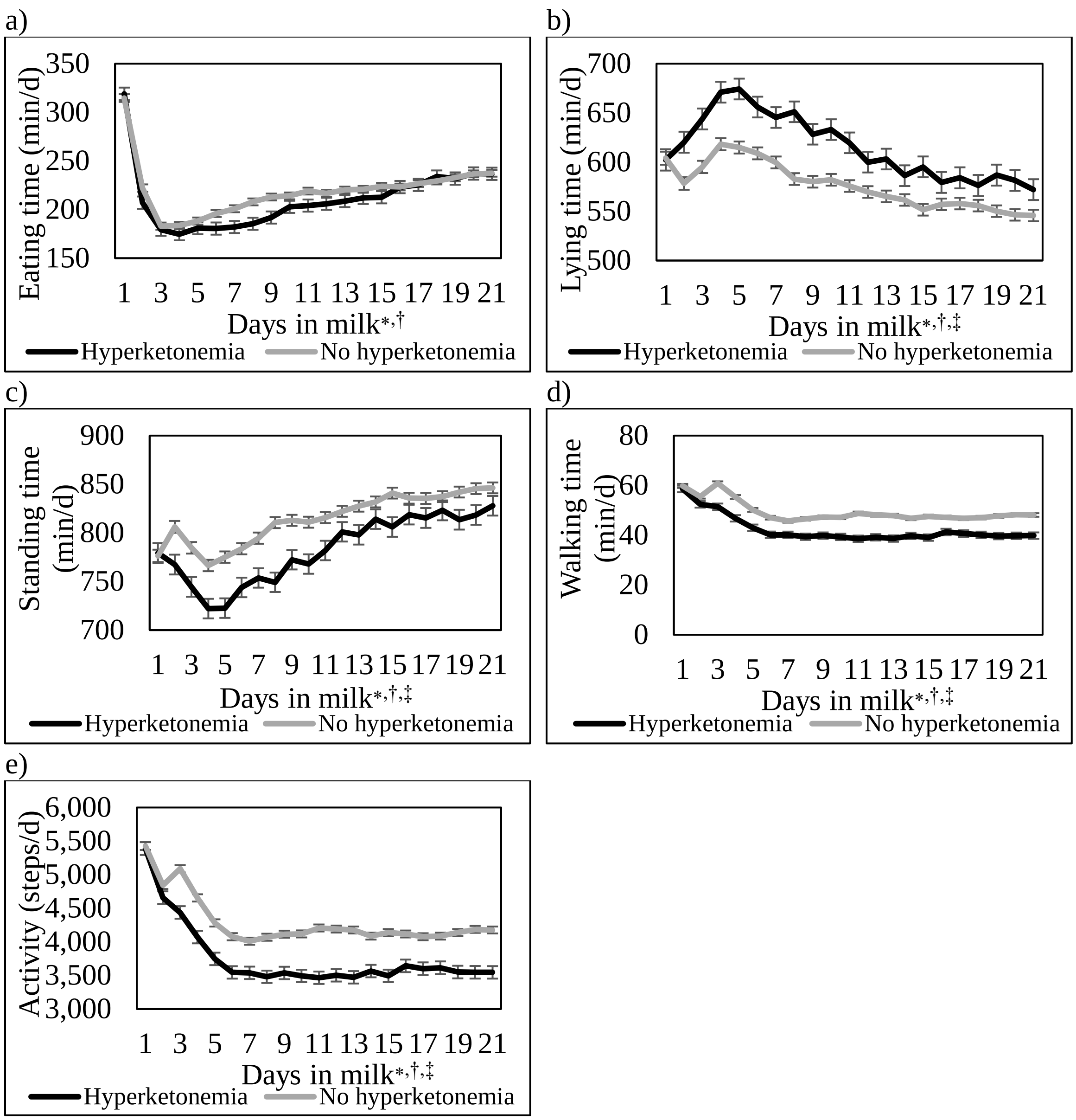

Figure 3.5. (cont.)

[1]Cows without any recorded subclinical or clinical hyperketonemia events by the lead author or the farm owners and staff within the first 21 DIM per lactation are depicted by the grey lines.
[2]Cows with any recorded subclinical or clinical hyperketonemia events (cows with β-hydroxybutyrate levels ≥ 1.2 mmol/mL were considered to have subclinical hyperketonemia; Nielen et al., 1994) by the lead author or the farm owners and staff within the first 21 DIM per lactation were considered to have hyperketonemia (black line).
[a)]Health status (no hyperketonemia events vs. recorded hyperketonemia events) and DIM impacted eating behavior throughout the first 21 DIM ($P < 0.01$, respectively)
[b)]Health status ($P < 0.01$), DIM ($P < 0.01$), and the interaction of health status and DIM ($P = 0.04$) impacted lying behavior throughout the first 21 DIM.
[c)]Health status ($P < 0.01$), DIM ($P < 0.01$), and the interaction of health status and DIM ($P < 0.05$) impacted standing behavior throughout the first 21 DIM.
[d)]Health status, DIM, and the interaction of health status and DIM impacted walking behavior throughout the first 21 DIM ($P < 0.01$, respectively).
[e)]Health status, DIM, and the interaction of health status and DIM impacted activity behavior throughout the first 21 DIM ($P < 0.01$, respectively).

Figure 3.6. LSMean ± SE eating time (a; min/d), lying time (b; min/d), standing time (c; min/d), walking time (d; min/d), and activity (e; steps/d) characterized by a precision dairy monitoring technology for cows without (n = 614; grey lines) or with (n = 554; black lines) hypocalcemia events[1,2] within the first 21 DIM on 1,168 cows observed across 4 farms from October 5, 2015 to October 31, 2016 calculated with the MIXED procedure of SAS 9.4 (Cary, NC). Statistically different LSMeans are represented as: * health status (hypocalcemia vs. none); † DIM; ‡ health status x DIM.

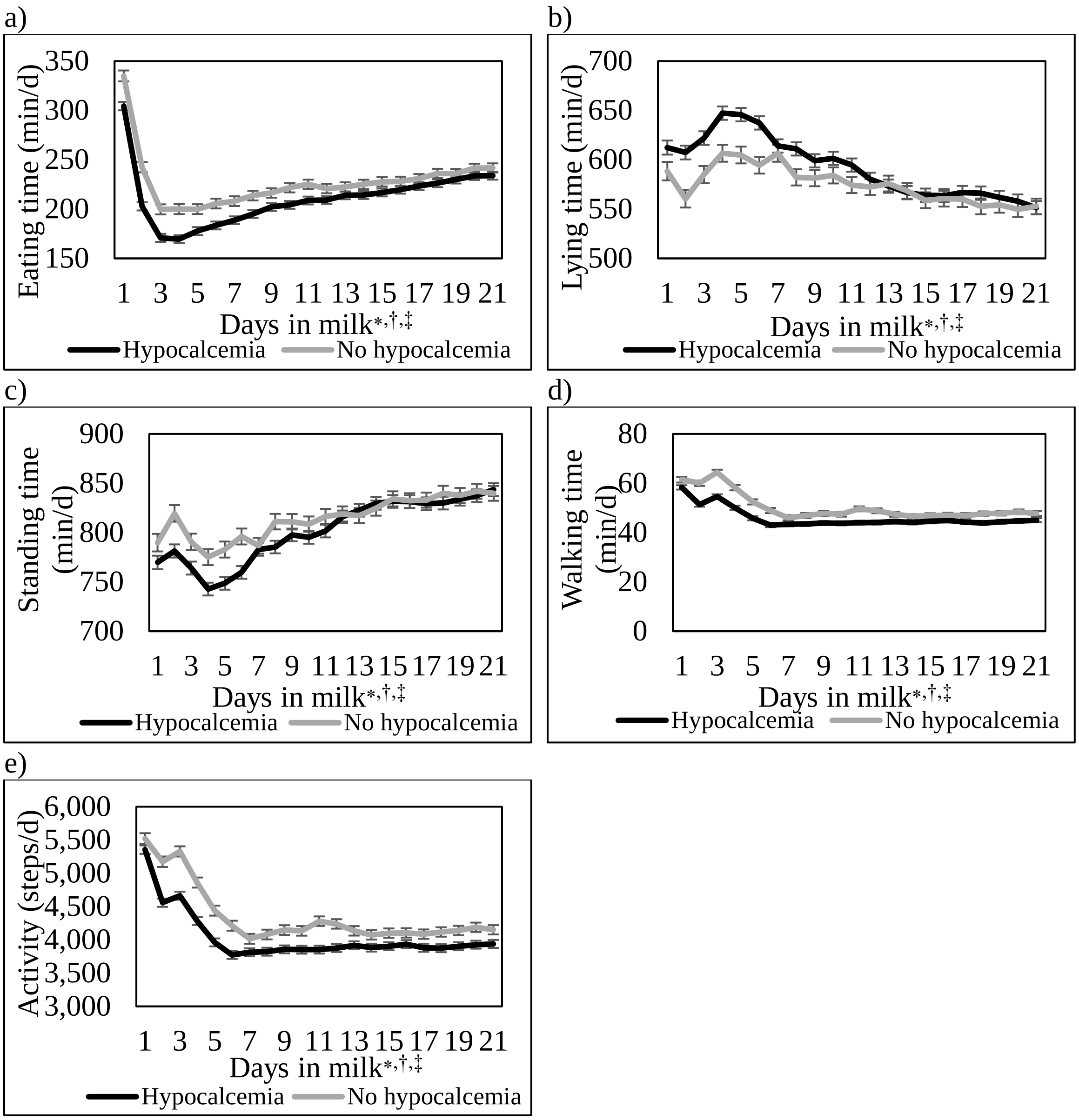

Figure 3.6. (cont.)

[1]Cows without any recorded subclinical or clinical hypocalcemia events by the lead author or the farm owners and staff within the first 21 DIM per lactation are depicted by the grey lines.
[2]Cows with any recorded subclinical or clinical hyperketonemia events (cows with blood serum calcium levels ≤ 8.6 mg/dL were considered to have subclinical hypocalcemia; Oetzel 2014, personal communication) by the lead author or the farm owners and staff within the first 21 DIM per lactation were considered to have metritis (black line).
[a)]Health status (no hypocalcemia events vs. recorded hypocalcemia events), DIM, and the interaction of health status and DIM impacted eating behavior throughout the first 21 DIM ($P < 0.01$, respectively)
[b)]Health status, DIM, and the interaction of health status and DIM impacted lying behavior throughout the first 21 DIM ($P < 0.01$, respectively).
[c)]Health status, DIM, and the interaction of health status and DIM impacted standing behavior throughout the first 21 DIM ($P < 0.01$, respectively).
[d)]Health status, DIM, and the interaction of health status and DIM impacted walking behavior throughout the first 21 DIM ($P < 0.01$, respectively).
[e)]Health status, DIM, and the interaction of health status and DIM impacted activity behavior throughout the first 21 DIM ($P < 0.01$, respectively).

CHAPTER FOUR

A decision support tool for investment analysis of a wearable precision dairy management technology for detection of estrus and disease

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INTRODUCTION

Precision dairy technologies allow producers to monitor dairy cattle production, health, and welfare (Bewley et al., 2017). Precision dairy technologies may increase efficiency and decrease costs (Boehlje et al., 1999, Bewley et al., 2017). Producing high-quality milk more efficiently can improve a dairy farm's financial performance (Fetrow and Eicker, 2017). Milk production can be decreased by disease (Bar et al., 2008, McArt et al., 2015, Liang et al., 2017), reproductive performance (Groenendaal et al., 2004, De Vries, 2006), housing (Fregonesi and Leaver, 2001, 2002, Simensen et al., 2007), nutrition (Eastridge, 2006, Bach and Cabrera, 2017), and management (Goodger et al., 1988, Dufour et al., 2011). Lost or discarded milk production is a central component in many economic models evaluating disease, and makes up most of the disease costs for mastitis, metabolic disorders, and reproductive disorders (McArt et al., 2015, Raboisson et al., 2015, Liang et al., 2017). Dairy producers may make decisions to improve milk production by reducing disease incidence, improving reproductive performance, and reducing involuntary culls and death loss.

Wearable precision dairy monitoring technologies (neck, leg, or ear devices) can improve estrus and health disorder detection. Mastitis, metabolic disorders, and metritis can be detected 0.5 to 3.0 d before visual identification by farm owners or staff (Titler et al., 2013, Stangaferro et al., 2016a, b, c). Early disease detection could prevent disease progression, improve response to treatment, reduce treatment cost, reduce discarded milk because of treatment, and improve overall lactation performance (Milner et al., 1997, Stangaferro et al., 2016a).

