Association between daily cow data and milk production in dairy herds milked with automatic milking systems

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Chapter 1

Literature review

PRECISION DAIRY FARMING

Automation is defined as the use of computerized or automated control systems for operating equipment. The adoption of automation technologies in dairy production has increased considerably worldwide in the last few years and is changing the way farmers manage their herds. Early reports mentioned improvements of animal welfare, working conditions, and milk quality, protection of the environment, and reduction in production costs as the main goals of automation on dairy farms (Gravert, 1988). A more recent study conducted in the U.S. showed that flexibility of labor with a potential reduction in the need for employees was among the primary reasons reported by producers when considering the adoption of a new automated technology (i.e., automatic milking systems; de Jong et al., 2003). According to a survey by Adcock et al. (2015), over 50% of dairy farm workers are immigrants and they are present on the 34% of U.S. dairy farms that produce 79% of the milk. However, the constant changes in immigration policies have increased the difficulty of dairy farmers to find the help they need. Therefore, technology may help offset the need for hired labor to a certain extent.

Besides the aforementioned benefits of automated systems in dairy production, an additional advantage is the possibility of integration with other technologies. One of the most widespread automated systems on dairy farms is the automatic milking system (**AMS**), in which additional sensors can be easily incorporated. Wearable sensors are helpful management tools that provide producers with large amounts of data, which may be used to make data-driven decisions. Other current or proposed technologies used on dairy farms include devices to record or quantify body temperature, milk conductivity, daily body weight, ruminal pH, rumination behavior, feeding behavior, location within the barn or pasture paddocks, and more (Bewley, 2010). The combined use of technologies aiming to improve management, animal, and farm performance has been referred to as *Precision Dairy Farming* (Bewley, 2010), which was formally defined as "*the use of information and communication technologies for improved control of fine-scale animal physical resource variability to optimize economic, social, and environmental dairy farm performance*" (Eastwood et al., 2012). Precision Dairy Farming technologies provide data for producers on the individual- and herd-level, allowing for real-time monitoring and decision-making. These technologies are generally user-friendly since system interfaces send alerts based on built-in algorithms for tracked data, such as alerts for production drops, potential health issues, and timing of calving and insemination events.

AUTOMATIC MILKING SYSTEMS

Attempts to develop an AMS date back to the 70's and 80's in Japan and Germany, respectively (Notsuki and Ueno, 1977; Ordolff, 1983). However, it was only in 1992 that the first AMS was installed on a dairy farm in the Netherlands. Improvements have made the AMS a viable option for dairy farmers resulting in a rapid increase in the number of AMS farms throughout the world. Besides being a substitute for traditional milking equipment and labor, the AMS and its associated technologies have the potential to monitor a series of production variables, such as milk production, rumination, activity, body weight, udder health, and reproductive status. Some of these measurements are possible due to sensor technologies, which can be easily linked to the AMS software, allowing for thorough monitoring of the herd. The most common brands of AMS in the U.S. are Lely and DeLaval. Other manufacturers are slowly seeking their space in the market, such as GEA, Boumatic, AMS-Galaxy and Fullwood.

There are an estimated 50,000 AMS units currently in use on 25,000 dairy farms worldwide (personal communication, DeLaval, Tumba, Sweden). The majority (> 80%) of the AMS units are located in Europe, mostly in the Northwestern region, whereas only approximately 10% are in North America. The region where AMS are more common in the US is the Upper Midwest, with an estimated > 500 farms. However, even in states known for their large herd sizes (e.g., California) there has been a recent increase in interest for AMS. The adoption rate varies around the world, being greater in Europe (~ 10 to 30%), followed by Canada (~ 20%), and the US (~ 5%) (personal communication, DeLaval, Tumba, Sweden). A greater adoption rate and number of AMS units in Europe should not be a surprise, as the first AMS farms originated there and the shortage of labor is normally more severe compared to the U.S. The situation in Canada is similar, where there is less available and affordable labor, and a smaller herd size, which makes the adoption of AMS more economically appealing. Other countries are just recently noticing a small number of farms adopting AMS, such as Chile, Brazil, Australia, and countries in Asia, but they still represent a small percent of the overall number of AMS worldwide. The largest AMS farm in the world is located in Chile with 72 DeLaval AMS units and approximately 4,500 cows, where a 10% increase in milk production and a 40% increase in labor efficiency were achieved after the adoption of AMS (Melendez et al., 2019). Additionally, the longevity of the cows increased by one lactation and overall profitability of the farm also increased. The largest AMS dairy farm in the U.S. is located in the state of Indiana with 36 Lely AMS units and approximately 2,100 cows. Since the installation of the AMS, milk production, pregnancy rate, and overall herd health increased (Houin, 2019).

The main driving factor for developing AMS technologies was to address the difficulty of hiring staff to milk cows, as it has always been a labor-intensive and time-consuming chore on dairy farms (Rossing et al., 1985; Rossing and Hogewerf, 1997). This remains as one of the main reasons influencing the adoption of this system along with improved quality of life, mostly due to flexibility and reduction of labor (de Jong et al., 2003; Butler et al., 2012; Salfer et al., 2018). Additionally, labor efficiency is another motivating factor for dairy producers to switch to AMS. Salfer et al. (2018) investigated the number of cows per full-time employee (FTE) on AMS farms and found a median of 96 cows per FTE. The same metric on conventional milking farms was found to be between 40 and 84 cows per FTE (Bewley et al., 2001; Caraviello et al., 2010). A study comparing AMS and conventional farms reported an average reduction of 29% in labor, whereas conventional farms used approximately 20 hours more of labor per week (Bijl et al., 2007). However, other studies showed that the goal of decreased work hours seems difficult to achieve (de Jong et al., 2003; Butler et al., 2012). The AMS changes the type of labor, requiring more data analysis, technological, and mechanical skills. This shift in type of labor may also be a means of prolonging the working life of farmers, as the work may be not as physically exhausting (Butler et al., 2012). Most AMS farms are small (less than 200 cows) and have 2 to 3 AMS units on average (Salfer et al., 2018), which means most or all of the labor is provided by the family. For those farms, the adoption of

AMS results in a more flexible work schedule, as milking is done by the AMS at all times and the labor can be directed towards different aspects of the farm. For larger farms, the AMS may reduce the need for hired labor and provide employees with improved work conditions and quality of life. De Jong et al. (2003) surveyed 25 farms in North America and 84% of the farmers reported a flexible work schedule as reason for purchasing the AMS technology, and 70% of the respondents reported a decrease in the hired labor costs. The high level of technology in AMS and the less intense labor may also make dairy farming more attractive to the younger generations.

Most AMS farms use freestall barns as their main housing system. However, automated milking has also been successfully implemented in compost bedded pack barns and pasture-based systems. Grazing farms with AMS are more commonly found in Europe, Australia, and New Zealand. Retrofitted barns and new facilities built specially for the AMS have both been used to accommodate the AMS in freestall systems. A recent study by Salfer et al. (2018) in the Midwestern U.S. reported that 56% of the farms had new facilities, 37% were retrofitted, and 7% were a combination.

Cow traffic flow refers to the way animals move in their freestall pen on an AMS farm. The main traffic systems are “free flow” and “guided flow”, with some potential modifications of these systems, depending on the preferences of the farmer or even for research purposes. In a free flow system, cows are allowed unrestricted access to all the areas of the pen, including the AMS. In a guided flow, on the other hand, cows follow a pre-established pattern guided by pre-selection gates. A “milk first” guided flow system requires that cows go through a selection gate and the system decides whether it is time for milking before they can access feed. If that is the case, they need to go through the

AMS first. Alternatively, a "feed first" guided flow requires that the animals go through the feed alley before accessing the AMS. Recently, it has been possible to notice an increased preference for milk-first on farms adopting the guided flow traffic system in the U.S.

Each traffic flow system has its own characteristics, and the decision for the adoption of one type over the other is normally driven by management preferences of the producer. Milk production, both per cow and per AMS, was higher in free flow farms (Tremblay et al., 2016). However, other studies found no difference in milk production between different traffic systems (Bach et al., 2009; Munksgaard et al., 2011). The number of fetched cows (i.e. cows overdue for milking that need to be manually brought to the AMS) was higher in free flow systems, which requires additional labor (Bach et al., 2009; Salfer et al., 2018). When cows had free access to the feed bunk in a free flow system, the number of daily meals increased, and duration and size (kg of DM) of each meal decreased compared to guided flow (Bach et al., 2009). In contrast, Melin et al. (2007) found no difference in feed intake, number of meals, and rumination time between different traffic flow systems. The percentage of milk fat and milk protein was higher in free flow farms (Bach et al., 2009). Although there was no statistical difference, milking frequency was numerically higher in guided flow systems (Melin et al., 2007; Bach et al., 2009).

Efficiency on AMS farms can be assessed using a variety of variables, as the term efficiency may have a different meaning on each farm. Producers have different goals when adopting AMS, which may include improved labor efficiency, milk production or quality, quality of life for the workers, or a combination of all of those. However, a common goal for all farmers should be to improve operation profitability (Rodenburg, 2013).

HERD MONITORING USING AUTOMATIC MILKING SYSTEMS

The AMS software along with associated technologies (e.g., rumination and activity sensors) generate an abundance of daily behavior and production data; and translating these data into timely and useful actions is one of the challenges currently facing the dairy industry. In spite of the various benefits associated with AMS adoption, ease to use the technology and managing the amount of information provided by the system are some of the limiting factors influencing farmers’ decisions (Borchers and Bewley, 2015). Producers need to learn and adapt their management skills to interpret the information provided by the software (e.g., health reports, insemination list, etc.), while the advisors and researchers must find ways to better utilize these valuable data to improve animal health, welfare, productivity, and profitability of the dairy enterprises. Furthermore, the individual cow data recorded automatically in these systems allow researchers and equipment manufacturers to extrapolate some of the findings to cows milked with systems other than AMS.

Milk Production

Milk production per cow and per AMS unit are efficiency metrics commonly used on AMS farms. Different studies in North America have shown a trend for an increase in milk production over the years, both per cow and per AMS, demonstrating that along with genetics and nutrition, management has improved, making AMS farms more efficient and potentially more profitable and sustainable. Daily milk production per cow milked with AMS was, on average, 26.4 kg (Wagner-Storch and Palmer, 2003), 35.1 kg

(Deming et al., 2013), 33.7 kg (King et al., 2016), 32.0 kg (Tremblay et al., 2016), 33.2 kg (Siewert et al., 2018), and 37.6 kg (Peiter et al., 2019a). Average daily milk production per AMS has been reported to be between 1,627 kg and 2,224 kg (King et al., 2016; Tremblay et al., 2016; Siewert et al., 2018; Peiter et al., 2019b). A reasonable and achievable goal for milk production per AMS seems to be 2,300 kg per day, but well-managed farms may achieve up to 3,000 daily kg per AMS. Research has shown that various management factors may be associated with milk production, including feed push-up schedule and method, amount of concentrate offered in the AMS, number of cows per AMS (Siewert et al., 2018), and feed bunk space (Deming et al., 2013). Cow health and comfort may also be associated with milk production on AMS farms, as lameness was associated with decreased milk production (King et al., 2016). Individual cow factors such as breed, stage of lactation, lactation number, and milking speed have also been shown to be related to milk production on AMS farms (Deming et al., 2013; Tremblay et al., 2016; Siewert et al., 2018). Overall management and the ability of making decisions based on variables recorded daily by the technology software are important aspects that can lead to the success or failure of any AMS farm. Therefore, management strategies and AMS data analyses aiming to improve milk production deserve further research.

Milk Components. Besides measuring milk production, some AMS are capable of estimating milk fat and protein content. Monitoring milk components may be helpful especially for farmers who are paid for solids content in the milk. Furthermore, milk fat and protein content for individual cows have attracted increased interest due to their associations with metabolic and energy status of the animals. Studies have reported fat to protein ratio (**FPR**) as a sensitive and consistent indicator of changes in the nutritional status of cows since it is considered an accurate predictor of energy status (Grieve et al., 1986) and pregnancy risk (Loeffler et al., 1999). This ratio has been shown to be negatively associated with energy balance, especially in early lactation when the energy balance is negative for most cows (Grieve et al., 1986; Čejna and Chládek, 2005; Buttchereit et al., 2010). The average FPR for Holstein primiparous cows has been shown to be 1.10, while for multiparous cows the average was 1.14 (Buttchereit et al., 2010). A FPR > 1.5 indicates very high lipolysis and has been shown to be associated with displaced abomasum, ketosis, ovarian cyst, lameness, and mastitis (Geishauser et al., 1998; Heuer et al., 1999; Jamrozik and Schaeffer, 2012). Low values of FPR (< 1.0 – 1.1) could be indicative of subacute ruminal acidosis (Zschiesche et al., 2020). Therefore, FPR may be a valuable metric with potential for further applicability, especially on farms such as the ones with AMS, where components are monitored frequently.

Milk Quality

Due to the automated nature of the AMS, the use of sensors measuring milk electrical conductivity, color, composition, and yield is critical for identifying abnormalities in the milk and potential cases of mastitis, which prevents abnormal milk from entering the tank. More recently, DeLaval released the online cell counter, which can measure SCC in real time for each milking and help with the detection of mastitis (Sørensen et al., 2015). These sensors are constantly recording data; algorithms built into the AMS software create alerts for the farmer. Suspicious cows are placed on attention lists and the herdsman can assess each individual case and decide whether to treat the animal or not. A survey by de Jong et al. (2003) showed that 84% of AMS producers used deviation in daily milk production to include cows on the attention list, while 73% of the farms used milking interval, and 47% of the respondents used milk conductivity for mastitis detection as inclusion criteria for the attention list. The respondents mentioned that the attention list is a helpful tool, but management is key to prevent mastitis and other health issues. A recent survey conducted with Canadian AMS farmers reported that 80% of the producers perceived disease detection to be easier after adopting the AMS, mostly due to the health reports provided, which include udder health (Tse et al., 2017).

Milking Frequency and Milking Interval

Cows tend to visit the AMS more frequently during the day, usually between 1000 and 2200 h (Wagner-Storch and Palmer, 2003; Munksgaard et al., 2011). Increased milking frequency was associated with an increase in milk production per cow in conventional systems (Bar-Peled et al., 1995; Hale et al., 2003; Soberon et al., 2011) and also on AMS farms (Tremblay et al., 2016; Siewert et al., 2018). The concentrate offered at the AMS and the voluntary nature of the system make it relatively easy to achieve a higher milking frequency compared to a typical twice a day milking routine. Milking frequency on AMS farms was reported to be between 2.4 and 3.0 daily milkings per cow (Wagner-Storch and Palmer, 2003; King et al., 2016; Siewert et al., 2018). Cows in early lactation visited the AMS more often to be milked and that frequency decreased as they progressed in their lactations, especially for multiparous cows (Penry et al., 2017).

Although milking frequency and milking interval are related parameters, they tell different stories. The frequency measures how many times the cow was milked in one day, whereas the milking interval is the average time between milkings. It was suggested that the consistency of milking interval is important, since large variation in interval time decreased milk production, especially in multiparous cows (Bach and Busto, 2005). Milking interval may be affected by the milking permission settings and fetching frequency of the farm. Each farmer can set milking permissions (i.e., how often cows can be milked) to their preference, according to DIM, number of lactations, or milk production, which may underestimate the actual milking frequency some cows could achieve, if they were not limited. Cows allowed to be milked every 4 h were milked, on average, 3.2 times daily and produced more milk compared to cows allowed to be milked every 8 h, which were milked 2.1 times per day (Melin et al., 2005). An alternative to optimize milk production would be to use DIM and expected milk production along with the behavior of each cow based on AMS data to set optimal milking intervals for individual animals (André et al., 2010).

Refusals. A refused visit occurs when a cow visits the AMS but has not reached the minimum milking interval time, according to the milking permission settings. Refusals indicate cows are visiting the AMS voluntarily and frequently, therefore a certain number is desirable. Refusals had a negative association with milk production per cow and per AMS (Tremblay et al., 2016; Siewert et al., 2018) and offering more concentrate in the AMS seemed to increase the number of refusals (Tremblay et al., 2016). Refused visits can affect cow behavior, such as standing and lying time (Stefanowska et al., 2000), which may potentially increase the risk for lameness and contribute to decreased milk production (King et al., 2016). Moreover, cows with excessive refused visits may interfere with cow flow in the AMS area, as they are using AMS time and potentially creating a longer queue. Therefore, it is preferable to have a low number of daily refusals per cow, since refusals use AMS time and decrease overall productivity and efficiency of the AMS.

Failures. A failed visit is related to the inability of the AMS to attach the milking units. Udder quarter size variation and undesirable teat position are the most common known reasons for unsuccessful attachment (Jacobs and Siegford, 2012). For primiparous cows, the small distance between rear teats (average of 15 cm) seems to create difficulties for attachment, whereas the large distance between front teats (average of 34 cm) for multiparous cows creates difficulties (Miller et al., 1995). Although sensors have improved the ability to detect teats, when rear teats touch or are close together, sensors tend to register them as one single teat. Close rear teats was reported by Rodenburg (2002) to be the main reason for extra culling on AMS farms. The distance from the lowest point of the udder to the floor decreases as cows get older, and can also make it difficult for the AMS to attach the milking units (Miller et al., 1995). Rodenburg (2002) stated that very high rear udders are an issue, as it is hard for the sensors to see the rear teats in a horizontal plane. Milk production at the quarter level decreased in the subsequent milking following a failure, and that effect increased as DIM increased (Bach and Busto, 2005). Culling cows after their first calving if their udder conformation is not appropriate for AMS could potentially reduce the number of failures and improve overall efficiency on the farm.

Rumination and Activity

Neck-collar activity monitors can measure both activity and rumination time (**RT**). Activity is measured by taking into consideration head and neck motion and averages between 309 and 412 daily units, depending on lactation stage (King et al., 2017). The RT is on average 434 min/d (Zebeli et al., 2006), and it occurs mostly at night when cows are less disrupted by management tasks (Beauchemin, 2018). However, as RT increases, the proportion of rumination at night has been shown to decrease (Stone et al., 2017). The RT had a negative correlation with eating time, potentially due to feed restriction or to compensate for long particle size consumed due to feed restriction (Beauchemin, 2018). There was also a positive correlation between RT and milk production, and between RT and neck activity, whereas a negative correlation was found between RT and lying time (Stone et al., 2017). Furthermore, cows experiencing ruminal acidosis had a lower RT (Devries et al., 2009). Daily RT can be used as a potential estrus detection tool, as it has been shown to decrease by 60 to 94 min (14 and 24%) on day of estrus (Reith and Hoy, 2012). Additionally, RT has been shown to begin decreasing up to 48 h before calving, which underlines the potential for RT to be a predictor for calving time in combination with other parameters (Schirmann et al., 2013). Activity increases around estrus (Firk et al., 2002; Dolecheck et al., 2015; Mayo et al., 2019) and it has been used to help farmers identify animals to be inseminated. In addition, the combination of RT and activity has been shown to be a useful tool to identify health disorders and other behavioral changes in cows' normal patterns. Metabolic and digestive disorders during the transition period may also be detected by wearable sensors when combining measurements, such as activity and RT (Stangaferro et al., 2016). Both parameters declined for cows diagnosed as sick, starting at up to eight days before the diagnosis occurred (Stangaferro et al., 2016; King et al., 2017). Along with milk production parameters, body weight, milking behavior, RT, and activity data can be used to identify sick cows during the transition period (Steensels et al., 2016). Therefore, behavior data have the potential to help detect health disorders, estrus, and calving time. Understanding management and feeding strategies that may influence activity and RT behavior on AMS farms can be helpful to improve the detection of abnormalities in cow health and behavior.

Body Weight

Farms using AMS have access to cow daily body weight (**BW**) data if the system is equipped with a scale, which weighs the cow every time she is milked and generates a daily average of all observations, eliminating some of the variability in BW during the day. It has been shown that cows milked with AMS lose weight in earlylactation regardless of their metabolic status (Caixeta et al., 2015). However, Caixeta et al. (2015) found that the change in BW may be exacerbated depending on calcium and energy balance levels, and disease status. King et al. (2017) showed that BW declines 4 days before pneumonia and metritis diagnosis, 5 days prior to hoof disorders diagnosis, and 6 days before subclinical ketosis. Therefore, BW change has potential as a predictor of disease and metabolic issues and as a tool for management decisions on AMS farms.

Concentrate Intake in the AMS

According to producers, feeding management is ranked as one of the top priorities and concerns on AMS farms (Rodenburg, 2013; Salfer et al., 2018). Unlike the traditional total mixed ration fed to cows on conventional farms, cows on AMS are offered a pelleted concentrate at the AMS, along with a partial mixed ration (**PMR**) at the feed bunk. The PMR is commonly formulated for a milk production level about 8 to 10 kg below the target group production average, so the concentrate at the AMS provides the remaining required nutrients (Rodenburg, 2015). Offering a palatable concentrate at the

AMS motivates the cows to visit the milking stall more than the motivation to be milked (Prescott et al., 1998), leading to greater milking frequency, increased milk production, and reduced number of fetched cows. This alternative feeding system can be challenging, but also presents an opportunity for feeding cows (Bach and Cabrera, 2017). Each cow is assigned to a different concentrate feeding table, receiving different daily amounts of concentrate to meet specific individual requirements and help avoid metabolic issues.

