THESIS

EFFECTS OF PRE-MILKING WAITING TIME AND SELECTION BEHAVIOR IN COWS MILKED IN AN AUTOMATED BATCH MILKING SYSTEM

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ABSTRACT

EFFECTS OF PRE-MILKING WAITING TIME AND SELECTION BEHAVIOR IN COWS MILKED IN AN AUTOMATED BATCH MILKING SYSTEM

The adoption of automated milking systems (AMS) has transformed the dairy industry by improving efficiency, animal welfare, and milk production. DeLaval's Batch Voluntary Milking System (Batch VMS) provides a structured alternative to traditional AMS for larger dairy herds. Unlike continuous voluntary milking, Batch VMS organizes cows into groups and schedules their milking at set intervals, enhancing herd management while reducing labor demands. As a hybrid approach, it offers a seamless transition from conventional milking methods to automation. Through a literature review and two research studies, this thesis explores how Batch VMS may affect cow health and performance.

Chapter 1 contains the literature review. It introduces the changes in the AMS technologies in recent years and compares it to Batch VMS. Secondly, it discusses the effects of pre-milking waiting time on milking performance and cow health in terms of mastitis and lameness. And lastly, it discusses selection behavior in cows, comparing behaviors in conventional and automated milking systems.

Chapter 2 explores the effects of pre-milking waiting time (WT) in an automated batch milking system (ABMS). Visit information was collected to calculate pre-milking WT, defined as the time elapsed between the entrance of the cow to the milking barn, as indicated by pedometers attached to each cow that were read by sensors located at the parlor, and the entrance of each individual cow to the robot milking box. WT were categorized into quartiles within each parity

group as Q1 ≤ 9 min, Q2 = 10 to 24 min, Q3 = 25 to 46 min and Q4 ≥ 47 mins for primiparous and Q1 ≤ 11 min Q2 = 12 to 30 min, Q3 = 31 to 51 min and Q4 ≥ 52 mins for multiparous. To assess the association between lameness and WT, individual cow WT averages were calculated separately for primiparous and multiparous groups. Lameness was treated as a categorical variable, where 1 indicated a cow diagnosed with lameness and 0 indicated non-lame cow.

The results show that the average waiting time for all milking events was 33.6 min (± SD = 28.5), 34.5 ± 28.9 for PP, and 30.7 ± 27.3 for MP. The means for each breed were 25.6 ± 15.2, 42.3 ± 16.8, and 42.3 ± 23.4, for HO, JE, and HJ, respectively. While significant differences in LSM were observed between breeds for most variables, there was little to no significant association between WT and the analyzed outcomes. An increase of 10 minutes in WT was associated with a 23.7% increase in the odds of lameness in multiparous cows (95% CI: 10.2–39.0; $p < 0.001$). However, no significant association was found in primiparous cows (OR: 1.09, 95% CI: 0.85–1.38, $p = 0.462$).

Chapter 3 discusses selection behavior in an ABMS where cows select between 22 robots each time there are brought to the milking parlor. The objective of this study was to analyze the robotic milking station selection behavior of three breeds including Holstein, Jersey, and Holstein × Jersey crossbred cows in a multibreed dairy farm with a batch milking system with automatic milking units. The study used data from 1,762,461 milking events in 3705 HO (n=1355), JE (1876) and HJ (475) cows from May 2023 to September 2024 in a commercial organic grass-fed dairy in TX. Cows were moved to the milking center twice per day, where they could select their milking visits among 22 robot units (DeLaval, Sweden).

For the analysis, robots were also classified by barn location [East (n=11); West] and arm configuration [left (n=11); right]. Milking visit information was collected to determine the frequency of specific robot usage per cow during the study period. Subsequently, the frequencies of selection for the top 1, 3, and 5 robotic milking stations, top barn location, and top arm configuration were calculated for each cow. Preference consistency scores (PCS) were calculated considering the frequency of access to each robotic milking station, barn side, and arm configuration in 30 days periods. Overall, multiparous and HO cows evidenced more consistent behaviors in milking station preference. Dairy cow selection behavior should be considered when analyzing the efficiency of milking procedures.