Adoption of precision dairy monitoring (**PDM**) technology has been limited, despite PDM variety and availability (Eleveld et al., 1992, Huirne et al., 1997, Gelb et al., 2001). Slow adoption occurs throughout agriculture, not just in the dairy sector (Rosskopf and Wagner, 2003). Producers have stated unknown or undesirable cost-to-benefit ratio and the initial investment cost deter investment in technology (Daberkow and McBride, 1998, Russell and Bewley, 2013, Borchers and Bewley, 2015). To date, little research has been conducted on the economic impact of investing in PDM for dairy producers (van der Voort et al., 2017). Bewley et al. (2010a; b) described a detailed cow simulation model to determine investment in any PDM or an automated body condition scoring system. Precision dairy monitoring was economically beneficial, but the benefits were linked to many variables including culling changes, reproductive performance, and production. Improving body condition score through PDM improved reproduction and decreased disease occurrence, resulting in an overall reduction in discarded or unrealized milk production (Bewley et al., 2010a). More analyses have been conducted using PDM for estrus detection (Fricke et al., 2014b, Rutten et al., 2014, Dolecheck et al., 2016a).

Dolecheck et al. (2016a) noted the two most important factors for economic profitability were the installation price and the cost of the individual device.

The objective of this research was to create a partial budget for investing in PDM based on potential disease detection and estrus detection benefits. Two simulations were created, a baseline herd before PDM investment and a concurrent simulation after PDM investment. Changes in milk yield, estrus detection rate, and early lactation culling were considered individually and together. The stochastic simulation was used to account for price volatility in herd and technology prices by randomly drawing numbers from reasonable, representative distributions (Fetrow and Eicker, 2017). Both the economic profitability and payback period of the initial investment and continued upkeep of the system were calculated.

MATERIALS AND METHODS

A Microsoft Excel Spreadsheet (Microsoft Excel 2013, Microsoft, Seattle, WA) partial budget model was developed to evaluate the profitability and financial feasibility of PDM investment. The @Risk 7.5 (Palisade Corporation, Ithaca, New York) add-in for Excel allowed key-model inputs to be modeled stochastically. Stochastic simulations allow specific inputs and assumptions to be selected randomly from a distribution of likely values (Fetrow and Eicker, 2017). Stochastic simulations allowed a model to account for variability in prices, costs, and impacts of an investment decision. The model included a cost prediction for installation of a PDM system, PDM technology cost, and continued upkeep of a PDM. All milk yield, DMI, and body weight calculations were conducted for an average cow in the herd on a daily basis within a lactation. Economic analyses were run on yearly changes in herd milk yield, DMI, reproductive performance, culling, and death, expanded from the average cow.

Stochastic model structure

The partial budget model was developed using equations from published literature and a model described by Bewley et al. (2010a; b), Dolecheck et al. (2016a), and Liang et al. (2017). A cow-level stochastic Monte Carlo simulation model was created as first described by Bewley et al. (2010b) and modified by Liang et al. (2017). Briefly, the model simulates the life of an average dairy cow through daily time steps. Each cow life (one simulation) was calculated 10,000 times (iterations). Daily information from an average cow was expanded to model a whole herd (1,000 lactating cows) based on Table 4.1. Revenues associated with milk yield and calf production along with costs associated with feeding, breeding, veterinary costs, culling, and mortality were calculated on a daily basis. Table 4.1 presents default values, stochastic ranges, and assumptions used in the model.

The stochastic nature of the model allowed vital inputs to change with each of the 10,000 model iterations (Fetrow and Eicker, 2017). The price of essential inputs was modeled stochastically from historical US prices from 1971 to 2017 for milk price, replacement heifers, alfalfa, corn, and soybeans were collected from "Understanding Dairy Markets" website (Gould, 2017). Dry matter intake was calculated daily using the National Resource Council (NRC, 2001) equations as explained in Bewley et al. (2010b). Slaughter prices from 1970 to 2008 were collected from the USDA-National Agricultural Statistics Service historical prices for beef cow and cull dairy cows sold for slaughter (USDA-NASS, 2009). Future prices, except replacement heifer price, were collected from the *2017 US Baseline Briefing Book: Projections for Agricultural and Biofuel Markets* (FAPRI, 2017). Replacement price, heifer price, and bull calf price were calculated according to Bewley et al. (2010b) as updated by Liang et al. (2017). Milk yield, fat %, protein %, age at first calving, estrus detection rate (**EDR**), conception rate (**CR**), voluntary waiting period (**VWP**), culling rate, and mortality rate were collected from DairyMetrics (2017). The DairyMetrics report was limited to Holstein only herds with ≥ 100 lactating cows. The report was also restricted to herds with a 21-d EDR between 10 and 70 to attempt removal of herds with a distorted EDR (Dolecheck et al., 2016a). The collected information was used to establish a representative herd based on the average cow. The representative herd's performance was used to calculate yearly changes in revenues and costs associated with PDM investment.

Within the model, two average cow simulations were run simultaneously, as described in Bewley et al. (2010b). Each simulation was controlled by the inputs listed in Table 4.1 and the stochastic prices calculated from historical and futures prices. One cow simulation was based on the average cow in a herd before investment in a PDM (baseline) with a parallel simulation based on the stochastic change in daily milk yield, estrus detection rate, culling rate, and death rate following investment in PDM (PDM change). Four sensitivity tests were run on 1) milk yield adjustments only, 2) estrus detection rate adjustments only, 3) culling and death rate adjustments only, and 4) all adjustments run concurrently.

Model adjustments: Milk yield. Decreased milk yield has been a central factor in disease modeling, and a significant contributor to the cost of any disease (Hogeveen et al., 2011, McArt et al., 2014, Raboisson et al., 2015). Identifying diseases earlier can lead to decreased milk loss, thereby reducing the overall cost of a disease event (Milner et al., 1997). Early detection and treatment of mastitis led to decreased milk yield loss and lactation yield similar to herd mates without mastitis (Milner et al., 1997). Although studies evaluating early intervention effects on discarded milk and unrealized milk production are scarce, early disease detection could improve milk production over herd mates that do not receive early intervention. Stangaferro et al. (2016c, 2016b, 2016a) reported disease detection through behavioral changes 0.5 to 3.0 d before clinical diagnosis for metabolic disorders, digestive diseases, metritis, and mastitis suggesting early intervention could be possible. Many studies have discussed the interwoven nature of diseases, further increasing the difficulty in modeling such a complex system (Vergara et al., 2014, Raboisson et al., 2015, Mostert et al., 2017). To account for an overall benefit instead of a disease-specific change, an overall improvement in rolling herd average actual milk production (**RHAM**) was modeled following PDM investment. The change in herd daily milk yield was based on adding a random number chosen from a PERT distribution (minimum, mean, maximum) times 365.25 to the baseline herd RHAM. The distribution was a minimum = 0.0, mean = 0.4, maximum = 0.9 kg/d for additional milk yield. Dairy producers were assumed to use the technology for early detection of mastitis, metabolic, digestive, and reproductive disorders. Identifying a portion of these diseases earlier and treating them would result in decreased milk loss from 1) discarded milk and 2) reduced production throughout that lactation. Complete removal of the milk production affects associated with a particular disease was not assumed. Because a cow would have already contracted the disease, complete amelioration of the disease effects was unrealistic.

The resulting RHAM was used to calculate a daily milk yield in the PDM investment simulation using the lactation curve developed by Oltenacu et al. (1981) modified by Marsh et al. (1988) and Skidmore (1990) as described in Bewley et al. (2010b). Milk production per d was calculated as Eq. 4.1 (Skidmore, 1990):

$$MY_D = A\,(DIM)^b\, e^{cDIM}\, e^{gDCC} \qquad \text{Equation 4.1}$$

where MY_D was the daily milk production calculation, A was the adjustment factor calculated from RHAM, DIM was the d in milk of the production calculation, DCC was the number of d in gestation, and b, c, and g were constants from Skidmore (1990). The adjustment factor A was different for lactation 1 and ≥ 2; constants b, c, and g were specific for lactation 1, 2, and ≥ 3 (Skidmore, 1990).

The resulting simulation provided a mean production per d, an adjusted DMI based on milk production, and the associated cost of lactating cow feed and milk revenue over an entire lactation.

Model adjustments: Estrus detection rate. The ability of PDM to detect estrus has been well documented (Fricke et al., 2014b, Dolecheck et al., 2016b, Giordano and Fricke, 2017) and is one of the oldest uses for PDM (Farris, 1954). Improved EDR improves pregnancy rate, decreases calving interval, improves overall herd performance, and increases a herd's profitability per calendar yr. The change in EDR was based on the stochastic baseline EDR. The baseline EDR was chosen from a normal distribution (mean ± SD: 49.2 ± 14.2%; DairyMetrics, 2017) limited to 10% minimum and 80% maximum EDR. The change in EDR following PDM investment was created from a PERT distribution (minimum = 50, mean = 60, maximum = 80%). From these distributions, two EDR were calculated for each iteration of the model, an EDR before PDM and an

EDR after PDM. Because it is unlikely that EDR would decrease following PDM investment, the EDR after PDM was set equal to the baseline EDR if the random EDR after PDM was lower than the baseline EDR. The EDR was used to calculate calving interval as Eq. 4.2 (Groenendaal et al., 2004):

$$CI = (VWP + 21 / (EDR \times CR) + GL) \qquad \text{Equation 4.2}$$

where CI was the calving interval, VWP was the voluntary waiting period, EDR was the estrus detection rate, CR was the conception rate calculated from a normal distribution (mean ± SD: 25.2 ± 9.9% limited to a 10% minimum and 80% maximum; DairyMetrics, 2017), and GL was the gestation length (Table 4.1).

Calving interval was used to calculate DIM, DIM at conception, start of lactation for each parity (2 to ≥ 6), services per pregnancy, and the semen cost per pregnancy for the baseline and PDM simulations. The resulting outcomes provided DIM/yr, adjusted milk yield/yr, adjusted DMI/yr, adjusted milk revenue/yr, adjusted lactating and dry feed costs/yr, and adjusted breeding costs/yr.

Another key to reproductive performance is the cost of days open (**CDO**). This is the associated cost of each day past the voluntary waiting period (59 DIM; DairyMetrics, 2017) the producer incurs based on pregnancy rate. Pregnancy rate is a function of EDR and CR calculated as EDR multiplied by CR. If CR is held constant, an improvement in EDR will improve pregnancy rate, which will reduce the number of days open. The cost of days open was calculated based on the equations created by Dolecheck et al. (2016a). The full equations are available online at https://afs.ca.uky.edu/dairy/decision-tools/CostDaysOpen. Incorporating these equations allowed the model to simulate the change in CDO between the baseline herd and the PDM herd with the change in EDR.

Model adjustments: Culling and mortality rate. Retention pay-off (**RPO**) estimates the value of a cow currently in the herd versus her hypothetical replacement. Retention pay-off is highest after calving and increases again during late gestation (dry period). Retention pay-off changes daily throughout lactation, decreasing until the optimum moment of replacement – when the cow's value drops below the value of her replacement. This point occurs for each lactation, with a cow's value peaking again following calving (Groenendaal et al., 2004). Consequently, early lactation involuntary culls from transition issues are costly to dairy producers. The highest percentage of culls and mortalities occur during the first 60 DIM (7.0 to 8.9% of all culls; 16.0 to 23.8% of all mortalities; Hadley, 2003; Table 4.1) because of transition diseases and calving complications (LeBlanc, 2010, Vergara et al., 2014, Raboisson et al., 2015). Decreasing early lactation culls and mortalities through improved management can result in decreased losses to the dairy producer.

