Using Cow Monitoring for Nutritional Goals

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INTRODUCTION

Precision dairy monitoring is "the use of information and communication technologies for improved control of fine-scale animal and physical resource variability to optimize economic, social, and environmental dairy farm performance (Eastwood et al., 2012)." Precision dairy monitoring inherently lends itself to an interdisciplinary approach of different disciplines among informatics, biostatistics, ethology, economics, animal breeding, animal husbandry, animal nutrition, and process engineering (Spilke and Fahr, 2003). Precision technologies are successful in other industries. Originally, precision technologies started with confined swine and poultry and was named precision livestock farming (Frost, 2001). Though precision technologies originated in swine and poultry, they are successfully adaptable to many different species (Frost, 2001). However, cattle add a complexity to proper use of systems (Wathes et al., 2008).

Sensors fall into 2 categories that measure the response variable: attached or un-attached (Rutten et al., 2013). An attached sensor is one that is either on the cow, for example fitted to the cow's body with a strap, or is in the cow, as is the case with rumen sensing boluses. Un-attached sensors are ones that a cow can walk past, through, or over. Two specific forms of un-attached sensors sense a response variable in-line or on-line. An in-line sensor senses the response variable continuously, and sits in the milk line. On-line sensors take a sample automatically that is then analyzed by the sensor (Rutten et al., 2013). Technologies can be divided into 4 different processes that help alert the producer to a health event:

1) The technology that measures variables (e.g. activity),
2) The measured variable information is used in an algorithm that will provide information about the cow,
3) The information is used to provide advice in a decision support type model combined with economic information or other information devised from the producer and,
4) The decision about the health event is made by the producer, or is autonomously made by the technology itself.

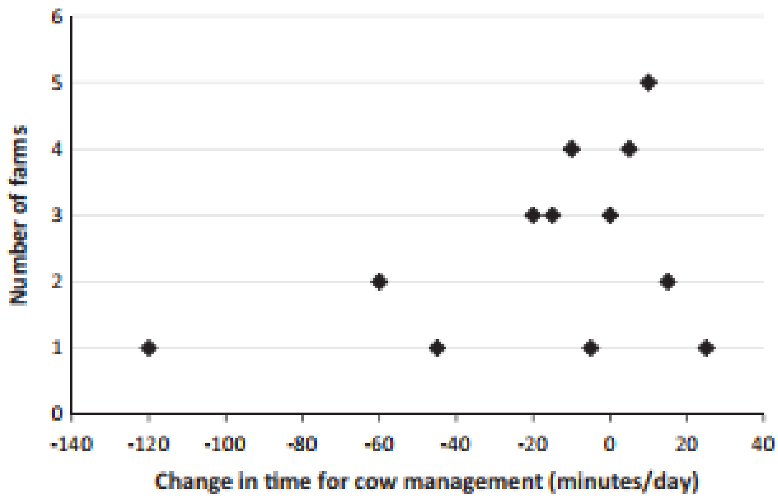
As the worldwide trend continues with smaller numbers of larger dairy farms (Bewley, 2010), producers have less time to monitor their herd; therefore, precision dairy monitoring technologies are able to help them monitor (Van Nuffel et al., 2015) and manage cattle individually (Wathes et al., 2008). Precision dairy monitoring technologies are becoming a reality as labor costs increase on farms (Rutten et al., 2013). Automatically measuring different behaviors saves producers' time and is less subjective (Bewley et al., 2010). However, a clear disconnect exists in the focus area of precision dairy monitoring technology research and on-farm application for the end user. Producers may not have established clear priorities yet for technology use and the market may be driving the research and application of precision dairy monitoring technologies (Wathes et al., 2008).

The dairy industry has gone through rapid changes in the last few years. Dairy producers have conventionally relied on labor; however, with technological advances more farms have adopted technology (Khanal et al., 2010). Khanal et al. (2010) found that larger farms adopted technology more than smaller farms, suggesting an economies of size benefit. As farms become larger, the amount of time spent with each cow diagnosing problems decreases. Utilizing a precision dairy monitoring technology could help producers move from reactive management to proactive management (Eastwood et al., 2012). Therefore, using precision dairy monitoring technologies can aid in early detection of health events (de Mol et al., 2013).

