Symposium review: Precision technologies for dairy calves and management applications*

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ABSTRACT

There is an increasing interest in using precision dairy technologies (PDT) to monitor real-time animal behavior and physiology in livestock systems around the world. Although PDT in adult cattle is extensively reviewed, PDT use for the management of preweaned dairy calves has not been reviewed. We systematically reviewed research on the use and application of precision technologies in calves. Accelerometers have the potential to be used to monitor lying behavior, step activity, and rumination, which are useful to detect changes in behavior that may be indicative of disease, responses to painful procedures, or positive welfare behaviors such as play. Automated calf feeding systems can control delivery of nutritional plans to individualize feeding and weaning of calves; changes in feeding behaviors (such as milk intake, drinking speed, and unrewarded visits) may also be used to identify early onset of disease. The PDT devices also measure physiological and physical attributes in dairy calves. For instance, temperature monitoring devices such as infrared thermography, ruminal boluses, and implanted microchips have been assessed in calves, but no herd management-based commercial system is available. Many other PDT are in development with potential to be used in dairy calf management, such as image and acoustic-based monitoring, real-time location, and use of enrichment items for monitoring positive emotional states. We conclude that PDT have great potential for application in dairy calf management, enabling precise behavioral and physiological monitoring, targeted feeding programs, and identification of calves with poor health or behavioral impairments. We strongly encourage further development and validation of commercially available

technologies for on-farm application of the monitoring of dairy calf welfare, performance, and health.

Key words: accelerometer, automated feeder, bovine respiratory disease, calf disease, animal welfare

INTRODUCTION

Precision livestock farming can be defined as the use of real-time monitoring technologies to manage animals in commercial environments, especially to measure individual data and detect temporal variability (Halachmi and Guarino, 2016). Precision dairy technology (PDT) is a broadly used term that includes technologies used with farm equipment (e.g., sort gates, production measurements, or automated scales), including technologies that can be worn by the animal (wearables). Although many technologies are labeled PDT, for the purpose of this review, we define PDT as a technology that automatically collects information in real time from each animal, known as the per animal approach (Halachmi and Guarino, 2016).

Animal management based on PDT data is adopted on dairy farms around the world, but PDT has traditionally been used on adult animals, not calves and heifers. For example, according to producer surveys, the most common use of PDT is to manage milk production in New Zealand (Edwards et al., 2015) and Australia (Mackinnon et al., 2010) and to monitor for estrus, mastitis, and milk production in the United States (Borchers and Bewley, 2015) and the Netherlands (Steeneveld and Hogeveen, 2015). Furthermore, a producer- and veterinarian-reported survey based in Europe showed significant interest in using PDT to manage estrus, health, and milk production of dairy cattle, but adoption has been slow for reasons related to limited research that outlines useful applications on-farm (Palczynski, 2016). Therefore, European and other producers may adopt PDT in the near future if the usefulness of these technologies is made clear. Indeed, producers around the world adopt PDT to monitor changes in individual animal behavior and physiology in real time (Halachmi and Guarino, 2016).

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Typically, PDT establish a behavioral baseline on an individual level, and deviations from normal behavior trigger an alert to producers (Lokhorst et al., 2019). Changes in behavior often occur for reasons that need human intervention (e.g., estrus; Dolecheck et al., 2015) or illness (Stangaferro et al., 2016). Similarly, PDT in adult cattle can monitor the individual for physiological deviations from her established baseline (reviewed by Dominiak and Kristensen, 2017). Precision dairy technologies are also used to manage dairy calves, but to our knowledge there has been no review of PDT regarding the management of preweaned dairy calves.

The use of PDT with confidence requires validation of individual animal data to ensure trustworthy measurements of behavioral and physiological variables; this is done by assessing precision, accuracy, and bias of the technology operating in the production setting. Validation studies compare behavior data recorded by the technology to a known measure of behavior, such as visual observation, or to another validated technology known as the gold standard. Validation studies have highlighted the importance of validating multiple PDT in one location (Borchers et al., 2016), as well as validating the same technology (ear-based accelerometer in this instance) in different settings such as on pasture (Pereira et al., 2018), in tiestalls (Zambelis et al., 2019), or in freestalls (Borchers et al., 2016), and in cattle of different ages (Reynolds et al., 2019). This type of validation of PDT is essential to establish that it is precise and accurate in multiple settings. Here we will discuss the validation of and the parameters evaluated for PDT used in calf management. For the purpose of this review, we adopted the following specifications for validation of PDT against a gold standard: studies that obtained high ($r > 0.90$) correlations (Hinkle, 1988), acceptable sensitivity and specificity ($>0.80\%$), and near-perfect agreement (Cohen's Kappa $r > 0.81$; McHugh, 2012). The PDT that met these criteria were stated as validated for measuring specific behaviors, whereas studies that did not meet these criteria were considered to require further development.

The objective of this narrative review is to critically review the literature on the use of PDT for managing the performance and health of preweaned calves. We focus on 3 general categories of PDT: tri-axial accelerometers, automated calf feeding systems (AFS), and PDT that measure physiological or physical attributes (e.g., infrared imaging, heart rate monitors, ruminal boluses, and 3-dimensional cameras). Moreover, some studies evaluated herd management-based PDT, which have a long battery life and are worn by the animal for months at a time, and other studies used research-based PDT, which have shorter sampling intervals, and due to a shorter battery life, often require frequent

removal of the technology to retrieve data. Therefore, we clarify which research used herd management-based or research-based PDT during our review.

For each of these categories of PDT, we describe the specific available technologies, their validation, and application in calf management. We also describe opportunities and limitations to the use of these PDT to improve the management and welfare of young calves on-farm. Where possible, we include recommendations for future research and considerations for application on-farm.

TRI-AXIAL ACCELEROMETERS

Tri-axial, or 3-dimensional, accelerometers are devices that measure the angle of tilt with respect to the earth and the amount of dynamic acceleration; the data provided by accelerometers can be used to determine position relative to the ground (i.e., vertical, horizontal) and the speed and direction of movement. Three-dimensional accelerometers provide a noninvasive, objective measure of normal behavior patterns using algorithms to process raw position, speed, and direction data; these devices have been used for decades (Robert et al., 2009). Due to their small size and weight, low cost, and potential ability to record high-resolution behavioral data for days or months at a time, these devices are increasingly used to monitor behavior of livestock. This is no different for dairy calves, where accelerometers are a predominant PDT and appear in the form of pedometers, ear tags, collars, and sleep monitors.