Retention pay-off was calculated according to Bewley et al. (2010b) as described by Groenendaal et al. (2004). Briefly, RPO is calculated from a cow's marginal net revenue (**MNR**) and expected maximum annuity net revenue (**ANR**). Marginal net revenue was calculated as Eq. 4.3:

$$MNR_i = (R_i - C_i) + (S_i - S_{i-1}) - (D_i \text{ x } D_F) \qquad \text{Equation 4.3}$$

where MNR_i was the marginal net revenue at mo *i*, R_i was the revenues generated from milk production and calving in mo *i*, C_i was the costs generated from feed, veterinary, breeding, and mortality costs in mo *i*, S_i was the slaughter value in mo *i* minus the slaughter value in the previous mo (S_{i-1}), D_i was the probability of disposal at each mo in lactation, and D_F was the financial loss at disposal in mo *i*. Annuity net revenue was calculated as Eq. 4.4:

$$ANR_j = [\ \textstyle\sum_{i = 1\ldots.j} p_i \text{ x } 1 / 1 (1 + r)^I \text{ x } MNR_i\ ] \qquad \text{Equation 4.4}$$

$$\text{x } r / [1 – (1 + r)^{-\sum_{i = 1\ldots j} p_i \text{ x } mo_i}$$

where ANR_j was the annuity of the net revenue of a cow's immediate replacement per mo, i was the decision moment of replacement (mo), j was the period (mo) when the cow could be replaced, r was the discount rate per mo, p was the probability of a cow's survival to the end of mo *i*, and MNR was the associated marginal net revenue in mo *i*. Retention pay-off was calculated as Eq. 4.5:

$$RPO_j = \textstyle\sum_{j=j+1..d} \times p_j \times 1 / (1+r)^j \times (MNR_j - ANR_{max} \times mo_j) \qquad \text{Equation 4.5}$$

where RPO_i was the retention pay-off at the decision moment of culling *j*, d was the optimal moment of replacement when $MNR_j < ANR_{max}$, r was the discount rate per mo, p was the probability of a cow's survival to the end of the following mo, j was the period (mo) when the cow could be replaced, MNR_j was the marginal net revenue in mo *i*, and ANR_{max} was the maximum annuity net revenue per mo.

According to Groenendaal et al. (2004), RPO reaches the lowest value at mo 7, 8, or 9 in lactation. To calculate the value of an early lactation cow, daily RPO was averaged for the first 30 DIM and 31 to 60 DIM. To calculate the value of an early lactation cull (within the first or second mo of lactation), the average daily RPO from mo 7 to 9 was subtracted from the early lactation cow value. This value was used to calculate the opportunity cost of culling, which will be explained in more detail below.

The changes in early lactation culling and early lactation mortality were based on adjusting the percent of cows culled or died during the first 60 DIM. The percent of cows culled or died in the first 30 and 60 DIM were collected from Hadley (2003) as described in Bewley et al. (2010b; Table 4.1). The change in early lactation culling and mortality rate was based on subtracting a random percentage chosen from a PERT distribution (minimum = 0%, most likely value = 25%, maximum = 50%) from the baseline culling and mortality percentage from 0 to 30 DIM and 31 to 60 DIM. The changes in culling and mortality rate were used in the herd module to calculate the change in RPO and death cost. Early lactation culls were calculated by multiplying the baseline and PDM culling rate in mo 1 and 2 of lactation by the number of cows in parity 1 to ≥ 6, respectively. The number of cows culled was then multiplied by the associated stochastic RPO for that mo and parity. Early lactation deaths were calculated by multiplying the baseline and PDM death rate in mo 1 and 2 of lactation by the number of cows in parity 1 to 6+, respectively. The number of cows died was then multiplied by the stochastic replacement heifer price. When a cow died, they were automatically removed from the herd, and no associated revenue was collected from a dead cow. Because of this, the cost was higher, the full cost of a new heifer replacement.

To calculate the change in costs and revenues, the baseline herd values were subtracted from the PDM herd values. The values used for revenues were the total value of milk produced (all lactations for a yr), the total value of calves born and survived during the yr (total calves minus calves born dead and calf mortality), the change in RPO, and the change in death loss. The values used for costs were the total lactating feed costs, total dry cow feed costs, and total breeding costs. With each sensitivity analysis, the revenues were altered, but all the costs were included.

Technology assumptions. Installation cost and device price were modeled stochastically to account for differences in price per device and a one-time installation cost. The one-time installation cost included installation of any hardware, antennas to transmit signals, software to interpret signals, and labor to install the system. A PERT distribution was used for installation cost (minimum = \$5,000, mean = \$10,000, maximum = \$20,000) and individual device cost (minimum = \$50, mean = \$100, maximum = \$200) adjusted from Dolecheck et al. (2016a). Yearly upkeep costs were set at \$3.90/PDM based on the cost a dairy producer pays for replacement attachment devices (personal communication with the dairy producer) times the number of cows culled or died during a yr. Because PDM attachment devices (straps, bands, collars) may not be transferable from cow to cow, new attachment devices may be required to transfer PDM from one cow to another. Investment length was set at 5 yr as suggested by Giordano (2015), 2 yr shorter than the 7 yr lifetime of the PDM (Dolecheck et al., 2016a) with an 8% discount rate (Hyde and Engel, 2002; Table 4.2).

Device replacement rate was modeled stochastically with a PERT distribution (minimum = 0, mean = 5, maximum = 10%). Device replacement referred to the number of units that were defective or lost during a yr. Additional labor from the PDM was set at 3.5 h/wk as suggested by Dolecheck et al. (2016a) with a labor cost of \$15.77/h adjusted for inflation from Galvão et al. (2013; Table 4.2).

Net present value and payback period

Concurrently, baseline and PDM simulations were run for 10,000 iterations to calculate an associated net present value (**NPV**) from 1 to 10 yr following initial investment. Net present value of the PDM system was calculated as Eq. 4.6 (Boehlje and Ehmke, 2005):

$$NPV = \sum_{n=0}^{n} \left(\frac{\Delta F}{(1+DR)^n}\right) - TIC \qquad \text{Equation 4.6}$$

where NPV was the net present value of the PDM system over the investment period, n was the year of investment, ΔF was the change in revenues and costs for each year n, DR was the discount rate, and TIC was the total investment cost of the PDM (initial investment price plus the total device costs (PDM price x herd size)). Changes in revenues included Δ milk revenue (PDM simulation – baseline; $/yr), Δ calf revenue ($/yr), Δ death loss ($/yr), and Δ culling loss ($/yr). Changes in costs included replacement device cost ($ per device x replacement rate), maintenance cost ($3.90 per attachment device x cows died and culled per yr), Δ DMI cost ($/yr), Δ breeding costs ($/yr), and labor cost (additional 3.5 h/wk at $15.77/h with PDM investment). Changes in costs and revenues were held constant for yr 1 to yr 10 of investment. Changes were held constant because the herd was assumed to progress identically through time, with the only change being the intervention of the technology.

Cash flow (ΔF) was used to calculate payback period in yr for the PDM system as Eq. 4.7:

$$PP = \frac{L_n}{(CC_n/CA_{n+1})} \qquad \text{Equation 4.7}$$

where PP was payback period, L_n was the last year (n) where cumulative ΔF was negative. CC_n was the absolute value of cumulative ΔF in year n, and CA_{n+1} was the actual ΔF in the year after n. Changes in inputs, changes in costs and revenue, net present value, and PP were collected for each iteration of the simulation.

Model limitations

No economic model can perfectly describe a situation or account for all potential variables (Bethard, 1997). However, even oversimplification in a model will inform the user beyond the cognitive abilities of producers and managers (Delorenzo and Thomas, 1996). A limitation of the model is relying on historical data to predict future trends in the dairy industry and commodity pricing. Although relying on historical data has been used in many models, the future will continue to be volatile. The stochastic nature of analyses should account for some future price volatility, but it will still be imperfect. There may also be some correlation among commodity pricing, including milk price, not currently accounted for in the model. Correlation in pricing may be addressed in future modeling efforts.

An additional area of oversimplification was the use of PERT distributions for stochastic inputs. The PERT distribution allowed the model to be defined based on ranges from the literature. This allowed the distribution to be tailored to the needs of the model, particularly when subjective decisions were made. This distribution does limit the ability to model extreme highs or lows outside of the determined range. The model also assumes that the distributions chosen are correct, and accurately represent the true state of the industry.

Within each sensitivity analysis, an additional limitation was investment in technology could only improve or not change current production, reproduction, or culling rate. Farm management of a technology will influence its usefulness and overall impact on the farm. Poor management of a technology and poor incorporation into the farm may negatively influence production, reproduction, or culling rate. Without more on-farm data, negative consequences are more difficult to model, and were not included in the current analyses.

RESULTS AND DISCUSSION

The goal of economic analysis is not to decide for the end-user, but to inform the end-user of their options (Fetrow and Eicker, 2017). Conducting sensitivity analyses provided insight into the individual benefits possible with PDM and the potential additive benefit if all potential benefits were considered. The assumptions for the 1,000-cow herd were the same for each sensitivity analysis. Distributions are listed for stochastic variables of importance for NPV and payback period in Table 4.3.

Sensitivity analysis: Milk yield

Milk yield improvement occurred at 0.45 ± 0.17 kg/d (0.02 to 0.89 kg/d). Overall, herd RHAM improvement was 167.59 ± 144.50 kg/yr with an associated herd DMI increase of 56.27 ± 21.93 kg/yr following PDM investment. An improvement in MY resulted in a NPV ≥ 0 for 75.6% of 10,000 iterations (Figure 4.1). The positive NPV ($14.87 ± 20.27 per cow per yr) indicated investment in a PDM for health monitoring was an economically sound investment. Along with a positive NPV, the payback period was ≤ 5 yr for 75.6% of the 10,000 iterations. The payback period was 4.03 ± 2.92 yr overall, indicating that the technology would pay for itself well within the lifetime of the technology, and within the investment period suggested by Giordano (2015).

The regression correlations identified by @Risk 7.5 are depicted in Figure 4.2a,b. For every SD increase in milk yield change, CR, EDR, lactating feed price, replacement heifer price, baseline RHAM, individual device price, and installation price NPV was adjusted by a portion of a SD. As shown in Figure 4.2a, the largest NPV influencers were change in milk yield (0.84 SD), individual device price (-0.33 SD), baseline EDR (0.13 SD), and CR (0.13 SD). As shown in Figure 4.2b, the largest payback period influencers were change in milk yield (-0.76 SD), individual device price (0.34 SD), baseline EDR (- 0.10 SD), and CR (- 0.10 SD). When no additional changes occurred in EDR, a herd with improved reproductive performance experienced greater benefit from PDM investment. A herd with improved reproductive performance would experience shorter calving intervals and fewer services per pregnancy. This would translate to greater potential milk yield per yr that was amplified with improved milk yield attributed to reduced disease events.

Similar to Dolecheck et al. (2016a), increased device price decreased NPV and increased payback period. Installation price was a small influencer of NPV and payback period, whereas Dolecheck et al. (2016a) found installation price to be one of the most critical factors for automated estrus detection technology. In a preliminary analysis, André et al. (2007) suggested increased milk production and precision concentrate feeding improved farm profitability. André et al. (2007) modeled a 0.9 and 0.7 kg per cow per d increase in roughage and concentrate intake, respectively, and an associated 2.1 kg per cow per d milk yield increase. Overall, the producer would net $0.64 per cow per d. Similarly, van Asseldonk et al. (1999b) stated improved milk production from 7,500 to 9,000 kg per cow per yr of fat and protein corrected milk production, attributed to a precision feeding system, resulted in increased milk revenue from $3,168 up to $3,849 per cow (converted from Dfl. to USD). However, van Asseldonk et al. (1999b) and André et al. (2007) did not account for technology investment in either study and no economic analyses were conducted. In a companion study, van Asseldonk et al. (1999a) reported a positive NPV with a 1.27 benefit to cost ratio when automated concentrate feeders and activity monitoring were invested in concurrently. As with a positive NPV, a benefit to cost ratio > 1 indicates a sound economic investment, as seen in our results.

Sensitivity analysis: Estrus detection rate

Estrus detection rate after PDM investment was 70.3 ± 3.8% (60.1 to 80.0% EDR). In the baseline herd, EDR was 48.8 ± 13.4%, dramatically lower than PDM EDR. An improvement in EDR resulted in a NPV ≥ 0 for 85.4% of 10,000 iterations (Figure 4.3). The positive NPV ($179.29 ± 220.40 per cow per yr) indicated investment in a PDM for estrus detection was an economically sound investment. Along with a positive NPV, the payback period was ≤ 5 yr for 85.4% of the 10,000 iterations. The payback period was 2.26 ± 3.46 yr overall, indicating that the technology would pay for itself well within the lifetime of the technology, and within the investment period suggested by Giordano (2015). Dolecheck et al. (2016a) noted in 7 out of 8 simulations with a positive NPV, automated estrus detection technology payback period occurred < 5 yr. Under assumptions like our study (no previous precision technology use), NPV was always positive and payback period occurred from 1.6 to 4.5 yr (Dolecheck et al., 2016a). Although Dolecheck et al. (2016a) observed a lower NPV ($15.32 ± 5.55 per cow per yr), she assumed a lower herd number (323 cows vs. 1,000). Dolecheck et al. (2016a) also calculated deterministic outputs and gathered results based on specific changes in input values. Including more herd information stochastically and linking changes in EDR to overall herd performance contributed to our higher NPV through increased milk yield

(715.15 ± 764.47 kg added per yr; $278,451.62 ± 302,827.82 total milk revenue per yr) and increased calf revenue (94 ± 76 calves/yr; $23,298.92 ± 20,346.37 total calf revenue per yr).

