TITLE: 'Machine-learning-based calving prediction from activity, lying, and ruminating behaviors in dairy cattle

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JOURNAL: Journal of Dairy Science

PUBLISHER: Elsevier

PUBLICATION DATE: 10 May 2017 (online)

DOI: 10.3168/jds.2016-11526

Interpretive summary: *Machine-learning based calving prediction from activity, lying, and ruminating behaviors in dairy cattle. Borchers.* Frequent visual inspection has long served as the primary method to identify cattle in labor. Precision dairy technologies monitoring behavior before calving may have potential to predict calving. This study quantified cow activity, time spent ruminating, and lying behaviors before calving and applied machine-learning methods to retrospectively determine the calving prediction efficacy of these variables. A combination of activity, rumination time, and lying behaviors in prediction models was effective in predicting calving and show promise in future research and commercial application.

BEHAVIORAL MONITORING AND CALVING PREDICTION

Machine-learning based calving prediction from activity, lying, and ruminating behaviors in dairy cattle

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ABSTRACT

The objective of this study was to use automated activity, lying, and rumination monitors to characterize prepartum behavior and predict calving in dairy cattle. Data were collected from 20 primiparous and 33 multiparous Holstein dairy cattle from September 2011 to May 2013 at the University of Kentucky Coldstream Dairy. The HR Tag (SCR Engineers, Ltd., Netanya, Israel) automatically collected neck activity and rumination data in 2 h increments. The IceQube (IceRobotics, Ltd., Scotland) automatically collected number of steps, lying time, standing time, the number of transitions from a standing position to a lying position (lying bouts), and total motion, summed in 15-min increments. IceQube data were summed in 2 h increments to match HR Tag data. All behavioral data were collected for 14 d before predicted calving date. Retrospective data analysis was performed using mixed linear models to examine behavioral changes by day in the 14 d before calving. Bihourly behavioral differences from baseline values over the 14 d before calving were also evaluated using mixed linear models. Changes in daily rumination time, total motion, lying time, and lying bouts occurred in the 14 d before calving. In the bihourly analysis, extreme values for all behaviors occurred in the final 24 h, indicating the monitored behaviors may be useful in calving prediction. To determine whether technologies were useful at predicting calving, random forest, linear discriminant analysis, and neural network machine-learning techniques were constructed and implemented using R version 3.1.0 (R Foundation for Statistical Computing, Vienna, Austria). These methods predicted calving events using 14 d of behavioral data. These methods were used on variables from each technology and all combined variables from both technologies. A neural network analysis combining variables from both technologies at the daily level yielded 100.0% sensitivity, and 86.8% specificity. A neural network analysis combining variables from both technologies in bihourly increments was

used to identify bihourly periods in the 8 h period before calving with 82.8% sensitivity and 80.4% specificity. Changes in behavior and machine-learning alerts indicate commercially marketed behavioral monitors may have calving prediction potential.

Key Words: calving prediction, precision dairy monitoring technology, machine learning

INTRODUCTION

Parturition is an important period for both cows and their calves. Dystocia and calf mortality in this period can negatively impact farm economics and animal welfare (Mee, 2004). In the United States, 19% of primiparous and 11% of multiparous cows experience mild to severe dystocia at calving (USDA, 2010). Cows laboring more than 70 min past the appearance of the amniotic sac outside the vulva are at increased risk for dystocia (Schuenemann et al., 2011). Providing timely calving assistance may reduce the risk of dystocia, reduce the pain associated with assisted labor (Mainau and Manteca, 2011), and improve reproductive performance in the subsequent lactation (Bellows et al., 1988). Identifying laboring cattle allows managers to assist in cases of dystocia. Dairy producers currently use a combination of breeding records and visual cues to estimate calving time; however, even experienced personnel may not accurately detect all calvings because perceptible behavioral and physiological changes do not occur for every cow or at a consistent time across all calvings (Hofmann et al., 2006; Sendag et al., 2008).

Precision dairy monitoring technologies provide alternatives to the subjective observation and assessment of calving behaviors. Precision dairy monitoring technologies represent an alternative approach for predicting calving time compared to visual monitoring. To date, the application of precision technologies in calving detection has primarily consisted of maternal body temperature monitors. Maternal body temperatures have been shown to decrease approximately 48 h before calving (Lammoglia et al., 1997; Burfeind et al., 2011). Commercially marketed temperature monitors measure dairy cattle reticulorumen temperature, skin temperature, and vaginal temperature, but none have been validated for calving prediction. Monitors inserted in the vagina and expelled at the beginning of the second stage of labor also exist (Palombi et al., 2013), but these tools have also not been validated. Additionally, these technologies are costly, and to the knowledge of the authors, no economic research establishing their feasibility on dairy farms has been completed.

Validated measures of activity (Champion et al., 1997; Robert et al., 2009; Bikker et al., 2014), lying behavior (McGowan et al., 2007; Ledgerwood et al., 2010; Mattachini et al., 2013a; Borchers et al., 2016), and rumination (Schirmann et al., 2009; Bikker et al., 2014; Borchers et al., 2016) exist and may offer other options for calving prediction. Many of these technologies and the variables they monitor are already commonly used on dairy farms (Borchers and Bewley, 2015). Evidence exists that dairy cows change feeding, rumination (Huzzey et al., 2005; Schirmann et al., 2013; Pahl et al., 2014), and lying behavior (Huzzey et al., 2005; Miedema et al., 2011; Jensen, 2012) as calving approaches, making technologies measuring these behaviors potentially useful calving prediction tools. Some research has endeavored to predict calving events using these measures. Clark et al. (2015) used the SCR HR Tag (SCR Engineers, Ltd., Netanya, Israel) to monitor rumination behavior and predict calving events, achieving a 70% sensitivity and 70% specificity in predicting the day of calving. Similarly, Ouellet et al. (2016) evaluated systems monitoring rumination time, vaginal temperature, and lying behaviors for their calving prediction accuracy and found a combination of these variables to achieve a greater level of prediction accuracy than considering them alone (77% sensitivity, 77% specificity).

Most algorithm development and usage implements elements of statistical process control (MacGregor and Kourti, 1995) and requires the use of trial and error and deviations from baseline values to be developed. A newer approach in event prediction is the use of machine-learning event prediction. Most machine-learning research in the dairy sciences has been applied for mastitis and estrus detection (Firk et al., 2003; Cavero et al., 2008; Sun et al., 2010), but no research has addressed their usage in calving prediction. Additionally, to the knowledge of the authors, no commercial precision dairy monitoring technologies use machine-learning techniques in alert creation.