Validation of Accelerometers

Accelerometers have been developed and validated to measure a variety of behaviors in calves. A summary of the studies ($n = 24$) that evaluated validity of accelerometers in young calves in the last decade is presented in Table 1. The behavior most commonly validated in calves is lying time, using pedometer accelerometers for herd management (Trénel et al., 2009; Swartz et al., 2016), ear-based accelerometers for herd management (Roland et al., 2018a), and pedometer accelerometers for research (Bonk et al., 2013). Indeed, one accelerometer for herd management showed high agreement with visual observation by different research groups to measure lying activity in calves (Trénel et al., 2009; Finney et al., 2018). Another accelerometer for herd management was also validated to record lying bouts and step activity (Swartz et al., 2016). Similarly, an accelerometer for research was validated for multiple locomotor behaviors including lying bouts (Bonk et al., 2013), gait (de Passillé et al., 2010), and acceleration

associated with locomotor play (Luu et al., 2013). A published methodology for this research-based accelerometer for data sampling, processing, and interpretation of activity behaviors is available (Ledgerwood et al., 2010). This work demonstrates that several accelerometers (both herd management-based and research-based) are available to measure lying time in calves.

However, validation of accelerometers to measure rumination and feeding behavior for herd management has had mixed results. For example, one ear-tag accelerometer for herd management was validated for rumination against live observation in one study (Hill et al., 2017), but was not validated for rumination or feeding time against video observations in another study (Reynolds et al., 2019). A different in-ear herd-management accelerometer also had moderate agreement for rumination but poor agreement for feeding behaviors such as milk intake from a teat, water, and solid feed intake (Roland et al., 2018a) and milk intake from a bucket (Roland et al., 2018b). Moreover, a halter-based research accelerometer was validated in calves for measuring rumination, provided that events less than 5 min in duration were removed (Eslamizad et al., 2018). These differences between studies suggest that further technology development is needed to reliably measure rumination in calves, and feed intake cannot yet be recorded by accelerometers. Next, we discuss the application of accelerometers for use in calves including disease detection, monitoring performance, and identification of emotional states such as play and pain.

Accelerometers for Disease Detection and Monitoring Performance

Accelerometers may be useful technologies to identify changes in step activity and lying behavior of calves before illness. For example, young steers experimentally induced with bovine respiratory disease (BRD) complex had increased lying time (Toaff-Rosenstein et al., 2016) compared with control calves, observed with research-based accelerometers. Calves fitted with the same research-based accelerometer and infected with *Mannheimia haemolytica* demonstrated laterality of lying toward the left side compared with control calves, though lying time did not differ (Hixson et al., 2018). Similar findings are seen in calves with naturally occurring BRD and fitted with a herd-management accelerometer; calves had fewer daily steps from d 1 to 3 after BRD diagnosis and fewer lying bouts 2 d before diagnosis up to the day of antibiotic treatment, but did not differ in lying time (Swartz et al., 2017) compared with matched healthy calves. Thus, the association between lying bouts and disease may be used as a sensi-

tive indicator for induced and naturally occurring BRD illness in future research.

Accelerometers have also been used to detect changes in lying behaviors during the development of navel inflammation and diarrhea. For example, calves wearing research-based accelerometers had less lying time than healthy calves when presenting navel swelling, yet diarrhea status did not affect lying bouts (Studds et al., 2018). However, others found that calves wearing research-based accelerometers and presenting severe diarrhea due to *Salmonella* had decreased lying bouts and increased lying bout duration in the 3 d before diagnosis (Lowe et al., 2019a). Lying bouts also decreased in veal calves from 2 d before to 9 d after diarrhea diagnosis (Belaid et al., 2020); however, the validation study for measuring lying bouts for this herd-management accelerometer was only moderately correlated with video observations in older steers, and thus more research is needed to determine whether this accelerometer is acceptable for use in young calves (Wolfger et al., 2015). A research-based accelerometer study has also detected reduced lying time in calves 2 d before diarrhea and increased lying time on the day of diarrhea diagnosis (Sutherland et al., 2018). Therefore, it is likely that disease affects activity in calves and that this activity change can be detected with accelerometers. Given the extensive development and validation of accelerometers for measuring lying activity, the differences noted among individuals and between studies in terms of activity are most likely related to other factors rather than a limitation of the technology, such as how calves respond to illness.

Changes in rumination behavior have been associated with disease in dairy cattle (Beauchemin, 2018), and therefore have a potential to detect disease in calves. However, automated monitoring of rumination in calves has had limited application. This is likely related to the variable ages at which accelerometers are able to measure rumination; for example, rumination was detected using herd-management accelerometers from 6 wk (Hill et al., 2017) to 8 wk of age (Reynolds et al., 2019), but there is debate about at what age true rumination occurs in calves (reviewed by Khan et al., 2016). Recent work evaluated rumination, activity, and eating with a herd-management accelerometer to assess calf performance on 4 different milk feeding programs (Dennis et al., 2018); although no differences were found in these behaviors between treatment groups, there is great potential for this technology to identify individual calves that may be performing poorly in response to particular feeding programs. To our knowledge, no study has monitored rumination or activity with PDT to identify calves that are performing poorly on farms.

Table 1. Studies¹ (n = 24) that evaluated validity of accelerometers for measuring activity-related behavior, including lying or inactivity, standing, walking, and locomotor play (n = 11), sleep (n = 1), or feeding behaviors (n = 9), including rumination time, drinking, or feeding time in young calves