The regression correlations identified by @Risk 7.5 are depicted in Figure 4.4a,b. For every SD increase in baseline EDR, PDM EDR, CR, baseline RHAM, individual device price, lactating feed price, and replacement heifer price NPV was adjusted by a portion of a SD. As shown in Figure 4.4a, the largest NPV influencers were baseline EDR (-0.87 SD), PDM EDR (0.43 SD), CR (-0.25 SD), and baseline RHAM (0.20 SD). For example, for every SD increase in baseline EDR (13.4%) the NPV decreased by 0.87 of a SD (-$191.75 per cow per yr). Conversely, for every SD increase in PDM EDR (3.8%) the NPV increased by 0.43 of a SD ($94.77 per cow per yr). As shown in Figure 4.4b, the largest payback period influencers were PDM EDR (0.66 SD), baseline EDR (0.62 SD), CR (0.11 SD), and baseline RHAM (- 0.10 SD). Unlike improving milk yield, a herd with strong reproductive performance (high EDR and CR) did not reap as many benefits following PDM investment as a herd with weak reproductive performance. Dolecheck et al. (2016a) modeled similar results, with herds currently using timed artificial insemination and achieving good pregnancy rates not realizing a NPV > 0 in 4 out of 8 simulations ($7.81 ± 19.11 per cow per yr). However, as with increased milk yield, a high producing herd (increased RHAM) would gain more benefit from PDM EDR and have a shorter payback period. The association with RHAM was tied to calving interval. A lower calving interval increased the amount of milk produced during a yr, instead of having milk yield from 1 lactation spread over a year or more. After investing in a PDM, calving interval decreased from 540 ± 112 d to 465 ± 49 d. Since CDO was not correlated with NPV or payback period, the contribution of decreased CDO did not play as large a role as increased production over the yr.

Sensitivity analysis: Early lactation removal

After PDM investment, the cow removal rate from early lactation culling or death was decreased by 25.0 ± 9.4% (0.5 to 49.8%). For example, if a heifer entered her first lactation, she had a 10.3% chance of being culled and a 1.3% chance of dying in her first lactation. Within that first lactation, she had a 1.6% chance of being culled within the first two mo after calving (16.0% of culls for first lactation cows occurred in the first 2 mo of lactation; Hadley, 2003). She also had a 0.4% chance of dying within the first two mo after calving (32.0% of mortalities for first lactation cows occurred in the first 2 mo of lactation; Hadley, 2003). The adjusted culling and death rate would be 1.2% and 0.3% for the first 2 mo in lactation, respectively, with a 25% decrease in culling and death rate.

Unlike adjusting milk production and EDR, adjusting removal rate did not result in a NPV ≥ 0 (-$23.49 ± 7.38 per cow per yr; Figure 4.5). The PP was always > 10 yr, indicating that the technology would not pay for itself within the lifetime of the technology, or within the investment period suggested by Giordano (2015). The regression correlations identified by @Risk 7.5 are depicted in Figure 4.6. For every SD increase in individual device price, change in removal rate, replacement device %, replacement heifer price, baseline RHAM, installation price, calf price, slaughter value, and baseline EDR NPV was adjusted by a portion of a SD. As shown in Figure 4.6, the largest NPV influencers were device price (-0.90 SD), change in removal rate (0.32 SD), replacement device % (-0.22 SD), and replacement heifer value (0.10 SD). Dolecheck et al. (2016a) based the bulk of investment on CDO, which is calculated from the difference in RPO between two identical cows, one pregnant and one not pregnant (Groenendaal et al., 2004). Using CDO could explain why installation cost and individual device price were large influencers of PDM investment in Dolecheck et al. (2016a) and were not in our milk yield and EDR sensitivity analyses.

The greatest total revenue possible from decreasing removal rate was $21,937.09 (mean ± SD; $4,377.54 ± 1,774.90 death loss; $4,436.73 ± 1,756.15 culling loss). The low revenue increase would only be profitable if the total investment (installation cost and individual device price) was ≤ $8,814.27 for most of the iterations. The most likely value for installation price was $10,000, $1,185.73 over the revenue earned. Groenendaal et al. (2004) modeled the maximum RPO of a cow at $1,995.00, assuming she produced 124% more than the herd mean milk yield. Within our model, the average cow was simulated and expanded to create an entire herd. A limitation of our design is assuming all cows in the herd will behave as the average cow, which we know is not biologically true. However, the added complexity and computer processing required for a model to create a herd based on creating individual cows would be cumbersome and not end-user friendly. Another limitation was assuming culling rate and mortality rate were fixed, along with the percentage of culls and mortalities occurring within the first two mo of lactation. Potentially, running removal rate stochastically could have resulted in a NPV > 0.

Sensitivity analysis: All adjustments

When the effect of technology on RHAM, EDR, culling rate, and death rate were considered concurrently, NPV was ≥ 0 for 98.8% of the 10,000 iterations. This outcome indicated investment in PDM was a sound economic decision ($233.25 ± 222.35 per cow per yr; Figure 4.7). Along with a positive NPV, payback period was ≤ 5 yr for 98.8% of 10,000 iterations and ≤ 10 yr for 99.7% of 10,000 iterations. The payback period was 0.82 ± 1.00 yr overall, indicating that the technology would pay for itself well within the 7 yr lifetime of the technology, and within the 5 yr investment period suggested by Giordano (2015). The regression correlations identified by the software are depicted in Figure 4.8a,b. For every SD increase in baseline EDR, PDM EDR, CR, baseline RHAM, change in milk yield, individual device price, lactating feed price, and change in removal rate NPV was adjusted by a portion of a SD. As shown in Figure 4.8a, the largest NPV influencers were baseline EDR (-0.86 SD), PDM EDR (0.42 SD), CR (-0.31 SD), and baseline RHAM (0.20 SD). For every SD increase in baseline EDR, PDM EDR, change in milk yield, individual device price, baseline RHAM, CR, change in removal rate, and replacement device % payback period was adjusted by a portion of a SD. As shown in Figure 4.8b, the largest payback period influencers were PDM EDR (0.55 SD), baseline EDR (0.51 SD), change in milk yield (-0.22 SD), and individual device price (0.20 SD).

Similar to the EDR and milk yield change only simulations, herds with a higher level of production (baseline RHAM) had greater profitability after PDM investment. Additionally, as baseline herd reproductive performance increased (baseline EDR and CR), NPV decreased. Dolecheck et al. (2016a) reported the same response, with herds already having above average reproductive performance not gaining as much benefit from automated estrus detection.

The high positive NPV percentage was attributed to multiple herd factors changing simultaneously. Within our model, the lowest NPV, -$24.35 per cow, occurred when all influencers occurred at or near 0. However, the lowest NPV when all changes could occur together was higher than when milk yield change, EDR, and removal rate were considered individually (-$52.55, -$44.22, and -$49.33, respectively). With any incremental change, positive benefits of investing in a PDM outweighed the initial investment and continued upkeep costs. Decreased NPV with increased device price was in line with Dolecheck et al. (2016a) investment analysis considering EDR changes only. Our installation costs ranged from $5,000 to $20,000, $10,000 over the maximum suggested by Dolecheck et al. (2016a). Unlike Dolecheck et al. (2016a), initial investment cost did not influence NPV or payback period when all three changes were considered. Additionally, change in RPO and death loss were not significant influencers of investment. Our reductions were strict for reduced involuntary removal, reducing at maximum involuntary removal by 50%. However, the adjustment reduced loss by a maximum of 12 (culling: $11,491/yr) or 5 cows (death: $10,129/yr). Although these savings are not trivial, the maximum savings if lowest death and culling losses were achieved simultaneously was $21,937/yr, only marginally more than the maximum installation cost of $20,000 without accounting for 1,000 individual tags priced at $108 ± 27.

Further discussion and considerations

No model can explain a biological system with 100% accuracy (Bethard, 1997). Oversimplification in a model may be a critique, but even simplified models exceed the cognitive and calculative abilities of individual dairy producers and farm managers (Delorenzo and Thomas, 1996). Creating models that incorporate all biological and physical parameters is not feasible, and can impede model adoption by end-users (Jalvingh, 1992, Delorenzo and Thomas, 1996). The goal of an economic simulation is not to provide exact results, but rather to "highlight relative consequences of different strategies" (Lien, 2003).

Several assumptions were made that could not be adequately defined in the model. As stated previously, a herd was created from the simulated life of an average cow. This meant that all parity information was collected from the life of an average cow, assuming every cow in the herd during that simulation began lactation the same way, had identical reproductive performance, the same culling value, and death loss. This is not biologically accurate, as a herd is made up of many individual cows with different starting points and performance throughout their lifetime. However, modeling 1,000 individual cows for a herd simulation and attempting to account for all variability and variety is overly complicated and computationally challenging.

Including stochastic inputs accounted for volatility between an "average" cow in each iteration. Values that were pulled randomly from reasonable distributions improved model accuracy, and allowed our study to report values based on 10,000 iterations. This meant 10,000 possible scenarios were run for each sensitivity analysis. However, reasonable ranges were determined by the authors. Although these changes were based on research and were conservative, real-life situations rarely respond identically to a modeled scenario. Results should be interpreted with this limitation in mind while encouraging producers to input farm-specific values into a deterministic model.

CONCLUSIONS

Stochastic simulations can be a useful tool to determine investment under volatile market conditions. By running stochastic variables, researchers can capture changes throughout lactation, and the influence of price volatility. Our study results indicated that if using a PDM improved milk production or estrus detection rate, NPV was ≥ 0 for most iterations. Although increased individual device price would decrease NPV and increase payback period, initial installation cost had little to no impact. Providing a deterministic model for dairy producers could improve adoption rate by showing producers the potential improvement in different sectors of their dairy, and the low investment risk under the current assumptions.

ACKNOWLEDGEMENTS

The authors would like to thank Karmella Dolecheck, Derek Nolan, and Di Liang for their help with the model development.

Table 4.1. Fixed and stochastic variable inputs for average cow and herd outputs used to calculate net present value and payback period in a precision dairy technology purchased for early disease detection, improved estrus detection, or both. Revenue changes from reduced milk production loss attributed to decreased disease events, improved estrus detection rate, and decreased early lactation herd removal individually or in combination were calculated for 10,000 iterations with an @Risk add-in for Microsoft Excel.

Parameter	Fixed value	Stochastic value	Reference
Number of milking cows	1,000	NA	Model input
Heifers (0 to 12 mo as % of total herd)	47.8	NA	DairyMetrics (2017)
Heifers (≥ 13 mo as % of total herd)	48.7	NA	DairyMetrics (2017)
Percentage of herd in 1^{st} lactation	36.1	NA	Dhuyvetter et al. (2007)
Percentage of herd in 2^{nd} lactation	26.0	NA	Dhuyvetter et al. (2007)
Percentage of herd in 3^{rd} lactation	17.7	NA	Dhuyvetter et al. (2007)
Percentage of herd in 4^{th} lactation	11.0	NA	Dhuyvetter et al. (2007)
Percentage of herd in 5^{th} lactation	5.8	NA	Dhuyvetter et al. (2007)
Percentage of herd in ≥ 6^{th} lactation	3.4	NA	Dhuyvetter et al. (2007)
Mature cow live body weight (kg)	723.5	NA	NRC (2001)
Calf birth body weight (kg)	41.7	NA	Kertz et al. (1997)
Voluntary waiting period (d)	59	NA	DairyMetrics (2017)
Gestation length (d)	279	NA	Norman et al. (2009)
Age at first calving (mo)[1]	NA	20 to 41	DairyMetrics (2017)
Days dry (d)	57	NA	NAHMS (2014)
Estrus detection rate (%/21-d period)[2]	NA	49.2 ± 14.2	DairyMetrics (2017)
Conception rate (%)[3]	NA	25.2 ± 9.9	DairyMetrics (2017)
Initial RHAM (kg/yr)[4]	NA	3,211 to 16,984	DairyMetrics (2017)
Butterfat (%)	3.7	NA	DairyMetrics (2017)
Protein (%)	3.1	NA	DairyMetrics (2017)
Culling rate (% of total herd culls in 1^{st} lactation)	10.3	NA	DairyMetrics (2017)
0 to 30 DIM (% of 1^{st} lactation culls)	8.0	NA	Hadley (2003)
31 to 60 DIM (% of 1^{st} lactation culls)	8.0	NA	Hadley (2003)

Table 4.1. (cont.)