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CHAPTER 1: LITERATURE REVIEW

Introduction

The adoption of automated milking systems (AMS) has transformed the dairy industry by improving efficiency, animal welfare, milk production, and employee safety. Traditionally, milking has been a labor-intensive task carried out manually or through conventional milking parlors. The first AMS prototype emerged in the late 20th century, with initial trials in the 1980s and commercial adoption beginning in the 1990s. The Netherlands played a key role in pioneering AMS technology, with Lely introducing the first robotic milking system in 1992 (Baiju, 2020). Since then, AMS technology has advanced rapidly, integrating precision technologies and data analytics to optimize dairy farm operations. Recent market estimates value the milking robot industry at approximately USD 3.2 billion in 2024, with projections indicating growth to USD 5.3 billion by 2029, at an annual rate of 11.7% (Research and Markets, 2024).

Initially, AMS adoption has had a few roadblocks for dairy producers such as high costs, farmer skepticism, and concerns over cow adaptation. However, through improved system reliability and efficiency, AMS has become increasingly popular worldwide. Gradual acceptance of AMS as a different option to conventional milking methods has been demonstrated in a significant rise in usage in North America, Europe, and Australia reaching over 8,000 farms by 2009 (De Koning, 2010). Additionally, Svennersten-Sjaunja & Pettersson (2008), and Jacobs & Siegford (2012) discuss the role of AMS in improving milk yield and animal welfare, further promoting its adoption. Salfer et al (2017) and Örs et al. (2022) emphasize that the economic feasibility of AMS has improved over time due to advancements in milking efficiency and labor reduction in smaller farms, however, they may remain unprofitable for larger operations.

Today, Automatic Milking Systems (AMS) have become an essential component of modern dairy farming, offering significant economic, environmental, and animal welfare benefits. This literature review explores the technological advancements and advantages of AMS while also examining the potential impact of Automated Batch Milking Systems (ABMS), a newly developed milking strategy, on cow health, performance, and behavior, as ABMS may become a viable option for larger dairy operations looking to adopt AMS technology.

Farmer Perception of Adoption of Voluntary Milking Systems

The adoption of voluntary milking systems (VMS) has been met with mixed reactions from dairy farmers. Studies indicate that while many farmers recognize the labor-saving benefits of VMS, concerns about initial costs, system reliability, and cow adaptation remain significant barriers (Hansen, 2015). Butler et al. (2012) show that farmers with positive experiences using VMS report increased milk yields, improved herd health, and enhanced work-life balance. However, others express concerns regarding system maintenance, high investment costs, and the need for ongoing technical support.

Tse et al. (2018) found that farmer perceptions are heavily influenced by prior experience, farm size, and available financial resources. Smaller farms often struggle to justify the high capital investment required for VMS, while larger operations see greater economic benefits through labor cost reduction and improved herd management. Additionally, studies suggest that effective training and support programs can significantly enhance farmer confidence in VMS adoption (Rodenburg, 2017). Ultimately, overcoming skepticism and demonstrating the long-term benefits of VMS will be critical for broader adoption in the dairy industry.

Technological Advancements in Automated Milking Systems

AMS technology has evolved significantly, incorporating robotics, artificial intelligence, and data analytics. Early AMS models primarily focused on replacing manual milking with robotic arms, while modern systems now integrate real-time monitoring of cow health, milk quality assessment, and predictive maintenance. De Koning (2010) and Jacobs & Siegford (2012) highlight improvements in sensor technologies, such as infrared thermography and conductivity sensors, which enhance early disease detection and improve overall herd management.

Recent advancements in machine learning and big data analytics have further improved AMS performance. AI-driven models can analyze large datasets to predict milking patterns, detect anomalies in milk production, and optimize cow health management. Additionally, Internet of Things integration allows remote monitoring of AMS performance, reducing the need for on-site supervision and improving overall efficiency.