Behavior	Device and attachment location	Sample size and observation period	Device sampling strategy	Validation	Reference
Lying behaviors					
Lying time	IceQube (IceRobotics, Edinburgh, Scotland); attached to leg	9 calves (12 h)	1 reading/s	Mean sensitivity (99.6%), specificity (98.0%) in reference to video recordings	Trénel et al., 2009
Lying time	HOBOPendant G data logger (Onset Computer Corp., Bourne, MA); attached to leg	Experiment 1 = 8 calves (37 2-h periods); Experiment 2 = 19 calves (19 24-h periods)	30-s or 60-s intervals; processed as unfiltered, 1-min or 2-min filters	Best correlation with direct observation (0.99 for 60-s interval on right hind leg); Bland-Altman (mean difference = 0.0 ± 3.1 min); predictability (99.3%), sensitivity (99.2%), and specificity (97.7%)	Bonk et al., 2013
Lying time	AfiTag II (Afirmilk Ltd., Kibbutz Afikim, Israel); attached to leg	5 calves (7 h)	Nearest 1 min, reported in 3-min intervals	Correlation with video (0.99) and HOBOPendant (0.99)	Swartz et al., 2016
Lying time	IceQube (IceRobotics); attached to rear leg	12 calves (4 d; 96 consecutive h)	1 reading/s summed 15-min intervals Unfiltered and filtered	Bland-Altman against manual video observations (mean difference = 3.6 s; SD not reported), filtering method did not change outcome	Finney et al., 2018
Lying time	SMARTBOW ear tag (Smartbow GmbH, Weibern, Austria); attached to ear	15 calves (4 h)	10 readings/s	Cohen's kappa with video (0.88). Sensitivity (94.4%), specificity (94.3%), accuracy (94.3%), and precision (95.8%)	Roland et al., 2018a
Lying bouts	HOBOPendant G data logger (Onset Computer Corp.); attached to leg	Experiment 1 = 8 calves (37 2-h periods); Experiment 2 = 19 calves (19 24-h periods)	30-s or 60-s intervals; processed as unfiltered, 1-min or 2-min filters	Best correlation with direct observation (0.85 for 60-s interval on left hind leg); Bland-Altman (mean difference = 0.68 ± 0.75 bouts)	Bonk et al., 2013
Lying bouts	AfiTag II (Afirmilk Ltd.); attached to leg	5 calves (7 h)	1 bout = minimum of 3 min lying down	Correlation with video (0.99) and HOBOPendant (0.93)	Swartz et al., 2016
Activity behaviors					
Steps	AfiTag II (Afirmilk Ltd.); attached to leg	5 calves (7 h)	15-min intervals	Correlation with video (0.99)	Swartz et al., 2016
Gait (walking, trotting, and galloping)	HOBOPendant G data logger (Onset Computer Corp.); attached to leg	7 calves (10 min)	33 readings/s	Correlation between average number of peaks in acceleration data and number of steps observed from video in forward axis (0.92), vertical axis (0.93), and vector sum of forward and vertical axes (0.88); distribution of interpeak intervals in forward axis differed among gait types ($P < 0.001$)	de Passillé et al., 2010
Locomotor play	HOBOPendant G data logger (Onset Computer Corp.); attached to leg	30 calves (10 min)	33 readings/s during recording, simulated 11 readings and 1 reading/s during postprocessing	Correlation between duration of peaks of acceleration in vertical axis and duration of locomotor play in video (0.97 for 11 readings/s and 0.92 for 1 reading/s)	Luu et al., 2013
Inactive	CowManager SensOor (Agis, Harmelen, the Netherlands); attached to ear	16 calves (12 h/d for 4 d)	1 reading/min	Regression against live observations ($R^2 = 0.97$), slope not different from zero	Hill et al., 2017

Continued

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Behavior	Device and attachment location	Sample size and observation period	Device sampling strategy	Validation	Reference
Sleep ² (REM and NREM)	Purpose-built accelerometer; attached to neck collar	10 calves (24 h)	25 readings/s	Sensitivity for lying awake (40%), REM (66%) and NREM (81%)	Hokkanen et al., 2011
Feeding behaviors					
Rumination	Hi-Tag Electronic Rumination-Monitoring System (SCR Engineers Lmted., Netanya Israel); attached to neck collar	35 calves grouped by age (2-h intervals 3 times 1 d)	1 summed reading/2 h	Cohen's kappa with live observations (r = 0.99), moderate correlation (r = 0.89) and moderate regression ($R^2 = 0.79$) for calves at 8 wk bias for over- and under-estimation 20 min	Burfeind et al., 2011
Rumination	Rumiwatch System (GmbH Feeding Technology, Liestal, Switzerland); attached to halter	10 calves (12 h for 1 d)	1 reading/min	Regression against video recordings ($R^2 = 0.82$), slope 0.87; filtering out rumination events <5 min ($R^2 = 0.93$) slope 0.93	Eslamizad et al., 2018
Rumination	CowManager SensOor (Agis); attached to ear	16 calves (12 h/d for 4 d)	1 reading/min	Regression against live observations ($R^2 = 0.91$), slope not different from zero	Hill et al., 2017
Rumination	Hi-Tag Electronic Rumination-Monitoring System (SCR Engineers Lmted.); attached to neck collar	32 calves 4 (2 h) intervals pre- and postweaning	1 summed reading/2 h	Observer agreement correlation (r = 0.96), correlation pre- and postweaning rumination time to live observation (r = 0.70), probability distribution different ($P < 0.001$)	Rodrigues et al., 2019
Rumination	SMARTBOW ear tag (Smartbow GmbH); attached to ear	15 calves (4 h)	10 readings/s	Cohen's kappa with video (0.80), sensitivity (89.4%), specificity (94.9%), accuracy (93.9%), and precision (78.5%)	Roland et al., 2018a
Rumination	CowManager SensOor (Agis); attached to ear	24 weaned calves (two 2-h observation periods per calf)	1 reading/min	Concordance correlations (0.55) and correlations (r = 0.63) against visual observations, bias correction factor (0.88)	Reynolds et al., 2019
Solid feed intake	SMARTBOW ear tag (Smartbow GmbH); attached to ear	15 calves (4 h)	10 readings/s	Cohen's kappa with video (0.52), sensitivity (73.2%), specificity (83.7%), accuracy (81.2%), and precision (57.9%)	Roland et al., 2018a
Water intake	SMARTBOW ear tag (Smartbow GmbH); attached to ear	15 calves (4 h)	10 readings/s	Cohen's kappa with video (0.04), sensitivity (2.7%), specificity (99.9%), accuracy (99.4%), and precision (10.0%)	Roland et al., 2018a
Milk intake (teat fed)	SMARTBOW ear tag (Smartbow GmbH); attached to ear	15 calves (4 h)	10 readings/s	Cohen's kappa with video (0.07), sensitivity (4.2%), specificity (99.7%), accuracy (97.6%), and precision (27.1%)	Roland et al., 2018a
Milk intake (bucket fed)	SMARTBOW ear tag (Smartbow GmbH); attached to ear	3 calves (5 d, 24 h/d)	10 readings/s	Cohen's kappa with video (0.68), sensitivity (82.9%), specificity (96.9%), accuracy (96.2%), and precision (60.4%)	Roland et al., 2018b
Feeding time	CowManager SensOor (Agis); attached to ear	16 calves (12 h/d for 4 d)	1 reading/min	Regression against live observations ($R^2 = 0.75$), slope not different from zero	Hill et al., 2017
Feeding time	CowManager SensOor (Agis); attached to ear	24 weaned calves (two 2-h observations per calf)	1 reading/min	Concordance correlations (0.72) and correlations (r = 0.88) against visual observations, bias correction factor (= 0.83)	Reynolds et al., 2019

¹Studies were selected from manuscripts published in the last decade (2009–2019) after full text screening. Electronic databases searched included ScienceDirect, PubMed, Ebscohost, Google Scholar, and Web of Science.