Parameter	Fixed value	Stochastic value	Reference
Culling rate (% of total herd culls in 2nd lactation)	9.3	NA	DairyMetrics (2017)
0 to 30 DIM (% of 2nd lactation culls)	7.0	NA	Hadley (2003)
31 to 60 DIM (% of 2nd lactation culls)	7.0	NA	Hadley (2003)
Culling rate (% of total herd culls in ≥ 3rd lactation)	18.9	NA	DairyMetrics (2017)
0 to 30 DIM (% of ≥ 3rd lactation culls)	8.9	NA	Hadley (2003)
31 to 60 DIM (% of ≥ 3rd lactation culls)	8.9	NA	Hadley (2003)
Mortality rate (1st lactation)	1.3	NA	DairyMetrics (2017)
Percent culled 0 to 30 DIM	16.0	NA	Hadley (2003)
Percent culled 31 to 60 DIM	16.0	NA	Hadley (2003)
Mortality rate (2nd lactation)	1.3	NA	DairyMetrics (2017)
Percent culled 0 to 30 DIM	17.5	NA	Hadley (2003)
Percent culled 31 to 60 DIM	17.5	NA	Hadley (2003)
Mortality rate (≥ 3rd lactation)	3.2	NA	DairyMetrics (2017)
Percent culled 0 to 30 DIM	23.8	NA	Hadley (2003)
Percent culled 31 to 60 DIM	23.8	NA	Hadley (2003)
Yearly veterinary cost ($)	65.05	NA	Kalantari and Cabrera (2012)[5]
Semen costs ($ per unit)	15.54	NA	VanRaden and Cole (2014)[5]
Financial loss at disposal ($)	63.35	NA	Groenendaal et al. (2004)[5]

[1]Age at first calving was a stochastic input, with a random number drawn from a PERT distribution (minimum = 20.0, mean = 25.2, maximum = 41.0 mo) during each iteration of the model.

[2]Estrus detection rate was a stochastic input, with a random number drawn from a normal distribution (mean ± SD) restricted to a 10% minimum and 80% maximum value during each iteration of the model.

[3]Conception rate was a stochastic input, with a random number drawn from a normal distribution (mean ± SD) restricted to a 10% minimum and 80% maximum value during each iteration of the model.

[4]Initial rolling herd average actual milk production (RHAM) was a stochastic input, with a random number drawn from a PERT distribution (minimum = 3,211, mean = 10,906, maximum = 16,984 kg/yr) during each iteration of the model.

[5]Adjusted for inflation to 2017 dollar value.

Table 4.2. Costs associated with purchasing and implementing a precision dairy monitoring technology and potential improvement in milk production, estrus detection rate, and early lactation removal rate from monitoring dairy cow health and estrus.

Parameter	Value	Reference
Initial installation price ($)[1]	5,000 to 20,000	Dolecheck et al. (2016a)
Technology price ($/device)[2]	50 to 200	Dolecheck et al. (2016a)
Additional labor required (h/wk)	3.5	Dolecheck et al. (2016a)
Labor wages ($/h)[3]	15.77	Galvão et al. (2013)
Technology upkeep ($/device/yr)	3.90	personal communication, producer, 2017
Replacement device (%/yr)[4]	0 to 10	Dolecheck et al. (2016a)
Investment length (yr)	5	Model input
Discount rate (%)	8	Hyde and Engel (2002)
Change in milk production (kg/d)[5]	0.00 to 0.91	Model input
Estrus detection rate (%/21-d period)[6]	60 to 80	Model input
Change in early lactation removal rate (%)[7]	0 to 50	Model input

[1]Initial installation price was a stochastic input, with a random number drawn from a PERT distribution (minimum = $5,000, mean = $10,000, maximum = $20,000) during each iteration of the model. Initial installation was a one-time payment that occurred the yr the PDM was purchased.

[2]Technology price was a stochastic input, with a random number drawn from a PERT distribution (minimum = $50, mean = $100, maximum = $200) during each iteration of the model. Technology price was the price per unit (PDM device) purchased for the herd. The number of tags required was equal to the lactating herd number (1,000 cows).

[3]Adjusted for inflation to 2017 dollar value.

[4]Replacement device was a stochastic input, with a random number drawn from a PERT distribution (minimum = 0%, mean = 5%, maximum = 10%) during each iteration of the model. Replacement technology was the amount of new units (PDM tags) purchased to replace lost or defective units.

[5]Change in milk production was a stochastic input, with a random number drawn from a PERT distribution (minimum = 0.00 kg/d, mean = 0.45 kg/d, maximum = 0.91 kg/d) multiplied by 365.4 for a yearly total addition to the baseline simulation rolling herd average (Table 4.1).

Table 4.2. (cont.)

[6]Estrus detection rate with a precision dairy technology was a stochastic input, with a random number drawn from a PERT distribution (minimum = 60%, mean = 70%, maximum = 80%) during each iteration of the model. If estrus detection rate was lower than baseline estrus detection rate (Table 4.1), precision dairy technology estrus detection rate was set equal to the baseline value.
[7]Change in early lactation removal rate was a stochastic input, with a random number drawn from a PERT distribution (minimum = 0%, mean = 25%, maximum = 50%) during each iteration of the model. The adjustment factor was multiplied by the culling or mortality rate for the associated lactation (Table 4.1). The new culling or mortality rate was the baseline value minus the decreased value.

Table 4.3. Mean, standard deviation, minimum, and maximum values from the distributions of stochastic input values from 10,000 iterations of a simulation model run with an @Risk add-in to a Microsoft Excel based model.

Variable	Mean	Standard deviation	Minimum	Maximum
Baseline herd				
Age at first calving (mo)	26.97	3.74	20.06	39.79
Rolling herd average (kg/yr)	10,637	2,595	3,510	16,788
Calving interval (d)	540	112	389	2,066
Estrus detection rate (%/21-d period)	48.8	13.4	10.0	80.0
Conception rate (%)	26.5	8.7	10.0	63.3
Heifer calf value ($/calf)	396.76	144.03	234.94	677.66
Bull calf value ($/calf)	139.97	44.17	77.46	240.09
Replacement heifer value ($/heifer)	1,844.06	232.26	1,542.84	2,278.44
Milk price ($/kg)	0.39	0.06	0.29	0.49
Slaughter value ($/kg)	1.43	0.20	1.04	1.76
Lactating feed price ($/kg)[1]	0.15	0.02	0.11	0.20
Precision technology herd				
Change in milk yield (kg/d)	0.45	0.17	0.02	0.89
Estrus detection rate (%/21-d period)	70.3	3.8	20.1	39.8
Early lactation removal adjustment (%)	25.0	9.4	0.5	49.8
Rolling herd average (kg/yr)	10,802	2,596	3,705	17,074
Calving interval (d)	465	49	384	657
Individual technology price ($/device)	108.33	27.64	50.92	192.84
Installation price (one-time price)	10,833.33	2,763.95	5,091.64	19,354.43
Replacement device (%/yr)	5.0	1.9	0.1	9.8

[1]Lactating cow feed price was calculated stochastically from historic and future alfalfa hay, soybean, and corn prices from FAPRI (2017).

Figure 4.1. Net present value (NPV) distribution of investment in a precision dairy monitoring (PDM) system for early health detection when revenue was increased based on milk production increases. Investments were made assuming a 1,000-cow herd and a 5 yr investment period. Net present value was \$14.87 ± 20.26 per cow per yr in a 1,000-cow herd with a 5 yr investment length. Investment in PDM was a sound economic decision (NPV ≥ 0) in 75.6% of 10,000 iterations.

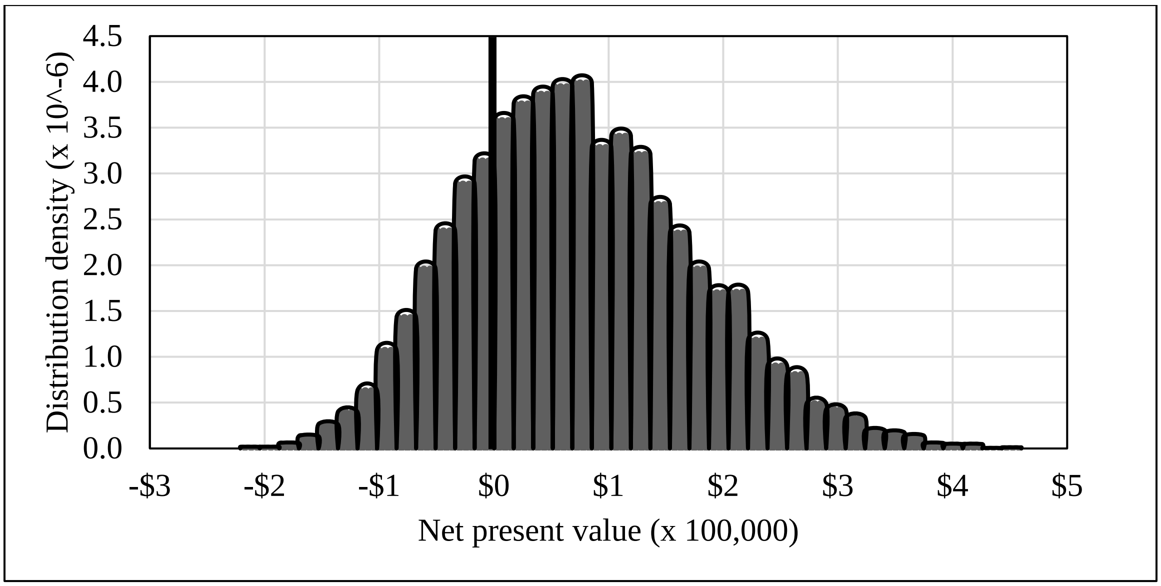


Figure 4.2. Regression coefficients for net present value (NPV; a) and payback period (PP; b) following investment in a precision dairy monitoring system for early health detection when revenue was increased based on milk production increases. Investments were made assuming a 1,000-cow herd and a 5 yr investment period. The regression coefficients were the change in NPV (a) and PP (b) standard deviation assuming a one standard deviation increase in the input variables (y-axis). One SD change in NPV was $20.26 per cow per yr. One SD change in PP was 2.9 yr. Input variable standard deviations and explanations are given in Table 4.3.

a)

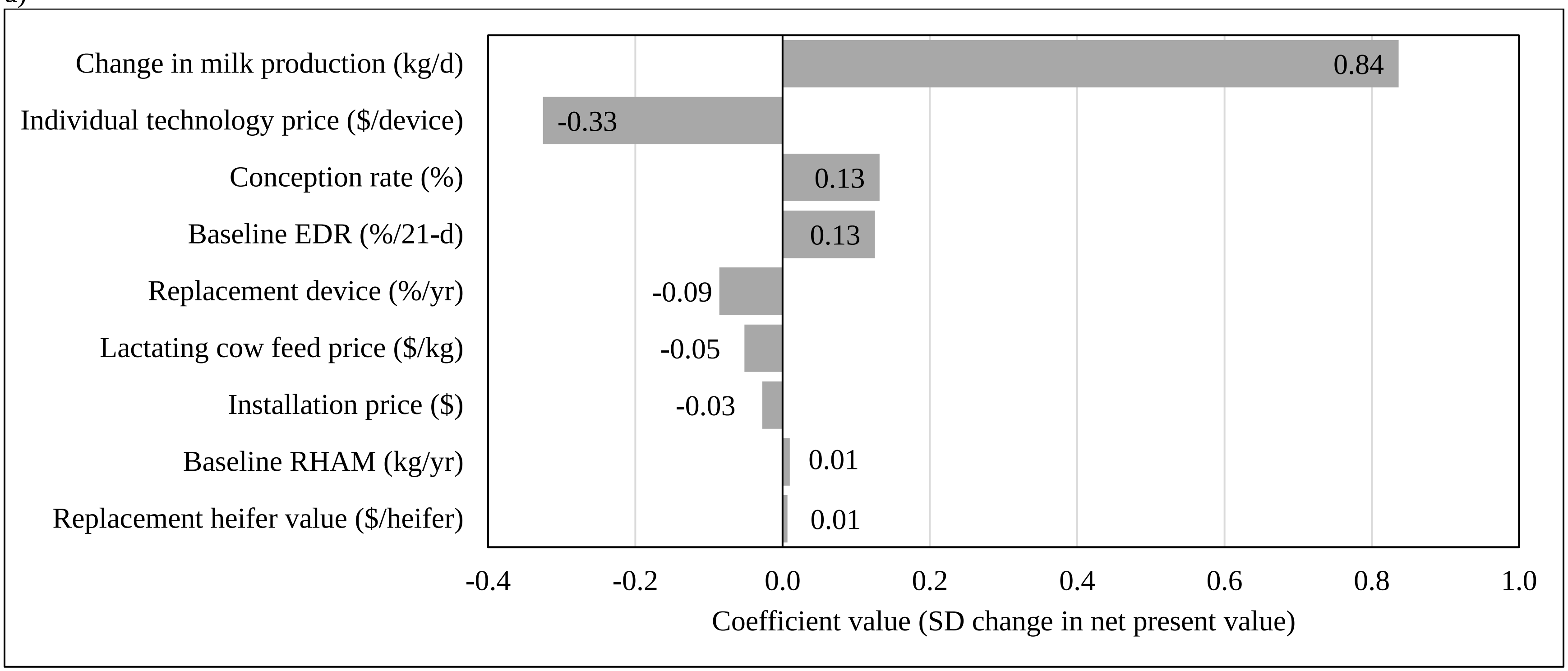


Figure 4.2. (cont.)