Before these technologies can become useful in calving prediction, research is needed to determine if the behaviors measured by the technologies (e.g., activity, rumination, and lying behavior) are highly sensitive and specific in detecting imminent calving. The objectives of this study were to first quantify activity, rumination, and lying behaviors before calving using two commercially available technologies and compare these behaviors to previous literature. The main objective was to determine the calving prediction efficacy of these technologies, both individually or in combination, using machine-learning prediction techniques. Cow-specific data commonly available through herd management software will also be included in these prediction methods. We hypothesize that activity, rumination, and lying behaviors will differ from typical values on the day of calving. In the calving prediction analysis, we hypothesize that a combination of variables from both technologies will generate greater prediction accuracy with machine-learning methods than either technology considered alone.

MATERIALS AND METHODS

Data were collected using 20 primiparous and 33 multiparous prepartum Holstein dairy cattle (mean ± SD; gestation length 277.6 ± 4.9 d; parity 2.3 ± 1.5) from September 2011 through May 2013 at the University of Kentucky Coldstream Dairy Facility (IACUC Protocol Number: 2010-0776). Beginning minimally 30 d before expected calving date, cows were moved to dry cow facilities and housed in a 9.15 x 21.34 m sawdust bedded pack with constant access to 3.64 hectares of pasture. A TMR was delivered to the pen once daily.

Two technologies were fitted to each cow by 28 d before predicted calving. After calving, data was reduced to include only the 2 weeks of data before calving from each cow. The HR Tag (SCR Engineers, Ltd., Netanya, Israel) was placed on the left side of the neck and automatically collected neck activity and rumination data in 2 h periods using a 3-axis accelerometer and a microphone with microprocessor, respectively. The IceQube (IceRobotics, Ltd., Scotland) was attached to the left rear leg and automatically collected number of steps, time spent lying, time spent standing (inverse of time spent lying), the number of transitions from a standing position to a lying position (lying bouts), and a proprietary total motion variable in 15 min periods using a 3-axis accelerometer. Third-party technology variable validations were previously completed for the HR Tag (Schirmann et al., 2009) and IceQube (McGowan et al., 2007; Mattachini et al., 2013b; Borchers et al., 2016), with both technologies being found to accurately monitor their respective variables.

Cows in the dry pen were monitored for signs of calving every 3 h. Individual cows were monitored every 15 min after the first sign of labor was detected (e.g., the amniotic sac or calf feet became visible outside of the vulva). After laboring cows were identified, cows were separated into individual pens, preventing pasture access. For each calving, farm staff were instructed to record the calving date, the cow's parity, the time calving began, and the approximate time calves were fully outside the cow. Eleven cows were assisted during labor in the study population. These cows were included in all analyses. The need for assistance in the birthing process was assessed and provided at the farm manager's discretion, or according to the farm's standard operating procedure.

Statistical Analysis

To quantify changes in behavior before calving, neck activity and rumination data from the HR Tag, as well as number of steps, time spent lying, number of lying bouts, and total motion data from the IceQube were used to create two data sets; daily and bihourly (behavior per 2 h period) calving behavior. For daily and bihourly analyses, data were averaged in 24 h periods relative to calving. For bihourly analyses, the time of calving was used to retrospectively generate cow-specific number of hours before calving in 2 h periods. This was performed on each variable in order to place all cows on the same timeline regardless of the time of day, similar to the methods of Schirmann et al. (2013).

A mixed linear model (MIXED procedure of SAS version 9.3; Cary, NC) generated daily least-squares means, with parity group (primiparous or multiparous) and day before calving (**Day -1 to -14**) serving as categorical fixed effects. Cows served as repeated subjects for all variables and an autoregressive covariance structure (AR-1) was used to account for multiple observations being collected from subjects over time. All two-way interactions were tested in daily models, and non-significant ($P \geq 0.05$) interactions were removed using backwards stepwise elimination. All main effects remained in final models regardless of significance. Tukey's range test was used to identify significant differences between days before calving.

All bihourly data were adjusted similarly to the methods of Jensen (2012). All 2 h periods were assigned a label (**Hour -2 to -334**) for each behavior and cow. For every cow, the 2 h behavioral data value minus the average of the same 2 h time of day for the previous three days (to account for differences in circadian patterns) was used to determine deviation from baseline values (Jensen, 2012). This procedure was applied to all variables (neck activity, rumination, number of steps, time spent lying, number of lying bouts, and total motion), individually. Least-squares means were calculated from these differences, with parity (primiparous or multiparous), time of day (0000 h to 2359 h in 2 h periods), and bihourly period before calving (-334 to -2, in 2 h periods) as fixed effects. Cows served as repeated subjects. All two-way interactions were tested and non-significant ($P \geq 0.05$) interactions were removed using backwards stepwise elimination. All main effects remained in final models regardless of significance.

Residual plots were generated and inspected to assess normality and detect potential outliers for each analysis. Data transformations were performed to meet normal distribution for daily number of steps and total motion, as well as bihourly neck activity, total motion, and number of steps. A natural logarithm transformation was performed on these variables to meet residual normality assumptions for mixed linear models.

Prediction Model Development

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

All analyses were constructed and implemented using the <caret> package in R version 3.1.0 (R Foundation for Statistical Computing, Vienna, Austria). To make the prediction methods as applicable to actual calving situations as possible, prediction models were developed, with the intent to be sequentially performed. The day of calving would first be identified using daily calving behaviors data. The 8 h period immediately preceding calving would then be determined using the bihourly data from the day of calving. Separate random forest, linear discriminant analysis, and neural network analyses were performed for the IceQube, the HR Tag, and a combination of variables from both technologies, for a total of 18 prediction models (3 technologies x 3 analyses x 2 time periods predicted).

The datasets used in each model were prepared in the same way. A data subset consisting of 80% of observations was used as a "training" set to generate prediction models. A leave-one-out cross-validation method was performed for each machine-learning method to develop training phase models. The remaining 20% of observations in the "testing" subset were used to evaluate the performance of the models. During the testing phase, trained models were used to predict periods of interest. True positives, false positives, true negatives, and false negatives were calculated for each daily and 2 h period and the sensitivity, specificity, positive predictive value, and negative predictive values were calculated to evaluate the performance of different machine-learning techniques and technology.

Daily Calving Prediction Models. For daily calving prediction, the predicted variable was the day before calving (from Day -1 to -14). The ability of models to predict the day before calving was used as the outcome of interest, but all days were included in the model. Data were summed by day in a 24 h format, from 0000 h through 2359 h. Day 0 was not considered in daily prediction models to exclude periods in which calving occurred and remove any incomplete time periods.

Data were presented to machine-learning techniques in three separate ways. Analyses were performed individually analyzing complete daily data from each technology and combined, analyzing complete daily and bihourly data from both technologies. For example, only cows with complete data for the IceQube included in IceQube calving prediction models, and cows missing data from either technology or all data from both technologies were removed from combined calving prediction models. For this reason, sample sizes differed by day relative to calving because of missing data originating from technology failure or data transfer error. From Day -1 to Day -14 d prepartum, sample sizes ranged from n = 43 cows to n = 51 cows for the HR Tag. For the same period sample sizes for the IceQube ranged from n = 43 to n = 53. For the combination analysis, only instances where data was available from each technology were analyzed (n = 43 to n = 51). Parity and days until estimated calving date (from breeding records) data were included in the daily prediction models. Variables measured by each technology were also included in their respective prediction models (IceQube models: number of steps, time spent lying, number of lying bouts, and total motion; HR Tag models: neck activity and rumination; technology combination models: all variables from both technologies). The IceQube also monitored standing time (the inverse of lying time). Standing time was a variable supplied by the technology and all available variables were used in prediction models to simulate actual conditions.