²REM = rapid eye movement; NREM = nonrapid eye movement sleep.

There is substantial opportunity to apply machine learning models to predict a calf's risk for disease, or to identify a calf's negative response to environmental change such as weaning (Lopreiato et al., 2018) or cold stress (Olson et al., 1980). This could be done by classifying positioning and acceleration of behaviors into rumination and lying activities, and monitoring for changes in these behaviors using a herd-management accelerometer. Machine learning is a broad term that refers to several types of statistical analysis beyond linear modeling (Alpaydin, 2004). For example, one of the most common machine learning approaches is forward neural networks, which establish nodes with raw input data trained to known outcomes, then the weight of different input nodes calculates error, and this trained error is compared with the remaining learning data set integrated into the nodes (Alpaydin, 2004). However, further research is needed to develop a machine learning model that automatically uses deep learning to interpret accelerometer activity and classify these behaviors. A calf behavior-based predictive algorithm should include a myriad of measurements to assess calf health, such as lying behavior from accelerometers, milk and solid feed intake behaviors from AFS, grooming, or social behaviors. It is unclear whether rumination and play behaviors measured from accelerometers also change during early onset of illness, and particularly if there are sensitive behavioral indicators specific to BRD and diarrhea; these areas merit further investigation for inclusion in a machine learning algorithm.

Other Applications for Accelerometers

Accelerometer technologies have the potential to assess behaviors that reflect positive or negative welfare states (Rushen et al., 2012). Play behavior, such as running, kicking, jumping, and bucking, is widely supported as an indicator of improved animal welfare (Ahloy-Dallaire et al., 2018); play is thought to improve emotional states and is typically not expressed when the animal is under threat or if its fitness is challenged (Held and Spinka, 2011). Indeed, play behavior is reduced in calves under stressful conditions such as weaning (Mintline et al., 2013) and during nutritional restriction (Rushen et al., 2016). Play behavior has been measured automatically using research-based accelerometers (Luu et al., 2013), making it possible to monitor the expression of and changes in play behavior that indicate an increase or decrease in positive welfare. Accelerometers can also monitor for negative welfare indicators such as changes in activity patterns associated with painful procedures such as dehorning (Sutherland et al., 2018) and castration (White et al.,

2008). We caution that accelerometers in these studies were set to higher sampling frequencies than herd-management accelerometers. It remains to be seen if changes in these activity patterns (indicating possible positive or negative welfare states such as play or pain) can be detected at lower sampling frequencies and with herd-management accelerometers that are more practical for commercial farm use.

AUTOMATED FEEDING SYSTEMS TO MEASURE FEEDING BEHAVIOR

Automated calf feeders have gained popularity as a calf-management tool and are the most extensively used PDT in calves. Automated calf feeders have the versatility of administering nutritional plans (i.e., milk and grain) and can be used to monitor feeding behavior of individual calves. One of the great advantages of AFS for dairy calves is the ability to feed higher volumes of milk without increasing labor requirements (Kung et al., 1997). A Canadian survey showed that producers who implement AFS already fed calves more milk and already used PDT elsewhere on their farm compared with producers who manually fed their calves (Medrano-Galarza et al., 2017). Also, some AFS can monitor and record individual feeding behavior of dairy calves. The AFS technologies record daily milk or solid feed intake, drinking speed per minute, and visits to the feeder (rewarded with milk or solid feed, or unrewarded without milk or solid feed), and are very useful for the management of dairy calves. We describe validation and 2 main areas of application for AFS on farms, including individualized feeding programs and disease detection.

Validation of Automated Feeders

Automated calf feeders must be accurate and precise in quantity for each delivery of milk or grain to calves. Therefore, the system must be calibrated following manufacturer recommendations. Calibration is fundamental to the accuracy and precision of these systems, where the user is able to adjust the measured output from the AFS based on true recorded milk, water, or grain output. To our knowledge, there is no validation of the accuracy and precision of the AFS systems at the farm level or under different on-farm circumstances. Some AFS can also record visits to the feeder when feed is received (rewarded) and visits to the feeder when the calf is not eligible for feed (unrewarded). Both nutritive rewarded visits and unrewarded visits in AFS have been compared with video recordings of stall-occupancy behavior during competitive feeding conditions at the AFS (Jensen, 2004) and when calves experienced

hunger (De Paula Vieira et al., 2008). However, these behaviors have not been formally validated by direct video observation.

Automated Feeders for Individualized Feeding Programs

One of the most important features of an AFS is the measurement of feeding behaviors of individual calves when fed with different milk allowances and restrictions. The AFS allocates daily milk allowance in meals or portion sizes over a 24-h period, when the allocation of ad libitum versus restricted milk allowances affects AFS feeding behavior. For instance, calves fed restricted milk allowances (<6 L/d, compared with higher or ad libitum allowances) consumed fewer meals, drank immediately at the time of delivery rather than throughout the day (Miller-Cushon et al., 2013), had more unrewarded visits to the milk feeder (Jensen, 2006; Rosenberger et al., 2017), and spent more time in the AFS before weaning, which lowered the efficiency of the system (Jensen, 2006). Milk flow and meal size also have important effects on feeding behavior; limited flow (300 mL/min) in 2-L meal sizes decreased daily milk intake in calves offered 8 L of milk/d (Nielsen et al., 2018), and large milk meal sizes (compared with smaller meals) reduced competition and improved feeder efficiency for calves housed in large groups (24 calves per nipple; Jensen, 2004). Moreover, one study suggested that the timing of offering peak milk is important: calves had higher milk intake when peak milk (12 L/d) was offered at 3 wk compared with 4 wk of age, but postweaning weight and time at the solid feed bunk was not affected (Cantor et al., 2019). This work together suggests that restricting milk leads to abnormal meal patterns and increased unrewarded visits, which may indicate hunger in calves, and that milk feeding strategy affects how calves use the system. Therefore, we suggest that the AFS should be programmed to offer calves free-flow milk at a minimum of 2-L meal sizes and at least 8 L/d to ensure calves can express their natural feeding behaviors and to optimize AFS efficiency.