BENEFITS OF PRECISION DAIRY MONITORING TECHNOLOGIES

Benefits of precision dairy monitoring technologies are available both to the producer and the animal. Apparent benefits include increased efficiency, improved product quality, reduced economic costs, reduced opposing environmental impacts, and improved animal health and well-being (Bewley, 2010). Producer time budgets is also a

Figure 1. Farms using conventional milking systems decreased time spent on cow management on average by 10 min/d after investing in technologies[1].



[1]Figure was reproduced from Steeneveld, et al. (2015).

perceived benefit of adopting precision dairy monitoring technologies. Steeneveld et al. (2015) found that as producers adopted technologies, less time was spent on cow management (Figure 1). Though the researchers did not state exclusively, producers may have allocated more time toward important aspects of the farm, like business management. Automatic detection is an important piece of precision dairy monitoring technologies (Neethirajan, 2017). Early detection allows for more rapid recovery, reducing the spread of the disease, reducing the misuse of antibiotics, and reducing the related production, social, and economic consequences (Neethirajan, 2017).

Investment in Technologies

Although benefits of precision dairy monitoring technologies exist, adoption of these technologies is relatively slow and low compared to other industries (Bewley et al., 2010; Russell and Bewley, 2013). Adopting and applying a technology presents a significant investment for a producer; one which often has the challenge of choosing a single technology that will serve the producer for many years (Borchers and Bewley, 2015). More research is needed in investment economics and accuracy of technologies on farms because acquiring an unproductive technology could be detrimental to a producer; therefore, investments are made with caution (Borchers and Bewley, 2015). Borchers and Bewley (2015) designed a survey to assess considerations producers use to invest in a technology and to evaluate variables measured by technologies producers find most useful. Table 1 displays the standards that producers use when considering precision dairy monitoring technology adoption and their importance. Producers considered benefit-to-cost ratio as the most important criteria when investing in a technology, highlighting the need for more investment economic research. Table 2 displays the variables producers found most useful when using precision dairy monitoring technologies.

Before investing in a precision dairy monitoring technology, producer considerations and questions asked of the technology company may include:

1) What is the cost of the technology?
2) Are all technology parts under warranty?
3) How will the technology be used to manage the herd?
4) What is the customer service model of the company?
5) Is representation of the company available in the producer's area?
6) What is the sensitivity/specificity of the variable of interest?

Table 1. Standards producers use when considering precision dairy monitoring technology adoption and their importance[1].

Standard	Response, %				
	Unimportant	Of little importance	Moderately important	Somewhat important	Important
Benefit to cost ratio	0.9	0.0	3.7	31.5	63.9
Total investment cost	0.9	1.8	12.8	36.7	47.7
Simplicity and ease of use	0.9	0.9	10.1	47.4	40.4
Proven performance through independent research	1.9	0.0	7.5	53.3	37.4
Availability of local support	1.8	3.7	17.4	34.9	42.2
Compatibility with existing dairy practices and systems	0.9	4.6	11.9	46.8	35.8
Time involved using the technology	1.9	2.8	15.7	45.4	34.3

[1]Information for the table was reproduced from Borchers and Bewley (2015).

Validation and Usefulness of Technologies

Validation of technologies demonstrates that precision dairy monitoring technologies are viable for use in dairy cattle operations for management purposes. Third party groups validate many technological variables; however, not all are validated and the need for validation is strong. Many similar variables may have different results when measured on the same cow simultaneously. This may be due to the exact way the technology measures the variable, along with the algorithm the technology company has devised to output the measurement value. These differences may not mean that either technology variable is right or wrong, it may just mean that the measurement of the variable for each technology is different.