b)

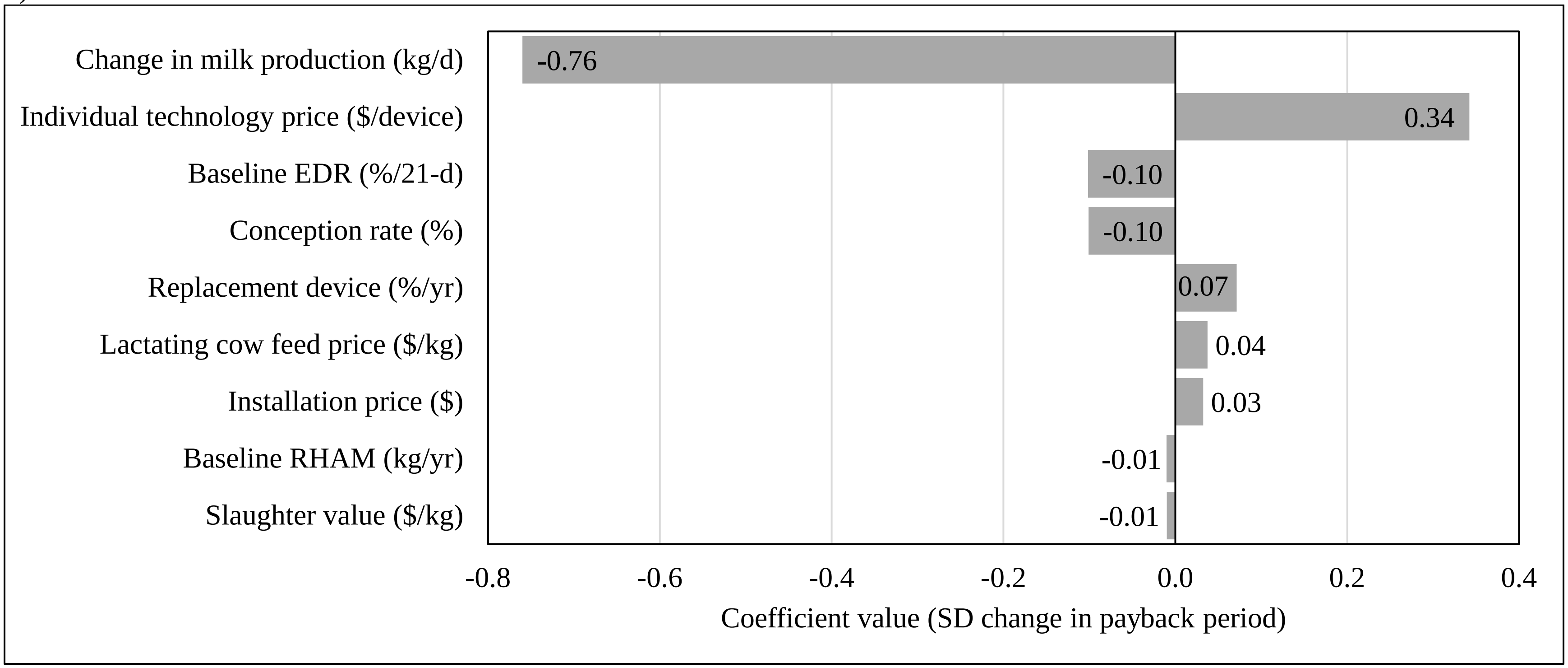


Figure 4.3. Net present value (NPV) distribution of investment in a precision dairy monitoring (PDM) system for estrus detection when revenue was increased based on improved reproductive performance. Investments were made assuming a 1,000-cow herd and a 5 yr investment period. Net present value was $179.29 ± 220.40 per cow per yr in a 1,000-cow herd with a 5 yr investment length. Investment in PDM was a sound economic decision (NPV ≥ 0) in 85.4% of 10,000 iterations.

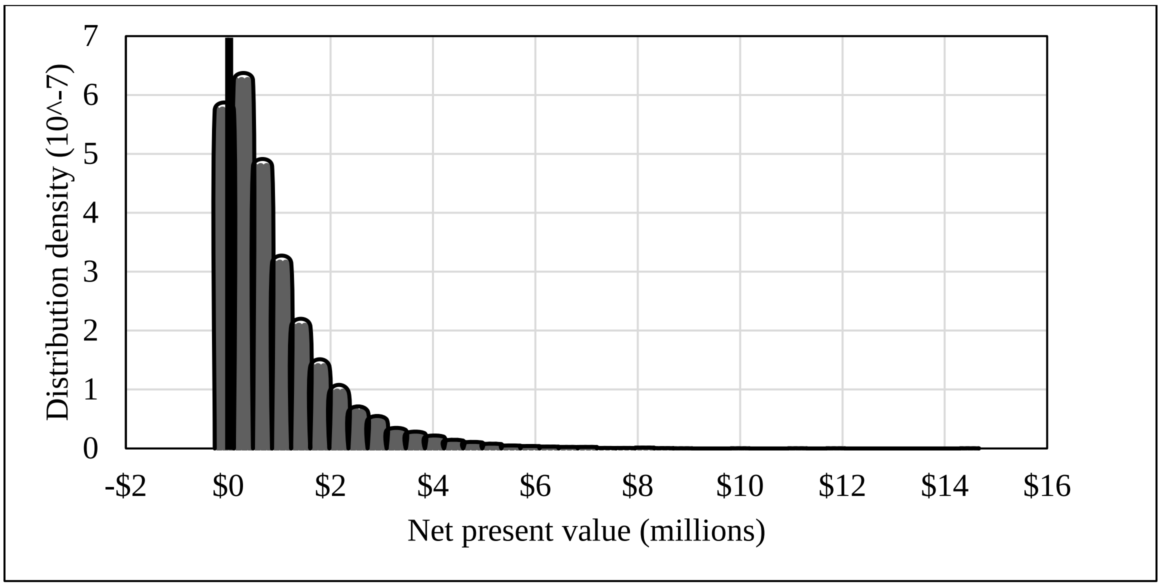


Figure 4.4. Regression coefficients for net present value (NPV; a) and payback period (PP; b) following investment in a precision dairy monitoring system for estrus detection when revenue was increased based on improved reproductive performance. Investments were made assuming a 1,000-cow herd and a 5 yr investment period. The regression coefficients were the change in NPV (a) and PP (b) standard deviation assuming a one standard deviation increase in the input variables (y-axis). One SD change in NPV was $220.40 per cow per yr. One SD change in PP was 3.5 yr. Input variable standard deviations and explanations are given in Table 4.3.

a)

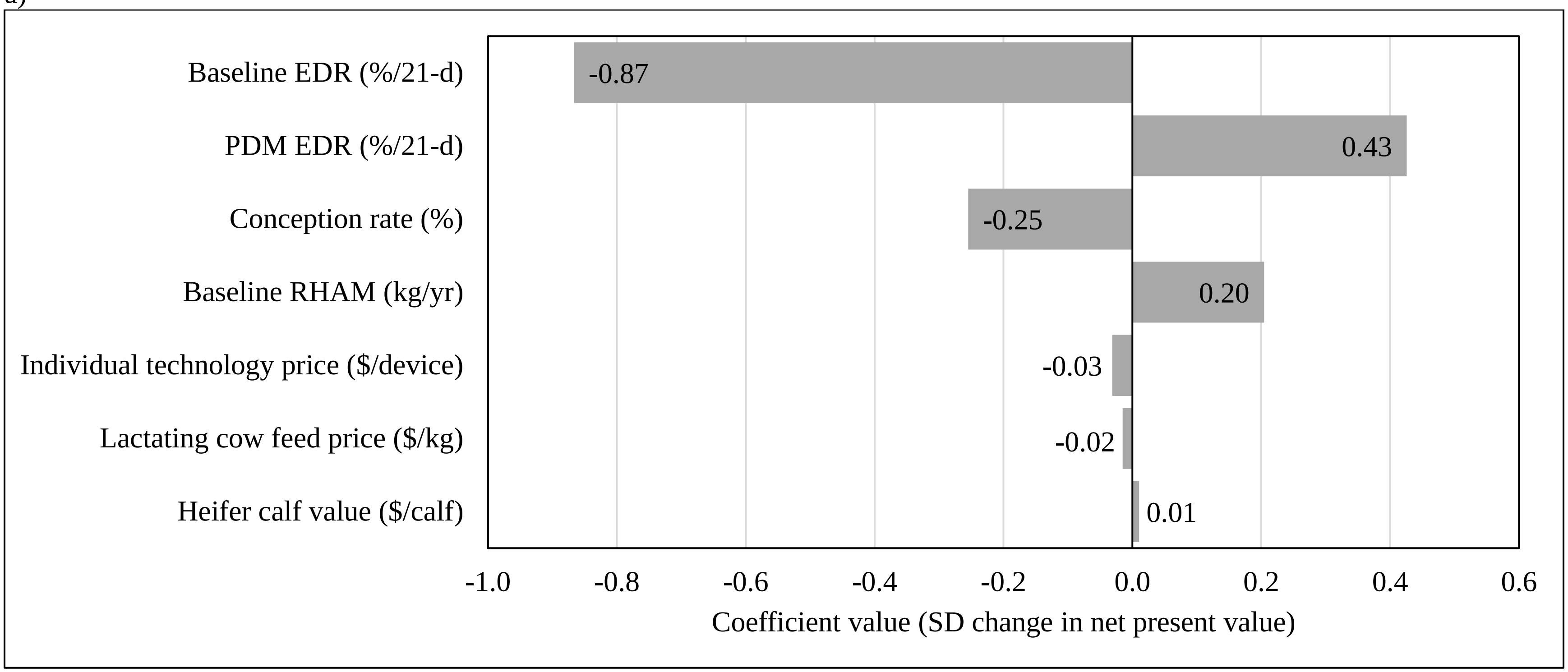


Figure 4.4. (cont.)

b)