Another important advantage of AFS technologies is the ability to wean and transition individual calves onto solid feed diets. When feeding calves higher amounts of milk, it is critical to consider a feeding strategy that appropriately weans calves onto a solid-feed diet that promotes appropriate rumen development and avoids a growth check (reviewed by Khan et al., 2011; Kertz et al., 2017). Step-down weaning is a weaning scheme that reduces the daily milk provided to calves in a 2-part process (Khan et al., 2007), providing time for appropriate lower gut transitioning (Steele et al., 2017)

and encouraging calves to consume grain without compromising growth (Welboren et al., 2018). However, there is large individual variability when calves begin to consume solid feed on this type of weaning program; some of this individual variation can be explained by personality traits, where more exploratory calves ate more solid feed and gained more weight (Neave et al., 2018, 2019). Therefore, calves fed high milk allowances may benefit from plans tailored to the individual calf's needs and traits. For instance, recent work showed that a tailored weaning strategy (where milk was removed based on individual intake of grain) resulted in less overall milk consumption and greater grain intake from the AFS but similar growth to those calves weaned at a set age (Benetton et al., 2019). This suggests that some calves are able to successfully wean earlier than others (i.e., they cope appropriately with the weaning transition while maintaining growth), making it economical to remove milk from these individuals and offer more milk to those requiring more time to wean; recent work suggests that calves needing more time to wean are slower to learn to use the milk-feeding equipment (Neave et al., 2019). Others have used AFS to implement different gradual weaning strategies for calves fed ad libitum milk in the first month of age; calves weaned based on initial individual milk consumption had greater postweaning weights than calves weaned by removing fixed quantities of milk at fixed ages (Welboren et al., 2018). Overall this work suggests that AFS are able to maximize nutritional accommodation of individual calves in a group setting. Further research should identify best methods to individually wean calves on the basis of their needs and traits and develop software for automatically weaning calves once these traits are identified.

Automated Feeders for Disease Detection

Automated calf feeding systems automatically record daily feeding behaviors of individual calves, which serve as baseline measures from which deviations may indicate illness. Changes in feeding behavior measured by AFS have been associated with diarrhea and BRD diagnosis. For example, a retrospective study of 10 US AFS farm records of calves fed >7 L of milk/d found that the drinking speed of sick calves changed 3 d before treatment for diarrhea and on the day of BRD detection compared with pair-matched healthy calves (Knauer et al., 2017). Unrewarded visits can also serve as an indicator of illness; studies found a decrease in visits 2 d before clinical signs of BRD in calves fed 6 or 8 L of milk/d (Svensson and Jensen, 2007), 2 to 3 d before diagnosis with diarrhea in calves fed 6 L of milk/d (Sutherland et al., 2018; Lowe et al., 2019a), and 4 d

before illness in calves fed >7 L of milk/d (Knauer et al., 2017). However, changes in these behaviors that are associated with illness appear to be related to milk allowance. Calves receiving 12 L/d or ad libitum milk had lower milk intake, fewer visits, and greater duration of visits to the feeder in the days preceding illness detection, and calves fed restricted amounts of milk (4 L/d) only showed reduced duration of visits to the feeder on the day of illness detection (Borderas et al., 2009). However, calves fed an intermediate volume of milk from an AFS (6 L/d) reduced milk intake in the 4 d before diarrhea diagnosis (Sutherland et al., 2018). This work suggests that some changes in feeding behaviors associated with illness may depend on milk-feeding strategy (e.g., drinking speed and milk intake), but other behaviors (e.g., unrewarded visits) appear to decrease before and during a disease bout in calves fed a range of milk allowances. Unrewarded visits are known to be an indicator of hunger (increasing in frequency with decreasing daily milk allowances; Rosenberger et al., 2017), and thus may be a sensitive feeding-behavior measure that will change with the onset of disease due to their low biological necessity to the calf. In summary, calves that become sick may change feeding behaviors before disease onset, but milk-feeding strategy affects this relationship. Future research should investigate the potential of feeding behaviors to predict disease onset with more complex predictive models.

Statistical integration techniques have been explored to combine AFS feeding behaviors to predict which calves will soon become sick, but the system was no more sensitive than visual inspection of calves (Knauer et al., 2018). As described previously for accelerometers, machine learning processes have successfully integrated multiple behaviors such as rumination and activity recorded with accelerometers to detect parturition in cattle (Borchers et al., 2017). Future research should determine whether machine learning can integrate AFS feeding behaviors with other PDT, such as accelerometers, that together may effectively and efficiently identify potentially sick calves sooner than by visual inspection.

MONITORING PHYSIOLOGICAL AND PHYSICAL ATTRIBUTES

Although AFS and accelerometers are the most used PDT in young calves, other PDT for measuring physiological or physical attributes of calves have recently been investigated for their validity and applications in calves (Table 2). Several PDT measure body temperatures through various means, such as reticulorumenal temperature (herd management-based bolus meter; Knauer et al., 2016), implantable temperature micro-

chips (research-based; Hill et al., 2016; Lee et al., 2016), tympanic ear temperature (herd management-based; McCorkell et al., 2014), and infrared thermography imaging (IRT; research-based for measuring ocular, side or shoulder temperature; Schaefer et al., 2007). Recently, IRT was also validated for thermal fluctuations around the nostrils to measure respiration rate (Lowe et al., 2019b). Moreover, an algorithm has been validated to automatically process temperatures recorded from IRT; previously these temperatures required manual calculation in the software (Lowe et al., 2020). There are also several reports using research-based heart rate monitors (Grøndahl-Nielsen et al., 1999; Stewart et al., 2008; Byrd et al., 2019), and one herd management-based technology to measure rumination using a microphone (Burfeind et al., 2011). Currently only 2 studies have described measuring the physical condition of calves, including a validated herd-management partial weight scale (Cantor et al., 2020) and a research-based 3-dimensional camera to estimate body condition (Song et al., 2014). However, implementation of a 3-dimensional camera for herd management in calves is not yet available, owing to validity issues or lack of development for data processing to make the software appropriate for herd-management use in calves. We further describe the validity and applications of these PDT in the monitoring of physiological and physical attributes of calves.