DeVries (2017) discusses how automated systems contribute to improved dairy cow behavior and welfare, noting that voluntary milking schedules reduce competition for milking and enable cows to maintain more natural behavioral patterns. These behavioral insights further refine AMS technologies by ensuring better cow adaptation and optimizing milking routines.

Benefits of Automated Milking Systems

Research has demonstrated multiple advantages of AMS. Jacobs & Siegford (2012) report that AMS increases milking frequency, leading to higher milk yields. Additionally, AMS reduces labor dependency and enhances cow comfort by allowing voluntary milking. Improved animal welfare and reduced stress levels contribute to better milk production efficiency. Furthermore, data collection capabilities enable farmers to make informed decisions regarding herd management, nutrition, and disease prevention.

Another significant benefit of AMS is improved udder health and reduced mastitis incidence. Studies indicate that AMS minimizes over-milking and ensures optimal milking times, leading to lower stress on the udder (Rodenburg, 2017). Additionally, built-in sensors detect early signs of mastitis by analyzing milk conductivity, temperature, and somatic cell counts, enabling prompt intervention and reducing the need for antibiotics. By maintaining a cleaner and more hygienic milking environment, AMS significantly enhances overall herd health.

AMS also provides economic benefits. While the initial investment in AMS is substantial, long-term financial gains include reduced labor costs, increased milk yield, and improved herd health, leading to lower veterinary expenses (Bijl et al., 2007). Studies indicate that AMS can lead to better resource management by optimizing feed consumption and reducing energy costs associated with traditional milking systems.

Comparison to Automated Batch Milking Systems

In addition to individual voluntary milking systems, batch voluntary milking systems (Batch VMS) have been developed by DeLaval as an alternative solution for larger dairy herds. Unlike traditional AMS units that operate on a continuous voluntary milking basis, Batch VMS organizes cows into groups that are milked at scheduled intervals. This system allows for more structured herd management while still reducing labor compared to conventional parlors. This means transitioning from a conventional milking routine to a Batch VMS system may be a smoother transition for producers as it is a hybrid of both. (DeLaval, 2024).

Batch VMS may not provide the same level of flexibility as fully voluntary AMS, where cows have the freedom to choose when they are milked. However, one key advantage of Batch VMS is its ability to maintain better cow flow and reduce idle time by grouping cows based on their expected milking times. This approach may minimize down periods and ensure that cows have a balanced daily routine, optimizing their time budget. Batch VMS could increase overall system efficiency by reducing congestion at milking stations, particularly in high-production herds (DeLaval, 2024).

Milking efficiency in Batch VMS systems is a critical aspect of its effectiveness compared to traditional AMS. This system can facilitate higher throughput by streamlining cow movement and optimizing milking schedules. However, batch milking may lead to increased waiting times for certain cows, particularly those lower in the social hierarchy, which can impact overall milk yield and cow comfort. Proper barn design, strategic grouping, and careful scheduling are essential to mitigating these potential drawbacks and ensuring optimal efficiency in Batch VMS operations.

Cows in a Batch VMS system may experience higher stress levels compared to traditional AMS due to the imposed schedule, although proper barn design and management practices may help mitigate these effects. Later chapters in this thesis explore how pre-milking waiting time affects cow health and performance, and how multi-breed systems interact and develop selection behaviors.

Effects of Pre-Milking Waiting Time

Pre-milking waiting time is a critical factor influencing dairy cow welfare, milk production efficiency, and overall farm management. Extended waiting periods before milking have been associated with increased stress levels in cows, which can negatively affect milk letdown and overall yield. Prolonged standing in holding areas elevates cortisol levels, potentially inhibiting oxytocin release, a hormone essential for efficient milk ejection. Additionally, extended waiting times can lead to discomfort, increased competition, and altered social behaviors among cows, which may contribute to health issues such as lameness and mastitis.