Validation of different precision dairy monitoring technologies that may help with meeting producers' nutritional goals is done by third party vendors. Canadian researchers compared the Hi-tag (SCR Engineers Ltd., Netanya, Israel) to observations made by 2 humans to validate measures generated. The researchers discovered that human observations and Hi-tag data were highly correlated, r = 0.96; $P < 0.001$, r = 0.92; $P < 0.001$, and r = 0.96; $P < 0.001$ in three trials (Schirmann et al., 2009). Similarly, Borchers et al. (2016) validated feeding and rumination behaviors in the CowManager® SensOor™ ear tag (Agis, Harmelen, the Netherlands), Smartbow® ear tag (Smartbow GmbH, Jutogasse, Austria), and Trackacow leg tag (ENGS, Rosh Pina, Israel). Where CowManager SensOor and Trackacow measured feeding behaviors; CowManager SensOor and Smartbow measured rumination behaviors. For feeding behaviors, CowManager SensOor and Trackacow both correlated well with visual observation at r = 0.88; $P < 0.01$ and r = 0.93; $P < 0.01$, respectively. For rumination behaviors, CowManager SensOor was less strongly correlated with visual observation than Smartbow at r = 0.69; $P < 0.01$ and r = 0.97; $P < 0.01$, respectively. Bikker et al. (2014) also found that the CowManager SensOor rumination time was also highly correlated to visual observation (r = 0.93; $P < 0.01$) and that eating time was less strongly correlated to visual observation (r = 0.86; $P < 0.01$). Kaniyamattam and De Vries (2014) found that an AfiLab real-time milk analyzer (Afimilk, Kibbutz Afikim, Israel) was not always in agreement with a Bentley 2000 analyzer (Bentley Instruments Inc., Chaska, MN); where fat, protein, and lactose correlations were 0.59, 0.67, and 0.46, respectively. Lohölter et al. (2013) validated a pH bolus (KB 3/04 bolus, Kahne Limited, New Zealand) and found that it was moderately correlated to manual pH measurements (r = 0.59; $P < 0.01$).

For producers to use technology for herd management purposes, the purchased technologies must perform at optimal levels. Researchers have removed data from cows or have removed cows entirely from data sets in research projects due to technologies not performing at optimal levels (de Mol et al., 2013; Borchers et al., 2016; Stone et al., 2017). In fact, de Mol et al. (2013) found that only 78 % of cow days in the model had viable measurements. The researchers found that the unreliability of the technology made it difficult to collect data consistently and stated that automated monitoring is only useful when technology systems are functioning at optimal performance levels.

Table 2. Variables producers find most useful when using precision dairy monitoring technologies[1].

Variable	Response, %				
	Not useful	**Of little usefulness**	**Moderately useful**	**Somewhat useful**	**Useful**
Mastitis	0.0	0.0	1.9	19.4	78.7
Standing estrus	0.0	0.9	2.8	16.5	79.8
Daily milk yield	0.0	09	6.4	11.9	80.7
Cow activity	1.8	1.8	5.5	16.5	74.3
Temperature	3.8	2.8	11.3	22.6	59.4
Feeding behavior	0.9	0.0	15.7	35.2	48.1
Milk components	0.9	4.6	13.8	27.5	53.2
Lameness	0.0	4.6	17.4	26.6	51.4
Rumination	3.8	3.8	18.9	28.3	45.3
Hoof health	0.9	3.7	19.4	39.8	36.1
Rumen activity	4.6	3.7	24.1	27.8	39.8
Lying and standing behavior	2.8	8.3	25.7	33.9	29.4
Rumen pH	5.5	11.0	26.6	29.4	27.5
Jaw movement and chewing activity	4.6	13.0	25.9	29.6	26.9
Respiration rate	7.5	13.2	29.2	32.1	17.9
Body weight	8.3	18.5	30.6	24.1	18.5
Body condition score	9.2	12.8	36.7	25.7	15.6
Heat rate	11.2	16.8	38.3	21.5	12.1
Animal position and location	19.3	23.9	31.2	13.8	11.9
Methane emissions	34.3	30.6	20.4	10.2	4.6

[1]Information for the table was reproduced from Borchers and Bewley (2015).

Economics of Technologies

Investing in precision dairy monitoring technologies is usually a complicated chore. The standard net present value approach can be misleading and the costs and benefits of acquiring new technologies is often complex and requires interactions of many variables (Bewley et al., 2010). A real dearth of information exists for economics of investing in technologies, especially when using the technologies to detect health events. However, Steeneveld et al. (2015) researched the overall economics of investing in technologies. The researchers discovered that farms using automated milking systems had a total capital costs of €9.72 and €13.97/100 kg of milk before and after technology adoption, respectively. However, labor costs and variable costs did not change. For farms with conventional milking systems economic change did not occur for capital costs, labor costs, or variable costs after implementing a precision dairy monitoring technology. Farms with automated milking systems saw an increase in total revenue from €43.93 to €46.38/100 kg of milk before and after technology adoption, respectively. The authors speculated that the increased revenue may have been from the increase in milk production after technology implementation. Farms with conventional milking systems saw no change in revenues after technology adoption.