Validation and Application of PDT for Monitoring Physiological Attributes

Several PDT can be used to monitor body temperature of dairy calves, including indwelling reticulorumenal boluses, tympanic temperature sensors, implanted microchips, and infrared imaging cameras. However, some PDT have not yet been validated in calves. For example, indwelling reticulorumenal boluses were able to measure reticulorumenal temperature when water intake was accounted for in adult lactating cattle (Cantor et al., 2018), but sensitivity and positive predictive ability to identify fever ($\geq 39.5^{\circ}\text{C}$) in calves were poor (Knauer et al., 2016). Therefore, the use of reticulorumenal boluses to estimate core temperature or fever in calves is currently limited. An alternative method of estimating core temperature is using tympanic temperature, initially described by Wiersma and Stott (1983) in cattle; subsequently, a sensor recording inner ear tympanic temperature of calves was developed to alert the producer when fevers were detected, but a high fever threshold was required to eliminate false positive readings (McCorkell et al., 2014). Other methods of measuring core temperature have had limited validity in calves; for instance, implanted microchips were affected by implant site (but no validation was

Table 2. Studies¹ (n = 12) which evaluated validity of devices for measuring physiological (n = 10) or physical (n = 2) attributes of dairy calves

Measured attribute	Device and attachment location	Sample size and observation period	Device sampling strategy	Validation	Reference
Body temperature measures					
Indwelling rumen temperature bolus	Bella Ag Cattle Temperature System (Bella Ag LLC, Loveland, CO); administered into reticulorumen	10 calves (wk 1, 3, 7, and 9 of age)	Hourly, over 6-h period, once per week	Comparison with water bath temperature [$r = 0.98$; Lin's concordance correlation coefficient (CCC) = 0.95]. Comparison with rectal temperature ($r = 0.40$; CCC = 0.29). Repeatability metric not provided.	Knauer et al., 2016
Implanted microchip	iButton (DS1922L, Maxim Integrated, San Jose, CA); implanted into 3 different neck regions	Seven 5-mo-old steers (autumn/winter, summer season)	1-h intervals	Compared with rectal temperature, but metrics for accuracy, precision, and repeatability not provided.	Lee et al., 2016
Microchip temperature logger	Thermocron (model DS1922L-F5#, Maxim Integrated Products Inc.); taped to the skin over the tail vein opposing the rectum	56 calves (4 to 60 d of age)	10-min intervals	Comparison with rectal temperature ($R^2 = 0.62$). Comparison with water bath temperature (paired temperatures did not differ). Repeatability metric not provided.	Hill et al., 2016
Tympanic temperature	Fever Tags (Amarillo, TX); applied as ear tag with probe into the external auditory meatus of the ear	113 calves (10 to 20 d after arrival at auction)	15-min intervals	Tags correctly activate over 39.8°C threshold: repeatability 57.1% in 40.2°C water bath; repeatability 85.7% in 40.5°C water bath. No false positives due to high temperature threshold.	McCorkell et al., 2014
Infrared thermography imaging (IRT)	Hand-held FLIR S60 camera (FLIR Comp. Boston, MA), capturing eye temperature	65 weaned calves with true positive diagnosis for bovine respiratory disease (BRD), of which 37 had IRT images for 4–6 d before diagnosis	4–6 d before BRD diagnosis (number of images not reported)	Compared with clinical disease scoring, 4 to 6 d before diagnosis: sensitivity = 69% vs. 14%; specificity = 77% vs. 19%. No available means to determine true eye temperature. Repeatability metric not reported.	Schaefer et al., 2007
IRT	Automated FLIR S60 camera (FLIR Comp.); mounted on a motorized shaft at the water station, capturing eye temperature	9 weaned calves with true positive diagnosis for BRD, 44 weaned calves with true negative diagnosis for BRD	1 image each time calf came to the water station (resulting in about 20 images per calf per day) to detect clinical onset of illness	Compared with clinical disease scoring, day of diagnosis: sensitivity = 100% vs. 100%; specificity = 97% vs. 90%. No available means to determine true eye temperature. Repeatability metric not reported.	Schaefer et al., 2012
IRT	Hand-held IRT camera (ThermaCAM S60; FLIR Systems AB, Danderyd, Sweden), capturing eye, back, side and shoulder areas	43 calves diagnosed with any illness (7 d before to 7 d after diagnosis)	1 image taken daily	Compared temperatures pre- and postclinical diagnosis. Clinical illness verified, but no diagnosis threshold reported for back, side and shoulder areas (i.e., change in temperature used to identify illness). Side temperature increased, and shoulder decreased, before diagnosis. No available means to determine true back, side, and shoulder temperatures. Repeatability metric not reported.	Lowe et al., 2019a

Continued

Table 2 (Continued). Studies¹ (n = 12) which evaluated validity of devices for measuring physiological (n = 10) or physical (n = 2) attributes of dairy calves

Measured attribute	Device and attachment location	Sample size and observation period	Device sampling strategy	Validation	Reference
IRT	Hand-held IRT camera (ThermaCAM S60; FLIR Systems AB), capturing temperature fluctuations positioned at nostril	5 calves with 47 sets of 5 breaths	12 recordings	Compared nostril temperature fluctuations against video observations of nostril flare to flank movements. High regression ($R^2 = 0.93$), and no bias with Bland-Altman.	Lowe et al., 2019b
Heart rate (HR) measures HR and HR variability (HRV) (linear measures)	Polar HR monitors (S810i, Polar Electro Oy, Helsinki, Finland); strapped around thorax of calf, immediately behind forelimbs	30 calves, 6 wk old (total 40 min, before and after disbudding)	Continuous	Compared HR and HRV pre- and postdisbudding. No threshold for pain reported (i.e., change in HR/HRV used to identify pain). HR/HRV increased in 5 min postdisbudding. No available means to determine true HR/HRV. Repeatability metric not reported.	Stewart et al., 2008
HRV (nonlinear measures)	Polar H10 (Polar Electro Oy, Kempele, Finland); strapped around thorax of calf, immediately behind forelimbs	25 calves, 4–7 wk old (d -1, 0, 1, 3, and 5 relative to disbudding)	Continuous for 2 h (d -1), 8 h (d 0), 2 h (d 1, 3, 5) relative to disbudding. 5-min data set selected for analysis within each sampling period	Compared nonlinear HRV measures pre- and postdisbudding. No threshold for pain reported (i.e., change in HRV used to identify pain). Detrended fluctuation analysis scaling exponent was greater in medicated disbudded calves compared with sham. No available means to determine true HR/HRV. Repeatability metric not reported.	Byrd et al., 2019
Rumination	Hi-Tag rumination-monitoring system (SCR Engineers Ltd., Netanya, Israel); using microphone on a neck collar positioned behind the left ear	15 calves in 3 groups of 4, 6, and 9 wk of age	Three 2-h periods on a single day at resolution of 2 min	Compared with direct observation: correlation coefficient ($r = 0.65, 0.70, 0.89$); coefficient of determination ($R^2 = 0.42, 0.49, 0.79$). Repeatability metric not reported.	Burfeind et al., 2011
Body condition (hip height and weight)	PMDTM 3-D ToF camera (IFM Electronic GmbH, Essen, Germany); mounted above the automated milk feeder	68 calves, 6 to 110 d of age	3-dimensional image of calf's back taken when in feeder at 8 frames/s	Compared with BW on scale: coefficient of determination ($R^2 = 0.91$). Compared with manual hip height measures: accuracy = 0.028 m. Repeatability metric not reported.	Song et al., 2014
BW	Partial scale attached to an automated milk feeder (Combi; DeLaval, Tumba, Sweden)	20 calves, 5 to 85 d of age (including 14 d postweaning)	19 weights per calf. Total of 376 weights after cleaning algorithm removed deviations of 15% from average of previous 3 d	Compared with BW on full-body scale: correlation coefficient ($r = 0.99$), coefficient of determination ($R^2 = 0.99$). Bland-Altman plots showed low bias. Repeatability metric not possible with this technology.	Cantor et al., 2020