Feeding concentrate at the AMS can be expensive; therefore, the amount offered has to be sufficient to keep a high milking frequency, but it cannot be so high that it becomes economically unfavorable. A limiting factor for concentrate allowance and intake is the time constraint faced once cows enter the milking station (Bach and Cabrera, 2017). The PMR intake rate is between 250 and 400 g per min (Kertz et al., 1981), and the average time cows spend in the AMS is 6.8 min (Tremblay et al., 2016), which means cows are able to consume on average only 2.7 kg each visit. Considering the average number of daily milkings of 2.9 (Tremblay et al., 2016), the average maximum intake would be 7.8 kg per day. Salfer et al. (2018) reported an average concentrate allowance per cow of 1.9 kg per day for guided flow and 6.6 kg per day for free flow systems. Milking frequency, number of fetched cows, and milk production were not different between cows offered 3 vs. 8 kg of concentrate per day (2.6 vs 6.8 kg per day actual concentrate intake, respectively) in a free flow system (Bach et al., 2007). Small concentrate amounts, such as 300 g per milking, on a pasture-based system was shown to be effective at attracting cows to the AMS (Scott et al., 2014). Bach and Cabrera (2017), after an extensive literature review, suggested a daily concentrate allowance of 3 to 4 kg under a free flow traffic system. However, producers normally adjust the concentrate allowance according to stage of lactation and milk production, starting with a low amount at calving, followed by a linear increase until cows reach their lactation peak. Then, it starts to decrease until they are near dry off, when they receive little concentrate.

Concentrate residual is positively correlated with allowance, and it seems that when cows are offered over 4 kg per day there is more concentrate leftover, which makes the concentrate feeding at the AMS less precise (Bach and Cabrera, 2017). Also, Bach et al. (2007) showed that for every kg increase in concentrate at the AMS, the PMR intake decreased by 1.15 kg, which could reduce the intake of fiber and increase the risk of metabolic issues, such as ruminal acidosis. On the other hand, concentrate offered has been shown to have a positive association with milk production per cow and per AMS (Siewert et al., 2018). Conversely, Tremblay et al. (2016) found a weak negative relationship between concentrate offered and milk production, both on the cow- and AMS-level. Tentatively, each farmer should find a farm-specific concentrate allowance, taking into consideration the feed costs and the return in milk production for each additional kg offered.

DISSERTATION OBJECTIVES

Even though there has been extensive research conducted with AMS worldwide over the last two decades, the U.S. ranks sixth in number of studies published using these technologies (Cogato et al., 2021). Considering the recent increase in the number of cows milked with AMS paired with the increased yearly adoption rate of AMS in the U.S., the optimization of the use of the technology is imperative to ensure the success and sustainability of such farms in the U.S. Therefore, we aimed to use data from AMS farms to investigate the relationship between the daily interaction of the animals with the milking system and milk production. Moreover, we made use of physiological measurements taken daily for each cow to investigate their association with milk production later in lactation. Three independent studies were conducted to address the main goals of this dissertation, with the following specific objectives:

1. Association between visit behavior and milk production on automatic milking system farms.
2. Association between early postpartum RT and peak milk yield in dairy cows:
    a. Investigate the association of change in RT and average RT during the immediate postpartum period with peak milk yield in dairy cows;
    b. Determine the best statistical model based on number of days in milk to evaluate this association.
3. Association between change in BW during early lactation and milk production variables in automatic milking system herds:
    a. Investigate the association between FPR and BW change in early lactation by parity group, while controlling for number of milkings and concentrate intake in the AMS box;
    b. Investigate the association between early lactation BW change and 90-d milk yield.

Chapter 2

Association between cow visit behavior and milk production on automatic milking system farms

SUMMARY

The objective of this observational study was to investigate the associations between visit behavior and daily milk production of cows on automatic milking system (**AMS**) farms. Visit behavior and milk production data recorded by the AMS software were collected from 47 AMS dairy farms in Minnesota and Wisconsin, where 36 used the Lely Astronaut (**LA**) and 11 used the DeLaval VMS (**DV**) to milk their cows. To measure cow productivity, fat- and protein-corrected milk production (**FPCM**) was used for LA farms and unadjusted milk production for DV farms. Results from mixed linear regression models showed that milking interval had the greatest association with FPCM on LA farms, where one hour increase in milking interval was associated with a 2.1 ± 0.0 kg/d decrease in FPCM; however, the same association was surprisingly positive on DV farms, with an estimate of 0.5 ± 0.02 kg/d greater milk production. Refusals were only evaluated on LA farms, and each unit increase in refusals was associated with a 0.02 ± 0.0 kg/d decrease in FPCM. It was interesting to find a positive association between failures and cow productivity on both farm clusters, with an estimate of 4.0 ± 0.01 kg/d greater FPCM on LA farms and 1.2 ± 0.04 kg/d greater milk production on DV farms. Concentrate intake in the AMS had a positive association with productivity on both farm clusters, where each kg increase in concentrate intake was associated with a 0.4 ± 0.0 kg/d greater FPCM and 7.6 ± 0.04 kg/d greater milk production on LA and DV farms, respectively. Each kg of additional residual concentrate in the AMS was associated with a 0.5 ± 0.01 kg/d greater FPCM on farms with LA. One unit increase in milking speed (kg/min) was associated with a 4.6 ± 0.01 kg/d increase in FPCM on LA farms and 4.8 ± 0.07 kg/d increase in milk production of cows on DV farms. The visit time budget of cows on LA farms was evaluated through a series of variables. Milking time (3.0 ± 0.0 kg/d), pre-treatment time (0.01 ± 0.0 kg/d), and post-treatment time (0.15 ± 0.0 kg/d) were all positively associated with FPCM, whereas connection time (−0.01 ± 0.0 kg/d) and dead milk time (−0.11 ± 0.0 kg/d) were both negatively associated with FPCM. Only the total box time was available for farms with the DV, and it had a positive association with milk production (0.2 ± 0.03 kg/d). Findings from this study may be used to adjust management practices and software settings aiming improved productivity and efficiency and to select more suitable and productive cows for AMS herds.

Key words: automatic milking system, dairy cows, behavior, traffic flow

INTRODUCTION

Attempts to develop an automatic milking system (**AMS**) date back to the 70's and 80's in Japan and Germany, respectively (Notsuki and Ueno, 1977; Ordolff, 1983). However, it was only in 1992 that the first AMS was installed on a dairy farm in the Netherlands. Improvements have made the AMS a viable option for dairy farmers, as it can fulfill all necessary milking-related tasks performed by human labor in conventional milking systems, including cow preparation, milking machine attachment, and post-milk teat disinfection, in a consistent manner. Today, approximately 50,000 AMS units are in operation on over 25,000 dairy farms worldwide (personal communication, DeLaval, Tumba, Sweden). It is also estimated that over 80% of AMS farms are in Europe and only approximately 10% are in North America, but there has been recent growth in AMS adoption in the latter region. The Netherlands, which is one of the countries that pioneered the AMS, currently has approximately 25% of the dairy farms operating with such a technology (van de Wetering, 2019). Census data showed that approximately 9% of Canadian dairy farms operate with AMS (CDIC, 2019). However, Canada has a quota system that could make investments like AMS less risky compared to U.S. farms. The exact number of AMS farms in the U.S. is not known, but an increased adoption rate year after year is clear. In the Upper Midwest U.S. alone, experts estimate that over 400 dairy farms use AMS (Siewert et al., 2018). Recently, an increased interest in AMS by large U.S. dairy operations has been noted by the authors, as opposed to a historical adoption by smaller herds (< 200 cows). This trend will most likely result in a substantial number of U.S. cows milked with AMS in the near future. Therefore, optimizing AMS use on U.S. dairy farms is imperative to ensure their success.

The AMS pen is normally designed to accommodate one of two cow traffic flow systems (which refers to the way cows can move throughout the pen): free flow, where the cows have unrestricted access to all areas of the pen, including the AMS; or guided flow, in which the cows need to go through pre-selection gates to access different areas of the pen. There are two main types of guided flow systems, referred to as milk-first and feed-first. In the milk-first system, cows leaving the resting area must pass through a pre-selection gate that determines if they are eligible for milking. If a cow meets the requirement to be milked, she is guided to a commitment pen that contains the AMS. If she is not eligible for milking, she is allowed to enter the feed bunk area and can only re-enter the resting area through a one-way gate. Pre-selection gates can also be installed in crossovers away from the AMS box and open only for cows not eligible for milking. In the feed-first system, cow traffic is the reversal of the milk-first system. After eating, the cow enters a selection gate that determines if she is eligible for milking. The gate either guides her to the commitment pen for milking or to the resting area. The commitment pen is a gated area next to the AMS box that cows eligible for milking cannot leave until they are milked. The choice of traffic flow type is generally driven by management preferences of the producer. Studies investigating the association of some visit behavior parameters with productivity have been conducted with AMS farms in North America (Tremblay et al., 2016; Siewert et al., 2019); however, those previous studies focused on only one brand of AMS (Lely Astronaut, Lely Industries, the Netherlands), or included both feed- and milk-first guided flow farms.

Milk production is one of the commonly used parameters to evaluate productivity and efficiency on dairy farms. Previous research studies showed that management factors such as feed push-up frequency, amount of concentrate offered in the AMS box, and number of cows per AMS are associated with productivity on AMS dairy farms (Siewert et al., 2018). Furthermore, cow-level factors, such as milking speed and number of successful milkings, showed an association with daily milk production (Tremblay et al., 2016; Siewert et al., 2018). However, a more recent, comprehensive analysis of cow visit behavior data recorded by the AMS software including the specific duration of each AMS procedure (i.e., pre-treatment time, connection time, dead milk time, milking time, and post-treatment time) and interval between milkings has not been documented for AMS farms using free flow traffic system in the U.S. Additionally, cow visit behavior on U.S. dairy farms with milk-first guided flow traffic systems has not yet been reported.

Understanding the interaction cows have with the AMS and how such behavior impacts productivity is crucial to improve efficiency on AMS farms. Therefore, the objective of this study was to investigate the associations between visit behavior and milk production of cows on AMS farms.

MATERIALS AND METHODS

Farms and Data Collection

Forty-seven U.S. dairy farms (located in Minnesota and Wisconsin) using AMS as the only milking system were enrolled in the current study. Potential farms were identified with the help of extension educators, consultants, equipment dealers, and producers. After identification of farms, producers were contacted and participation in this study was voluntary. Thirty-six farms used Lely Astronaut (**LA**; Lely Industries NV, Maassluis, the Netherlands) and 11 farms used DeLaval VMS (**DV**; DeLaval International AB, Tumba, Sweden) to milk their cows. Free flow cow traffic system was used on 38 farms (36 Lely and 2 DeLaval) and milk-first guided flow was used on 9 of the guided flow farms (all DeLaval). Herds enrolled in this study were comprised of Holsteins and all the cows were housed in freestall barns with no access to pasture. Each farm was visited once for data collection.

Farms using Lely Astronaut. Retrospective data were collected from the T4C software (Lely Industries NV, Maassluis, the Netherlands) for a period of 12 months (2017 – 2018). A file containing one observation per cow per visit (successful milkings and failures only) included the following variables: cow identification, DIM, date and time of visit, milking interval (sec), box time (sec), average milking speed (kg/min), milking time (sec), pre-treatment time (sec), connection time (sec), dead milk time (sec), and post-treatment time (sec). A second file with one daily observation per cow included data on: cow identification, date, parity number, DIM, total milk production (kg), average milk fat percentage, average milk protein percentage, total successful milkings (count), total refusals (count), total failures (count), total concentrate allowed (kg), total concentrate intake (kg), and total residual concentrate (kg). Milking interval was the time between visits with milking permission – successful milking or failure. Box time was the total time spent in the AMS unit per visit. A failure was recorded when the cow had an incomplete milking – i.e., the milking unit(s) failed to attach, or the milking was not carried to completion. Reasons for failures included: ‘automatic robot stop’, ‘connection attempts’, ‘connection time’, ‘dead milk time’, ‘teats not found’, and ‘stopped by user’. Cows were refused by the AMS when they had not reached the minimum milking interval time established by the milking permission settings for each cow, so it did not generate a cow milking record. Residual concentrate was the amount of concentrate not consumed by the cow at the end of a visit (i.e., allowance minus intake).

Farms using DeLaval VMS. Six months of retrospective visit-level data were collected from the DelPro software (DeLaval International AB, Tumba, Sweden) for the year 2019. Unlike T4C, the DelPro software only stored data for 6 months on the enrolled farms. The file collected from each farm included data on: cow identification, date and time of visit, parity number, DIM, box time (sec), milk production (kg), total daily milkings (count), milking unit kick-off by udder quarter (yes/no), incomplete milking by udder quarter (yes/no), enabled milking by udder quarter (yes/no), total daily concentrate intake (kg), and average milking speed by udder quarter (kg/min). The occurrence of either a milking unit kick-off or an incomplete milking was considered the equivalent to failures on farms using the Lely AMS. Number of refusals was not available, as they are less common in guided flow systems, because cows go through a pre-selection gate prior to visiting the AMS, which only allows cows to visit the AMS if the minimum milking interval has been reached.

Data Processing and Statistical Analysis

All post-collection data management procedures and statistical analyses were performed in RStudio (R Core Team, 2020). Cows were categorized according to parity into primiparous (i.e., first lactation cows) or multiparous (i.e., cows on their second or greater lactation), based on previous knowledge of clear production differences between these two groups of cows (Siewert et al., 2019). The variable DIM represented the day of the lactation period, which began with 1 following the day of calving. Day of calving (i.e., DIM = 0) was removed from the dataset, as cows calved at different times of day, which yielded less than 24 h of data. Eight categories were created for DIM, representing different stages of lactation. The postpartum period represents a more challenging time for cows as they are adapting to the AMS and facing a rapidly changing milk production with normally increased visit frequency to the AMS. Therefore, 2 categories of 15 d in length each were created from 1 to 30 DIM (stages 1 and 2). Five categories were created from 31 to 210 DIM (stages 3 to 8), with each period being 30 d long. Later lactation stages were not included due to common management changes that could be confounding factors for the objective of this study, such as a reduction in daily milking permissions and concentrate allowance. Data collected from each software were different and from different years; therefore, data were analyzed separately by AMS brand.

Farms using Lely Astronaut. Data collected per visit were aggregated into daily values and merged with the daily data collected from the T4C software. Visual inspection of the data suggested the presence of unusual values. Therefore, for the detection of potential outlier observations, each data value had a z-score calculated (Rousseeuw and Hubert, 2011). Daily observations with a z-score > 3 were considered outliers and removed. A z-score tells us how many standard deviations away each observation is from the overall mean of a variable. The final dataset included 1,407,281 daily observations from 63,742 stages of lactation for 9,504 cows from 36 free flow farms. The number of cows enrolled from each farm ranged from 77 to 659. Fat- and protein-corrected milk production (**FPCM**) was calculated, so that production was standardized for all the cows milked with the LA system in this study with 4% fat content and 3.3% protein content (FPCM = milk production * (0.1226 * fat % + 0.0776 * protein % + 0.2534); IDF, 2015). It is suggested that a collinearity problem exists when factors with a Pearson's $r > 0.7$ are included as explanatory variables in the same statistical model (Dormann et al., 2013; Tremblay et al., 2016). Therefore, pairwise correlations were calculated, and when the coefficient between two variables was > 0.7 they were considered collinear and only one of them was included in the statistical model. Number of daily successful milkings, average daily box time, and total daily concentrate allowance were not included in the final model due to collinearity.

For the association between FPCM and AMS visit behavior data, a mixed linear regression model was created with explanatory variables consisting of: stage of lactation (8 categories), parity (2 categories), average daily milking interval (continuous), total daily refusals (continuous), total daily failures (continuous), average pre-treatment time (continuous), average connection time (continuous), average dead milk time (continuous), average milking time (continuous), average post-treatment time (continuous), average milking speed (continuous), total daily concentrate intake (continuous), total daily residual concentrate (continuous), and the interaction between parity and stage of lactation. Fat- and protein-corrected milk (continuous) was included as the outcome variable and cow nested within farm was included as random effect. Model fit was assessed by visual observation of residual plots. The denominator degrees of freedom were estimated using Satterthwaite's method. The Tukey *P*-value adjustment was used for pairwise comparisons.

Farms using DeLaval VMS. A single dataset was collected for DeLaval farms with one observation per robot visit, which were aggregated into daily values per cow. If a cow had either a milking unit kick-off or an incomplete milking for an udder quarter, the visit was categorized as a failure, as it was not carried to completion. Quarter milking speed was summed for each visit to create a visit milking speed then a daily average was calculated. Milking interval was calculated based on the timestamps provided. Unlike the Lely dataset, most variables in this dataset were normally distributed, except for failures, which had a right-skewed distribution. Therefore, data cleaning procedures were not applied, as the data had no apparent outliers and the values were biologically plausible. A total of 296,906 daily observations from 13,122 stages of lactation for 2,730 cows from 11 farms were included in the final dataset. Number of cows per farm in the final dataset ranged from 74 to 461. Two of the farms used free flow traffic system and the inclusion of these farms did not change the interpretation of the results. Therefore, they remained in the dataset for the statistical analysis. Pairwise correlations were calculated, and collinearity was considered when the coefficient between two variables was > 0.7. Number of daily milkings was not included in the final model due to collinearity with milking interval.

A mixed linear regression model was created with cow daily milk production (continuous) as the outcome variable. Parity (2 categories), stage of lactation (8 categories), milking interval (continuous), failures (continuous), concentrate intake (continuous), box time (continuous), milking speed (continuous), and the interaction between parity and stage of lactation were included as explanatory variables. Cow nested within farm was considered as random effect. Model fit was assessed by visual observation of residual plots. The denominator degrees of freedom were estimated using Satterthwaite's method. The Tukey *P*-value adjustment was used for pairwise comparisons.

RESULTS AND DISCUSSION

Fat- and protein-corrected milk production was highly correlated with daily milk production on farms using the LA, with a coefficient of 0.95 ($P < .0001$). Least squares means of daily FPCM are reported in Table 1 for each stage of lactation by parity group. Multiparous cows had a greater average FPCM compared to primiparous cows during all the lactation stages from 1 to 210 DIM ($P < .0001$). To the authors' knowledge, there has been no documentation of FPCM on AMS farms in the U.S. Siewert et al. (2019) reported similar findings with unadjusted milk production values, where primiparous cows on farms using LA had lower milk production from 1 to 238 DIM compared to older cows. Milk components were not available on farms using the DV system in the current study; therefore, unadjusted daily milk production was used to measure cow productivity. Multiparous cows had greater daily milk production compared to primiparous cows from lactation stage 1 (1 to 15 DIM) to 7 (151 to 180 DIM). During the 8^{th} lactation stage (181 to 210 DIM), daily milk production was not different between parity groups, as illustrated by the least squares means shown in Table 2. In contrast, a study on farms using the DV system in the same geographical region as the current study found that primiparous cows produced less milk than multiparous cows during all lactation stages from 1 to 328 DIM (Siewert et al., 2019).

Visits to the AMS

The success of an AMS farm depends on the willingness and frequency of the cows to voluntarily visit the AMS to ensure the economic viability of the operation (Rodenburg, 2013). Cows tend to visit the AMS more frequently during the day, usually between 1000 and 2200 h (Wagner-Storch and Palmer, 2003; Munksgaard et al., 2011). The concentrate offered at the AMS and the voluntary nature of the system make it possible to achieve a higher milking frequency compared to a typical twice a day milking routine. Our results showed that the average number of daily milkings for primiparous cows was highest from 31 to 60 DIM on farms using LA, when they achieved an average of 3 milkings a day (Table 3), and from 61 to 90 DIM on farms with DV, when the average number of daily milkings was 2.9 (Table 4). Siewert et al. (2019) found that primiparous cows on LA farms had a lower and later peak milking frequency than the same parity in the current study, at 2.8 milkings/d between 119 and 148 DIM. The peak milking frequency for primiparous on DV farms was lower, at 2.7 milkings/d, but occurred around the same time, between 69 and 88 DIM (Siewert et al., 2019). Older cows on farms with LA in the current study reached the highest milking frequency earlier in their lactation, from 16 to 30 DIM, which started to decrease in the next stage of lactation (Table 3). Multiparous cows on farms with the DV reached the highest number of milkings during the same stage, when they were milked on average 3.1 times daily (Table 4). However, cows in DV systems were able to maintain the same average number of daily milkings until lactation stage 4 (61 to 90 DIM). A peak milking frequency occurring around the same time for multiparous cows was reported by Siewert et al. (2019), where cows were milked on average 3.2 times a day on LA farms and 2.7 on DV farms. An experimental study showed that cows allowed to be milked every 4 h on a guided flow system were milked on average 3.2 ± 0.1 times daily and produced more milk compared to cows allowed to be milked every 8 h, which were milked on average 2.1 ± 0.1 times per day (Melin et al., 2005). Therefore, our findings suggest that improvements in management on AMS farms over recent years are enabling cows to achieve higher milking frequency during the period when production is increasing, as the peak milking frequencies reported herein are greater than numbers reported in other studies thus far. Furthermore, similar to the findings of Penry et al. (2017), cows in early lactation visited the AMS more often to be milked and frequency decreased as they progressed in their lactations, which was especially evident in multiparous cows milked with the LA system. In practice, producers limit milking frequency and concentrate intake near dry off by adjusting the AMS settings to ensure a healthy transition into the dry period. Even though the highest average daily milking frequency was 3.5 for multiparous cows, individual cows were able to achieve up to 8 milkings/d on DV farms and 9 milkings/d on LA farms during early lactation.