The physiological impact of prolonged waiting times is well-documented, particularly in relation to stress responses and hormone regulation. Elevated cortisol levels, a key indicator of stress, can suppress oxytocin release, delaying milk letdown and reducing overall milk yield (Bruckmaier & Wellnitz, 2008). Studies have also shown that cows subjected to longer waiting periods exhibit increased heart rates and behavioral agitation, further suggesting heightened stress levels (Gygax et al., 2008). This stress can also compromise immune function, making cows more susceptible to infections and reducing overall herd health (Sutherland et al., 2012).

From a behavioral perspective, extended waiting times can alter cow interactions and increase aggressive behaviors. In confined waiting areas, cows experience higher stocking densities, leading to greater competition for space and resources (Cook & Nordlund, 2004). This increased competition can result in displacement behaviors, where dominant cows push subordinate cows away from preferred positions, creating further stress and disrupting social stability within the herd. Over time, these disruptions can lead to chronic stress, which has long-term implications for cow well-being and productivity.

Another critical aspect of prolonged waiting times is its impact on udder health and milk quality. Extended standing periods have been linked to a higher incidence of lameness, which in turn affects cow comfort and mobility (Chapinal et al., 2013). Poor udder health not only reduces milk yield but also affects milk composition, potentially leading to higher somatic cell counts and lower milk quality.

With the growing adoption of automated milking systems (AMS), efficient cow traffic management has become essential in minimizing waiting times and improving milking efficiency. AMS allows cows to be milked voluntarily, reducing the need for prolonged waiting periods and optimizing milking schedules based on individual cow preferences. Research suggests that well-designed barn layouts and strategic use of real-time data can significantly reduce waiting times, enhancing both productivity and cow welfare (Ketelaar-de Lauwere et al., 1999).

Milking Waiting Time Effects on the Cow Time Budget

The time budget of dairy cows is an essential factor in maintaining their overall well-being, and pre-milking waiting time can significantly influence how cows allocate their daily activities. Dairy cows naturally divide their time among essential activities, including lying, feeding, social interactions, and milking (DeVries et al., 2017). Excessive waiting times before milking can disrupt this balance, leading to reduced resting and feeding periods, which are crucial for optimal milk production and cow health (Rodenburg, 2017).

Research has shown that prolonged standing in holding areas reduces the time available for lying and ruminating, potentially leading to lameness and other health issues (Cook & Nordlund, 2009). Manriquez et al. (2022) demonstrate that cows experiencing extended pre-milking waiting times exhibit changes in lying behavior post-milking. AMS, by contrast, offer the advantage of voluntary and more evenly distributed milking schedules, allowing cows to maintain a more natural daily routine (Jacobs & Siegford, 2012).

By minimizing waiting times, we ensure that cows spend more time engaging in natural behaviors such as resting and feeding, ultimately improving milk production efficiency and animal welfare. Future research should focus on optimizing barn and traffic designs to further reduce pre-milking waiting times and promote a balanced time budget for dairy cows.

Mastitis

Mastitis, characterized by inflammation of the mammary gland, is a leading cause of economic loss in the dairy industry due to decreased milk yield, altered milk composition, and increased culling rates (Bradley, 2002). It is commonly caused by bacterial infections, which can be categorized into contagious and environmental pathogens.

Mastitis results from the invasion of pathogens into the mammary gland, triggering an immune response that leads to tissue damage and changes in milk quality (Rainard et al., 2018). Contagious pathogens, such as *Staphylococcus aureus* and *Streptococcus agalactiae*, primarily spread during milking, whereas environmental pathogens like *Escherichia coli* and *Streptococcus uberis* originate from bedding materials and manure (Keane, 2019). The severity of mastitis varies, ranging from subclinical cases, detected by increased somatic cell counts (SCC), to clinical presentations involving swelling, pain, and systemic illness.

Diagnostic Approaches

Accurate and early detection of mastitis is essential for effective control. Traditional diagnostic methods include the California Mastitis Test (CMT) and SCC measurement, which serve as indicators of inflammation (Pyörälä, 2003). Advanced molecular techniques, such as polymerase chain reaction (PCR) and matrix-assisted laser desorption/ionization-time of flight mass spectrometry (MALDI-TOF MS), enable rapid pathogen identification (Heikkilä et al., 2018). Additionally, biosensors and electrical conductivity measurements are emerging as potential tools for real-time mastitis detection (Khatun et al., 2018).