¹Studies were selected from manuscripts published since 2007 after full text screening. Electronic databases searched included ScienceDirect, PubMed, Ebscohost, Google Scholar, and Web of Science.

performed; Lee et al., 2016), and temperature sensors taped on the skin under the tail head were only moderately related to rectal temperature and were influenced by ambient temperatures (Hill et al., 2017). Overall, temperature-sensing technologies hold potentially important applications in calves, especially for the iden-

tification of fever; however, further work is required to validate temperature sensors for monitoring changes in body temperature as an indicator of disease onset.

A noninvasive temperature-sensing technology such as IRT can measure radiating heat. The true temperature of body locations such as the eye, shoulder, or side

is unknown in calves (i.e., there is no gold standard to determine accuracy of IRT devices); thus, IRT is almost exclusively used to determine relative change in body temperature, most often in response to illness or pain. A high precision for imaging eye temperature of feedlot calves is evident in IRT and can detect increased eye temperature 4 to 6 d before clinical expression of BRD symptoms in research settings (Schaefer et al., 2007). This technology was also able to identify calves with clinical BRD symptoms (sensitivity 100%, specificity 97%) on the day of diagnosis when automatically recording eye temperature at a water station (Schaefer et al., 2012). A decrease in eye temperature of dairy calves was also observed using IRT immediately following disbudding, followed by an increase for 15 min after disbudding, suggesting that IRT may also be useful to identify individuals experiencing discomfort (Stewart et al., 2008). However, IRT requires controlled positioning and lighting, which is an important drawback for its commercial application. Therefore, others have explored the use of hand-held IRT cameras to determine if their integration into an AFS would be practical. Most recently, Lowe et al. (2019a) found that IRT temperature of the shoulder decreased and side increased before diarrhea onset in calves experiencing a natural outbreak of *Salmonella*, but there was no observed change in eye temperature. This suggests that changes in body temperature at different locations such as eye, shoulder, or side may depend on the type of illness (e.g., BRD vs. diarrhea) and may suggest the experience of discomfort or pain, which warrants further investigation.

Heart rate monitors have been used to identify individuals that may be experiencing pain after disbudding, including measures of sympathetic activity such as heart rate variability, high frequency to low frequency ratio (Stewart et al., 2008), and parasympathetic activity by measuring root mean square of successive differences (Stewart et al., 2009). As with IRT devices, heart rate monitors have been used to detect relative changes in linear and nonlinear measures that would indicate if the animal is experiencing pain or stress (Stewart et al., 2008; Byrd et al., 2019). Heart rate was found to increase after disbudding, but there were inconsistent findings between studies for heart rate variability, depending on which measure was analyzed (Stewart et al., 2008, 2009). Most recently, nonlinear approaches to the measurement of heart rate variability have been used to assess pain responses to disbudding (Byrd et al., 2019), but with limited findings. Decreased heart rate variability has also been described as an indicator of stress associated with separation from the cow and isolation in an individual pen for neonatal calves (Clapp et al., 2015). Ede et al. (2019) noted that heart

rate variability may reflect physical activity rather than emotional state in response to pain or stress; indeed, this was reported in healthy dairy cattle (Hagen et al., 2005), but has yet to be documented in dairy calves. Therefore, more work is needed to understand if physical activity affects heart rate in calves, or if heart rate variability is associated with pain. Thus, we suggest that the current use of heart rate monitors is limited to research-based settings because girth straps must remain in proper position, proper electrode placement is required for transmission of data, and the identification of pain using heart rate variability has produced mixed results.

Finally, though rumination behavior is most commonly recorded with accelerometers, other herd management-based PDT have recorded rumination using a microphone. Rumination patterns have been reported in calves as young as 2 d of age (Lopreiato et al., 2018), but this PDT failed to find agreement between auditory rumination records against live observations in calves less than 9 wk of age (Rodrigues et al., 2019), despite its validity in heifers older than 9 mo (Burfiend et al., 2010). Therefore, caution should be applied when interpreting results from studies when the validity of the PDT has not been determined in a range of calf ages.

Validation and Application of PDT for Monitoring Physical Attributes

Monitoring of BW and structural growth is critical for the successful rearing of dairy calves but is labor intensive and requires handling of animals. A herd-management partial weight scale attached to an AFS is validated for estimating calf BW using a software algorithm with a further data-cleaning step (Cantor et al., 2020). In a recent paper, the use of 3-dimensional cameras to measure BW, BCS, and dairy type traits of Holstein heifers have a good prospect for future commercial use, and either lateral or dorsal images could be used for BW prediction. Although the measurement of BCS and dairy type traits were shown to be possible, models still need improvements (Martins et al., 2020). Machine vision has also been used to automatically measure physical attributes of calves entering an AFS; a 3-dimensional camera using time-of-flight technology (measuring return time of reflected light) accurately recorded hip height and weight measures, suggesting that this technology could be used to automatically monitor the growth of calves; however, currently it is only used in research settings (Song et al., 2014). Future research should investigate the application of these systems for individually weaning calves based on weight, structural measures, or individual traits in early life.

FUTURE DEVELOPMENTS AND POSSIBLE ADAPTATIONS

In addition to the technologies described above, there are several other devices that have shown valuable applications in adult dairy cattle or other species, and thus show promise for use in dairy calf management, but published reports in calves are not yet available. Here we describe a few examples, but this list is not exhaustive and technologies develop at a fast pace.