Increased milking frequency was associated with an increase in daily milk production per cow on conventional milking system farms (Bar-Peled et al., 1995; Hale et al., 2003; Soberon et al., 2011). In the current study, number of daily milkings and milking interval had a correlation coefficient of −0.94 ($P < .0001$) and −0.79 ($P < .0001$) on farms with the LA and DV systems, respectively; therefore, we opted to keep milking interval in both statistical models for the association with milk production, as this variable has not been investigated extensively. A negative association between milking interval and FPCM was found on LA farms, where each hour increase in milking interval was associated with an estimated 2.1 kg lower daily FPCM (Table 5). In fact, milking interval had the greatest association with FPCM in the current study ($t = −967$; $P < .0001$). On the other hand, it was interesting to find a positive association of reduced magnitude ($t = 25.0$; $P < .0001$) between average milking interval and daily milk production for cows on farms using the DV system (Table 6); we had hypothesized that increased interval between milkings would be associated with reduced daily milk production, regardless of the traffic flow system or AMS brand. Each hour increase in average milking interval was associated with a 0.46 kg greater daily milk production on farms using the DV system. Further investigation of this association on farms using such system is encouraged. Previous research showed that milk production per milking increased as the milking interval increased in cows milked with AMS (Bach and Busto, 2005; André et al., 2010), because, to a certain extent, udder fill increases along with milking interval. However, our findings for LA farms showed that daily milk production decreased as average interval between milkings increased. It has been shown that the consistency of milking interval is important, as large variations in interval decreased milk production per milking and per day, especially in multiparous cows (Bach and Busto, 2005). The milking permission settings and fetching frequency on each farm may influence milking interval, as farmers can set milking permissions (i.e., how often cows can be milked) to their preference, according to stage of lactation, parity number, or milk production level, which might underestimate the actual milking frequency some cows could achieve. Cows on farms using the LA system in the current study were allowed to be milked up to (mean ± SD) 5.9 ± 0.5 times daily from calving to 43.8 ± 16.4 DIM, which decreased to an average of 5.0 ± 0.6 daily milkings until 210 DIM (data not collected on farms using DV). Cow fetching is normally performed every 8 to 12 hours on AMS farms. Cows were fetched on average 2.2 ± 0.6 times daily on farms enrolled in the current study.

Refusals indicate cows are visiting the AMS voluntarily and frequently, therefore a certain number is desirable. On farms with guided flow traffic system, cows go through a pre-selection gate before entering the AMS area, which makes the number of refusals almost inexistent. Therefore, refusals were only investigated on farms using the LA system. The average number of refusals on free flow farms was between 0.8 and 1.9 per cow per day, and it had a negative association with milk production per cow and per AMS (Tremblay et al., 2016; Siewert et al., 2018). However, in the current study, the average number of refusals was highly influenced by a relatively small number of cows, which drove the distribution to be right-skewed. The median number of daily refusals was 0 during all stages of lactation for both parity groups (Table 3), which means that the vast majority of cows had no daily refusals. Tremblay et al. (2016) reported a positive association between the amount of concentrate offered in the AMS box and the number of refusals. These unsuccessful visits can affect cow behavior, such as standing and lying time (Stefanowska et al., 2000), which may potentially increase the risk for lameness and contribute to decreased milk production (King et al., 2016). Our findings showed that the average number of daily refusals had a negative association with FPCM on LA farms, similar to the findings of Tremblay et al. (2016), who found that milk production per cow and per AMS decreased as refusals increased. However, even though significant, the estimate for this association in the current study was only −0.02, which means that each unit increase in average daily refusals was associated with an average decrease of 20 g in daily FPCM (Table 5). Siewert et al. (2019) reported that industry recommends daily refusals to be at least 1 per cow, but not much higher, as it could mean problems with the software settings or feed bunk management, for example. Based on our findings, an increased number of refusals does not substantially influence the productivity per cow on LA farms.

The average number of failures on AMS farms was 0.08 per cow per day (Siewert et al., 2018) and 5.5 daily failures per AMS unit (Tremblay et al., 2016). However, similarly to the number of refusals, we observed a right-skewed distribution for failures on both clusters of farms, where the median was 0 for both parity groups during all the lactation stages. Udder quarter size variation and undesirable teat position were reported to be the most common known reasons for unsuccessful cluster attachment (Jacobs and Siegford, 2012). Bach and Busto (2005) found that milk production at the quarter level decreased in the subsequent milking following a failure, and this effect increased as DIM increased. The association between number of failures and FPCM on LA farms was positive, where each extra failure was associated with a 4 kg average greater FPCM

(Table 5). Similarly, the average number of daily failures per cow had a positive association with milk production on DV farms enrolled in the current study, with an estimate of 1.2 kg in daily milk production per cow (Table 6). It was surprising to find a positive association between daily number of failures per cow and milk production, as previous research showed the opposite – a negative association between failures and daily milk production per cow and per AMS (Tremblay et al., 2016; Siewert et al., 2018). Even though there was a positive association between failures and productivity, failures pose a significant problem for AMS efficiency, as cows leave the milking unit with one or multiple quarters not milked or partially milked, which could contribute to udder health issues. It has been shown that cows that experienced a failure returned sooner to the AMS compared with cows with complete milking events and it has been suggested that such effect could be due to the cow's desire to obtain additional concentrate, or due to the discomfort of the udder fill for not having a complete previous milking (Stefanowska et al., 1999). Siewert et al. (2019) indicated that industry recommends daily failures to be under 5 per AMS unit, as each failure was estimated to take an average of 8 min of AMS time. The continuous improvement of the technologies for teat identification, and the genetic selection for cows with udder conformation more appropriate for AMS may reduce failures and improve efficiency of the technology.

Concentrate in the AMS Box

Most farms with AMS offer a pelleted concentrate in the AMS box along with a partial mixed ration (**PMR**) at the feed bunk. Offering a palatable concentrate in the AMS box was shown to motivate cows to visit the AMS unit more than the motivation to be milked (Prescott et al., 1998), leading to a greater milking frequency and reduced number of fetched cows. Salfer et al. (2018) reported an average daily concentrate allowance per cow of 6.6 kg/d for LA systems and 1.9 kg/d for DV farms. Average concentrate allowance on farms with LA enrolled in the current study ranged from 4.5 kg/d for primiparous cows during the 1st stage of lactation to 7.2 kg/d for multiparous cows during the 3rd stage of lactation (Table 3). Concentrate intake was highest for primiparous cows from 31 to 90 DIM and from 61 to 90 DIM on farms with LA and DV, with an intake of 5.6 and 3.4 kg/d, respectively. Multiparous cows had the greatest average daily concentrate intake from 31 to 60 DIM, at 6.9 and 3.6 kg on farms with LA and DV, respectively. The amount of daily concentrate allowance had a correlation of 0.88 ($P < .0001$) with concentrate intake; therefore, to avoid collinearity issues, only intake remained in the model for farms with the LA system. We found a positive association between concentrate intake and FPCM, with an estimate of 0.4 kg greater FPCM for each kg of concentrate intake at the AMS (Table 5). Concentrate intake had the greatest association with daily milk production on farms with the DV system, which was 7.6 kg greater for each kg of greater concentrate intake (Table 6). A greater association of concentrate intake and daily cow productivity on farms with DV can be expected, as these farms usually offer less concentrate in the AMS box; thus, each additional kg might make a greater difference compared to LA farms, where the allowance is higher. Similarly, Siewert et al. (2018) found that daily milk production per cow increased by 1.2 kg for each kg increase in concentrate offered at the AMS on farms with LA. However, Bach et al. (2007) showed that for every kg increase in concentrate consumed at the AMS, PMR intake decreased by 1.2 kg, which could reduce the intake of fiber and increase the risk of metabolic issues, such as ruminal acidosis. Bach and

Cabrera (2017), after an extensive literature review, suggested a daily concentrate allowance of 3 to 4 kg under a free flow traffic system. In practice, we observed that producers adjust the concentrate allowance according to stage of lactation and milk production level, starting with smaller amounts at calving, followed by a linear increase until the time when most cows reach their lactation peak (data not shown). Then, it starts to decrease until they are near dry off, when cows are offered little concentrate.

Bach and Cabrera (2017) reported that residual concentrate in the AMS unit had a positive correlation with allowance. In contrast, we found very weak correlations between residual concentrate and the amount of concentrate offered or actual concentrate intake on LA farms (Pearson's *r* of 0.11 and −0.04, respectively). Siewert et al. (2018) showed that the daily residual concentrate at the AMS was 0.27 ± 0.12 kg per cow. In the current study, we found an average residual concentrate ranging from 0.2 to 0.4 kg/cow per day, depending on lactation stage (Table 3), and it was positively associated with FPCM on LA farms (Table 5). Each extra kg of residual concentrate was associated with a 0.5 kg increase in FPCM. Our results agree with the findings of Tremblay et al. (2016), where a positive association was shown between residual concentrate and daily milk production per cow and per AMS. Siewert et al. (2018), on the other hand, reported a negative association of residual concentrate with daily milk production per cow and per AMS. Concentrate feeding at the AMS is a topic that deserves further research, including concentrate composition.

Milking Speed

Milking speed refers to the rate of milk flow during milking in the AMS. Median milking speed of cows milked with the LA system was reported by Siewert et al. (2018)

to be 2.74 kg/min, while Tremblay et al. (2016) reported an average of 2.59 kg/min. The average milking speed in the current study ranged from 2.6 to 3.1 kg/min for primiparous cows and from 3.2 to 3.3 kg/min for multiparous cows on farms with the LA (Table 3). However, on farms milking cows with the DV, milking speed ranged from 3.5 to 4.2 kg/min and from 4.6 to 4.8 kg/min for primiparous and multiparous cows, respectively (Table 4). The apparent differences in milking speed between farm clusters may be due to differences in the technology used to measure this parameter. Milking speed had a positive association with milk production for both brands. On farms with the LA system, each extra kg milked per min was associated with 4.6 kg greater daily FPCM (Table 5), whereas on farms with the DV system this estimate was 4.8 kg of daily milk production. Our findings agree with those by Tremblay et al. (2016) and Siewert et al. (2018), who reported a positive association between milking speed and daily milk production per cow and per AMS. Tremblay et al. (2016) suggested that cows with increased milking speed could be placed in pens with greater number of cows per AMS unit, as they can be milked faster. Also, producers could select cows for increased milking speed to improve efficiency. However, milking speed was shown to have a positive association with milking interval (Hogeveen et al., 2001), which, in turn, had a negative association with FPCM on LA farms in the current study. Cows with longer milking intervals may have greater udder fill (Bruckmaier and Hilger, 2001), which could increase the internal udder pressure, hence increasing milking speed. Therefore, we suggest that cows with a high milking speed at their optimum milking interval (based on milking permissions) would be preferred when trying to select for efficiency on AMS farms.

Visit Time Budget

Milking time and box time had a correlation of 0.94 ($P < .0001$) on farms with the LA system; therefore, only milking time remained in the model. The average milking time ranged from 4.4 to 5.3 min and from 3.9 to 5.3 min for primiparous and multiparous cows, respectively, on farms with the LA system (Table 3). A greater average milking time of 5.5 min was reported by Siewert et al. (2018). The shorter average milking time found herein suggests potential improvements in the technology or management practices over recent years, enabling the LA system to milk cows in a shorter period of time. We found a positive association between milking time and FPCM, where each extra min milking was associated with an estimated 3 kg increase in daily FPCM (Table 5). Siewert et al. (2018) found similar results, with an estimate of 3.8 kg more milk produced daily per cow for each extra min spent milking. Similarly, box time was positively associated with daily milk production on farms with the DV system, with an estimated 0.2 kg greater production for each extra min spent in the milking unit (Table 6). Cows with longer milking and box times are most likely either high producing cows, who necessarily need longer to be milked, or cows with low milking speed.

To our knowledge, there has been no documentation of specific times for the different preparation procedures of teat cleaning and disinfection on farms using AMS. Pre-treatment time refers to the process of teat cleaning, which includes pre-dipping and drying teats on conventional milking system farms. We found a positive association between average pre-treatment time and daily FPCM on LA farms, where each 10 sec increase in pre-treatment time was associated with an average 0.1 kg increase in FPCM (Table 5). Longer pre-treatment time could contribute to improved udder health and increased stimulation time, which might explain the relationship found herein. The average time the AMS takes to attach the milking units is called connection time, where longer times could mean that the technology is having difficulties identifying the teats to make the cluster attachment. In the current study, connection time had a negative relationship with daily FPCM. Each extra 10 sec spent with connection was associated with a reduction of 0.1 kg in FPCM (Table 5). Dead milk time is the time between milking unit attachment and the start of milk flow, while the vacuum is on. Each additional sec spent with dead milk was associated with a decrease of 0.1 kg in daily FPCM (Table 5). Lely's recommendation is for dead milk time to be under 12 sec per milking, as long periods with vacuum on without milk flow may damage the teats. It was interesting to observe average dead milk times greater than 12 sec during all lactation stages for primiparous cows in this study (Table 3). The last procedure performed by the AMS before releasing the cow is the post-treatment, which would correspond to post-dipping in conventional milking system farms. Similar to the results found for pre-treatment time, each sec increase in post-treatment time was associated with a 0.15 kg greater daily FPCM (Table 5). It is possible that farms with greater post-treatment times had cows with improved udder health, leading to increased FPCM. However, a more in-depth investigation of milking preparation procedures on farms using AMS to milk their cows is needed for a better understanding of the relationships with cow productivity.

CONCLUSIONS

Various factors of cow visit behavior were found to be associated with productivity on farms using Lely Astronaut and DeLaval VMS to milk their cows. Results of this study indicate that the interval between milkings is negatively associated with daily cow productivity on farms using the Lely technology, whereas a positive association of smaller magnitude was found on farms milking cows with the DeLaval AMS. Further investigation is needed to understand these differences. Our findings may help AMS producers and advisors adjust management practices and software settings to improve milk production and efficiency. In addition, our study may provide insights for producers and companies looking for parameters to be used to select cows more suitable and productive for AMS. Further research is warranted under more controlled settings to better understand the relationship between visit behavior and productivity of cows milked with AMS.

Chapter 3

Association between early postpartum rumination time and peak milk yield in dairy cows*

SUMMARY

There is limited information on the relationship between rumination time (RT) in the early postpartum period and milk production parameters later in lactation. Therefore, the objectives of this study were to 1) investigate the association of change in RT and average RT during the immediate postpartum period with peak milk yield (PMY) in dairy cows, and 2) determine the best model based on days in milk (DIM) to evaluate this association. Cows from 33 free-flow automatic milking system (AMS) farms were included in this study, where retrospective milk production and RT data were collected for 12 months. Cows were categorized by parity number into parity 1 (P1, n = 1,538), parity 2 (P2, n = 1,354) or parity ≥ 3 (P3+, n = 1,770). For each cow, PMY was identified as the highest daily milk yield up to 180 DIM for P1 and 120 DIM for P2 and P3+ cows. Five change in RT variables and 5 average RT variables were created corresponding to the first 2 – 6 DIM. Change in RT variables were the slope coefficients for change in RT/d related to DIM = 1 extracted from simple linear regressions, and average RT variables were the arithmetic mean RT. Five models analyzing PMY and corresponding variables calculated over the first 2 – 6 DIM had fixed effects of average RT, change in RT, parity, the average RT × parity interaction, the change in RT × parity interaction, and

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a random intercept for farm. Peak milk yield occurred at (median) 75, 44, and 46 DIM for P1, P2, and P3+, respectively. Overall PMY was (mean ± SD) 54 ± 11 kg and it increased as parity increased. A positive association was found between change in RT and PMY, and average RT and PMY for P2 and P3+ cows in all five models corresponding to the first 2 – 6 DIM, indicating that greater average RT and quicker increase in RT after calving are associated with greater PMY for multiparous cows. Although the model including all 6 DIM had the greatest accuracy, results indicated that rumination data collected over the first 2 DIM may also provide adequate information for the association of average RT and change in RT with PMY in P2 and P3+ cows. For each 100 min/d increase in change in RT over the first 6 DIM, PMY increased by 4.3 (95% CI: 2.2 – 6.3) and 4.8 (95% CI: 3.2 – 6.5) kg for P2 and P3+ cows, respectively. Peak milk yield increased by 2.3 (95% CI: 1.7 – 2.8) and 2.2 (95% CI: 1.7 – 2.6) kg for each 100 min increase in average RT over the first 6 DIM for P2 and P3+ cows, respectively. There was no association between rumination behaviors and PMY for P1 cows. Results from this study indicate that how long it takes for multiparous cows to achieve a stable RT in the early postpartum period combined with average RT during the same period may be useful in predicting their overall lactation milk production.

Key words: rumination, peak milk yield, automatic milking system, parity

INTRODUCTION

Automated monitoring of cow behavior using non-invasive technologies is a reality on many dairy farms. For instance, rumination can be accurately measured with different devices by analyzing jaw movements (Kononoff et al., 2002; Braun et al., 2015) or sounds of mastication (Soriani et al., 2012; Elischer et al., 2013; Ambriz-Vilchis et al., 2015). These methods are an alternative to the traditional labor-intensive visual live or video observation and eliminate observer bias and the disruption effect that observers may have on the animals. Such devices collect continuous data, which can be stored and used by producers, consultants, and researchers. Furthermore, the sensors can be paired with other technologies, such as the automatic milking system (**AMS**), allowing for the integration of behavior and production parameter data for holistic monitoring of the herd.

Rumination is a cyclical process that consists of regurgitation, remastication, and reswallowing of feed boluses, and it is necessary for particle breakdown and rumen pH balance. Dairy cows ruminate on average 7 to 8 hours per day (Zebeli et al., 2006; Soriani et al., 2012), which mostly occurs at night when there are fewer disruptive management tasks being performed (Pahl et al., 2015; Beauchemin, 2018). Rumination time (**RT**) decreases on average by 70% of the average RT observed during the dry period on the day of calving (Calamari et al., 2014), reaching a minimum daily average of approximately 4 hours (Soriani et al., 2012; Kaufman et al., 2016). Rumination time in the prepartum period was shown to be associated with postpartum RT (Soriani et al., 2012; Liboreiro et al., 2015).

The metabolic and health status of the cow during the transition period are associated with deviations in RT. Numerous previous studies reported an association between decreased RT and metabolic or digestive disorders, such as subclinical ketosis, displaced abomasum, indigestion, and ruminal acidosis (Devries et al., 2009; Kaufman et al., 2016; Stangaferro et al., 2016). Similarly, other studies reported that RT decreased during lameness and pneumonia events (King et al., 2017; King and DeVries, 2018). Furthermore, cows that delivered twins exhibited a decrease in postpartum RT compared to cows that delivered singletons, which was likely explained by uterine and metabolic issues related to the occurrence of twins (Liboreiro et al., 2015). Soriani et al. (2012) found that cows that underwent a severe inflammatory response in the peripartum period had a reduced RT in early lactation. Therefore, the aforementioned studies provide evidence that RT may be used as a proxy for cow health in the postpartum period, where subtle changes in RT may indicate a health disorder in early lactation.

Furthermore, early lactation RT has been shown to be positively associated with short-term milk yield (**MY**) (Liboreiro et al., 2015; Stone et al., 2017; Kaufman et al., 2018), which may have been due to healthier animals and rumens, and increased feed intake. Cows with greater RT from 3 to 6 days in milk (**DIM**) produced up to 8 kg more milk per day during the first 30 DIM (Calamari et al., 2014). Additionally, King et al. (2017) showed that RT and MY followed a similar pattern around the period of disease diagnosis, where both began to decrease a few days prior to disease detection. Lactation peak milk yield (**PMY**) normally occurs between 45 and 100 DIM, with primiparous cows peaking later than multiparous cows (Siewert et al., 2019). In a simple linear regression model, Mellado et al. (2011) showed that PMY accounted for a majority of the variability in total 305-d MY ($R^2 = 0.69$), where each 1 kg increase in PMY was associated with a 157 kg increase in total 305-d MY on average. However, the association between immediate postpartum RT and PMY has not been documented. Daily values of RT are more commonly used as a predictor of health and production in most studies. Nevertheless, it has been speculated that the change in RT over a certain period may be a preferred predictor as opposed to daily RT values (Liboreiro et al., 2015). Therefore, the objectives of this study were to: 1) investigate the association of change in

RT and average RT during the immediate postpartum period with PMY in dairy cows, and 2) determine the best statistical model based on number of DIM to evaluate this association. We hypothesized that cows with a greater postpartum change in RT and with a greater average postpartum RT would have greater PMY.

MATERIALS AND METHODS

Data were collected from 33 AMS farms in the U.S. (located in Minnesota and Wisconsin). All farms in this study used a free-flow cow traffic system, such that cows had unrestricted access to all areas of the pen, including the AMS. Retrospective data recorded daily on cow production and RT were collected from the AMS software (T4C, Lely Industries, Maassluis, The Netherlands) for a period of 12 months during the years of 2017 and 2018. The data included cow identification and respective parity, total daily MY (kg), and total daily RT (min). Herds enrolled in this study were comprised of Holsteins and all the cows were housed in freestall barns with no access to pasture.

Rumination time was measured using Hi-Tag rumination sensors (SCR Engineers, Netanya, Israel), in which the logger was positioned on the left side of the neck and held in place by a collar. A built-in microphone recorded sounds of regurgitation and rumination, which were aggregated by the software and displayed as 24-h daily RT in min. The Hi-Tag rumination monitoring system was validated as a tool to accurately measure RT when compared with direct human observation, Pearson's $r = 0.93$, $P < 0.001$ (Schirmann et al., 2009).

Data Processing and Statistical Analysis

All post-collection data management procedures and statistical analyses were performed in RStudio (R Core Team, 2020). The variable DIM represented the day of the lactation period, which began with 1 following the day of calving. Day of calving (i.e., DIM = 0) was removed from the dataset, as cows calved at different times of day resulting in less than 24 h of data. Cows were categorized according to parity: parity 1 (**P1**), parity 2 (**P2**), or parity ≥ 3 (**P3+**). New variables for PMY (kg) and DIM at peak (d) were created, which described the highest daily milk yield for each cow. A data-driven threshold of 180 DIM for P1 cows and 120 DIM for P2 and P3+ cows was established for the identification of PMY, which represented the range of DIM where the vast majority of cows in this study reached the highest daily MY. Daily RT continued to increase from DIM 1 until DIM 6 when it reached stable levels; therefore, only the first 6 DIM were considered for calculating early lactation rumination predictor variables, as the change in RT was of interest to build the statistical model. Daily MY for the first 150 DIM and daily rumination for the first 14 DIM were visually assessed prior to analyses by plotting the estimated local averages and standard errors from generalized additive models fit with a cubic spline by parity group.