Bihourly Calving Prediction Models. A 24 h backwards moving average was calculated for each cows' behavior and 2 h period to account for differences in circadian patterns. Machine-learning techniques were applied to 22 h of backwards moving averaged data before calving. The 2 h period immediately preceding calving was excluded from analysis because alerts would be generated following or at calving completion and would not be obtained in a timely manner for a producer to execute meaningful interventions. Behavioral data, parity, and time of day were used to predict each 2 h period before calving (bihourly periods from -2 h to -22 h before calving; 11 total time points). The variable of interest was the 2 h period before calving (representing data from -2 to -4 hours before calving), but due to large calving behavior variation, this period was extended to the 8 h period preceding calving. All sensitivity, specificity, positive predictive value, and negative predictive values were performed using combined true positives, false positives, true negative, and false negative data from this 8 h period (data from periods -2 to -4, -4 to -6, -6 to -8, and -8 to -10) periods. Variables measured by each technology were also included in their respective prediction models (IceQube models: number of steps, time spent lying, number of lying bouts, and total motion; HR Tag models neck activity and rumination; technology combination models: all variables from both technologies). Standing time was also added to models including IceQube data, similar to the daily analyses.

RESULTS

Interactions and parity effects on behavior

Significant interactions were found between parity and day before calving (Day -1 to Day -14) for daily lying time (Table 1; $P = 0.02$). Significant interactions were also found for parity and 2 h period before calving for difference in bihourly neck activity (Figure 1; $P = 0.03$). Primiparous cows differed from multiparous cows in lying behavior and neck activity, with primiparous cows lying less and becoming more active before calving.

Behavioral Comparisons

Differences between days before calving were observed for rumination time, total motion, lying time, and lying bouts (Table 1). No differences were found for neck activity and number of steps between days before calving. Behavioral changes by 2 h period for the 72 h before calving are shown in Figure 1a to f. In the 24 h before calving, all measured variables were significantly ($P < 0.05$) affected by 2 h periods, indicating an effect of time, and therefore stage of labor before calving on differences in behavior.

Activity Variables: Neck Activity, Number of Steps, Total Motion

Neck activity and the number of steps taken were not different by day before calving (Table 1), but were affected by 2 h period before calving (Table 1a). First parity neck activity decreased to its least value 18 h before calving, and then increased to its greatest value 2 h before calving. This indicates that these variables may not be useful for calving prediction at the daily level, but may be at the 2 h level.

Rumination Behavior: Rumination Time

Daily rumination time decreased throughout the prepartum period and was least on the day before calving (Table 1), but no differences were observed. Similarly, the difference from baseline values in rumination at the 2 h level was below baseline values for the entire 24 h before calving (Figure 1b). Rumination time decreased to its least value 8 h before calving. An increase in rumination time beginning 8 h before calving was observed but values remained far below baseline values. This suggests that preparturient cows decrease rumination behavior as calving time approaches.

Lying Behaviors: Lying Time and Lying Bouts

Lying time decreased from Day -14 to Day -2 (Table 1). Differences between parities were found for the final 7 days before calving. Lying times were least on the final day before calving for both parities (Primiparous, 7.0 ± 0.6 h; Multiparous, 10.2 ± 0.5 h). When data were analyzed for differences in 2 h intervals, a similar trend was observed in the 24 h to 48 h period before calving (Figure 1e). The 2 h periods throughout the 24 h preceding calving were variable for lying time, but lying time decreased to its least value, 8 h before calving (a decrease of 34.7 ± 9.3 min from baseline values). Lying time increased and exceeded baseline values 4 h before calving, indicating a return to normal behavior. This behavioral change indicates that although daily lying time decreased on the day of calving, cows lay more in the hours immediately preceding calving. Similarly, lying bouts increased on the day before calving (Table 1). Cows also steadily increased lying bout frequency per 2 h period on the day of calving (Figure 1f).

Machine-Learning Analyses

The machine-learning methods used in this study produce results and output not typical of other prediction methods where algorithms are produced. The authors have provided sample code and data, which are viewable at https://github.com/Mrborchers/Machine-learning-based-calving-prediction-from-activity-lying-and-rumination-behaviors. Prediction performance for daily methods is shown in Table 2. The ability to predict the day before calving was best when a combination of variables from the HR Tag and IceQube were used. The best daily calving prediction results were obtained in the combined variable neural network analysis.

The greatest sensitivity and specificity combinations were obtained when true positives, false positives, true negatives, and false negatives from the 2 h periods from -2 to -8 (data from periods -2 to -4, -4 to -6, -6 to -8, and -8 to -10) were combined. These results are presented in Table 3. Similar to the daily analysis, neural network results of the bihourly combination analysis were the greatest.

Daily variable data measured by the IceQube sensor also effectively predicted the day of calvings in the linear discriminant analysis. Similar results were also obtained at the bihourly level, where the IceQube best identified the 8 h period before calving in comparison to the HR Tag. The HR Tag alone was ineffective at the daily level, reaching the best prediction efficiency in the linear discriminant analysis. At the bihourly level, the HR Tag variables were best able to identify the 8 h period before calving in the linear discriminant analysis.

DISCUSSION

Behavioral Comparisons

Primiparous cows showed differences in daily lying times, and bihourly neck activity. Primiparous cow lying times decreased in the days before calving and were different from multiparous counterparts beginning 7 d before calving. Lying time was least on the day of calving for both primiparous and multiparous cows. When separated by parity, neck activity may have use in calving prediction over shorter periods, and may be useful in predicting first parity calvings. Similar to this study, Owens et al. (1985) and Wehrend et al. (2006) found primiparous cattle to become more restless before calving. This indicates parity to be important in describing the change in daily lying time and neck activity. Accordingly, parity was included in all prediction models.

Previous studies have shown activity increases as calving approaches (Miedema et al., 2011; Jensen, 2012), but their measurement of activity and methodology differed from this study. For example, Miedema et al. (2011) used a within-cow comparison and observed that walking duration increased from control periods during the dry period to the 24 h before calving (21.0 ± 7.4 vs. 31.5 ± 13.1 min; $P < 0.01$). Similarly, Jensen (2012) observed an activity (calculated as acceleration not associated with gravity) increase beginning 6 h before calving ($F = 5.46$; $P < 0.01$), compared to the same time of day during the 3 d before calving. These findings are similar to the findings for the total motion variable used in this study. In the current study, differences between days before calving were identified for the total motion variable. Total motion is a proprietary motion variable monitored by the IceQube, and the method by which this variable was calculated were not known. This variable may encompass all overall movement of the leg, as well as step number. This could include motions associated with lying and standing bouts, lateral movement, as well as steps. A variable analogous to lying bouts is standing bouts. Lying and standing bouts would be approximately equivalent if measured individually. Standing bouts were not measured in this study but may be represented in total motion. The motions associated with a standing or lying event, if captured in total motion, would be potentially additive. This additive effect may have led to the overall total motion increase seen in this study.