The ability to rapidly identify and track the behavior of individual animals, or a group as a whole, is becoming a reality (reviewed by Siegford et al., 2016). Movement patterns of broiler flocks using “optical flow” on recorded video correlated with mortality rate, poor gait movements, and birds with hock burn (Dawkins et al., 2009, 2012); optical flow algorithms could predict feather pecking in laying hens (Lee et al., 2011) and tail biting in pigs (Li et al., 2020). A major advantage of this technology is that it operates by assessing movements of the whole group (i.e., does not require identification of individual animals). This technique could also be applied in dairy-calf barns to identify and predict outbreaks of disease by capturing changes in or expression of abnormal behaviors. Group housing is growing in popularity, and thus group-level monitoring would be a useful and applicable management tool.

Another PDT in development is the real-time localization of calves. In the past, real-time localization systems were predominantly used in human healthcare and product-processing facilities for tracking locations of staff and equipment as they travel through the facility (Islam et al., 2018). Such devices can automatically record animals’ locations; for example, local positioning has been used to locate dairy cattle within a barn (Gygax et al., 2007), and such a system is already commercially available for adult dairy animals (Wolfger et al., 2017). An animal’s use of space can provide information on its health and welfare, making real-time localization information a useful technology. For instance, lame cows can be identified by changes in time at the feed bunk and by daily distance traveled in the barn (Barker et al., 2018). Livestock use of specific areas of a barn can indicate design flaws (e.g., crowding at entrance areas, feeder, or waterer), ventilation and heat-stress related issues (e.g., crowding at particular ends of the pen to access or avoid air flow; Erbez et al., 2012), or use of lying stalls (e.g., increased time spent standing fully inside the stall in heifers diagnosed with metritis; Lomb et al., 2018). In these cases, location tracking can be used to determine occupancy in particular areas of the barn that may affect the welfare of adult cattle. Others have integrated location data with that of accelerometers to describe the activity

patterns of sows affected by lameness (Traulsen et al., 2016). Similar applications may be possible in dairy calves, where real-time localization could be useful for monitoring health.

The development of software and algorithms to identify and classify vocalizations is an interesting development in other livestock industries. The acoustic analysis of sound amplitude produced by pigs can offer insight into their responses to changes to their environment and change as they age (Cordeiro et al., 2018). Additionally, it can detect coughs by piglets (Exadaktylos et al., 2008). Acoustic analysis of webcam footage recorded in a farrowing barn has been used to identify and prevent piglet crushing (Manteuffel et al., 2017). This concept has also been applied to the monitoring and analysis of coughs in dairy calves (Ferrari et al., 2010), which could be extended to automated detection of respiratory illness. Acoustic analysis of vocalizations can also offer information on emotional valence and arousal in several mammalian species, including positive and negative valence vocalizations in cattle, pigs, horses, and goats (Briefer et al., 2017; Manteuffel et al., 2017; Green et al., 2020). It is of particular interest that discriminant function analysis could identify positive and negative vocalizations belonging to particular individuals in cattle, suggesting that vocalizations are individually distinct (Green et al., 2020). Dairy calves vocalize in response to hunger (Thomas et al., 2001), and thus acoustic analysis could serve a role in the measurement of stress associated with weaning, when vocalization rate is most often highest in calves.

Ruminal pH boluses may be useful to monitor calf performance, especially metabolic status of calves during weaning. Ruminal acidosis occurs in calves during weaning (Kim et al., 2016), but provision of dietary forage such as hay can mitigate the time spent below a specific pH threshold (Laarman and Oba, 2011; Laarman et al., 2012). Moreover, providing dietary forage to calves changes gene expression and fatty acid profile ratios, which are associated with healthy ruminal epithelium (Kim et al., 2016). Ruminal pH boluses have been validated for use in sheep when compared with a manual pH meter, and thus show potential for use in calves. However, this technology requires regular calibration, has a very short lifespan of only weeks to a few months, and it cannot be retrieved from the calf until slaughter. Despite these limitations, ruminal pH meters show promising application for making decisions around the timing and process of weaning for individual calves.

An under-researched area for the use of PDT is to monitor use of enrichment items as an indicator of positive welfare (or change in use as an indicator of reduced welfare). Dairy calves are known to use a variety of “enrichment” items, e.g., stationary brushes, lollies,

and plastic chains (Pempek et al., 2017), and mechanical (automated) grooming brushes (Zobel et al., 2017; Horvath and Miller-Cushon, 2019). The use of brushes is known to decline when adult dairy cows experience negative welfare states, such as pain or illness (Fogsgaard et al., 2012; Moncada et al., 2020). This may also occur in dairy calves, and consequently the automated monitoring of enrichment use may be useful to identify positive or negative welfare states. One study used PDT to monitor brush use in heifers with a radio frequency identification system, but too many false positive recordings led to poor validity (Toaff-Rosenstein et al., 2017). Most recently, researchers developed an ultrahigh frequency system by incorporating a radio frequency identification system with a current-transducer sensor system to detect changes in voltage, indicating if the brush was on or off; this system successfully eliminated many false positive readings in calf brush use (Falk et al., 2018). These studies provide examples of how PDT can be applied to automatically monitor use, or change in use, of items in the environment that may be associated with positive or negative welfare states.

There are many other possibilities for the development and application of precision technologies for dairy calf management; the fast pace of the field means that new developments are always arising, and the integration of ethologists, engineers, and other professionals are fundamental to successful application of technologies in an on-farm setting (as already identified by other authors; Rushen et al., 2012). All novel PDT have advantages and disadvantages, but few currently are useful for longitudinal monitoring of individual animals. Moving forward, we first recommend that all PDT are appropriately validated for their intended use in dairy calves, particularly third-party validation for commercially available products. Methods for validation should follow some standardized reporting guidelines or developed standards that can be compared. Finally, the development of novel management approaches for dairy calves based on the information provided by PDT is fundamental in the future.

CONCLUSIONS

Several PDT are able to monitor behavioral and physiological measures in dairy calves, which has important applications. Accelerometers are validated for step activity, lying bouts, lying time, feeding time, rumination, and sleep in calves. Automated calf feeding systems can record a variety of feeding behaviors including milk and solid feed intake, feeding rate, feeding time, and visits, in addition to delivering specific quantities of milk and solid feeds to calves. Accelerometers and AFS can be used to identify deviations in behavior associated with

illness, and AFS have the added advantage of individualizing feeding and weaning programs and monitoring calf performance. Other PDT are able to measure body temperature, heart rate, and body condition of calves, but further software development is necessary to scale these technologies to automatic recording on commercial farms. Overall, PDT hold potential for serving as a tool in the management of dairy calves by tailoring nutritional management, identifying disease, and monitoring positive and negative welfare states.

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