Data cleansing was performed prior to analyses to improve the quality of the data by diagnosing and removing faulty data (Van Den Broeck et al., 2005). Lactation periods had to meet the following criteria, else they were removed: 1) complete daily RT observations for the first 6 DIM that had values ≥ 30 min; 2) a length of ≥ 120 d for P1 or ≥ 90 d for P2 and P3+; 3) no missing MY observations prior to identified PMY; 4) DIM at peak ≥ 7 d. Lastly, repeated lactations within cow were removed, and the longest lactation meeting the selection criteria remained in the dataset. Daily MY observations were considered outliers and not used when MY had a z-score ≥ 1.96, which was calculated based on 7-d MY averages for each cow (z = (MY – 7-d MY average) / 7-d SD for MY). Furthermore, a sample of random lactations with a wide range of DIM at peak was plotted for visual inspection of potential influential MY observations, to ensure that the identified PMY was not driven by outlier observations. The final dataset included 4,662 cows with one lactation each. The number of cows from each farm ranged from 34 to 416.

To demonstrate the differences in average RT and change in RT between different levels of PMY, we assigned cows to a production category within each farm and parity corresponding to percentiles for PMY values: ≥ 0.75 (top; **T25**) and ≤ 0.25 (low; **L25**). For these analyses, each model had either change in RT or average RT as outcome variable, and fixed effects of PMY percentile category, parity, the PMY percentile category × parity interaction, and a random intercept for farm.

Association of Change in Rumination Time and Average Rumination Time with Peak Milk Yield. Peak milk yield was used as the outcome variable in 6 mixed linear regression models using the lmer function of the lme4 package (Bates et al., 2015), which corresponded to the number of DIM, ranging from 1 to 6, used to calculate the predictor variables based on RT. Five change in RT variables were created, which corresponded to the slope coefficients for change in RT/d related to DIM = 1 extracted from simple linear regressions performed for each cow and for each of the first 2 – 6 DIM as continuous predictors with RT as the outcome variable. For instance, the change in RT over the first 6 DIM was the linear regression slope representing the change in RT from 1 to 6 DIM. The same procedure was done for the first 2, 3, 4, and 5 DIM for each cow. Similarly, 5 average RT variables were created, which corresponded to the arithmetic mean RT for each cow over the first 2 – 6 DIM. Lastly, a variable was created for the RT on DIM = 1. Therefore, 11 rumination variables were calculated for each cow. The Pearson`s correlation coefficients between average RT and change in RT were: $r = -0.04$ for the model containing the first 2 DIM, $r = 0.02$ over the first 3 DIM, $r = 0.05$ over the first 4 DIM, $r = 0.05$ over the first 5 DIM, and $r = 0.06$ for the model with 6 DIM. It is suggested that a collinearity problem exists when factors with a Pearson's $r > 0.7$ are included in the same statistical model (Dormann et al., 2013; Tremblay et al., 2016). Therefore, we included both average RT and change in RT in the final model.

For the statistical analyses of PMY, the 5 models corresponding to rumination predictor variables calculated over the first 2 – 6 DIM had PMY as outcome variable, with fixed effects of average RT (continuous), change in RT (continuous), parity (3 levels), the average RT × parity interaction, the change in RT × parity interaction, and a random intercept for farm (33 levels). In other words, each of the 5 models included 2 variables for rumination – the change in RT and the average RT over a specific period. For example, the model for 2 DIM had change in RT over the first 2 DIM (with respect to DIM 1) and the average RT for the first 2 DIM included as predictor variables. The model corresponding to RT on DIM =1 as a predictor variable had fixed effects of RT (continuous), parity, the RT × parity interaction, and a random intercept for farm.

Model Fit and Significance. For each model, the root mean square error (RMSE), marginal R^2 coefficient ($R^2_{(m)}$), and conditional R^2 coefficient ($R^2_{(c)}$) were calculated using tools in the merTools and MuMIn packages (Barton, 2019; Knowles and Frederick, 2020). Model fit was assessed by visual observation of residual plots. The denominator degrees of freedom were estimated using Satterthwaite's method. Restricted maximum likelihood estimates were obtained, and means are reported as least squares means.

Graphical visualizations of data were created using tools of the ggplot2 package (Wickham, 2016). Significance was declared at $P \leq 0.05$. The Tukey *P*-value adjustment was used for pairwise comparisons.

RESULTS AND DISCUSSION

The population of cows (N = 4,662) in this observational study was composed of 33% P1 (n = 1,538), 29% P2 (n = 1,354), and 38% P3+ (n = 1,770) cows. The DIM at peak variable had a right-skewed distribution, therefore the median is reported. The median DIM at peak was 52 (range: 7 to 180) across all parity groups. A recent study using 2013 – 2014 data from cows milked in AMS found that P1 cows reached PMY between 89 and 148 DIM, on average (Siewert et al., 2019). Likewise, Mellado et al. (2011) reported mean PMY at 123 DIM for P1 cows milked 3 times daily in a conventional parlor and injected with recombinant bovine somatotropin (rbST). Primiparous cows in the current study reached lactation peak considerably sooner, at a median of 75 DIM, ranging from 11 to 180 DIM. This may indicate that AMS farmers are adopting management strategies that allow P1 cows to adapt to the AMS more easily and consequently reach peak earlier in their lactation. Second and third parity cows in the current study peaked at a median of 44 (range: 8 – 120) and 46 (range: 7 – 120) DIM, respectively, in agreement with Siewert et al. (2019), who reported peak for multiparous cows (P2 and P3+ combined) between 29 and 58 DIM, on average. However, multiparous cows housed in open lots peaked at a mean of 106 DIM according to a previous study (Mellado et al., 2011), which is considerably later than cows in our study. Differences in genetics, nutrition, housing, management, and weather conditions may explain the discrepancy in days to reach peak, as the latter study was conducted on a dairy farm in Mexico (ibid).

Peak milk yield for cows in this study had an overall arithmetic mean of 53.6 ± 11.4 kg. The mean ± SD PMY was 43.1 ± 6.7 kg (range: 18.8 – 66.6 kg), 56.2 ± 8.8 (range: 21.1 – 84.9 kg), and 60.7 ± 9.7 (range: 20.6 – 89.1 kg) for cows in P1, P2, and P3+, respectively. Cows in P2 and P3+ had greater PMY than P1 cows, which was expected considering that primiparous cows have a biologically normal lower PMY compared to P2 and P3+ cows (Figure 1). Peak milk ratio was 0.77 and 0.71 between P1 and P2, and P1 and P3+ cows, respectively. Similarly, Siewert et al. (2019) reported a peak milk ratio between primiparous and multiparous cows (P2 and P3+ combined) of 0.71 to 0.74, depending on cow traffic flow. The industry recommended PMY for P1 cows has been 80% of the PMY of P2 cows and 75% of PMY of P3+ cows (Bailey and Currin, 2009). However, the latter authors considered lactation peak for P1 cows to be between 41 and 100 DIM based on Dairy Herd Improvement Association (DHIA) records, which are generally based on a once monthly sample collection per cow. Therefore, we suggest that the PMY reported herein and found by Siewert et al. (2019) might be a more accurate representation of the actual lactation peak of cows on AMS dairy farms, as both studies used complete daily MY observations.

The average PMY was (mean ± SD) 44.3 ± 8.8 kg, and 62.7 ± 10.0 kg for cows in the L25 (*n* = 1,215; P1 = 399, P2 = 357, P3+ = 459), and T25 (*n* = 1,211; P1 = 398, P2 = 355, P3+ = 458) categories for PMY, respectively, where cows in the T25 category had a 42% greater PMY compared to L25. The median DIM at peak was 52 (range: 7 – 180 DIM) for L25, and 54 (range: 9 – 178 DIM) for T25. Least squares means for change in

RT and average RT by parity and PMY percentile category are shown in Table 7. These results are provided to demonstrate the difference in RT parameters among parities. For P1 cows, there was no difference in change in RT and average RT between PMY percentile categories, whereas Parity 2 and P3+ cows categorized as T25 for PMY had a greater change in RT and average RT compared with the L25 category in all statistical models. The differences in RT are clear in Figure 2, where daily RT over the first 14 DIM is shown for the interaction between PMY percentile category and parity.

In recent years, information derived from rumination behaviors automatically monitored with sensors has been largely used for predicting a variety of outcomes, which has potential benefits of reduced human labor and minimal disruption of the animals. Important events in the life of a dairy cow, such as estrus and calving, can be predicted using RT (Reith and Hoy, 2012; Pahl et al., 2015; Schirmann et al., 2016). Furthermore, King et al. (2017) suggested that RT starts to decrease as early as 14 d prior to the diagnosis of health disorders, such as pneumonia and lameness. Rumination time has been shown to be associated with various health and metabolic disorders during the early postpartum period. Soriani et al. (2012) reported a negative correlation of prepartum and early postpartum average RT with non-esterified fatty acids (NEFA) and beta-hydroxybutyric acid (BHBA) values during the postpartum period (Pearson's $r = -0.35$, $P < 0.001$). A recent study reported that cows with subclinical ketosis had a reduced RT compared to healthy cows from 0 to 8 DIM (Liboreiro et al., 2015). The latter authors also showed that cows with retained placenta had a decreased RT from 2 to 7 DIM, and cows diagnosed with metritis exhibited a reduced RT from 2 to 9 DIM, when compared to healthy cows (ibid). Furthermore, hypocalcemic cows at calving had a lower RT at 1

DIM compared with healthy cows (ibid). Calamari et al. (2014) showed that 91% of cows in the < 0.50 quantile for RT from 3 to 6 DIM were diagnosed with at least one clinical disease in the early postpartum period, while only 42% of cows in the ≥ 0.50 quantile for RT from 3 to 6 DIM had been diagnosed with a clinical disease. Therefore, we suggest that RT may be used as a proxy for dairy cow health, especially during the early lactation period when cows are more susceptible to health disorders, which can then affect their overall milk production, including lactation PMY.

Association between Change in Rumination Time and Peak Milk Yield

To our knowledge, the association between change in RT in the immediate postpartum period and PMY has not been investigated. Our results (Table 8) show a positive association between the change in RT in the early postpartum and the outcome of PMY (Model 2 DIM: $F_{1, 4632} = 18.6$, $P < 0.0001$; Model 3 DIM: $F_{1, 4635} = 23.2$, $P < 0.0001$; Model 4 DIM: $F_{1, 4635} = 29.9$, $P < 0.0001$; Model 5 DIM: $F_{1, 4633} = 34.5$, $P < 0.0001$; Model 6 DIM: $F_{1, 4634} = 34.5$, $P < 0.0001$); however, the association differs by parity, as indicated by an interaction between change in RT and parity for the models from 2 to 6 DIM (Model 2 DIM: $F_{2, 4624} = 14.9$, $P < 0.0001$; Model 3 DIM: $F_{2, 4624} = 17.3$, $P < 0.0001$; Model 4 DIM: $F_{2, 4624} = 9.0$, $P = 0.0001$; Model 5 DIM: $F_{2, 4624} = 7.8$, $P = 0.0004$; Model 6 DIM: $F_{2, 4624} = 5.3$, $P = 0.005$). Change in RT was not associated with PMY for P1 cows in any of the models. For cows in P2 and P3+, change in RT was associated with PMY in all models from 2 to 6 DIM. For each 100 min/d increase in change in RT across models, the coefficients for the increase in PMY (model 2 DIM – model 6 DIM) ranged between 1.04 – 4.26 kg and 1.15 – 4.84 kg for cows in P2 and P3+, respectively (Table 8). The association between change in RT and PMY was not different between cows in P2 and P3+. Figure 4 shows these associations by reporting the least squares means of PMY for the interaction between parity and change in RT for the model 6 DIM. A similar pattern was found for models 2 – 5 DIM (graphs not shown). A greater positive change in RT indicates that cows increased their daily RT more rapidly after calving, and these are most likely healthier cows during the early postpartum period. Calamari et al. (2014) showed that cows take between 3 and 15 d to restore a stable level of daily RT after calving. In the current study, individual cows reached a stable daily RT at 6.2 ± 1.2 DIM, ranging from 5 to 12 DIM (Figure 3). A future algorithm for the prediction of PMY should consider including different parameters for primiparous and multiparous cows, as based on the findings of the current study change in RT was associated with PMY for cows in P2 and P3+, but not for P1 cows. The possible reasons for this difference between P1 and multiparous cows were not investigated in the current study. The fact P1 cows generally have a considerably lower PMY along with a less steep increase in daily RT in the early postpartum in comparison with multiparous cows could partially explain such findings. However, further research is warranted to better understand the lack of association between early postpartum change in RT and PMY in P1 cows.

The individual cow change in RT related to RT at DIM = 1 ranged from −353 to +431 min/d over the first 2 DIM, −195 to +322 min/d over the first 3 DIM, −131 to +207 min/d over the first 4 DIM, −103 to +164 over the first 5 DIM, and −80 to +136 min/d over the first 6 DIM. The range for change in RT decreased as the number of days included in the calculations increased. A significant number of cows were identified with a negative change in RT in early postpartum, such that their RT decreased relative to RT on DIM = 1. Negative values for change in RT were identified in 28, 19, 13, 11, and 9% of the cows in this study when calculated over the first 2, 3, 4, 5, and 6 DIM, respectively. This phenomenon was unexpected since the day of calving typically represents the timepoint when the lowest daily RT of approximately 4 h is observed (Soriani et al., 2012; Kaufman et al., 2016; Figure 3). Although health events were not collected for this study, it is reasonable to suggest that cows with a negative change in RT may have been experiencing serious issues related to transitioning. A greater change in RT was associated with greater PMY in the current study for multiparous cows, where each 100 min/d increase in RT resulted in up to 4.84 kg greater PMY. Ensuring that transition cows are healthy and have quality feed available at all times may increase RT in the early postpartum period and improve productivity and profitability on dairy farms. Our research suggests that the change in RT in early lactation may be used for future predictions of PMY, where data from the first 2 to 6 DIM resulted in useful associations for predictions. However, further research investigating other cow- and herd-level factors is encouraged.

Association between Average Rumination Time and Peak Milk Yield

Although the association between change in RT in early postpartum and PMY has not yet been investigated, the association between early lactation RT and MY has been previously documented. Average MY in the first 90 DIM has been shown to have a moderate positive association with 21-d average postpartum RT (Pearson's $r = 0.42$, $P < 0.01$) (Liboreiro et al., 2015). Calamari et al. (2014) found that cows with greater RT during 3 to 6 DIM had a greater average MY during the first month of lactation, resulting in almost 8 kg more milk per day. Moreover, a recent study showed that every 30-min increase in daily RT was associated with an increase in MY of approximately 0.2 kg/d for P1 and 0.5 kg/d for P2 cows from 4 to 28 DIM, and every 30-min increase in daily RT was associated with a 1.2 kg/d increase in MY for P3+ cows during the first week of lactation (Kaufman et al., 2018).

In the current study, the average RT across parity groups ranged from 301 min at 1 DIM to 383 min over the first 6 DIM, with individual daily RT ranging from 30 to 664 min. Our findings showed that average RT was associated with PMY in all statistical models (Model 1 DIM: $F_{1,\,4645} = 9.8$, $P = 0.0017$; Model 2 DIM: $F_{1,\,4647} = 32.5$, $P < 0.0001$; Model 3 DIM: $F_{1,\,4649} = 48.5$, $P < 0.0001$; Model 4 DIM: $F_{1,\,4650} = 64.6$, $P < 0.0001$; Model 5 DIM: $F_{1,\,4651} = 82.3$, $P < 0.0001$; Model 6 DIM: $F_{1,\,4651} = 96.1$, $P < 0.0001$), yet there was an interaction between average RT and parity (Model 2 DIM: $F_{2,\,4625} = 7.7$, $P = 0.0004$; Model 3 DIM: $F_{2,\,4625} = 11.6$, $P = 0.0001$; Model 4 DIM: $F_{2,\,4625} = 12.3$, $P < 0.0001$; Model 5 DIM: $F_{2,\,4625} = 14.7$, $P < 0.0001$; Model 6 DIM: $F_{2,\,4625} = 16.1$, $P < 0.0001$). Similar to the change in RT, there was no association between average RT and PMY for P1 cows in any of the models. However, average RT was associated with PMY in all models from 2 to 6 DIM for cows in P2 and P3+. For each 100 min increase in average RT across models, the regression coefficients for the increase in PMY (model 2 DIM – model 6 DIM) ranged between 1.34 – 2.26 kg, and 1.02 – 2.15 kg for cows in P2 and P3+, respectively (Table 8). The association of average RT with PMY was not different between cows in P2 and P3+ regardless of the model. Figure 4 shows these associations by reporting the least squares means of PMY for the interaction between parity and average RT for the model 6 DIM. A similar pattern was found for models 2 – 5 DIM.

Primiparous cows are known for having a lower average RT compared to multiparous cows. Soriani et al. (2012) reported that P1 cows had a consistently lower RT compared to multiparous cows (P2 and P3+) from 10 d prepartum until 40 DIM, and they suggested that P1 cows may display a lower RT due to the greater stress of environmental changes in early lactation compared to multiparous cows. Figure 3 shows that P1 cows in the current study indeed had a lower average daily RT compared to cows in P2 and P3+ during the first 14 DIM. Moreover, P1 cows normally have lower DMI in comparison with P2 and P3+ cows (Janovick and Drackley, 2010), which is expected as rumen capacity is positively correlated with body size (De Boever et al., 1990). However, even when adjusted to a percentage of body weight, DMI is reduced in P1 cows (Maekawa et al., 2002). The latter authors found that P1 cows had decreased DMI and also decreased RT compared to multiparous cows (ibid). Therefore, a lower average RT in early lactation along with a normally lower PMY for P1 cows could partially explain the lack of association between average early postpartum RT and PMY for this parity group.

Model Comparison

Considering the model fit parameters presented in Table 9, the model using data from the first 6 DIM explains the variability of the data the best — with lowest RMSE, and greatest $R^2_{(m)}$ and $R^2_{(c)}$ coefficients. However, data collected from only 2 to 3 DIM are capable of generating similar model fit for the association of RT variables and PMY. We decided to use only data for the first 6 DIM after a preliminary exploration of the data, which showed the average daily RT leveling off starting at 7 DIM (Figure 3). For the current study, including both change in RT and average RT in the statistical model improved the model fit and should therefore both be considered as predictors of PMY.

Ultimately, a prediction algorithm may be created to predict PMY using change in RT and average RT along with other factors to help producers make management decisions. Cows with reduced RT in early lactation may decrease PMY and overall lactation productivity. The prediction of such an outcome early on could help producers decide if, for instance, a special treatment or potential early removal from the herd is an option for those animals. Caution is warranted when generalizing results from the current study, considering that it was performed in a single geographical location, where all farms had the same type of housing and milking system. Furthermore, the analyses and the results of the current study are based on averages for thousands of cows across 33 dairy farms. Therefore, the associations found herein are not predictions and may differ at the cow level.

CONCLUSIONS

It was interesting to learn that the time it took to reach a more stable rumination time in the early postpartum period was not associated with peak milk yield for primiparous cows; however, it appeared to be an important factor associated with peak milk yield for multiparous cows. Results of this study indicate that multiparous cows that increase rumination time to stable levels more rapidly and with greater average daily rumination time soon after parturition may produce more milk during their lactation. Therefore, these rumination behavior indicators could help producers make management decisions related to animal health or early removal of cows from the herd. Even though the model with 6 DIM resulted in a better accuracy, the use of data over the first 2 DIM generated similar results. Furthermore, findings of this study warrant for future investigations using data collected via sensors and automatic milking systems.

Chapter 4

Association between change in body weight during early lactation and milk production variables in automatic milking system herds

SUMMARY

The objectives of this observational study were to investigate 1) the association between fat-to-protein ratio (**FPR**) and body weight (**BW**) change in early lactation, while controlling for daily number of milkings and concentrate intake; and 2) the association between early lactation BW change and 90-d milk yield of dairy cows in automatic milking system (**AMS**) herds. Retrospective daily cow data were collected from the Lely T4C software on 33 farms. Cows were categorized by parity into P1, P2, or P3+. The BW change was calculated over 7 and 21 DIM as a percentage related to DIM 1, and used as outcome in 2 mixed linear regression models, with daily FPR, milkings, and concentrate intake, parity, DIM, and interactions with parity and DIM as initial explanatory variables. Cow nested within farm was the random effect in these models (n = 5,329). Backward elimination was used until all factors had a $P < 0.05$. The 90-d milk yield was the outcome variable in 2 other models, with each BW change variable, parity, and their interaction as explanatory variables. Cow nested within farm was the random effect (n = 3,936). On average, cows in all 3 parity groups lost BW during the first 21 DIM. FPR had a positive association with 7-d BW change for P2 only (−0.12 ± 0.04%). Milkings had a positive association with 7-d BW change for P3+ only (0.04 ± 0.01%). Concentrate intake had a positive association with 7-d BW change for P2 (0.02 ± 0.01%), and a negative association for P3+ (−0.02 ± 0.01%). FPR was positively associated with

21-d BW change for P1 (0.14 ± 0.02%), while the association was negative for P2 (−0.05 ± 0.02%) and P3+ (−0.07 ± 0.02%). Milkings was negatively associated with 21-d BW change for P1 (−0.04 ± 0.01%) and P2 (−0.02 ± 0.01%), and positively associated with 21-d BW change for P3+ (0.03 ± 0.01%). Concentrate intake was positively associated with 21-d BW change for P1 (0.04 ± 0.00%) and P2 (0.01 ± 0.00%), and negatively associated with P3+ (−0.02 ± 0.00%). The 7-d BW change was not associated with 90-d milk yield for P1; however, the association was negatively quadratic for P2 and P3+. Cows in P2 and P3+ that maintained BW over 7 DIM had greater 90-d milk yield. The 21-d BW change had a negative quadratic relationship with 90-d milk yield for all parity groups; P1 cows with a 21-d BW change of −8.2% and P2 and P3+ cows with 21-d BW change of about −4% were more productive over 90 DIM. The associations between FPR and BW change were not as biologically significant as anticipated; cows that maintained or lost up to 10% of BW over 21 DIM were more productive during the first 90 DIM.