For rumination behaviors, Clark et al. (2015) showed a 33% decrease in rumination time over the 2 days prepartum. The same period in the current study only showed a decrease of 13%. Similarly, Schirmann et al. (2013) observed a 63 ± 30 min/24 h difference between the day of calving and a 2 d average rumination baseline value. A 45 min difference was seen in the current study between the day of calving and the day before. Ouellet et al. (2016) observed a 36 min decrease in this same period. In all studies, including the current study, a decrease in rumination was shown, but the magnitude of this decrease differed. Differences in environments and feedstuffs may explain these differences, but more research is needed.

In bihourly periods, rumination decreased by nearly 20 min from baseline values 8 hours before calving. Pahl et al. (2014) showed similar differences across bihourly periods, but found the largest differences immediately preceding calving. The differences in rumination time (although not significant at the daily level) indicate it may be a good predictor of calving across smaller periods immediately preceding calving. Although non-significant, differences in rumination may be useful in daily calving prediction models as well.

For lying behaviors, Jensen (2012) showed a gradual decrease in daily lying time from 16.6 h/d on Day -4 before calving to 16.2 h/d, on Day -2 before calving. When data were analyzed by individual 2 h periods in the 24 h before calving, Jensen (2012) found that lying time increased from 12 h before calving (31.4 min) to 2 h before calving (42.8 min). Cows remain recumbent during the second stage of labor as the calf moves through the birth canal (Schuenemann et al., 2011). These findings suggest cows may become more uncomfortable and spend less time lying down during the few days before calving, but increase their lying time in the hours before calving as they begin labor.

For lying bouts, Miedema et al. (2011) showed lying bout frequency increased from the dry period to the 24 h before calving (16.4 ± 4.8 vs. 24.2 ± 6.8 bouts per 24 h). Beginning 18 h before calving in the current study, subsequent individual 2 h periods significantly affected lying bouts. The greatest deviation from baseline values occurred in the 2 h immediately preceding calving (1.8 ± 0.1 lying bouts). Over a similar period, Jensen (2012) showed lying bouts per hour increased from 0.83 bouts per hour at 12 h before calving, to 2.79 bouts per hour at 2 h before calving. The incremental increase in lying bouts and the changes in lying time indicate dairy cattle may become restless in response to labor pain, but will remain recumbent longer for the final 4 h before calving.

Lying and rumination time are similarly correlated, with cows ruminating more frequently when lying (Albright, 1993; Schirmann et al., 2012). Although lying time decreased 8 h before calving in the current study, it increased and surpassed baseline levels for the final 4 h before calving. Simultaneously, an expected increase in rumination was not observed for this same period. This suggests an uncharacteristic change in normally correlated behaviors to occur in the hours immediate preceding calving, which could be used in calving prediction models.

Calving Prediction Methods

The bihourly prediction method reported in this study was developed under the assumption that following identification of the day before calving, the bihourly analysis could commence. A flaw with this approach would be if the daily analysis failed to identify the day before calving, the bihourly analysis would not commence. For example, a cow calving at 1030 h, would have a day of calving alert at 0000 h, and another alert identifying the 8 h period before calving between 0200 h and 0959 h on that same day. This was performed because fewer computations were required than examining all bihourly data, for all cows, at each individual time point. This method accomplished the same goal of providing a timely alert without the need for numerous computations.

Calving prediction using a combination of automatically collected behavioral variables has previously been attempted. Maltz and Antler (2007) described calving prediction methods using changes in daily step number, lying behavior, and number of times passing into a feeding area for 12 cows over 7 d. Maltz and Antler (2007) achieved a sensitivity of 83.3% and a specificity of 95.2% in predicting the day of calving. Ouellet et al. (2016) also evaluated a combination of variables (rumination time, vaginal temperature, and lying behaviors) for their calving prediction accuracy and achieved a 77% sensitivity, and 77% specificity. Similar to the current study, variable combinations were most useful in calving prediction than when variables were considered separately in these studies.

Although favorable results were observed in the current study, few technologies monitor rumination, lying behavior, and activity in combination. Commonly, technologies measure rumination and activity, or activity and lying behavior. To the knowledge of the authors, few technologies currently monitor all these behaviors in unison. A two-technology approach, such as that used in this study could be useful in calving prediction, but would not currently be economically justifiable on commercial farms. In the absence of a two-technology calving prediction approach, machine-learning techniques applied to technologies like the IceQube may be the best option in behavior-based calving prediction.

Farm-specific algorithms using neural networks may be useful in creating accurate alerts, particularly during calving because standard operating procedures vary between farms. Using data to train machine-learning techniques and create farm-specific prediction techniques could lead to more accurate and farm-specific event prediction for not only calving prediction, but health and estrus detection as well. Using technologies similar to the IceQube or HR Tag for calving prediction or applying machine-learning techniques to existing prediction techniques could provide additional uses for these technologies. This would increase perceived usefulness by producers and potentially increase technology adoption (Borchers and Bewley, 2015).

Future work in calving event prediction will need to focus on the sensitivity and specificity of these technologies. In comparison to calving alerts, larger specificity values have traditionally been more valued in estrus and health because of the cost associated with missed events (ISO, 2007; Hogeveen et al., 2010; Rutten et al., 2013). In animal illness detection, false positives (type I errors) can cause financial losses through unnecessary treatment (Burfeind et al., 2010). These same principles are not as applicable in calving prediction. Identifying a laboring non-laboring cow as calving could cause unnecessary treatment or handling. False negatives may be more costly with calving prediction because they are instances where systems do not detect actual calving events. The consequences of missed calving events could be extremely detrimental (dystocia, stillbirth, cow death, etc.) and may outweigh the comparative increase in farm labor from incorrectly identified calving events. Accordingly, calving prediction methods should be more sensitive and less specific if both cannot be concurrently obtained. Future research in calving prediction and economic modeling may need to explore this relationship more closely.

Additional benefits of calving prediction may be realized if calving alerts are generated from both large and small time intervals. Large time intervals would allow dairy producers ample time to move cows to maternity pens if they choose, and closely monitor cows during labor to provide assistance as necessary. Advanced knowledge of calving time would allow producers the opportunity to provide high-risk cows with calcium supplements to reduce the risk of hypocalcemia after calving (Oetzel and Miller, 2012), or potentially reduce labor-associated pain through the provision of NSAIDs during the calving process (Newby et al., 2013).