Available Precision Dairy Monitoring Technology Variables

The amount of technologies and variables being measured on the market is growing and in some sense, is saturated for a few measured variables. As precision dairy monitoring technologies grow, new variables and ways to monitor these variables have been fashioned (Borchers and Bewley, 2015). Variables currently measured include daily milk yield, milk components, step number, body temperature (at various places on or within the cow), milk conductivity, automatic estrous detection, daily body weight (Bewley, 2010), animal position/location, blood in milk content, activity (neck, head or total activity), jaw movements and chewing activity, lameness, progesterone, **LDH** (lactate dehydrogenase), **BHB** (beta-hydroxybutyrate), lying times, lying bouts, standing time, mastitis, milk flow, milk time, milk yield, rumen pH, somatic cell count, standing heat, vacuum in milk line, rumination time, feeding time, feeding bouts (Borchers and Bewley, 2013), and body condition score. Other proposed measured variables include reticular contractions, heart rate, vaginal mucus electrical resistance, odor, glucose, acoustics, color (an indicator of cleanliness), infrared udder surface temperature, and respiration rates (Bewley, 2010).

Utilizing Precision Dairy Monitoring Technologies for Nutritional Goals

When trying to meet nutritional goals, rumination and feeding behavior monitors are at the forefront of one's mind; however, automated body condition scoring, in-line sensors monitoring milk components, and rumen pH boluses will also aid in meeting nutritional goals. Rumination and feeding behavior monitors historically have been used to monitor and detect health events instead of meeting producer's nutritional goals. This empirical data is missing, especially feed intake for individual cows, which can hinder herd management decision making (McParland and Berry, 2016). Bach et al. (2007) discerned differences in automatically recorded feeding behavior between lame and sound cows and Van Hertem et al. (2013) discerned differences in automatically recorded rumination behavior for lame cows on day of lameness diagnosis compared to sound cows. Gonzalez et al. (2008) discovered that cows diagnosed with ketosis had decreased feed intake, feeding time, and feeding rate automatically recorded by roughage intake control feeders.

Body condition score assesses body reserves on an animal and can be used as an indirect gauge of reproductive and health status of an animal. Body condition reflects energy balance in cows (Fischer et al., 2015). Bewley et al. (2008) used digital images to discern body condition scores accurately. However, researchers stated that future efforts should automate this system to predict body condition scores. An automated system does exist currently, but more research is warranted for on-farm application.

Dairy farms offer a unique environment in that 2 to 3 times daily, cows are milked, offering a biological sample that could be used to analyze in-line the physiological state of the cow. Therefore, the daily analysis of milk and milk constituents provides a way to conduct daily farm management and decision making (McParland and Berry, 2016). Infrared spectroscopy (the scattering of light) is used to quantify milk quality variables already; therefore the information already gathered can be applied directly to on-farm applications. McParland and Berry (2016) discovered that the accuracy of predicting energy intake, energy balance, and feed efficiency was 0.88, 0.78, and 0.63, respectively, using spectroscopy. The authors did state that further investigation is warranted for on-farm applicability.

Subacute ruminal acidosis is when the rumen pH is below 5.5 for 3 h/d (Stone, 2004; Blowey, 2015). Continuous sensing of rumen pH may help determine the state of subacute ruminal acidosis in cattle (Lohölter et al., 2013); however, sensor drift when measuring rumen pH is a real concern. Further investigation on sensor drift is warranted (Lohölter et al., 2013). When using rumen pH boluses, it is unclear if the bolus depicts clear value to the producer (Rutten et al., 2013). The same may also be true with other sensors, but just because automation of a variable can occur, it does not necessarily mean as an industry we know what to do with the data. As an example, if we automatically detect daily body condition scores on cows as they exit the parlor, how would the producer use that knowledge to better manage the herd. As an industry, more work needs to be conducted to evaluate how the vast amount of information on individual cows may help with farm management and decision making on-farm. With all sensors, there is a need for improvement, heightened detection, and better data performance (Rutten et al., 2013).

CONCLUSION

Precision dairy monitoring technology is still in the early stages of development. Therefore, when investing in a technology producers may want to evaluate the following aspects:

1) What is the cost of the technology?
2) Are all technology parts under warranty?
3) How will the technology be used to manage the herd?
4) What is the customer service model of the company?
5) Is representation of the company available in the producer's area?
6) What is the sensitivity/specificity of the variable of interest?

More research is needed to understand the economic consequences of investing in a technology, especially to target specific health or feeding events. There is still a lack of information surrounding how feeding behavior, rumination behavior, automated body condition score, and rumen pH boluses can help producers meet individual nutritional goals. However, even with the lack of information of how precision dairy monitoring technologies may be applied to on-farm situations, the future looks bright.

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