Key words: automatic milking systems, body weight, fat-to-protein ratio, milk yield

INTRODUCTION

The early lactation represents a challenging period for dairy cows, as they are faced with calving and the sudden onset of a new lactation. The rapid increase of nutrient requirements for milk production is rarely met by the feed intake of cows in the early postpartum, resulting in a negative energy balance (**NEB**; Drackley, 1999; De Vries and Veerkamp, 2000; Weber et al., 2013). As a response mechanism to this increased unmet energy demand, adipose and muscle tissues are mobilized leading to losses in body condition and weight. However, this tissue mobilization has been shown to vary in magnitude among cows. Even within the same herd and same diet, the energy use for metabolic functions varied by up to 100% between animals (McNamara, 2012). A great variation in body weight (**BW**) and energy balance (**EB**) during the early lactation period in a herd of similar cows consuming the same diet was also reported (McNamara, 2012). Moreover, cows with greater NEB and BW loss in early lactation showed an impaired reproductive performance, including increased days open and delay of luteal activity (De Vries and Veerkamp, 2000; Zachut and Moallem, 2017).

Great efforts have been made to find easily available milk production variables that could be used as indicators of EB for dairy cows in early lactation stages. The body fat mobilization during periods of NEB leads to increased milk fat content, and De Vries and Veerkamp (2000) showed that the change in milk fat percentage had consistently high correlations with nadir of EB. Milk protein content is also normally increased at onset of lactation, which return to more stable levels within the first few weeks postpartum, following a similar pattern as fat content (Roche et al., 2007; Weber et al., 2013). Early research suggested that the milk fat-to-protein ratio (**FPR**) was a more sensitive and consistent indicator of energy status when compared to milk fat or protein alone (Grieve et al., 1986). Research has shown that the FPR is greatest in the early lactation period, coinciding with NEB, and it decreases reaching stable levels along with a positive EB (Buttchereit et al., 2010), reinforcing the potential utility of FPR as an indicator of energy status, especially during early lactation (Buttchereit et al., 2011).

Estimating the actual EB of a dairy cow may be challenging, especially on non-research dairy farms, as it requires the measurement of all energy inputs and outputs (i.e., milk, gestation, growth). Body condition score is commonly used to monitor changes in cow body fat reserves, as most farms do not measure animal BW regularly. However, BCS is an indirect measurement, subject to human error and bias, and it requires trained observers. Continuous monitoring of BW change for individual cows could provide farmers with more direct measures of energy status, especially during the early postpartum period and in combination with other factors such as FPR. Technologies such as the automatic milking system (**AMS**) have the capability of recording milk production variables and BW daily, which could facilitate the identification of animals at greater risk for metabolic disorders and help with management decisions on these farms. Early intense research performed over various trials in the Netherlands showed strong relationships between BW change and both predicted and calculated EB (Heuer et al., 2001). The health and metabolic status of the cow during the first 30 DIM affected the BW change differently in different parity groups (Caixeta et al., 2015). A positive correlation was found between liver fat concentrations in the postpartum and BW loss, and the milk production of cows with different levels of liver fat content was found to be similar (Weber et al., 2013). However, Zachut and Moallem (2017) showed that cows with greater than average BW loss between the first and fifth weeks of lactation had greater milk production during the first 30 DIM compared to cows with reduced BW loss.

Additional factors recorded daily by the AMS software, such as number of successful milkings and concentrate intake, have been shown to be associated with productivity (Siewert et al., 2018). However, the association between daily recorded milk production variables on AMS farms and BW change has not yet been documented on a large dataset of US dairy cows. Therefore, the objectives of this study were to investigate: 1) the association between FPR and BW change in early lactation by parity group, while controlling for number of milkings and concentrate intake in the AMS box; and 2) the association between early lactation BW change and 90-d milk yield. The findings of this study may help improve existing algorithms for the identification of animals at risk for health disorders and for the prediction of future milk production in herds using AMS.

MATERIALS AND METHODS

Data were collected from 33 AMS farms in the U.S. (located in Minnesota and Wisconsin). All farms in this observational study used a free flow cow traffic system, such that cows had unrestricted access to all areas of the pen, including the AMS. Retrospective daily data were collected from the AMS software (T4C, Lely Industries, Maassluis, The Netherlands) for a period of 12 months during the years of 2017 and 2018. The data included cow identification and respective parity, milk yield, milk fat and protein percentages, number of successful milkings, concentrate intake in the AMS box, and average BW. The data were recorded during each milking and transformed into daily values per cow by the AMS software. Herds enrolled in this study were comprised of Holsteins and all the cows were housed in freestall barns with no access to pasture.

Data Processing

All data management procedures and statistical analyses were performed in RStudio (R Core Team, 2020). Cows were categorized according to parity into parity 1 (**P1**), parity 2 (**P2**), or parity ≥ 3 (**P3+**). Day of calving (i.e., DIM = 0) was removed from the dataset, as cows calved at different times of day resulting in less than 24 h of data. A new data set was created for each objective. For objective 1, cows with complete observations from 1 to 21 DIM remained in the data set. A variable was created for FPR by dividing the daily average milk fat percentage by the daily average milk protein percentage for each cow. Two BW change variables were created for each cow, which corresponded to the difference in BW at 7 and 21 DIM with respect to DIM = 1, expressed as a percentage. The data set for objective 1 had the following variables with one daily observation each: farm, cow ID, parity, DIM, number of milkings, concentrate intake in the AMS box, FPR, 7-d BW change, and 21-d BW change. Visual inspection of the data suggested the presence of unusual values. Therefore, for the detection of potential outlier observations, each data value had a z-score calculated within each variable and parity group (Rousseeuw and Hubert, 2011). Daily observations with a z-score > 3 were considered outliers and revalued as missing data. A z-score tells us how many standard deviations away each observation is from the overall mean of a variable, where in a normal distribution ± 3 SD includes approximately 99.7% of the data. The final data set had 5,490 cows with 21 observations each. For the second objective, total milk production per cow was calculated over the first 90 DIM, and the data set had variables for farm, cow ID, parity, 7-d BW change, 21-d BW change, and 90-d milk yield, from 3,936 cows with one observation each.

Statistical Analysis

Factors associated with body weight change in early lactation. Each change in BW variable was used as the outcome variable in a mixed linear regression model using the lmer function of the lme4 package (Bates et al., 2015). Each model had fixed effects of FPR (continuous), milkings (continuous), concentrate intake in the AMS box (continuous), parity (3 categories), DIM (categorical), and all possible 2-way and 3-way interactions with parity and DIM. The number of DIM included in each model matched the outcome variable, where the first 7 DIM were included in the model for 7-d BW change, and 21 DIM were included in the model for 21-d BW change. Cow nested within farm was included as random effect. Backward elimination was used until all remaining factors had a $P < 0.05$. Model fit was assessed by visual observation of residual plots. The denominator degrees of freedom were estimated using Satterthwaite's method. Graphical visualizations of data were created using tools of the ggplot2 package (Wickham, 2016). Significance was declared at $P \leq 0.05$. The Tukey *P*-value adjustment was used for pairwise comparisons.

Association between body weight change and 90-d milk yield. Two mixed linear regression models were created for the outcome variable of 90-d milk yield per cow. Due to prior knowledge of a possible quadratic relationship between BW change and milk production, fixed effects included both the linear and quadratic term of 7-d or 21-d BW change (continuous), parity (3 categories), and the respective BW change × parity interaction, along with a random effect of cow nested within farm. The quadratic term fitted the data better, so only the interaction between the quadratic term and parity was included. Model fit was assessed by visual observation of residual plots. The denominator degrees of freedom were estimated using Satterthwaite's method. Graphical visualizations of data were created using tools of the ggplot2 package (Wickham, 2016). Significance was declared at $P \leq 0.05$. The Tukey *P*-value adjustment was used for pairwise comparisons.

RESULTS

The Pearson's correlation coefficient was 0.62 (P <.0001) for 7-d × 21-d changes in BW. On average, cows in all parity groups lost BW over the first 21 DIM (Figure 5). Of the 5,490 cows in the data set for objective 1, a total of 5,323 cows (P1 = 1,834, P2 = 1,540, and P3+ = 1,949) were included in the analysis of 7-d BW change, as some cows were ignored by the model because of missing data. Cows in P2 had the greatest negative estimated 7-d BW change (LSM ± SE: −3.01 ± 0.14%), while cows in P1 had an estimated −2.67 ± 0.14% change and those in P3+ had an estimated −2.15 ± 0.14% change of their BW from DIM 1. For the analysis of 21-d BW change, data from 5,329 cows (P1 = 1,829, P2 = 1,543, and P3+ = 1,957) were used. Similarly, P2 cows had the greatest estimated BW loss over the first 21 DIM (LSM ± SE: −5.03 ± 0.22%), followed by cows in P3+ with a −4.89 ± 0.22% change from DIM 1 BW, and P1 cows with a −3.99 ± 0.22% BW change from 1 to 21 DIM.

For the association between early lactation BW change and 90-d milk yield, we used data from 3,936 cows (P1 = 1,373, P2 = 1,131, and P3 = 1,432). The least squares means for 90-d milk yield were very similar between the 2 models (7- and 21- BW change as explanatory variables). The total 90-d milk yield was highest for P3+ cows, with a production of (LSM ± SE – model with 21-d BW change) 4,564 ± 53 kg, followed by P2 cows producing on average 4,264 ± 54 kg, and P1 cows with a 90-d milk yield of 3,087 ± 53 kg.

Factors Associated with 7-d Body Weight Change

Fat-to-protein ratio. The overall average FPR over the first 7 DIM was (mean ± SD) 1.19 ± 0.25, ranging from 1.14 ± 0.23 for P2 to 1.23 ± 0.20 for P1 (Table 10). The variable FPR had significant 2-way interactions with parity and DIM, whereas the 3-way interaction was not present. The FPR slope was (estimate ± SE) 0.006 ± 0.04% (P = 0.88) for P1, −0.118 ± 0.04% (P = 0.002) for P2, and −0.017 ± 0.03 % (P = 0.59) for P3+ (Table 11; Figure 6A). A negative association between FPR and 7-d BW change was found for cows in P2 only. The slope was not different between P1 and P3+ (P = 0.60), but the slope for cows in P2 was different from the other two groups (*P* = 0.01). Furthermore, the association between FPR and 7-d BW change differed according to DIM during the first 7 DIM (Table 11).

Number of milkings. The 7-d average number of milkings across parities was (mean ± SD) 2.62 ± 0.95, with a range between 2.04 ± 0.49 for P1 and 2.94 ± 0.98 for P2 (Table 10). The number of milkings had an interaction with parity (Figure 6B), while the 2-way interaction with DIM and the 3-way interaction were not present. The association between number of milkings was different between all parity groups. Each unit increase in average number of milkings had a trend for a positive association of (estimate ± SE) 0.028 ± 0.016% increase in 7-d BW change for P1 cows (*P* = 0.07), and 0.036 ± 0.008% increase in 7-d BW change for cows in P3+ cows (*P* <.0001; Table 11). No association was found for cows in P2 (−0.006 ± 0.01%, *P* = 0.55).

Concentrate intake in the AMS. The average concentrate intake during the first 7 DIM across cows was (mean ± SD) 3.88 ± 1.07 kg/d (Table 10), with individual values ranging from 0.42 to 8.90 kg/d. As presented on Table 11, the concentrate intake in the AMS box had an interaction with parity. Each unit increase in concentrate intake was associated with a (estimate ± SE) 0.022 ± 0.009% increase in 7-d BW change for P2 cows (*P* = 0.018), whereas the association was negative for P3+ cows, with a 0.024 ± 0.008% decrease in 7-d BW change for each kg increase in daily concentrate intake (*P* = 0.003; Table 11). The concentrate intake was not associated with 7-d BW change for P1 cows (−0.01 ± 0.01%; *P* = 0.36; Figure 6C).

Factors Associated with 21-d Body Weight Change

Fat-to-protein ratio. Cows across parity groups averaged FPR at 1.23 ± 0.23, ranging from 1.20 ± 0.19 for P1 to 1.28 for P3+, over the first 21 DIM. The association between FPR over the first 21 DIM and 21-d BW change was different across parity groups (P <.0001; Figure 7A). The FPR was positively associated with 21-d BW change for P1 cows (0.137 ± 0.023%; P <.0001; Table 12). However, the association was negative for the other parity groups. Each unit increase in FPR was associated with a (estimate ± SE) 0.048 ± 0.021% (P = 0.025) and 0.073 ± 0.016% (P <.0001) decrease in 21-d BW change for P2 and P3+ cows, respectively. The slopes for P2 and P3+ cows were not different (P = 0.35).

Number of milkings. Over the first 21 DIM, the average number of milkings across parity groups was 2.95 ± 1.08, ranging from 2.30 ± 0.76 for P1 to 3.32 ± 1.06 for P2 cows. The number of milkings had a negative association with 21-d BW change for P1 and P2 cows, where each unit increase in average milking/d was associated with a 0.044 ± 0.007% (P <.0001; Table 12) and 0.015 ± 0.005% (P = 0.004) decrease in 21-d BW change, respectively. On the other hand, this association was positive for P3+ cows, with an estimated 0.029 ± 0.005% increase in 21-d BW change for each unit increase in number of milkings/d. The slopes differed across all parity groups (P <.0001; Figure 7B).

Concentrate intake in the AMS. Concentrate intake in the AMS during the first 21 DIM averaged (mean ± SD) 4.90 ± 1.48 kg/d across cows in this study (Table 10), with individual values ranging from 0.42 to 9.70 kg/d. Concentrate intake had an interaction with parity group. Each unit increase in concentrate intake was associated with a (estimate ± SE) 0.040 ± 0.004% (P <.0001) and 0.009 ± 0.003% (P = 0.006) increase in 21-d BW change for P1 and P2 cows, respectively. However, the association was negative for P3+ cows, with a 0.021 ± 0.003% decrease in 21-d BW change for each kg increase in concentrate intake (*P* <.0001; Table 12). The associations differed across all parity groups (i.e., slopes were different from each other; *P* <.0001; Figure 7C).

Association between Body Weight Change and 90-d Milk Yield

Cows had an average 7-d BW change of (mean ± SD) −2.56 ± 3.84% (Figure 5), meaning that on average cows lost 2.56% of their DIM 1 BW during the first 7 DIM. Cows in P1 had the greatest observed 7-d average BW loss at 3.01%, followed by P3+ cows with a 2.41% BW loss, and by P2 cows with a BW loss of 2.21%. The 7-d BW change was associated with 90-d milk yield, which differed according to parity group (*P* <.0001; Table 13). The BW change over the first 7 DIM was not associated with 90-d milk yield for cows in P1 linearly or quadratically (*P* = 0.89 and 0.36, respectively). However, a negative quadratic relationship was found for cows in P2 (estimate ± SE: −3.01 ± 0.51 kg; *P* <.0001) and P3+ (estimate ± SE: −3.15 ± 0.55 kg; *P* <.0001), as shown on Figure 8A. The curve (i.e., quadratic relationship) differed between these two groups (*P* <.0001) and the highest 90-d milk yields were achieved when 7-d BW change was near zero for both groups (−0.05%), with an estimated production of (LSM ± SE) 4,270 ± 55.2 kg for P2 and 4,575 ± 54.8 kg for P3+ cows.

The overall average 21-d BW change was (mean ± SD) −4.67 ± 4.93%, ranging from −3.83 ± 5.08% for P2 cows to −5.37 ± 4.97% for P1 cows (Figure 5). A negative quadratic association between 21-d BW change and 90-d milk yield was found for all parity groups (Table 13; Figure 8B), and associations differed between all parity groups (*P* <.0001). The curve turning point (i.e., greatest 90-d milk yield) decreased along with parity number, where P1 cows who lost an average of 8.18% of their DIM 1 BW produced an estimated (LSM ± SE) 3,100 ± 53.2 kg over the first 90 DIM; P2 cows achieved the greatest average production at 4,265 ± 53.8 kg when 21-d BW change averaged at −4.18%. Lastly, the turning point for cows in P3+ (4,567 ± 53.5 kg) was achieved when 21-d BW change averaged at −3.58% of their DIM 1 BW.

DISCUSSION

The main objectives of this study were to investigate the association between FPR and BW change in early lactation for cows on AMS farms, and also the association between BW change in early lactation and the total 90-d milk yield. One of the great advantages of automated technologies such as the AMS is the valuable monitoring of the herd through data recorded daily on the individual level, such as milk production variables and BW. Body weight measurements were recorded by AMS units equipped with scales every time cows entered the AMS to be milked, creating a daily average based on multiple daily observations, which decreases the effect of rumen and udder fill as opposed to single daily measurements. Frequent on-farm BW measuring showed potential to be used as an approximation metric for EB of cows in early lactation (Thorup et al., 2012). Heuer et al. (2001) calculated the BW change as the difference between weekly average BW per cow adjusted for rumen fill, which was strongly associated with both calculated and predicted EB over 7 independent feeding trials. In fact, adjusted BW change was referred to as a proxy for true EB (Heuer et al., 2001). Even though EB was not estimated for animals in the current study, it seems reasonable to suggest that cows with greater negative BW change were cows under more severe NEB. Our findings showed that most cows in all parity groups lost weight in the early lactation period, in agreement with a previous study (Mäntysaari and Mäntysaari, 2015). Our results also agree with Caixeta et al. (2015), who found that all cows in the 3 parity groups lost weight over the first 30 DIM, which was aggravated depending on blood calcium concentrations, NEB status, and concurrent health disorders. Parity 1 cows in the current study had the greatest observed mean BW loss as a percentage of their own BW at the first DIM over the first 7 and 21 DIM. The adjusted means (LSM), however, for both 7- and 21-d BW change were lowest for P2 cows. When Caixeta et al. (2015) measured BW change as a linear regression slope coefficient over the first 30 DIM, animals in P3+ had the greatest BW loss expressed in kg/d. It would be expected that cows in P3+ have a greater BW loss in kg/d as these are normally heavier animals. Therefore, the measurement of BW change as a percentage of the BW at DIM 1 may be a more desirable method, especially when thinking of NEB and its severity in the early postpartum period.

A study with data from 66 Irish dairy farms showed that greater BW loss from calving to day of BW nadir was associated with increased milk fat and lower protein content throughout lactation (Berry et al., 2007). Milk FPR has shown potential to be used as an indicator of metabolic disorders in dairy cows. Early research suggested a potential for FPR to be an indicator of subclinical ketosis, even though sensitivity and specificity were relatively low and the study only took into consideration one DHI test-day (Duffield et al., 1997). Indeed, further research demonstrated that FPR data derived from inline milk testers may help identifying cows with subclinical ketosis, where a cut-off of > 1.42 during 8 to 30 DIM had a sensitivity of 92% (Jenkins et al., 2015). A threshold of FPR > 1.5 has also been suggested as a metric with good sensitivity for the identification of cows with subclinical ketosis, ranging from 75 to 79% (Krogh et al., 2011; Jenkins et al., 2015). Furthermore, FPR was found to have a moderately high correlation with BHBA (Pearson's $r = 0.65$, $P < 0.001$) during early lactation (19 to 106 DIM; Garcia et al., 2015). A moderate genetic correlation between BHBA and FPR at first test-day was reported ($r_g = 0.49$; Koeck et al., 2014). Similarly, the FPR in the first DHI test showed that cows with a FPR ≥ 1.4 were 8.6 times more likely to have a displaced abomasum (Geishauser et al., 1997). Early lactation FPR > 2.0 was associated with an increase in postpartum diseases such as retained placenta and metritis (Toni et al., 2011). Moreover, FPR < 1.0 has been suggested to be an indication of subacute ruminal acidosis (Enemark et al., 2002). Also, FPR showed a relatively high sensitivity (72%) to diagnose subacute ruminal acidosis; however, specificity was fairly low at 31% (Rojo-Gimeno et al., 2018). Finally, Toni et al. (2011) reported a positive association between early lactation FPR and culling risk, where cows with a FPR between 1.0 and 1.5 had the lowest culling risk. Therefore, we were interested in the association between FPR and BW change in the early lactation period of cows in AMS herds, as it may be used to improve current built-in algorithms for the identification of animals at risk for health disorders or low production.

The milk FPR is normally increased during the early lactation stages, when cows normally undergo a NEB (Mäntysaari and Mäntysaari, 2015). Fat-to-protein ratio was reported to be a suitable indicator of energy status, as the lactation curves for FPR and EB mirrored each other, suggesting a causal relationship (Buttchereit et al., 2010). In a follow-up study, it was demonstrated that FPR may be a more adequate measure of EB in early lactation ($r_g = -0.62$, $P < 0.05$; at 15 DIM) than DMI, BCS, or individual milk components when P1 Holstein cows were evaluated for genetic indicator traits for EB

(Buttchereit et al., 2011). Therefore, it was hypothesized that cows in the current study would have a negative association between BW change and FPR, as early lactation is the time when most cows are in NEB associated with BW loss and a generally increased FPR. Indeed, as P2 cows lost more weight over the first 7 DIM, they also had a greater FPR, as demonstrated on Figure 6A. For P1 and P3+ cows, on the other hand, no association was found between 7-d BW change and FPR. When we investigated that same association over the first 21 DIM, the findings were different. Parity 1 cows presented a positive association between FPR and 21-d BW change, while for the other two parity groups 21-d BW change decreased as FPR increased. Previous literature suggested that multiparous cows are normally the ones with greater BW loss and NEB; therefore, we anticipated that multiparous cows with greater BW loss over the 21 DIM would have higher FPR, which was confirmed by the associations found in our data set.