Another use for calving prediction tools would be to distinguish between eutocial and dystocial calvings. Proudfoot et al. (2009) described cows experiencing dystocia as more restless 24 h before calving than eutocial cows. Including calving ease evaluations in future machine-learning techniques may allow models to discern between dystocial and eutocial calvings. In the current study, farm staff did not record adequately specific calving ease indications and this data were not included in machine-learning analyses. A follow-up study with a larger sample size of cows is required to determine if cows experiencing dystocia can be identified using precision dairy monitoring technologies.

CONCLUSIONS

Precision dairy monitoring technologies traditionally used for health and estrus alert generation effectively quantified behavioral changes around calving. Application of machine-learning-based calving prediction methods to this data was effective in performing retrospective calving prediction. Combining activity, rumination time, and lying behavior variables in neural network machine-learning methods generated sensitive and specific alerts at the daily and 8 h level. In the absence of rumination data, technologies monitoring only activity and lying behaviors could accurately predict the day and 8 h period before calving events using neural network machine-learning techniques. Future work will need to identify calving events within smaller periods to provide alerts on which farmers can make meaningful management decisions.

ACKNOWLEDGEMENTS

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

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Table 1. Adjusted least-squares means ± SE from daily mixed models accounting for parity for 14 d of prepartum behavioral data in dairy cattle (n = 53 calvings). Results for: neck activity[1], rumination time[1], natural logarithm for number of steps[2], total motion[2], lying time[2], and lying bouts[2] are shown.

Days before calving	HR Tag		IceQube				
	Neck activity (units/d)	Rumination time (min/d)	Number of steps (steps/d)	Total motion (units/d)	Lying time(h/d)[3]		Lying bouts (bouts/d)
					Primiparous	Multiparous	
-14	343.5 ± 22.7^{a}	395.9 ± 18.2^{a}	2121.8 ± 1.1^{a}	161776.8 ± 1.4^{d}	11.3 ± 0.6	12.9 ± 0.5	9.1 ± 0.6^{b}
-13	355.2 ± 22.6^{a}	401.5 ± 18.2^{a}	2209.5 ± 1.1^{a}	365338.0 ± 1.4^{cd}	11.0 ± 0.6	11.4 ± 0.5	8.2 ± 0.6^{b}
-12	359.4 ± 23.2^{a}	403.6 ± 18.7^{a}	2262.2 ± 1.1^{a}	323659.8 ± 1.4^{cd}	10.7 ± 0.6	11.8 ± 0.5	8.1 ± 0.6^{b}
-11	352.2 ± 24.3^{a}	365.0 ± 19.5^{ab}	2309.0 ± 1.1^{a}	294344.6 ± 1.5^{cd}	11.0 ± 0.6	11.7 ± 0.5	9.1 ± 0.6^{b}
-10	362.0 ± 24.7^{a}	378.8 ± 19.7^{a}	2215.3 ± 1.1^{a}	359216.3 ± 1.5^{cd}	10.8 ± 0.6	11.5 ± 0.5	9.3 ± 0.6^{b}
-9	352.5 ± 24.3^{a}	354.6 ± 19.4^{ab}	2130.3 ± 1.1^{a}	214432.7 ± 1.5^{d}	10.6 ± 0.6	12.3 ± 0.5	9.1 ± 0.6^{b}
-8	380.0 ± 23.7^{a}	359.9 ± 18.9^{ab}	2234.8 ± 1.1^{a}	304705.4 ± 1.5^{cd}	10.9 ± 0.6	11.6 ± 0.5	9.5 ± 0.6^{b}
-7	389.5 ± 23.9^{a}	368.3 ± 19.1^{a}	2420.7 ± 1.1^{a}	400696.5 ± 1.5^{cd}	9.9 ± 0.6	12.2 ± 0.5***	10.3 ± 0.6^{b}
-6	364.6 ± 23.2^{a}	321.1 ± 18.5^{ab}	2556.5 ± 1.1^{a}	570668.0 ± 1.4^{bcd}	9.1 ± 0.6	12.3 ± 0.5***	10.5 ± 0.6^{b}
-5	385.0 ± 23.0^{a}	339.0 ± 18.3^{ab}	2454.2 ± 1.1^{a}	578988.2 ± 1.4^{bcd}	9.3 ± 0.6	12.2 ± 0.5***	10.3 ± 0.6^{b}
-4	390.4 ± 22.6^{a}	338.0 ± 18.1^{ab}	2541.5 ± 1.1^{a}	1150505.3 ± 1.4^{abc}	8.2 ± 0.6	11.9 ± 0.5***	10.8 ± 0.6^{b}
-3	398.9 ± 22.1^{a}	322.7 ± 17.7^{ab}	2489.6 ± 1.1^{a}	1297357.4 ± 1.4^{abc}	8.1 ± 0.6	11.7 ± 0.5***	10.1 ± 0.6^{b}
-2	354.0 ± 22.0^{a}	326.7 ± 17.6^{ab}	2585.3 ± 1.1^{a}	2138156.7 ± 1.4^{ab}	7.4 ± 0.6	11.2 ± 0.4***	10.3 ± 0.6^{b}
-1	331.8 ± 22.0^{a}	281.7 ± 17.7^{b}	2708.3 ± 1.1^{a}	4087308.7 ± 1.4^{a}	7.0 ± 0.6	10.2 ± 0.5***	13.6 ± 0.6^{a}

[a-d]Least-squares means ± SE values within a column displaying different superscripts differ ($P < 0.05$).

[***]Least-squares means ± SE values displaying asterisk superscripts indicate a significant day by parity interaction ($P < 0.01$).