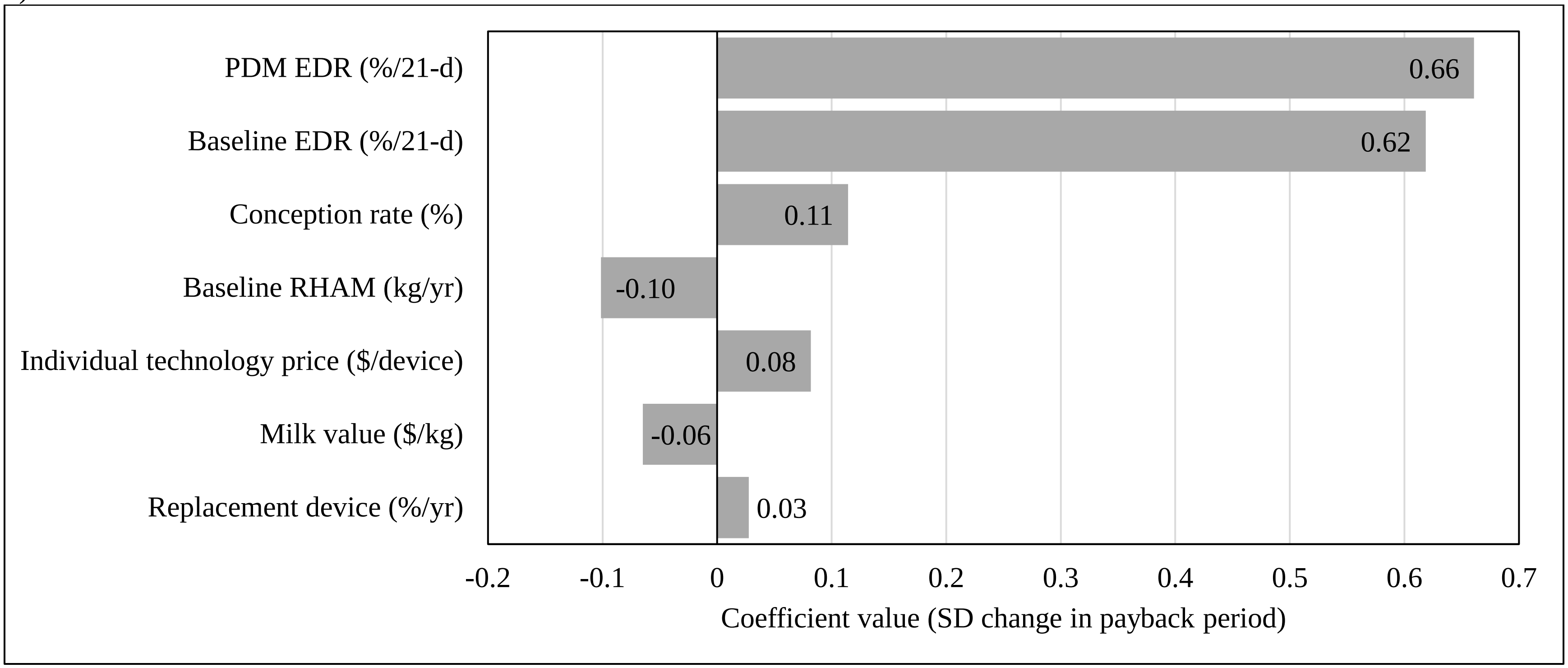


Figure 4.5. Net present value (NPV) distribution of investment in a precision dairy monitoring (PDM) system for early health detection when revenue was increased based on decreased culling and mortality loss in early lactation (mo 1 and 2 in lactation). Investments were made assuming a 1,000-cow herd and a 5 yr investment period. Net present value was -$23.49 ± 7.38 per cow per yr in a 1,000-cow herd with a 5 yr investment length. Investment in PDM was never a sound economic decision (NPV ≥ 0) in 10,000 iterations.

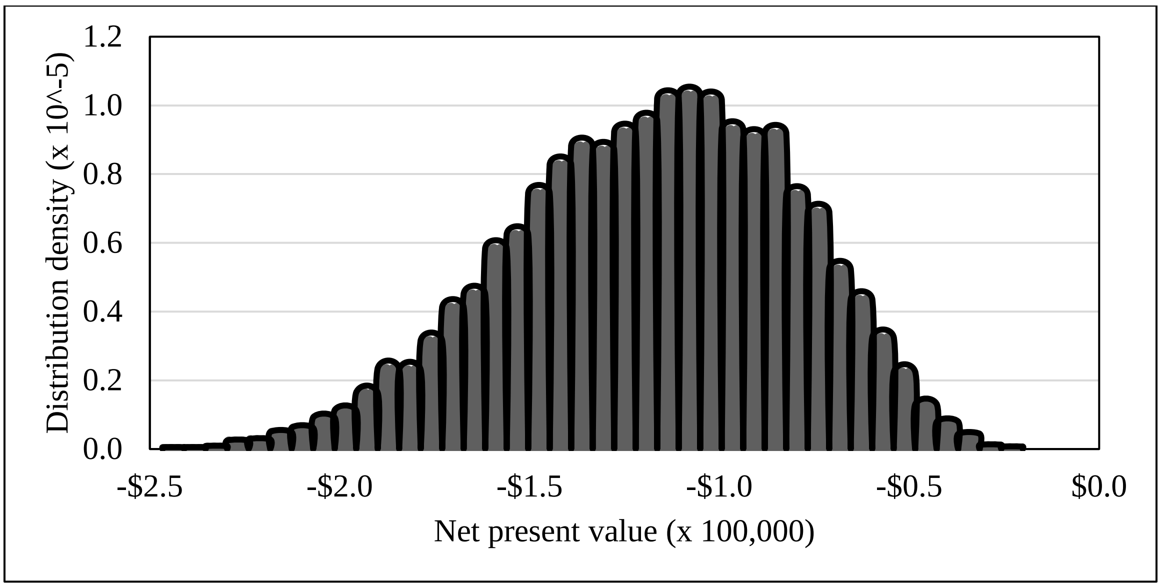


Figure 4.6. Regression coefficients for net present value (NPV) following investment in a precision dairy monitoring system for early health detection when revenue was increased based on decreased culling and mortality loss in early lactation (mo 1 and 2 in lactation). Investments were made assuming a 1,000-cow herd and a 5 yr investment period. The regression coefficients were the change in NPV standard deviation assuming a one standard deviation increase in the input variables (y-axis). One SD change in NPV was $7.38 per cow per yr. Net present value was always negative, and payback never occurred within 10 yr after investment. Input variable standard deviations and explanations are given in Table 4.3.

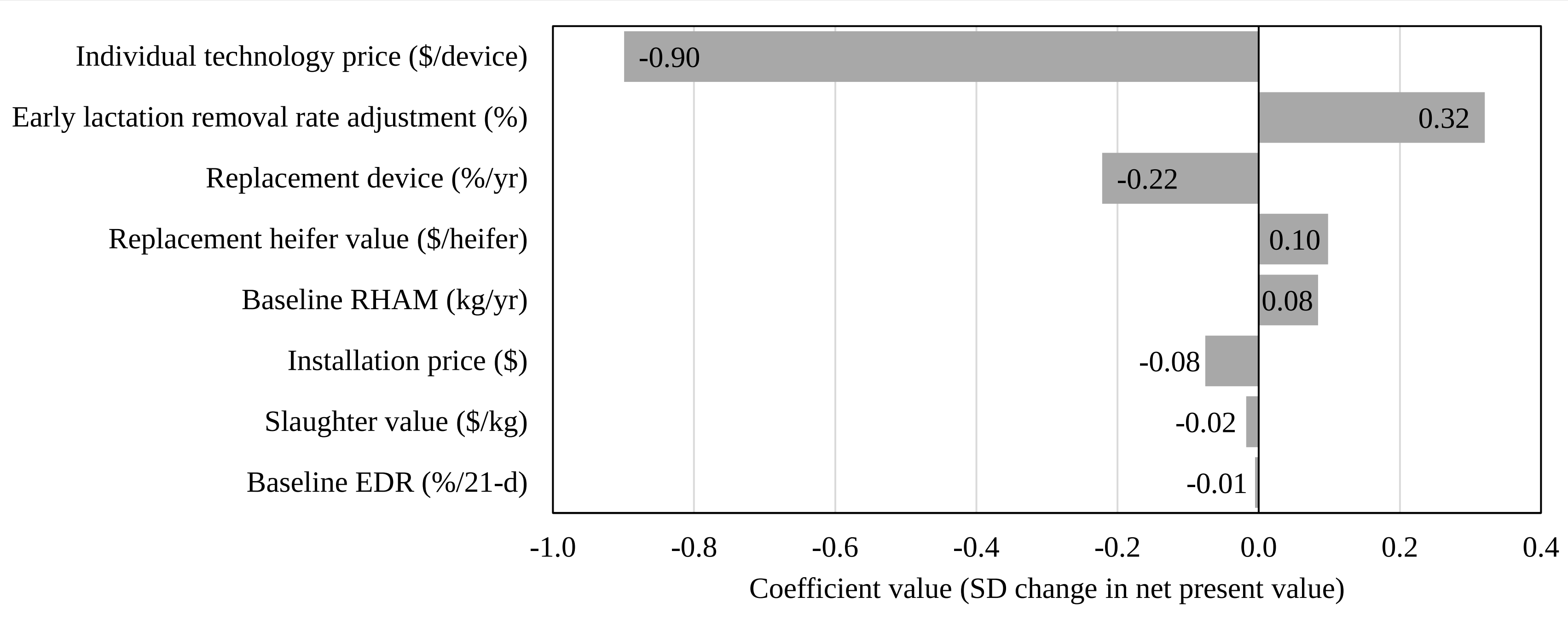


Figure 4.7. Net present value (NPV) distribution of investment in a precision dairy monitoring (PDM) system for estrus detection and early health detection when revenue was increased based on decreased culling and mortality loss in early lactation (mo 1 and 2 in lactation), reducing disease-related milk loss, and improving reproductive performance. Investments were made assuming a 1,000-cow herd and a 5 yr investment period. Net present value was \$233.25 ± 222.35 per cow per yr in a 1,000-cow herd with a 5 yr investment length. Investment in PDM was a sound economic decision (NPV ≥ 0) in 98.8% of 10,000 iterations.

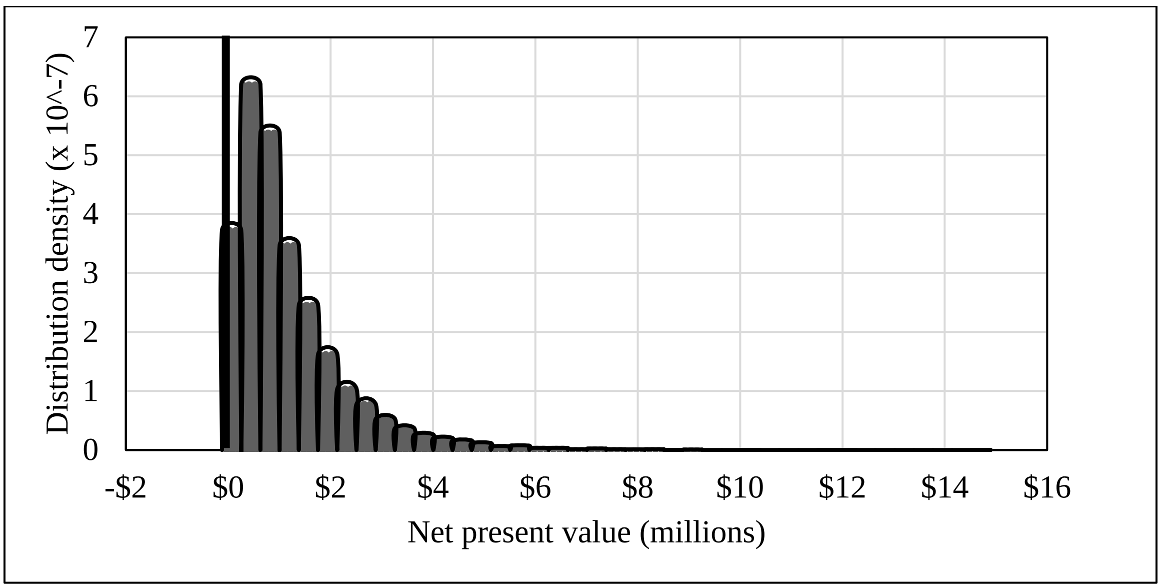


Figure 4.8. Regression coefficients for net present value (NPV; a) and payback period (PP; b) following investment in a precision dairy monitoring system for estrus detection and early health detection when revenue was increased based on decreased culling and mortality loss in early lactation (mo 1 and 2 in lactation), reducing disease-related milk loss, and improving reproductive performance. Investments were made assuming a 1,000-cow herd and a 5 yr investment period. The regression coefficients were the change in NPV (a) and PP (b) standard deviation assuming a one standard deviation increase in the input variables (y-axis). One SD change in NPV was $222.35 per cow per yr. One SD change in PP was 1.0 yr. Input variable standard deviations and explanations are given in Table 4.3.

a)