Even though the models for the association between FPR and BW change in the early lactation period of cows in AMS herds had conditional R^2 of 0.98 and 0.99 over the first 7 and 21 DIM, these associations were not as biologically meaningful as we had initially anticipated, especially as cows progressed in their lactations – over 21 DIM. The model fixed effects accounted for approximately 1% of the variability in the outcome variables, while the random effects of cow and farm accounted for the remaining portion of the R^2 (i.e., > 97%). A quadratic relationship between BW change and FPR was considered; however, the quadratic term resulted in no improvement of the model and was then disregarded. We encourage future research on the use of both variables (FPR and BW change) in combination as explanatory variables along with other cow factors for the prediction of health outcomes.

Besides the association between BW change and FPR in early lactation, we evaluated the association of number of daily successful milkings and concentrate intake in the AMS box with BW change, as these variables have been shown to be associated with milk production on AMS farms (Tremblay et al., 2016; Siewert et al., 2018). To the best of our knowledge, these associations have not been reported for cows in AMS herds. Research on conventional milking systems suggested that a reduced milking frequency during early lactation may improve EB and metabolic status (Patton et al., 2006; McNamara et al., 2008). Therefore, we hypothesized that cows in the current study would show a negative association between BW change and number of milkings. To our surprise, a positive association between these factors was found for P3+ cows for 7 and 21 DIM models. A negative association was present for number of milkings and 21-d BW change for P1 and P2. The associations found herein should be interpreted with caution, as, even though statistically significant, their biological meaning is questionable. For instance, each unit increase in number of milkings/d over the first 21 DIM was associated with a 0.015% decrease in 21-d BW change for P2 cows. We know that cows are milked on average only about 3 to 4 times daily on AMS farms. Thus, given our findings, even going from 1 to 6 milkings/d should not have a meaningful impact in BW loss.

As cows are able to consume more feed in early lactation, the NEB becomes less severe and cows lose less BW; however, concentrate intake represents a small percentage of the total feed intake of cows on AMS farms, as they also receive a partial mixed ration at the feed bunk. Therefore, we hypothesized that greater concentrate intake would be associated with greater positive BW change (i.e., reduced BW loss) during the early postpartum period. However, the association between concentrate intake in the AMS box and BW change was positive only for P2 cows over the first 7 DIM, and for P1 and P2 cows over 21 DIM, whereas greater concentrate intake for P3+ cows was associated with BW loss over both 7 and 21 DIM. It seems that the consumption of concentrate in the AMS box, even though of statistical significance, has minor to no biological influence on BW change during the early postpartum, as the estimates were of very small magnitude. However, further experimental research on the association of concentrate feeding strategies and EB in AMS herds is warranted, especially given the flexibility offered by the technology to meet individual requirements according to level of milk production and stage of lactation.

Total 90-d milk yield was chosen as a productivity measurement for being post lactation peak for most cows on AMS farms (Peiter et al., 2021), and therefore capturing the period when cows are most productive. In addition, 90-d milk yield had a Pearson's correlation coefficient of 0.95, 0.99, and 0.99 (P <.0001) with total milk yield over the first 30, 60, and 120 DIM, respectively. Similar to the current study, Caixeta et al. (2015) found the association between BW change and milk yield in early lactation to be different between parity groups, with a negative linear association between 30-d BW change and 30-d milk yield for P1 cows, where for each 45 kg of additional milk produced over the first 30 DIM, these animals lost an average 0.3 kg/d. The same authors reported a lack of association between milk yield and BW change for P2 cows during the first 30 DIM; however, a positive association of 0.1 kg/d gain in BW was reported for each 45 kg increase in 30-d milk yield for P3+ cows, even though it was considered unimportant by the authors (Caixeta et al., 2015).

Body weight change variables in the current study had a quadratic association with 90-d milk yield. Multiparous cows (P2 and P3+) achieved maximum estimated 90-d milk yield when they were able to maintain their BW over the first week postpartum, and when the BW loss over the 21 d postpartum was approximately 4% (Figure 8B). Besides, multiparous cows with exacerbated BW loss or BW gain (approx. ± 5% over 7 DIM and ± 10% over 21 DIM) experienced a significant impairment in their 90-d milk yield. For instance, P3+ cows that lost approximately 24.8% of their initial BW over 21 DIM were estimated (LSM ± SE) to have a 90-d milk yield of 3,480 ± 179.0 kg, and cows in the same parity group with a BW gain of 21% had an estimated 90-d milk yield of 3,100 ± 182.8 kg. If we compare those numbers to the 4,567 ± 53.5 kg of P3+ cows with a 21-d BW loss of 3.6%, it is possible to perceive the severe impairment in production of cows on both ends of the curve. Based on our findings, it seems that cows with the ability to maintain their BW or lose less than 10% of their DIM 1 BW over the postpartum transition period (i.e., 21 DIM) are more productive during early lactation. The relationship for primiparous cows (P1) was not present during the first 7 DIM; however, it followed a similar pattern as that for multiparous cows during the 21 DIM. The maximum estimated 90-d milk yield for P1 cows was reached when they lost approximately 8.2% of their DIM 1 BW, and greater BW loss showed not to have a major impact on 90-d milk yield. Primiparous cows that gained BW over the 21 DIM, on the other hand, presented a considerable drop in 90-d milk yield. For instance, P1 cows with a 21% BW gain over 21 DIM had an estimated 90-d milk yield of 2,192 ± 163.8 kg, as opposed to 3,100 ± 53.2 kg for the ones with an 8.2% BW loss during the same period.

Berry et al. (2007) reported that cows that lost 100 kg from calving to BW nadir produced an average of 139 kg more milk during the first 60 DIM compared to cows that lost 50 kg during the same time period. Similarly, energy-corrected milk yield was greater for cows with greater BW loss and NEFA concentrations in early lactation (Carvalho et al., 2014), suggesting that high producing cows mobilize greater body reserves to compensate for the NEB during this challenging time. Moreover, greater BW loss in early lactation was shown to be associated with increased lactation persistency and higher and earlier peak milk yield (Berry et al., 2007). Therefore, to some extent, our results agree with previous studies, where cows with BW loss in early lactation are those producing more milk. However, we suggest that cows with exacerbated BW loss in the postpartum transition period may be the ones that experience severe NEB and potentially other transition cow issues, which end up having a negative impact in their productivity.

The conditional R^2 for the models evaluating the association of 7- and 21-d BW change with 90-d milk yield were both 0.62, which means the models explained a considerable portion of the variability in 90-d milk yield, but 38% was not accounted for by the proposed models. The fixed effects of BW change and parity explained 47% of the total variability in 90-d milk yield in both models. Findings of the current study highlight the importance of closely monitoring BW of dairy cows during the challenging early lactation period. Also, numbers reported herein may be used for predictions of future milk production based on early lactation BW changes.

CONCLUSIONS

The relationship between FPR and BW change in the postpartum period deserves further investigation, as it resulted in unexpected and biologically unimportant associations, especially for older cows. We suggest further investigation of these factors in combination as explanatory variables of health and production outcomes. Body weight change over the first 7 and 21 DIM had strong quadratic associations with total milk production over 90 DIM, with differences between parity groups. Findings suggest that high producing primiparous cows lost about 8% of their BW over the first 21 DIM, while those with exacerbated BW gain had a much lower milk production over 90 DIM. Also, high producing multiparous cows on AMS farms are the ones maintaining their BW during the first 7 DIM and losing an average of 4% over 21 DIM. These findings demonstrate the usefulness of monitoring data from automated technologies and could be used to improve existing algorithms for the identification of animals at risk in early lactation and to predict later milk production in AMS herds.

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Appendix I – Tables

CHAPTER 2

Table 1. Least squares means and 95% confidence intervals of fat- and protein-corrected milk production (FPCM; kg/d)[1] by parity at different stages of lactation (DIM) on 36 automatic milking system (AMS) farms using free flow Lely Astronaut (1,407,281 cow-daily observations)

Stage of Lactation		Parity	
Stage	DIM	Primiparous	Multiparous
1	1 – 15	35.6 [34.9, 36.3][b]	39.8 [39.1, 40.4][a]
2	16 – 30	35.1 [34.4, 35.7][b]	42.0 [41.4, 42.7][a]
3	31 – 60	35.4 [34.7, 36.1][b]	41.6 [40.9, 42.2][a]
4	61 – 90	35.9 [35.3, 36.6][b]	40.8 [40.2, 41.5][a]
5	91 – 120	36.4 [35.7, 37.1][b]	40.3 [39.6, 41.0][a]
6	121 – 150	36.6 [36.0, 37.3][b]	39.8 [39.1, 40.4][a]
7	151 – 180	36.8 [36.1, 37.5][b]	39.2 [38.5, 39.8][a]
8	181 – 210	37.0 [36.3, 37.7][b]	38.6 [37.9, 39.3][a]

[1]FPCM = milk production * (0.1226 * fat % + 0.0776 * protein % + 0.2534) (IDF, 2015).
[a-b]Means without a common letter within stage of lactation are different at $P < 0.05$.

Table 2. Least squares means and 95% confidence intervals of milk production (kg/d) by parity at different stages of lactation (DIM) on 11 automatic milking system (AMS) farms using DeLaval VMS[1] (296,906 cow-daily observations)

Stage of Lactation		Parity	
Stage	DIM	Primiparous	Multiparous
1	1 – 15	35.6 [29.3, 42.0][b]	37.5 [31.2, 43.8][a]
2	16 – 30	36.7 [30.3, 43.0][b]	42.4 [36.1, 48.7][a]
3	31 – 60	37.7 [31.4, 44.0][b]	44.3 [38.0, 50.6][a]
4	61 – 90	37.9 [31.6, 44.3][b]	44.3 [37.9, 50.6][a]
5	91 – 120	38.6 [32.3, 45.0][b]	43.1 [36.8, 49.4][a]
6	121 – 150	38.9 [32.6, 45.2][b]	41.6 [35.3, 47.9][a]
7	151 – 180	38.8 [32.5, 45.1][b]	39.7 [33.3, 46.0][a]
8	181 – 210	38.4 [32.1, 44.7]	37.8 [31.5, 44.1]

[a-b]Means without a common letter within stage of lactation are different at $P < 0.05$.
[1]Nine farms used guided flow and 2 farms used free flow traffic system. The inclusion of the farms with free flow did not change the interpretation of the results; therefore, they remained in the dataset.

Table 3. Descriptive statistics[1] by parity and stage of lactation (DIM) of visit behavior data collected from 36 automatic milking system (AMS) farms using free flow Lely Astronaut (1,407,281 cow-daily observations)

Variable	Overall	Stage of Lactation (DIM)							
		1 (1 - 15)	2 (16 - 30)	3 (31 - 60)	4 (61 - 90)	5 (91 - 120)	6 (121 - 150)	7 (151 - 180)	8 (181 - 210)
Milkings, count									
Primiparous	2.9 ± 0.9	2.2 ± 0.7	2.8 ± 0.9	3.0 ± 0.9	2.9 ± 0.8	2.9 ± 0.8	2.9 ± 0.8	2.9 ± 0.8	2.8 ± 0.8
Multiparous	3.1 ± 0.9	3.2 ± 1.1	3.5 ± 1.0	3.3 ± 0.9	3.2 ± 0.9	3.1 ± 0.9	3.0 ± 0.9	2.9 ± 0.9	2.8 ± 0.8
Refusals, count									
Primiparous	0 (0 - 86)	0 (0 - 31)	0 (0 - 38)	0 (0 - 86)	0 (0 - 73)	0 (0 - 65)	0 (0 - 75)	0 (0 - 84)	0 (0 - 84)
Multiparous	0 (0 - 99)	0 (0 - 92)	0 (0 - 61)	0 (0 - 92)	0 (0 - 99)	0 (0 - 84)	0 (0 - 84)	0 (0 - 56)	0 (0 - 85)
Failures, count									
Primiparous	0 (0 - 17)	0 (0 - 8)	0 (0 - 17)	0 (0 - 9)	0 (0 - 7)	0 (0 - 6)	0 (0 - 6)	0 (0 - 5)	0 (0 - 6)
Multiparous	0 (0 - 10)	0 (0 - 10)	0 (0 - 7)	0 (0 - 6)	0 (0 - 6)	0 (0 - 6)	0 (0 - 7)	0 (0 - 7)	0 (0 - 6)
Concentrate Allowed, kg									
Primiparous	5.5 ± 1.3	4.5 ± 1.1	5.7 ± 1.1	5.9 ± 1.1	5.8 ± 1.2	5.7 ± 1.3	5.6 ± 1.3	5.4 ± 1.4	5.1 ± 1.3
Multiparous	6.4 ± 1.6	4.9 ± 1.1	6.7 ± 1.3	7.2 ± 1.4	7.0 ± 1.4	6.7 ± 1.5	6.4 ± 1.5	6.1 ± 1.5	5.7 ± 1.4
Concentrate Intake, kg									
Primiparous	5.3 ± 1.5	4.1 ± 1.2	5.4 ± 1.3	5.6 ± 1.4	5.6 ± 1.4	5.5 ± 1.5	5.4 ± 1.5	5.2 ± 1.6	4.9 ± 1.5
Multiparous	6.2 ± 1.8	4.7 ± 1.3	6.4 ± 1.5	6.9 ± 1.7	6.7 ± 1.7	6.5 ± 1.7	6.2 ± 1.7	5.9 ± 1.7	5.5 ± 1.7
Residual Concentrate, kg									
Primiparous	0.2 ± 0.3	0.4 ± 0.4	0.3 ± 0.4	0.2 ± 0.3	0.2 ± 0.3	0.2 ± 0.3	0.2 ± 0.3	0.2 ± 0.3	0.2 ± 0.3
Multiparous	0.3 ± 0.3	0.2 ± 0.3	0.2 ± 0.3	0.3 ± 0.3	0.3 ± 0.3	0.3 ± 0.3	0.3 ± 0.3	0.2 ± 0.3	0.2 ± 0.3
Milking Interval, h									
Primiparous	9.0 ± 2.6	11.4 ± 2.6	9.5 ± 2.9	8.8 ± 2.6	8.8 ± 2.4	8.7 ± 2.4	8.7 ± 2.3	8.8 ± 2.4	9.0 ± 2.4

Multiparous	8.3 ± 2.5	8.3 ± 2.9	7.5 ± 2.4	7.8 ± 2.3	8.1 ± 2.3	8.2 ± 2.3	8.4 ± 2.4	8.7 ± 2.5	9.1 ± 2.6
Milking Speed, kg/min									
Primiparous	2.9 ± 1.0	2.7 ± 1.0	2.6 ± 0.9	2.6 ± 0.9	2.8 ± 1.0	2.9 ± 1.0	3.0 ± 1.0	3.1 ± 1.0	3.1 ± 1.0
Multiparous	3.3 ± 1.1	3.3 ± 1.1	3.2 ± 1.1	3.3 ± 1.1	3.3 ± 1.1	3.3 ± 1.0	3.3 ± 1.1	3.3 ± 1.0	3.2 ± 1.0
Box Time, min									
Primiparous	7.0 ± 1.9	6.8 ± 2.0	7.4 ± 2.0	7.5 ± 2.0	7.4 ± 1.9	7.1 ± 1.8	6.9 ± 1.8	6.7 ± 1.7	6.6 ± 1.7
Multiparous	7.1 ± 1.9	6.2 ± 1.7	7.1 ± 2.0	7.4 ± 2.0	7.4 ± 1.9	7.3 ± 1.9	7.2 ± 1.9	7.0 ± 1.8	7.0 ± 1.8
Pre-treatment Time, sec									
Primiparous	56.2 ± 13.5	57.8 ± 13.4	56.5 ± 12.9	56.7 ± 13.4	56.4 ± 13.5	56.0 ± 13.4	55.8 ± 13.5	55.7 ± 13.7	55.8 ± 13.9
Multiparous	57.0 ± 15.7	57.4 ± 14.7	57.2 ± 15.4	57.3 ± 15.6	57.1 ± 15.7	56.9 ± 15.8	56.8 ± 15.8	56.8 ± 15.8	56.6 ± 15.8
Connection Time, sec									
Primiparous	38.6 ± 19.3	36.3 ± 19.7	35.5 ± 18.3	38.2 ± 19.6	40.0 ± 19.9	40.1 ± 19.7	39.4 ± 19.3	38.4 ± 18.7	37.9 ± 18.4
Multiparous	35.6 ± 16.0	40.0 ± 17.8	37.2 ± 16.4	35.9 ± 15.8	35.0 ± 15.5	35.0 ± 15.6	34.9 ± 15.8	34.8 ± 15.8	34.8 ± 16.0
Dead Milk Time, sec									
Primiparous	13.5 ± 4.8	12.6 ± 4.4	14.3 ± 5.1	14.6 ± 5.2	14.0 ± 5.0	13.5 ± 4.8	13.1 ± 4.6	13.0 ± 4.5	12.7 ± 4.4
Multiparous	12.0 ± 4.0	11.8 ± 3.9	12.0 ± 4.0	12.0 ± 3.9	12.0 ± 3.9	12.1 ± 4.0	12.1 ± 4.1	12.0 ± 4.0	12.0 ± 4.2
Milking Time, min									
Primiparous	4.8 ± 1.8	4.4 ± 1.9	5.1 ± 1.9	5.3 ± 1.9	5.2 ± 1.9	4.9 ± 1.8	4.6 ± 1.7	4.5 ± 1.7	4.4 ± 1.6
Multiparous	5.0 ± 1.9	3.9 ± 1.7	4.9 ± 1.9	5.3 ± 1.9	5.3 ± 1.9	5.1 ± 1.9	5.0 ± 1.8	4.9 ± 1.8	4.9 ± 1.8
Post-treatment Time, sec									

Primiparous	9.6 ± 1.4	9.7 ± 1.6	9.6 ± 1.4	9.6 ± 1.4	9.6 ± 1.4	9.5 ± 1.4	9.5 ± 1.4	9.6 ± 1.3	9.6 ± 1.3
Multiparous	9.8 ± 1.4	9.9 ± 1.4	9.9 ± 1.4	9.9 ± 1.4	9.9 ± 1.4	9.8 ± 1.4	9.7 ± 1.4	9.7 ± 1.4	9.6 ± 1.4

[1]Mean ± standard deviation reported for normally distributed variables, and median (range) reported for non-normally distributed variables.

Table 4. Descriptive statistics[1] by parity and stage of lactation (DIM) of visit behavior data collected from 11 automatic milking system (AMS) farms using DeLaval VMS[2] (296,906 cow-daily observations)

Variable	Overall	Stage of Lactation (DIM)							
		1 (1 - 15)	2 (16 - 30)	3 (31 - 60)	4 (61 - 90)	5 (91 - 120)	6 (121 - 150)	7 (151 - 180)	8 (181 - 210)
Milkings, count									
Primiparous	2.6 ± 0.7	2.3 ± 0.6	2.6 ± 0.8	2.8 ± 0.8	2.9 ± 0.8	2.7 ± 0.7	2.7 ± 0.8	2.6 ± 0.8	2.5 ± 0.7
Multiparous	2.8 ± 0.8	3.0 ± 0.9	3.1 ± 0.9	3.1 ± 0.9	3.1 ± 0.9	2.8 ± 0.8	2.7 ± 0.8	2.5 ± 0.7	2.3 ± 0.7
Failures, count									
Primiparous	0 (0 - 7)	0 (0 - 6)	0 (0 - 7)	0 (0 - 7)	0 (0 - 5)	0 (0 - 5)	0 (0 - 4)	0 (0 - 5)	0 (0 - 5)
Multiparous	0 (0 - 9)	0 (0 - 5)	0 (0 - 9)	0 (0 - 6)	0 (0 - 9)	0 (0 - 6)	0 (0 - 9)	0 (0 - 9)	0 (0 - 9)
Concentrate Intake, kg									
Primiparous	3.0 ± 1.3	2.3 ± 1.1	3.0 ± 1.3	3.3 ± 1.4	3.4 ± 1.4	3.1 ± 1.3	2.8 ± 1.2	2.8 ± 1.1	2.8 ± 1.1
Multiparous	3.2 ± 1.5	3.0 ± 1.2	3.5 ± 1.5	3.6 ± 1.6	3.5 ± 1.6	3.2 ± 1.6	3.0 ± 1.5	2.9 ± 1.4	2.8 ± 1.4
Milking Interval, h									
Primiparous	9.7 ± 2.5	11.1 ± 2.3	10.0 ± 2.7	9.3 ± 2.6	9.0 ± 2.4	9.5 ± 2.3	9.9 ± 2.3	10.0 ± 2.4	10.2 ± 2.4
Multiparous	9.1 ± 2.6	8.6 ± 2.5	8.3 ± 2.4	8.3 ± 2.4	8.4 ± 2.4	9.0 ± 2.5	9.5 ± 2.5	9.8 ± 2.6	10.1 ± 2.7
Milking Speed, kg/min									
Primiparous	3.8 ± 1.2	3.6 ± 1.1	3.5 ± 1.1	3.5 ± 1.1	3.6 ± 1.1	3.9 ± 1.1	4.0 ± 1.1	4.2 ± 1.2	4.2 ± 1.2
Multiparous	4.7 ± 1.3	4.7 ± 1.3	4.6 ± 1.3	4.7 ± 1.3	4.7 ± 1.3	4.7 ± 1.3	4.7 ± 1.3	4.8 ± 1.4	4.8 ± 1.3
Box Time, min									
Primiparous	7.6 ± 1.9	7.4 ± 2.1	8.1 ± 2.1	8.1 ± 2.0	7.8 ± 1.9	7.6 ± 1.9	7.4 ± 1.8	7.3 ± 1.8	7.2 ± 1.8
Multiparous	7.6 ± 2.0	7.0 ± 2.0	7.5 ± 2.0	7.6 ± 2.0	7.6 ± 2.0	7.7 ± 2.0	7.7 ± 1.9	7.6 ± 1.9	7.5 ± 1.8

[1]Mean ± standard deviation reported for normally distributed variables, and median (range) reported for non-normally distributed variables.