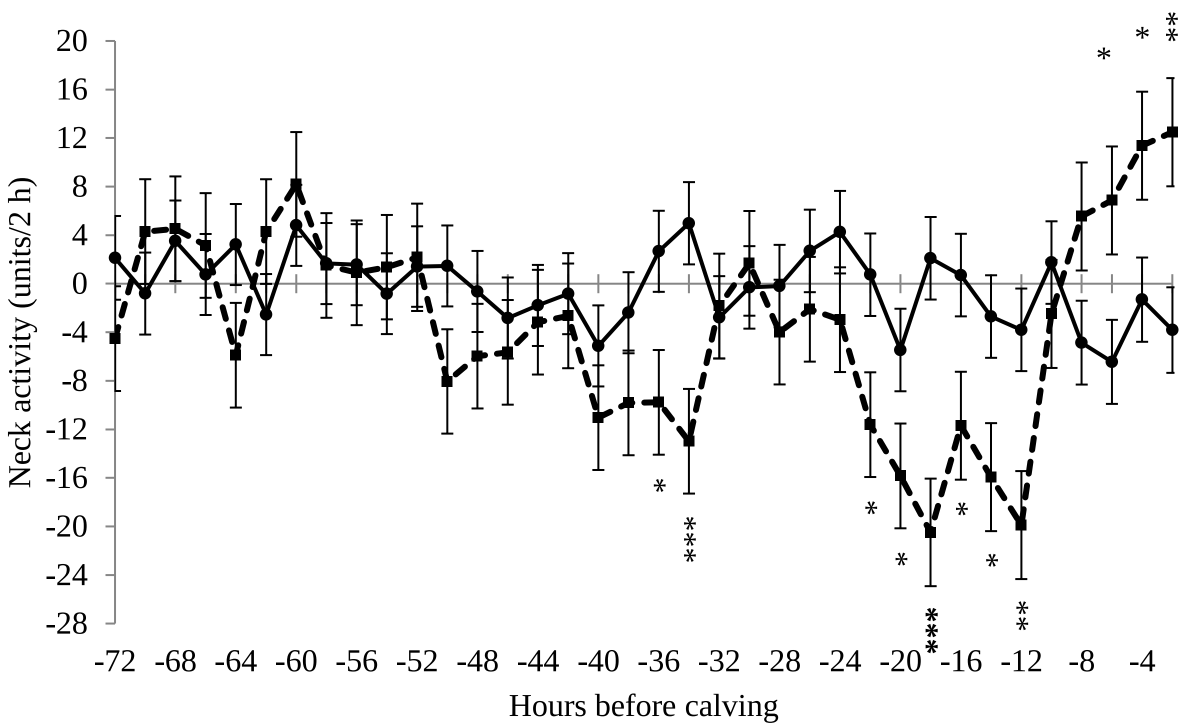
[1]Variable values measured by the HR Tag, SCR Engineers, Ltd., Netanya, Israel.

[2]Variable values measured by the IceQube sensor, IceRobotics, Ltd., Scotland.

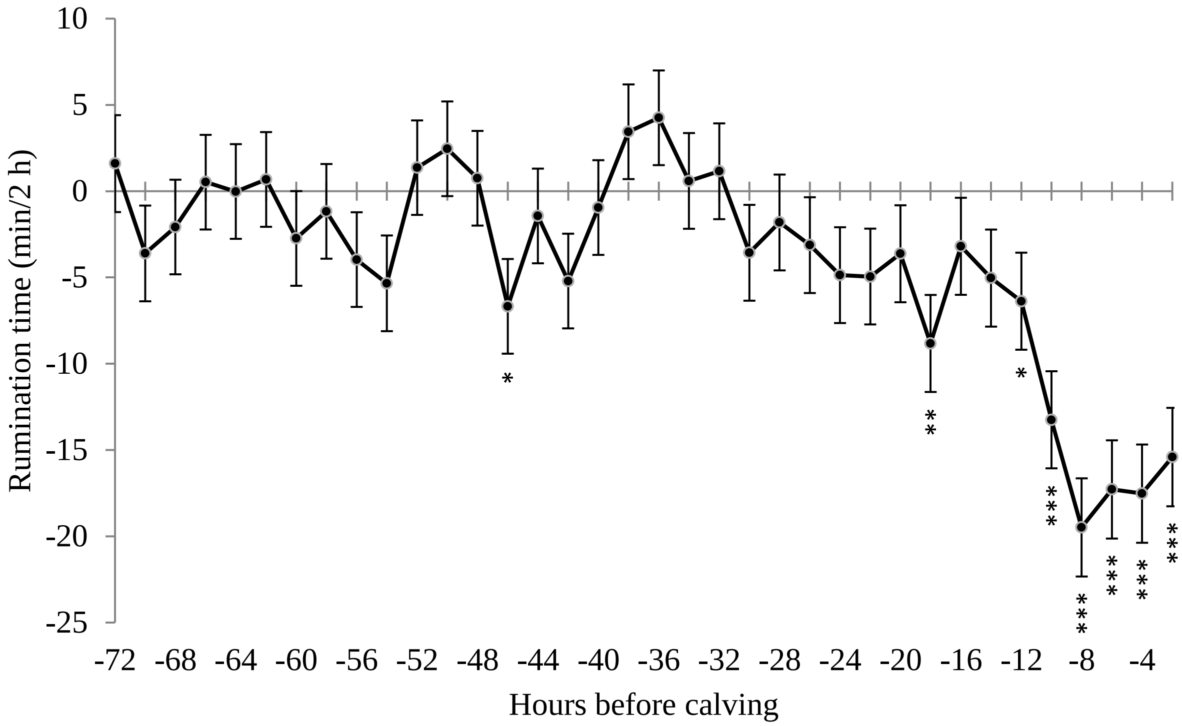
[3]A significant parity by day interaction was found for lying time. Lying time for primiparous and multiparous cows is reported.

Figure 1. Behavioral differences expressed as least-squares means ± SE in 2 h periods before calving for: **a)** neck activity[1,3], **b)** rumination time[1], **c)** number of steps[2], **d)** total motion units[2], **e)** lying time[2], and **f)** lying bouts[2]. Differences were calculated as each cow's 2 h behavioral data value minus the average of the same 2 h time of day for the previous three days. A mixed linear model calculated least-squares means for 14 d of 2 h data (72 h shown) of prepartum behavioral data (n = 53 calvings).

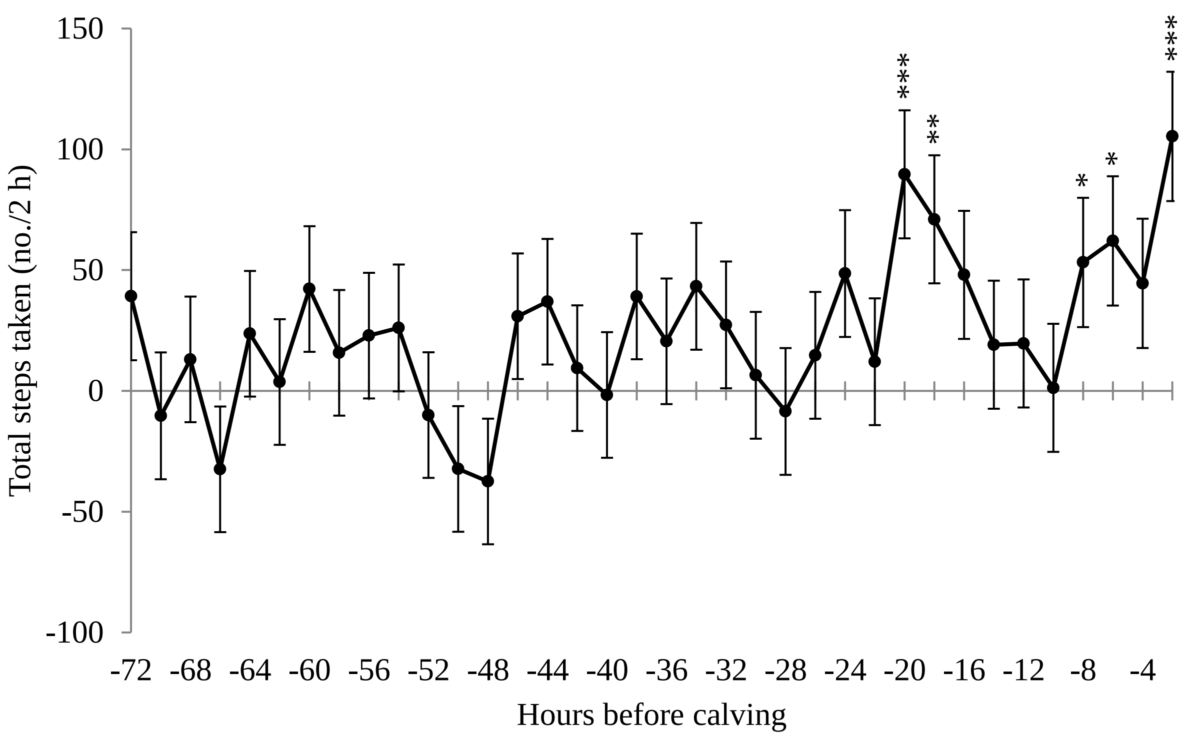
a)