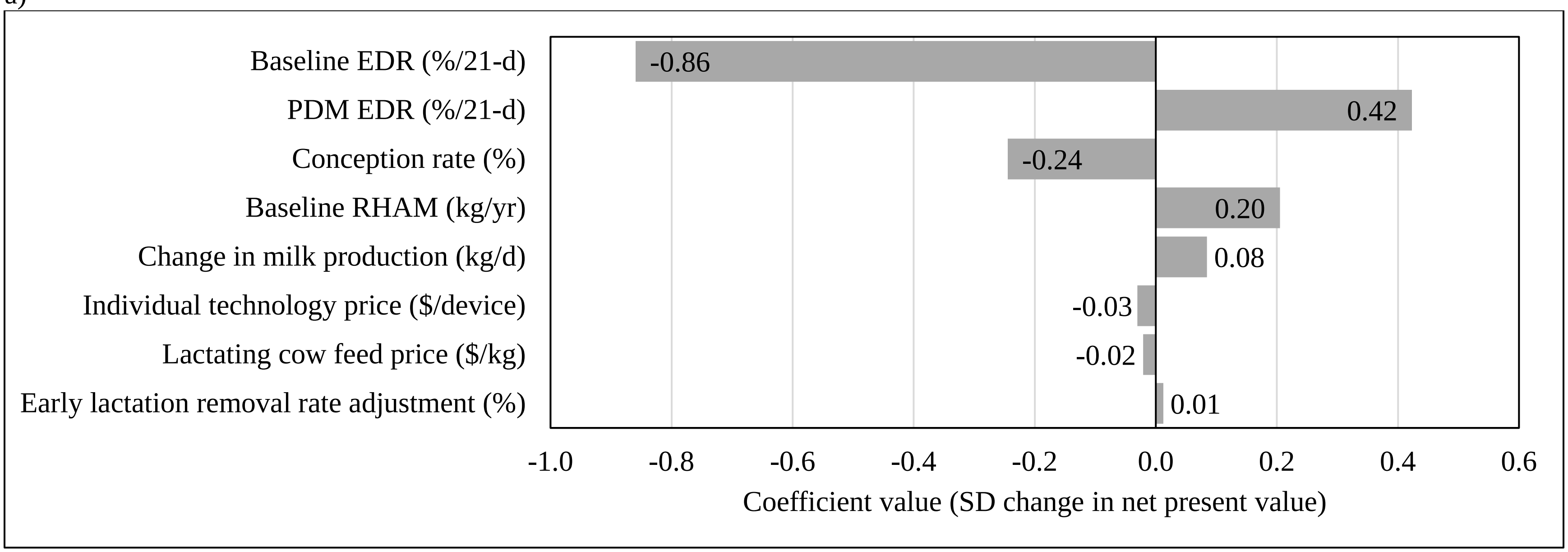
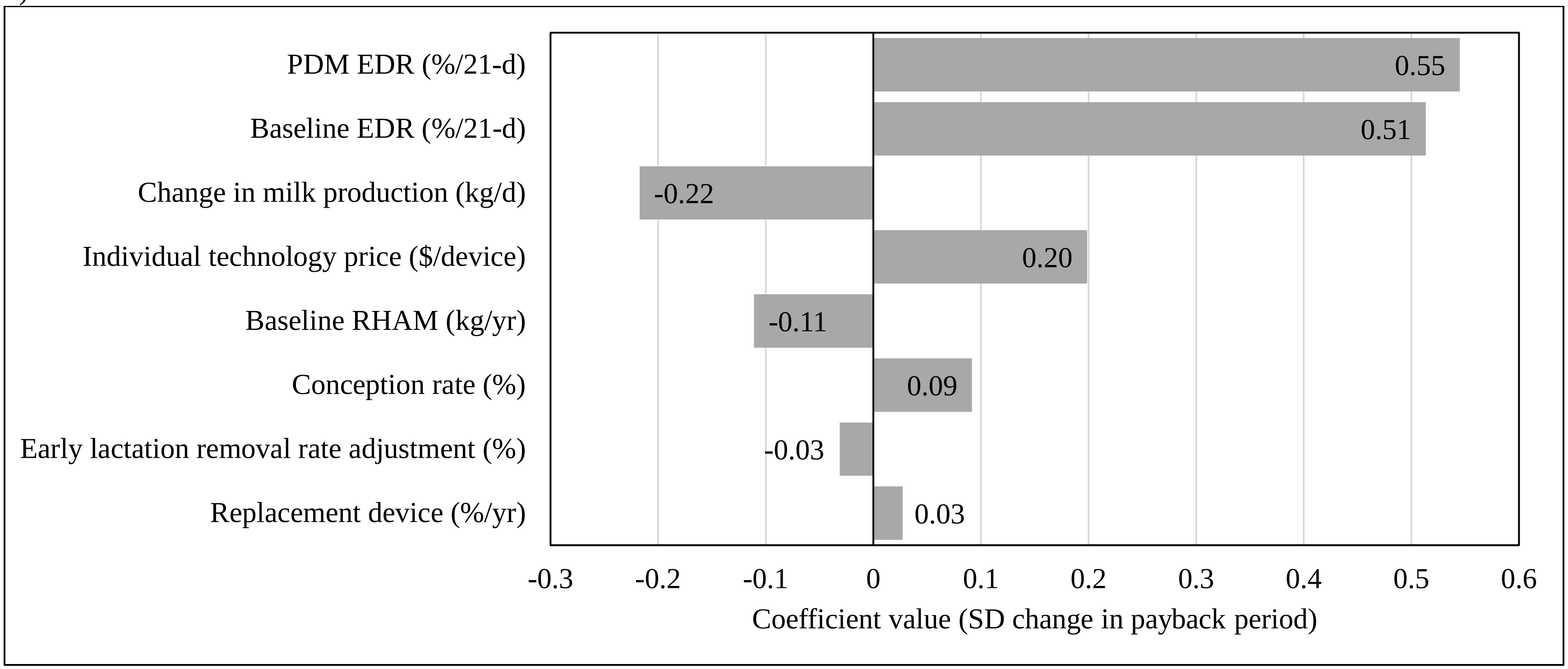


Figure 4.8. (cont.)

b)



CHAPTER FIVE

Conclusions

The first two studies (Chapters 2 and 3) focused on end-user implementation of disease alerts generated from precision dairy technology and the ability of the technology to detect diseases from behavioral changes. Four dairy producers in Kentucky purchased technologies including a neck collar measuring eating time (h/d) and a leg tag measuring lying time (h/d), standing time (h/d), walking time (h/d), and activity (steps/d). Daily, a disease alert report was generated on a web-interface from individual cow decreases in lying time, eating time, and activity. Dairy producers provided insight on how they categorized alerts, including if the cows were visually assessed because of the alert, if the behavior change was believed to be a true behavior change not linked to a disease event, or if the behavior change was not believed to be a true behavior change. Producers indicated only 21% of all generated alerts (5,034 out of 24,012 total alerts generated from 1,171 enrolled cows) were considered valid enough to visually check the cow. Odds-ratios with a generalized linear mixed model were used to assess the impacts of parity, temperature humidity index, behavioral change, day group (weekend or weekday), lactation stage (fresh, early, or late lactation), and number of cows on the daily health list (> 20 or ≤ 20 cows) on alert categorization. Producers were more likely to utilize eating or activity alerts, alerts in fresh or early lactation cows, during the work week, and when ≤ 20 cows were on the health list per d.

Additionally, validity of the disease alerts was assessed against recorded clinical disease events recorded by dairy producers and their staff. Subclinical and clinical hyperketonemia, hypocalcemia, and metritis events were also recorded by the lead author on all fresh cows between 3 to 6 DIM and 7 to 10 DIM. Disease events were not double-counted between farm staff and researchers. To increase the amount of time when a disease event and an alert could coincide, time-windows were created. True positives could occur when an alert occurred on the d of, d of to 1 d after, d of to 2 d after, d of to 3 d after, d of to 4 d after, d of to 5 d after, d of to 6 d after, d before to d after, 2 d before to 2 d after, 3 d before to 3 d after, and 5 d before to 2 d after the d of disease detection by producer or lead author. When alerts were created based on ≥ 30% decrease in behavior variables from a 10-d rolling mean, sensitivity remained between 13 to 48% with a 91 to 97% specificity. The maximum balanced accuracy achieved with technology-generated disease alerts was 59%. This occurred at the widest time-windows of 5 d before to 2 d after the d of disease detection and 3 d before to 3 d after the d of disease detection. The greatest balanced accuracy was also seen when all behavior changes were considered in combination and when the changes in behavior were predicting any possible disease instead of a specific disease. The best individual behavior for disease detection was eating time from the neck collar with a balanced accuracy between 50 to 59%.

Daily behavior information collected from the neck and leg technologies along with the daily difference from each cow's 10-d rolling mean eating, standing, lying, walking, and activity (steps/d) were run through three machine-learning analyses. The random forest, principle component neural network analysis, and linear discriminant analysis were all used to predict disease occurrence. Similar to behavior generated alerts, time-windows were created. True positives could occur when an alert occurred on d of, d before to d of, 3 d before to d of, and 5 d before to d of (-5 to 0) disease detection by the producer or lead author. All machine-learning analyses performed similarly and improved sensitivity and balanced accuracy compared to the technology-generated disease alerts. The linear discriminant analysis required the least processing capability and had the fastest run time compared to the random forest and principle component neural network analysis. Sensitivity ranged from 67 to 90%, specificity from 42 to 87%, accuracy 67 to 99%, and balanced accuracy from 66 to 87% across time-windows, disease categories, and behavior combinations. Unlike the technology-generated alerts, machine-learning predictions performed best during the 24 h before the d of disease identification and when individual diseases were predicted (hypocalcemia, hyperketonemia, or metritis).

The final study (Chapter 3) focused on the economic feasibility of precision dairy technology investment. The model created included changes to three of the costliest areas of opportunity on dairies: reproductive performance, disease, and early lactation culling or death. To incorporate the volatility inherent to dairy operations, the model was created in Microsoft Excel (Microsoft, Seattle, WA) with an @Risk add-in (Palisade Corporation, Ithaca, NY) to allow key inputs to be modeled stochastically within a Monte Carlo simulation. The lifetime of an average cow in the herd was modeled based on days at first calving, lactation performance, body weight, estrus detection rate, conception rate, dry matter intake, retention pay-off, and the cost of days open. Costs included were reproduction costs, treatment costs, veterinary costs, and feed costs. Technology investment in the model could alter milk production, estrus detection rate, or early lactation culling and mortality rate. Under the model assumptions, no improvement could occur but performance could not worsen after technology investment. The average cow was used as a baseline to compare changes in estrus detection, milk production, reduced culling and mortality, and all changes occurring concurrently. The baseline and investment average cows were each expanded to a 1,000-cow herd. Net present value analyses were used to determine the economic feasibility of technology investment. The net present value was calculated based on differences in costs and revenues between the baseline and investment herds over 10,000 iterations of the stochastic variables. All changes following technology investment were feasible except decreased early lactation culling and mortality. If early lactation removal was considered as the only benefit, technology investment was never feasible. However, improved estrus detection rate and improved milk production were positive economic decisions ≥ 76% of 10,000 iterations with a payback period < 5 yr.

Future research

Based on this research, precision technology-generated disease alerts based solely on behavior are not sufficient for dairy producers to visually assess cows. A large number of alerts were generated, and the detection accuracy was low. Because improved estrus detection rate and decreased milk loss from disease showed economic feasibility, improvement to disease detection is critical for companies marketing technologies and producers purchasing them. Future research should focus on combinations of behaviors instead of individual behaviors to detect diseases. Future studies should also take into consideration the inherent behavioral differences with different stages of lactation. Tailoring disease alerts to meet the needs of the end-user while emphasizing care of the cow has high potential. Great success has been made with estrus detection across technology companies, and increasing effectiveness of disease alerts should be the next logical step. A future study with large numbers of cows needs to be done with a portion of cows managed based on disease alerts and another based on regular management strategies to see the technology specific changes. One of the most glaring finds from the literature review and analyses was the lack of literature dealing with early intervention. Additional studies need to be conducted on the differences between early intervention and treatment and traditional intervention and treatment. Identifying case specific and lactation long differences would be a valuable addition to the literature and future economic assessments.

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Elizabeth Eckelkamp is from Sherman, Texas and has lived throughout the South. She began working with dairy cattle at Louisiana State University where she received her B.S. in Animal Sciences with a concentration in dairy in 2008. In 2012, she completed her M.S. in Animal Science at the University of Kentucky working with Dr. Jeffrey Bewley. Her thesis title was "Compost bedded pack barns for dairy cattle: Bedding performance and mastitis as compared to sand freestalls." She continued her education with Dr. Bewley through her PhD focusing on producer use of precision dairy technologies, their accuracy, and their economic feasibility. Through her work with Dr. Bewley, she found a passion for working with dairy producer and a desire to pursue an extension career. In the fall of 2017, Elizabeth will begin a position in the Animal Science Department of the University of Tennessee as an Assistant Professor Dairy Extension Specialist.