[2]Nine farms used guided flow and 2 farms used free flow traffic system. The inclusion of the farms with free flow did not change the interpretation of the results; therefore, they remained in the dataset.

Table 5. Mixed linear regression model estimates for the association with fat- and protein-corrected milk production (FPCM; kg/d)[1] on 36 automatic milking system (AMS) farms using free flow Lely Astronaut (1,407,281 cow-daily observations)

Effect	Estimate	SE	*t*-value	*P*-value
Intercept	21.29	0.34	63.14	<.0001
Parity (ref. Primiparous)	4.17	0.03	153.41	<.0001
Stage of Lactation (ref. 1)				
2	−0.54	0.02	−21.83	<.0001
3	−0.18	0.02	−8.17	<.0001
4	0.34	0.02	15.07	<.0001
5	0.79	0.02	34.72	<.0001
6	1.03	0.02	45.18	<.0001
7	1.20	0.02	52.65	<.0001
8	1.40	0.02	60.67	<.0001
Refusals	−0.02	0.00	−17.62	<.0001
Failures	3.99	0.01	309.27	<.0001
Concentrate Intake	0.43	0.00	40.73	<.0001
Residual Concentrate	0.49	0.01	163.68	<.0001
Milking Interval	−2.13	0.00	−966.92	<.0001
Milking Speed	4.64	0.01	657.85	<.0001
Pre-treatment Time	0.01	0.00	16.92	<.0001
Connection Time	−0.01	0.00	−50.46	<.0001
Dead Milk Time	−0.11	0.00	−94.04	<.0001
Milking Time	3.02	0.00	775.03	<.0001
Post-treatment Time	0.15	0.00	32.20	<.0001
Stage of Lactation : Parity (ref. 1 : Primiparous)				
2 : Multiparous	2.82	0.03	95.91	<.0001
3 : Multiparous	1.97	0.03	75.09	<.0001
4 : Multiparous	0.74	0.03	27.88	<.0001
5 : Multiparous	−0.25	0.03	−9.27	<.0001
6 : Multiparous	−1.03	0.03	−37.75	<.0001
7 : Multiparous	−1.80	0.03	−65.61	<.0001
8 : Multiparous	−2.58	0.03	−92.30	<.0001

[1]FPCM = milk production * (0.1226 * fat % + 0.0776 * protein % + 0.2534) (IDF, 2015).

Table 6. Mixed linear regression model estimates for the association with milk production (kg/d) on 11 automatic milking system (AMS) farms using DeLaval VMS[1] (296,906 cow-daily observations)

Effect	Estimate	SE	*t*-value	*P*-value
Intercept	−15.47	2.89	−5.36	0.0002
Parity (ref. Primiparous)	1.88	0.35	5.37	<.0001
Stage of Lactation (ref. 1)				
2	1.02	0.24	4.29	<.0001
3	2.06	0.22	9.37	<.0001
4	2.28	0.23	10.02	<.0001
5	2.99	0.23	12.92	<.0001
6	3.26	0.24	13.74	<.0001
7	3.15	0.24	12.88	<.0001
8	2.74	0.25	10.91	<.0001
Failures	1.17	0.04	29.23	<.0001
Concentrate Intake	7.64	0.04	194.29	<.0001
Milking Interval	0.46	0.02	24.97	<.0001
Milking Speed	4.75	0.07	65.20	<.0001
Box Time	0.18	0.03	6.27	<.0001
Stage of Lactation : Parity (ref. 1 : Primiparous)				
2 : Multiparous	3.86	0.29	13.20	<.0001
3 : Multiparous	4.72	0.27	17.73	<.0001
4 : Multiparous	4.44	0.28	16.13	<.0001
5 : Multiparous	2.58	0.28	9.13	<.0001
6 : Multiparous	0.79	0.29	2.74	0.0061
7 : Multiparous	−1.01	0.30	−3.38	0.0007
8 : Multiparous	−2.44	0.31	−7.96	<.0001

[1]Nine farms used guided flow and 2 farms used free flow traffic system. The inclusion of the farms with free flow did not change the interpretation of the results; therefore, they remained in the dataset.

CHAPTER 3

Table 7. Least squares means ± standard errors[1] of average rumination time (RT; min) and change in RT (min/d) for the interaction between peak milk yield (PMY) percentile[2] and parity[3] for 4,662 cows from 33 automatic milking system (AMS) dairy farms in the U.S.

Item	P1		P2		P3+	
	L25 (*n* = 402)	T25 (*n* = 399)	L25 (*n* = 358)	T25 (*n* = 354)	L25 (*n* = 457)	T25 (*n* = 458)
Average RT, min						
1 DIM	299 ± 7	306 ± 7	306 ± 7[b]	330 ± 7[a]	272 ± 7[b]	287 ± 7[a]
2 DIM	317 ± 7	319 ± 7	326 ± 7[b]	358 ± 7[a]	296 ± 7[b]	322 ± 7[a]
3 DIM	333 ± 7	335 ± 7	345 ± 7[b]	381 ± 7[a]	315 ± 7[b]	346 ± 7[a]
4 DIM	344 ± 7	350 ± 7	360 ± 7[b]	397 ± 7[a]	332 ± 7[b]	367 ± 7[a]
5 DIM	353 ± 7	360 ± 7	371 ± 7[b]	411 ± 7[a]	347 ± 6[b]	383 ± 6[a]
6 DIM	360 ± 6	368 ± 6	381 ± 7[b]	423 ± 7[a]	359 ± 6[b]	396 ± 6[a]
Change RT, min/d[4]						
2 DIM	34.7 ± 5.3	26.2 ± 5.3	39.1 ± 5.5[b]	57.3 ± 5.5[a]	48.1 ± 5.0[b]	68.4 ± 5.0[a]
3 DIM	32.1 ± 3.2	30.6 ± 3.2	38.6 ± 3.3[b]	47.7 ± 3.3[a]	40.2 ± 3.0[b]	54.2 ± 3.0[a]
4 DIM	26.4 ± 2.2	29.5 ± 2.2	33.1 ± 2.3[b]	39.3 ± 2.3[a]	37.2 ± 2.1[b]	46.0 ± 2.1[a]
5 DIM	22.5 ± 1.6	24.8 ± 1.6	27.8 ± 1.7[b]	33.7 ± 1.7[a]	33.0 ± 1.6[b]	39.9 ± 1.6[a]
6 DIM	18.5 ± 1.3	20.8 ± 1.3	24.4 ± 1.4[b]	29.4 ± 1.4[a]	29.2 ± 1.3[b]	33.8 ± 1.3[a]

[a-c]Means without a common letter within row and parity are different at $P < 0.05$.

[1]Statistical models corresponding to the number of DIM included in the calculation of rumination parameters with average RT (6 models [1 – 6 DIM]) and change in RT (5 models [2 – 6 DIM]) as outcome variables, and PMY percentile category, parity, and their interaction as predictor variables, considering farm as the random intercept.

[2]PMY percentile within farm and parity: L25 = ≤ 0.25 quantile; T25 = ≥ 0.75 quantile.

[3]Parity: P1 = parity 1; P2 = parity 2; P3+ = parity ≥ 3.

[4]Simple linear regression slope coefficient for daily RT.

Table 8. Fixed effect regression coefficients and 95% confidence intervals[1] (CIs) for the mixed linear regression model with peak milk yield (PMY; kg) as outcome variable and farm as random effect by parity[2] for 4,662 cows from 33 automatic milking system (AMS) dairy farms in the U.S.

Coefficient, kg	Parity			*P*-values[3]				
	P1 (*n* = 1,538)	P2 (*n* = 1,354)	P3+ (*n* = 1,770)	P	Ch RT	Avg RT	P×Ch RT	P×Avg RT
Model 1 DIM				***		**		NS
Intercept	42.0 [40.1, 43.9][c]	53.4 [51.4, 55.4][b]	59.3 [57.7, 61.0][a]					
RT	0.18 [−0.24, 0.61]	0.68 [0.23, 1.13]	0.29 [−0.05, 0.63]					
Model 2 DIM[4]				***	***	***	***	**
Intercept	42.6 [40.5, 44.7][c]	50.5 [48.3, 52.7][b]	56.3 [54.5, 58.2][a]					
Change RT[5]	−0.44 [−0.90, 0.03][b]	1.04 [0.54, 1.55][a]	1.15 [0.76, 1.54][a]					
Average RT	0.03 [−0.45, 0.53][b]	1.34 [0.84, 1.83][a]	1.02 [0.63, 1.41][a]					
Model 3 DIM				***	***	***	***	***
Intercept	42.6 [40.4, 44.9][c]	49.1 [46.8, 51.4][b]	54.1 [52.2, 56.1][a]					
Change RT	−0.67 [−1.50, 0.16][b]	1.60 [0.73, 2.47][a]	2.52 [1.84, 3.21][a]					
Average RT	0.04 [−0.49, 0.57][b]	1.60 [1.10, 2.11][a]	1.45 [1.04, 1.85][a]					
Model 4 DIM				***	***	***	**	***
Intercept	42.0 [39.6, 44.3][c]	47.7 [45.4, 50.1][b]	52.9 [50.9, 54.9][a]					
Change RT	−0.04 [−1.21, 1.14][b]	2.45 [1.18, 3.72][a]	3.24 [2.24, 4.24][a]					
Average RT	0.17 [−0.38, 0.73][b]	1.85 [1.33, 2.36][a]	1.68 [1.26, 2.10][a]					
Model 5 DIM				***	***	***	**	***
Intercept	41.6 [39.2, 44.1][c]	46.4 [44.0, 48.9][b]	51.4 [49.2, 53.5][a]					
Change RT	0.29 [−1.26, 1.83][b]	3.34 [1.70, 4.98][a]	4.27 [2.98, 5.57][a]					
Average RT	0.24 [−0.33, 0.81][b]	2.08 [1.56, 2.60][a]	1.98 [1.55, 2.41][a]					
Model 6 DIM				***	***	***	**	***
Intercept	41.3 [38.8, 43.8][c]	45.3 [42.8, 47.8][b]	50.5 [48.3, 52.7][a]					
Change RT	0.80 [−1.14, 2.75][b]	4.26 [2.21, 6.32][a]	4.84 [3.23, 6.45][a]					
Average RT	0.31 [−0.27, 0.89][b]	2.26 [1.74, 2.79][a]	2.15 [1.71, 2.59][a]					

[a-c]Estimates without a common letter within row are different at $P < 0.05$.

[1]Coefficients and 95% CIs for rumination time (RT), change in RT, and average RT are multiplied by 100. Therefore, for each 100 min or min/d increase in a certain fixed effect, PMY increases or decreases by [coefficient] kg.
[2]Parity: P1 = parity 1; P2 = parity 2; P3+ = parity ≥ 3.
[3]F-test *P*-values: P = parity; Ch RT = change in RT; Avg RT = average RT; P×Ch RT = parity × change in RT interaction; P×Avg RT = parity × average RT interaction; NS = ≥ 0.05; * = < 0.05 and ≥ 0.01; ** = < 0.01 and ≥ 0.0001; *** = < 0.0001.
[4]Each statistical model corresponds to the number of DIM included in the calculation of rumination parameters. For instance, Model 2 DIM includes the average RT for the first 2 DIM and change in RT over the first 2 DIM with respect to DIM = 1.
[5]Simple linear regression slope coefficient for daily RT.

Table 9. Model fit parameters of the 6 mixed linear regression models predicting peak milk yield (PMY), which included predictors of change in rumination time (RT), average RT, parity, and a random effect of farm

Model	RMSE[1]	Conditional R^2	Marginal R^2
1 DIM	7.81	0.54	0.43
2 DIM	7.74	0.55	0.44
3 DIM	7.70	0.55	0.45
4 DIM	7.69	0.56	0.45
5 DIM	7.66	0.56	0.45
6 DIM	7.65	0.56	0.45

[1]Root mean square error.

CHAPTER 4

Table 10. Mean ± standard deviation of explanatory variables, overall and by parity1, for 5,329 cows from 33 automatic milking system (AMS) dairy farms

Variable	Overall	P1 (n = 1,829)	P2 (n = 1,543)	P3+ (n = 1,957)
FPR[2]				
7-d FPR	1.19 ± 0.25	1.23 ± 0.20	1.14 ± 0.23	1.19 ± 0.28
21-d FPR	1.23 ± 0.23	1.20 ± 0.19	1.21 ± 0.22	1.28 ± 0.27
Milkings, count/d				
7-d Milkings	2.62 ± 0.95	2.04 ± 0.49	2.94 ± 0.98	2.92 ± 0.99
21-d Milkings	2.95 ± 1.08	2.30 ± 0.76	3.32 ± 1.06	3.27 ± 1.08
Concentrate Intake, kg/d				
7-d Concentrate Intake	3.88 ± 1.07	3.55 ± 1.01	4.05 ± 1.06	4.07 ± 1.05
21-d Concentrate Intake	4.90 ± 1.48	4.40 ± 1.34	5.15 ± 1.48	5.16 ± 1.48

[1]Parity: P1 = parity 1; P2 = parity 2; P3+ = parity ≥ 3.

[2]Milk fat to protein ratio (FPR).

Table 11. Mixed linear regression model[1] estimates for the association with change in body weight (BW; % with respect to DIM 1) from 1 to 7 DIM for 5,323 cows from 33 automatic milking system (AMS) dairy farms

Effect	Estimate	SE	*t*-value	*P*-value
(Intercept)	−2.726	1.510	−18.056	<.0001
FPR[2]	0.006	0.040	0.151	0.880
Milkings	0.028	0.016	1.812	0.070
Concentrate Intake	−0.010	0.011	−0.910	0.363
Parity (ref. P1)[3]				
P2	−0.023	0.078	−2.933	0.003
P3+	0.577	0.074	7.795	<.0001
DIM (ref. 1)				
2	0.068	0.042	1.615	0.106
3	0.110	0.051	2.184	0.029
4	0.200	0.054	3.719	0.0002
5	0.196	0.055	3.567	0.0004
6	0.201	0.055	3.670	0.0002
7	0.169	0.055	3.086	0.002
FPR × Parity (ref. P1)				
FPR × P2	−0.124	0.049	−2.546	0.011
FPR × P3+	−0.023	0.043	−0.529	0.597
FPR × DIM (ref. 1)				
FPR × DIM 2	−0.057	0.038	−1.524	0.127
FPR × DIM 3	−0.086	0.043	−1.976	0.048
FPR × DIM 4	−0.154	0.045	−3.434	0.0006
FPR × DIM 5	−0.145	0.045	−3.233	0.001
FPR × DIM 6	−0.147	0.044	−3.324	0.0009
FPR × DIM 7	−0.119	0.044	−2.709	0.007
Milkings × Parity (ref. P1)				
Milkings × P2	−0.034	0.018	−1.862	0.063
Milkings × P3+	0.008	0.018	0.463	0.643
Concentrate Intake × Parity (ref. P1)				
Concentrate Intake × P2	0.032	0.013	2.356	0.018
Concentrate Intake × P3+	−0.015	0.013	−1.157	0.247

[1]Cow nested within farm included as random effect. Backward elimination was used until all remaining variables had a $P < 0.05$. *P*-values of fixed effects: FPR <.0001; Milkings = 0.004; Concentrate intake = 0.49; Parity <.0001; DIM = 0.0006; FPR × Parity = 0.015; FPR × DIM = 0.005; Milkings × Parity = 0.004; Concentrate intake × Parity = 0.0005.
[2]Milk fat to protein ratio (FPR).
[3]Parity: P1 = parity 1; P2 = parity 2; P3+ = parity ≥ 3.

Table 12. Mixed linear regression model[1] estimates for the association with change in body weight (BW; % with respect to DIM 1) from 1 to 21 DIM for 5,329 cows from 33 automatic milking system (AMS) dairy farms

Effect	Estimate	SE	*t*-value	*P*-value
(Intercept)	−4.230	0.222	−19.063	<.0001
FPR[2]	0.137	0.023	5.829	<.0001
Milkings	−0.044	0.007	−6.700	<.0001
Concentrate Intake	0.040	0.004	10.258	<.0001
Parity (ref. P1)[3]				
P2	−0.740	0.051	−14.396	<.0001
P3+	−0.549	0.049	−11.217	<.0001
FPR × Parity (ref. P1)				
FPR : P2	−0.185	0.032	−5.823	<.0001
FPR : P3+	−0.210	0.028	−7.411	<.0001
Milkings × Parity (ref. P1)				
Milkings × P2	0.029	0.008	3.443	0.0006
Milkings × P3+	0.073	0.008	9.207	<.0001
Concentrate Intake × Parity (ref. P1)				
Concentrate Intake × P2	−0.031	0.005	−6.023	<.0001
Concentrate Intake × P3+	−0.061	0.005	−12.644	<.0001

[1]Cow nested within farm included as random effect. Backward elimination was used until all remaining variables had a $P < 0.05$. *P*-values of fixed effects: FPR = 0.67; Milkings = 0.002; Concentrate intake <.0001; Parity <.0001; FPR × Parity <.0001; Milkings × Parity <.0001; Concentrate intake × Parity <.0001.

[2]Milk fat to protein ratio (FPR).

[3]Parity: P1 = parity 1; P2 = parity 2; P3+ = parity ≥ 3.

Table 13. Mixed linear regression models[1] estimates for the association with 90-d milk yield (kg) for 3,936 cows from 33 automatic milking system (AMS) dairy farms

Effect	Estimate	SE	*t*-value	*P*-value
7-d BW change[2]				
(Intercept)	3073.36	55.01	55.87	<.0001
BW Change	−0.43	3.12	−0.14	0.891
BW Change^2	−0.47	0.51	−0.92	0.358
Parity (ref. P1)[3]				
P2	1196.91	29.21	40.97	<.0001
P3+	1501.15	28.12	53.38	<.0001
BW Change^2 × Parity (ref. P1)				
BW Change^2 × P2	−2.55	0.68	−3.77	0.0002
BW Change^2 × P3+	−2.68	0.69	−3.87	0.0001
21-d BW change[4]				
(Intercept)	3029.13	54.89	55.19	<.0001
BW Change	−17.40	2.66	−6.53	<.0001
BW Change^2	−1.07	0.28	−3.77	0.0002
Parity (ref. P1)				
P2	1199.14	30.77	38.97	<.0001
P3+	1506.59	30.09	50.07	<.0001
BW Change^2 × Parity (ref. P1)				
BW Change × P2	−1.00	0.38	−2.61	0.009
BW Change × P3+	−1.35	0.39	−3.52	0.0004

[1]One model for each variable of change in body weight (BW, % with respect to DIM 1; over 7 and 21 DIM). Cow nested within farm included as random effect.
[2]*P*-values of fixed effects: BW change = 0.89; BW Change^2 <.0001; Parity < .0001; BW Change^2 × Parity <.0001.
[3]Parity: P1 = parity 1; P2 = parity 2; P3+ = parity ≥ 3.
[4]*P*-values of fixed effects: BW change <.0001; BW Change^2 <.0001; Parity < .0001; BW Change^2 × Parity = 0.001.

Appendix II – Figures

CHAPTER 3

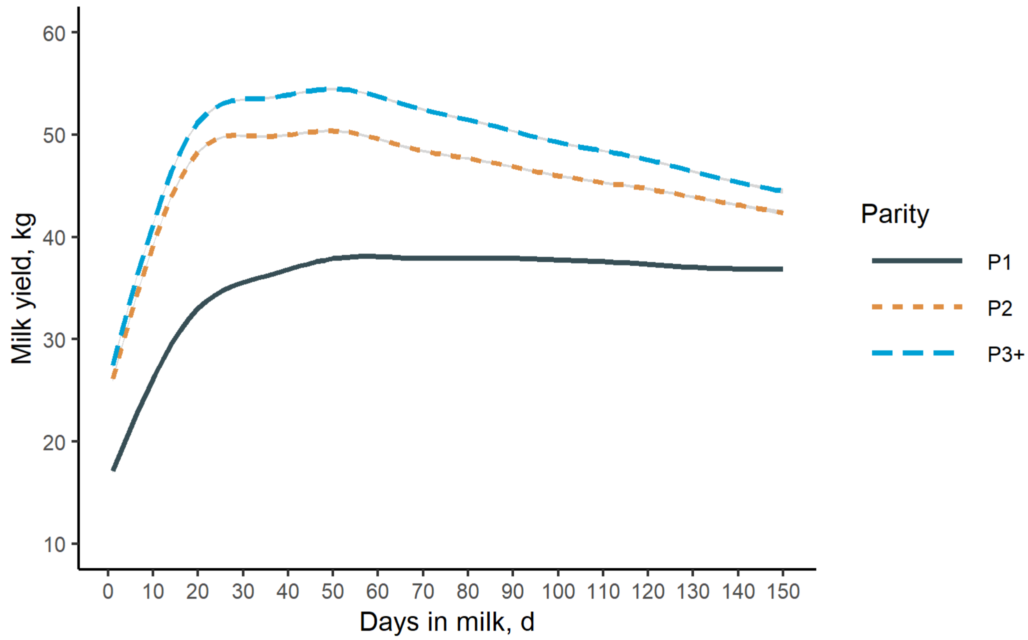

Figure 1. Estimated local averages and standard errors (grey bands) for daily milk yield (kg) during the first 150 DIM calculated from a generalized additive model fit with a cubic spline for parity 1 (P1; solid black line), parity 2 (P2; short-dash orange line), and parity ≥ 3 (P3+; long-dash blue line). *N* = 4,662 cows from 33 automatic milking system (AMS) dairy farms in the U.S.