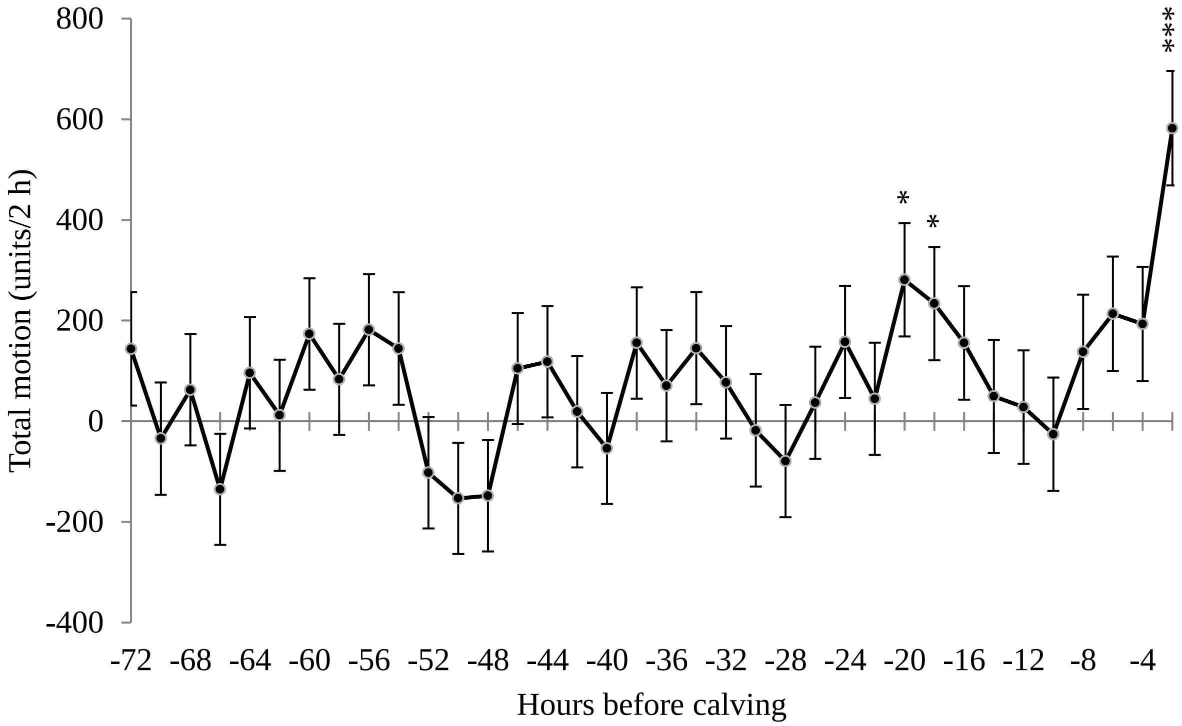
b)


Rumination time (min/2 h)
10
5
0
-5
-10
-15
-20
-25
-72 -68 -64 -60 -56 -52 -48 -44 -40 -36 -32 -28 -24 -20 -16 -12 -8 -4
Hours before calving
*
**
*
***
***
***
***
***

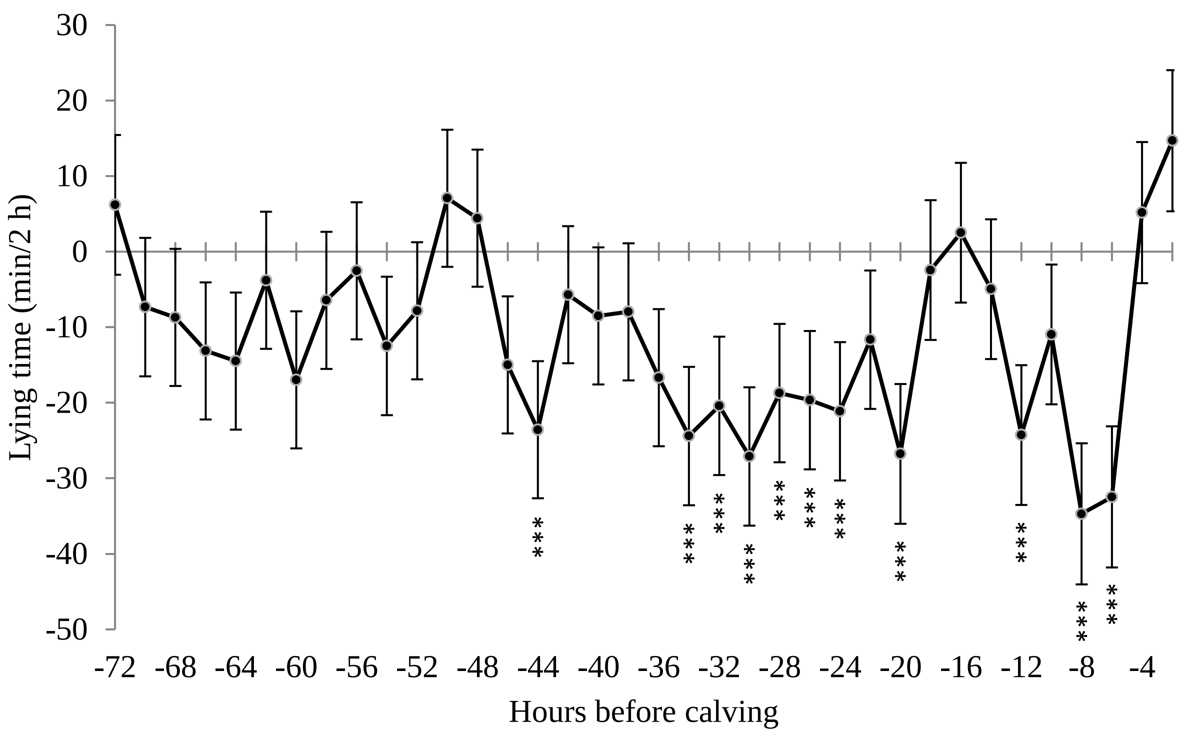
c)