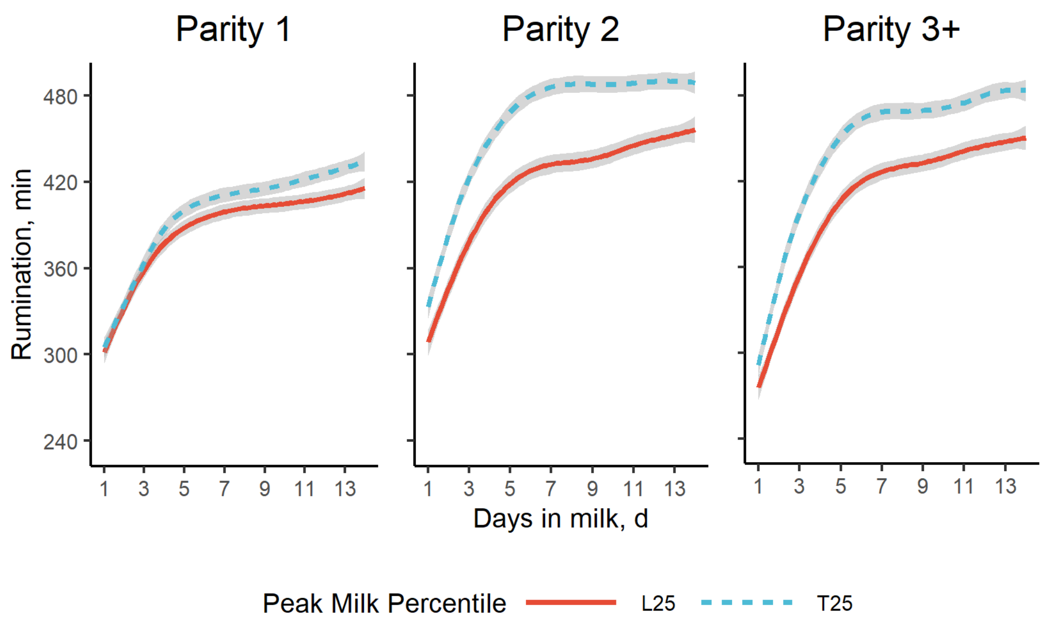

Figure 2. Estimated local averages and standard errors (grey bands) for daily rumination time (min) during the first 14 DIM calculated from a generalized additive model fit with a cubic spline for each parity for ≤ 0.25 quantile (L25; solid red line), and ≥ 0.75 quantile (T25; long-dash blue line). *N* = 4,662 cows from 33 automatic milking system (AMS) dairy farms in the U.S.

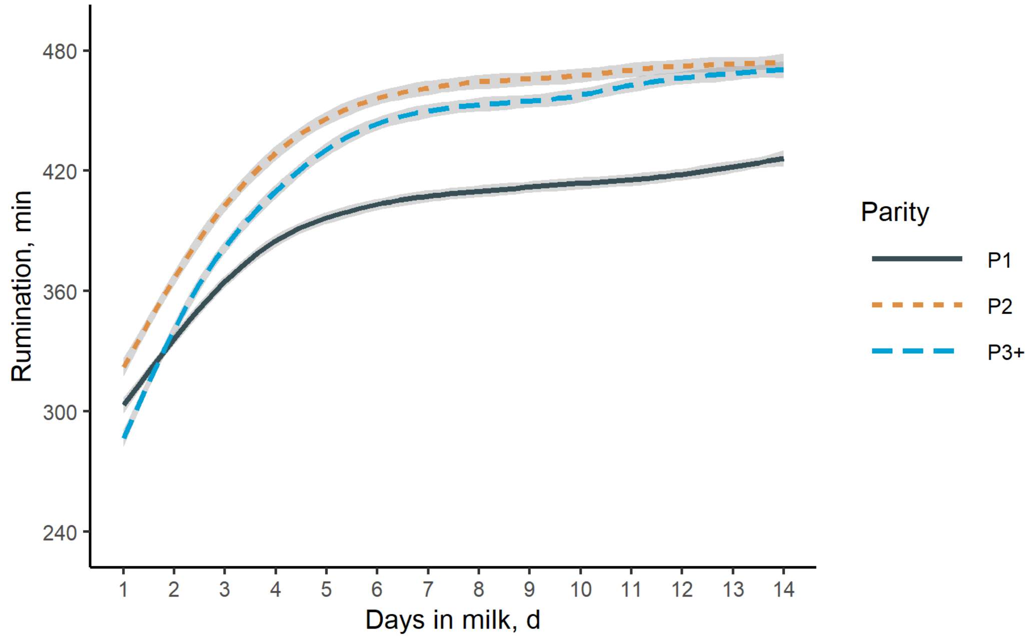

Figure 3. Estimated local averages and standard errors (grey bands) for daily rumination time (min) during the first 14 DIM calculated from a generalized additive model fit with a cubic spline for parity 1 (P1; solid black line), parity 2 (P2; short-dash orange line), and parity ≥ 3 (P3+; long-dash blue line). *N* = 4,662 cows from 33 automatic milking system (AMS) dairy farms in the U.S.

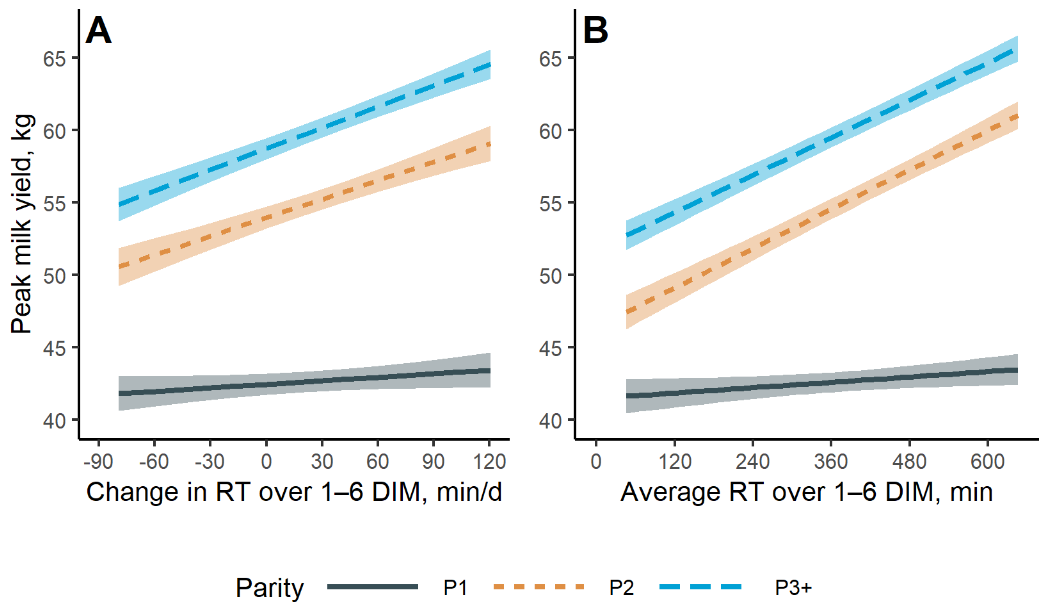

Figure 4. Least squares means and standard errors (transparent bands) of peak milk yield (PMY; kg) for the interaction between parity and: A) change in rumination time (RT) for the first 6 DIM (min/d); and B) average RT for the first 6 DIM (min). Parity 1 (P1) = solid black line, parity 2 (P2) = short-dash orange line, and parity ≥ 3 (P3+) = long-dash blue line. Fixed effects model: PMY = Parity + Change in RT over first 6 DIM + Average RT over first 6 DIM + Parity × Change in RT over first 6 DIM + Parity × Average RT over first 6 DIM. P-values of fixed effects: Parity < 0.0001; Change in RT over first 6 DIM < 0.0001; Average RT over first 6 DIM < 0.0001; Parity × Change in RT over first 6 DIM = 0.01; Parity × Average RT over first 6 DIM < 0.0001. *N* = 4,662 cows from 33 automatic milking system (AMS) dairy farms in the U.S.

CHAPTER 4

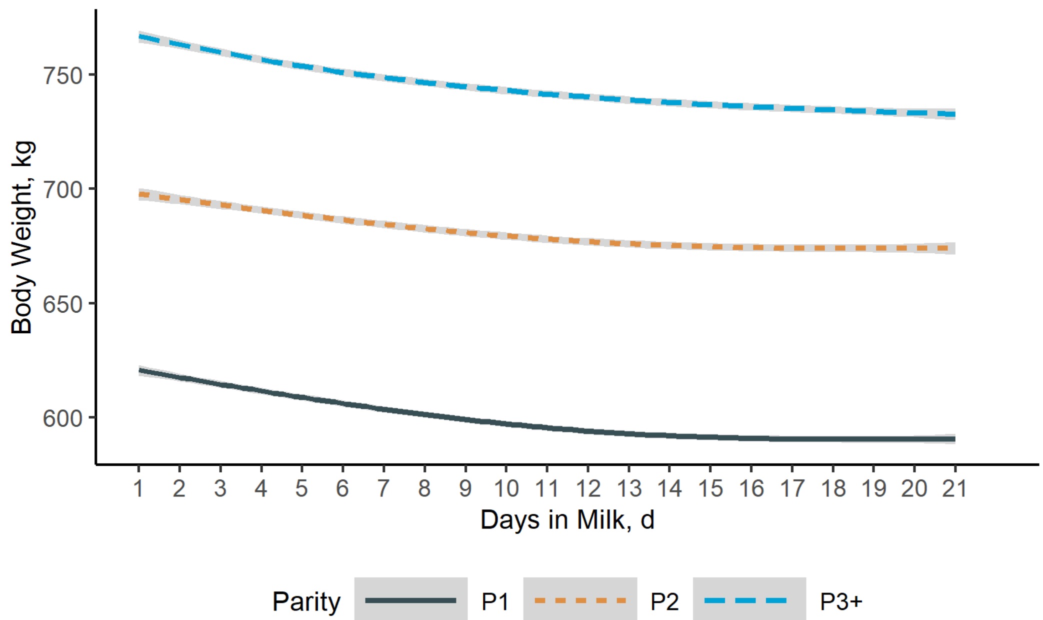

Figure 5. Estimated local averages and standard errors (grey bands) for daily body weight (kg) during the first 21 DIM calculated from a generalized additive model for parity 1 (P1; solid black line), parity 2 (P2; short-dash orange line), and parity ≥ 3 (P3+; long-dash blue line). *N* = 5,329 cows from 33 automatic milking system (AMS) dairy farms.

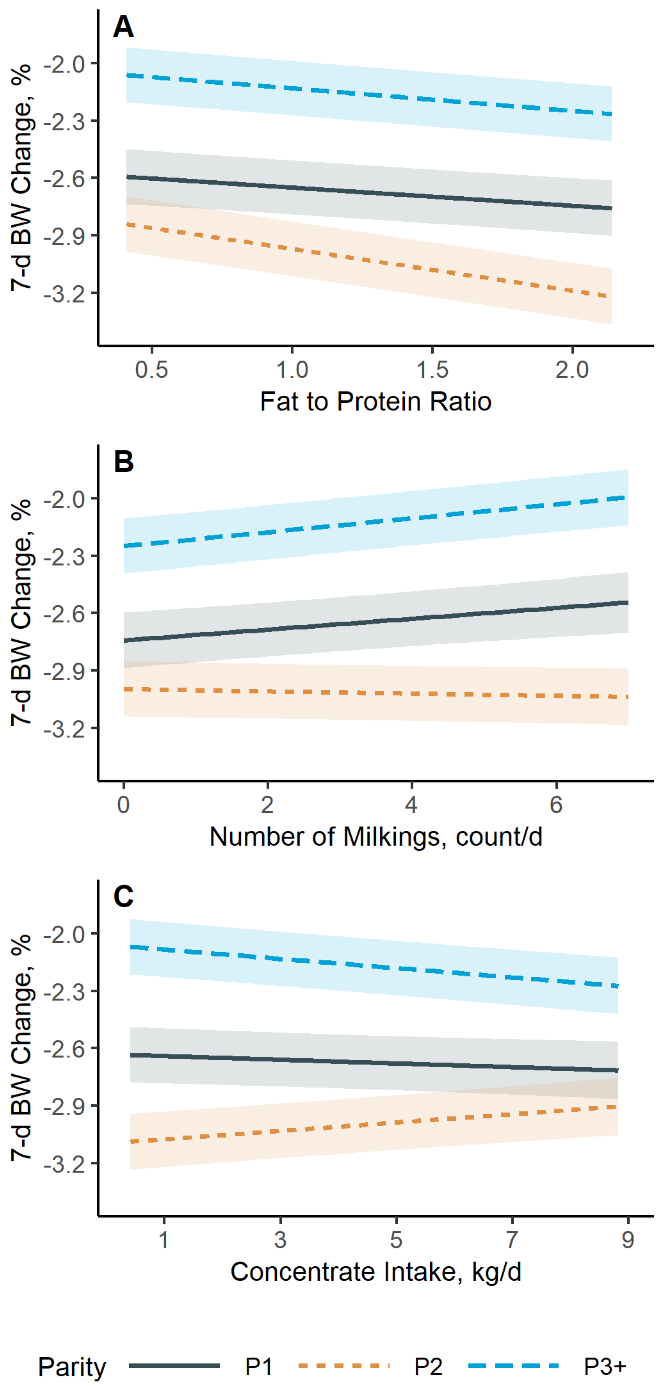

Figure 6. Least squares means and standard errors (transparent bands) of 7-d BW change (%, with respect to DIM 1) for the interaction between parity and: A) daily fat to protein ratio (FPR); B) daily number of milkings; C) daily concentrate intake in the AMS box (kg). Parity 1 (P1) = solid black line, parity 2 (P2) = short-dash orange line, and parity ≥ 3 (P3+) = long-dash blue line. Fixed effects model: 7-d Change in BW = FPR + Number of Milkings + Concentrate Intake + Parity + DIM + FPR × Parity + FPR × DIM + Number of Milkings × Parity + Concentrate Intake × Parity. P-values of fixed effects:

FPR <.0001; Milkings = 0.004; Concentrate Intake = 0.49; Parity <.0001; DIM = 0.0006; FPR × Parity = 0.015; FPR × DIM = 0.005; Milkings × Parity = 0.004; Concentrate Intake × Parity = 0.0005. n = 5,323 cows from 33 automatic milking system (AMS) dairy farms.

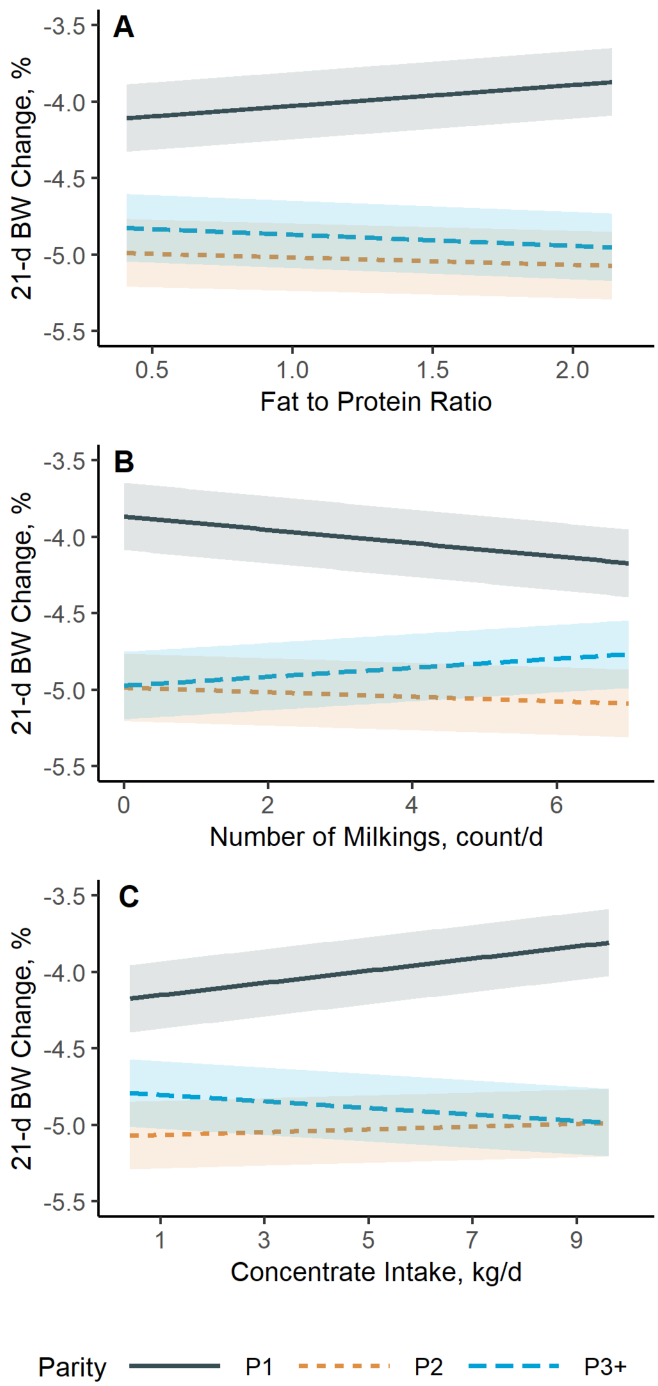

Figure 7. Least squares means and standard errors (transparent bands) of 21-d BW change (%, with respect to DIM 1) for the interaction between parity and: A) daily fat to protein ratio (FPR); B) daily number of milkings; C) daily concentrate intake in the AMS box (kg). Parity 1 (P1) = solid black line, parity 2 (P2) = short-dash orange line, and parity ≥ 3 (P3+) = long-dash blue line. Fixed effects model: 21-d Change in BW = FPR + Number of Milkings + Concentrate Intake + Parity + FPR × Parity + Number of Milkings × Parity + Concentrate Intake × Parity. P-values of fixed effects: FPR = 0.67; Milkings =

0.002; Concentrate Intake <.0001; Parity <.0001; FPR × Parity <.0001; Milkings × Parity <.0001; Concentrate Intake × Parity <.0001. n = 5,329 cows from 33 automatic milking system (AMS) dairy farms.

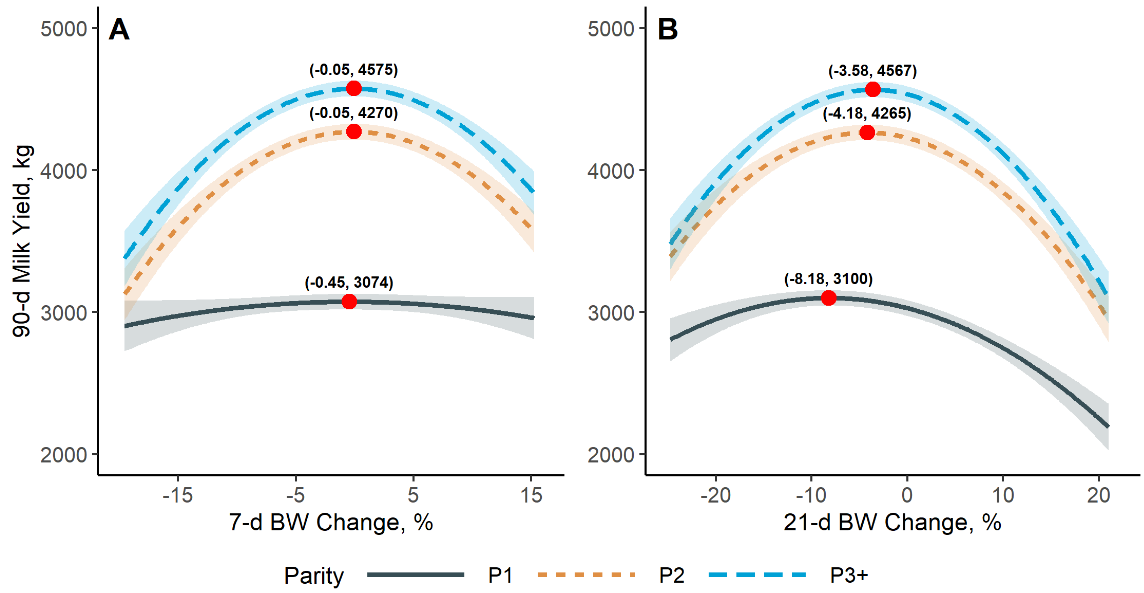

Figure 8. Least squares means and standard errors (transparent bands) of 90-d milk yield (kg) for the interaction between parity and: A) 7-d BW change (%, with respect to DIM 1). Fixed effects model: 7-d BW change + 7-d BW change^2 + Parity + 7-d BW change^2 × Parity. P-values of fixed effects: 7-d BW change = 0.89; 7-d BW change^2 <.0001; Parity <.0001; 7-d BW change^2 × Parity <.0001. B) 21-d BW change (%, with respect to DIM 1). Fixed effects model: 21-d BW change + 21-d BW change^2 + Parity + 21-d BW change^2 × Parity. P-values of fixed effects: 21-d BW change <.0001; 21-d BW change^2 <.0001; Parity <.0001; 21-d BW change^2 × Parity = 0.001. Parity 1 (P1) = solid black line, parity 2 (P2) = short-dash orange line, and parity ≥ 3 (P3+) = long-dash blue line. Red dots (x, y) represent the BW change % (x) for the maximum predicted outcome value (y). n = 3,936 cows from 33 automatic milking system (AMS) dairy farms.