Total steps taken (no./2 h)
150
100
50
0
-50
-100
-72 -68 -64 -60 -56 -52 -48 -44 -40 -36 -32 -28 -24 -20 -16 -12 -8 -4
Hours before calving
***
**
*
*
***

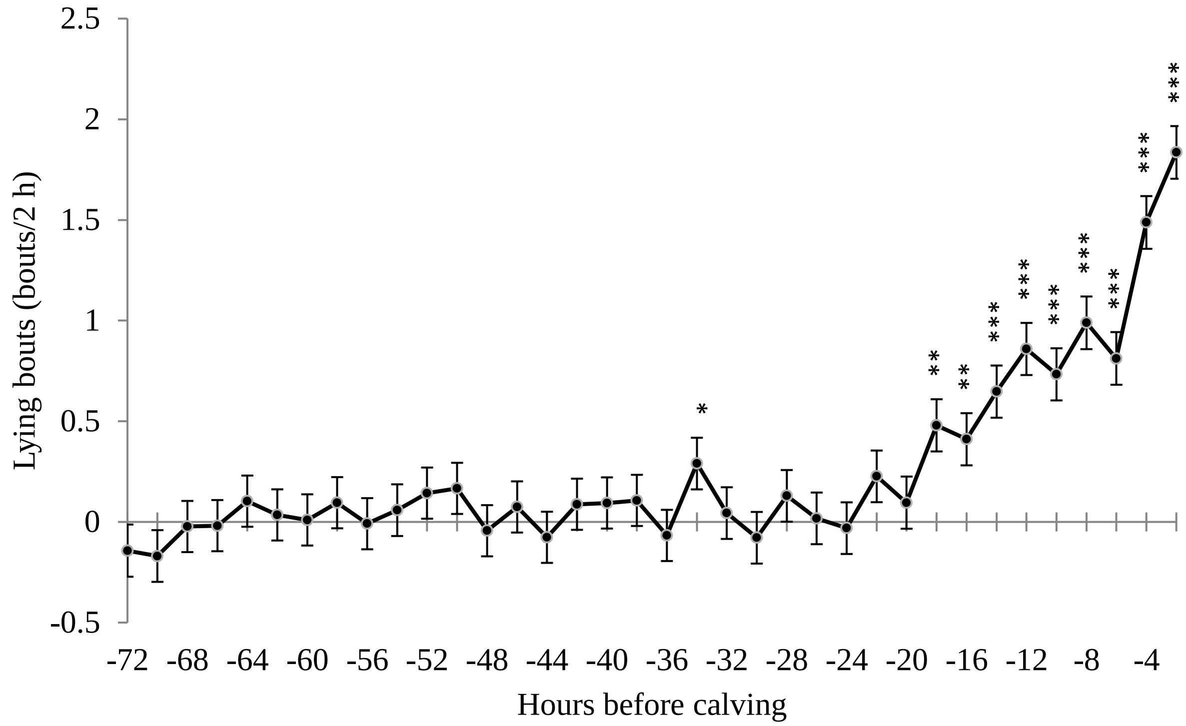
d)


Total motion (units/2 h)
800
600
400
200
0
-200
-400
-72 -68 -64 -60 -56 -52 -48 -44 -40 -36 -32 -28 -24 -20 -16 -12 -8 -4
Hours before calving

e)


Lying time (min/2 h)
30
20
10
0
-10
-20
-30
-40
-50
-72 -68 -64 -60 -56 -52 -48 -44 -40 -36 -32 -28 -24 -20 -16 -12 -8 -4
Hours before calving

f)



[1] Variable measured by the HR Tag, SCR Engineers, Ltd., Netanya, Israel.

[2] Variable measured by the IceQube sensor, IceRobotics, Ltd., Scotland.

[3]A significant parity by day interaction was found for neck activity. Neck activity for primiparous (dashed line) and multiparous (solid line) cows is reported.

* Denotes significance at *$P < 0.05$, **$P < 0.01$, and ***$P < 0.001$ for effects of 2 h time points, or effect of parity (in neck activity only) before calving on the deviation from baseline behavioral values.

Table 2. Prediction of the day before calving[1] using daily behavior data from the HR Tag[2] and IceQube[3] for 14 d before calving. Machine-learning models were developed using leave one out cross-validation methods on 80% of observations. Models were then tested using 20% of observations for testing (n = 53 calvings).[4]

Analysis	Technology	Sensitivity	Specificity	Positive predictive value	Negative predictive value
Random forest	HR Tag	12.5%	95.6%	20.0%	92.6%
	IceQube	37.5%	89.0%	23.1%	94.2%
	Combination[5]	25.0%	89.0%	16.7%	93.1%
Linear discriminant analysis	HR Tag	25.0%	96.7%	40.0%	93.6%
	IceQube	75.0%	91.2%	42.9%	97.6%
	Combination[5]	75.0%	93.4%	50.0%	97.7%
Neural network	HR Tag	0.0%	98.9%	0.0%	91.8%
	IceQube	50.0%	87.9%	26.7%	95.2%
	Combination[5]	100.0%	86.8%	40.0%	100%

[1] The day of calving was excluded from daily machine learning analyses.

[2]The HR Tag (SCR Engineers, Ltd., Netanya, Israel) measured neck activity and rumination.

[3]The IceQube (IceRobotics, Ltd., Scotland) measured lying bouts, lying time, standing time, step number, and total motion.

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

[5]Variables from both the HR Tag and the IceQube were used in combination analyses.

Table 3. Prediction of the 8 h period on the day of calving (22 h data)[1] before calving using 24 h backward moving averaged bihourly behavior data from the HR Tag[2] and IceQube[3]. Machine-learning models were developed using leave one out cross-validation methods on 80% of observations. Models were then tested using 20% of observations for testing (n = 53 calvings).[4]

Analysis	Technology	Sensitivity	Specificity	Positive predictive value	Negative predictive value
Random forest	HR Tag	72.4%	89.3%	77.8%	86.2%
	IceQube	65.5%	83.9%	67.9%	82.5%
	Combination[5]	72.4%	82.1%	67.7%	85.2%
Linear discriminant analysis	HR Tag	79.3%	80.4%	67.6%	88.2%
	IceQube	72.4%	78.6%	63.6%	84.6%
	Combination[5]	75.9%	75.0%	61.1%	85.7%
Neural network	HR Tag	58.6%	92.9%	80.9%	81.3%
	IceQube	79.3%	83.9%	71.9%	88.7%
	Combination[5]	82.8%	80.4%	68.6%	90.0%

[1]The bihourly period immediate preceding calving was excluded from machine learning analyses

[2]The HR Tag (SCR Engineers, Ltd., Netanya, Israel) measured neck activity and rumination.

[3]The IceQube (IceRobotics, Ltd., Scotland) measured lying bouts, lying time, standing time, step number, and total motion.

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

[5]Variables from both the HR Tag and the IceQube were used in combination analyses.