Control and Prevention Strategies

Mastitis control requires a comprehensive approach, including improved hygiene, selective antimicrobial therapy, and genetic selection for disease resistance (Ruegg, 2017). Proper milking protocols, such as post-milking teat disinfection and dry cow therapy, reduce the risk of infection (Dufour et al., 2019). The increasing concern over antimicrobial resistance has led to a shift towards targeted therapy based on pathogen identification (Doehring and Sundrum, 2019).

Additionally, genetic studies have identified markers associated with mastitis resistance, providing opportunities for selective breeding programs (Miglior et al., 2017).

Role of Automated Milking Systems in Mastitis Management

Automated milking systems (AMS) have revolutionized dairy farming by improving milking efficiency and animal welfare while reducing human error in milking practices. AMS offers advantages in mastitis management by enabling continuous monitoring of milk quality through real-time data collection on somatic cell counts, electrical conductivity, and milk flow patterns (Jacobs & Siegford, 2012). These systems help in the early detection of mastitis, allowing for prompt intervention and reducing the severity of infections. Furthermore, AMS maintains consistent and optimal milking hygiene, minimizing the risk of cross-contamination between cows and lowering the prevalence of contagious mastitis pathogens (Barkema et al., 2015). The integration of AMS with precision livestock farming technologies enhances the ability to track udder health trends and optimize mastitis control strategies.

Effects of Pre-Milking Waiting Time on Mastitis

Pre-milking waiting time, which refers to the duration cows spend in holding pens before milking, can significantly impact udder health and mastitis incidence. Extended waiting periods can lead to stress and increased bacterial exposure, elevating the risk of intramammary infections (Odorčić et al., 2019). Prolonged standing time before milking can also result in teat congestion and impaired teat sphincter function, making the udder more susceptible to bacterial invasion. Conversely, optimizing pre-milking waiting times through efficient milking parlor management reduces stress and bacterial contamination, contributing to lower mastitis rates and improved milk quality. Proper cow flow and reduced overcrowding in holding areas play a crucial role in maintaining udder health and minimizing infection risks.

Lameness

Lameness is a significant welfare and economic concern in the dairy industry, affecting productivity and longevity in dairy cows. It is a multifactorial condition influenced by management practices, housing systems, nutrition, and genetics (Huxley, 2012). Hoof disorders, metabolic conditions, and environmental factors contribute to lameness, leading to reduced milk yield and reproductive efficiency (Green et al., 2002). Early detection through locomotion scoring and advanced technologies, alongside effective mitigation strategies such as improved housing, hoof care, and nutritional management, are critical (Bicalho et al., 2007). Future research should focus on integrating genetic selection and technological advancements to enhance cow welfare and farm sustainability (Van Hertem et al., 2016). Understanding the underlying causes, consequences, and effective mitigation strategies is essential for sustainable dairy production.

Causes of Lameness and Consequences of Lameness

Lameness in dairy cows is primarily caused by hoof disorders, environmental stressors, and metabolic imbalances. Common hoof disorders include digital dermatitis, sole ulcers, and white line disease, often resulting from prolonged standing and inadequate flooring (Solano et al., 2015). Additionally, metabolic disorders such as ruminal acidosis contribute to laminitis, exacerbating lameness-related issues (Bicalho & Oikonomou, 2013). Identifying these contributing factors is essential for effective prevention and treatment.

Lameness adversely affects dairy production by reducing milk yield, impairing reproductive performance, and increasing culling rates. Studies indicate that lame cows exhibit lower conception rates and extended calving intervals due to stress and mobility issues (Randall et al., 2015). The economic impact includes increased veterinary costs, labor, and diminished productivity, highlighting the need for effective intervention strategies (Barker et al., 2010).

Detection and Diagnosis

Early detection of lameness is critical for mitigating its impact. Traditional methods such as visual locomotion scoring are widely used, while modern technologies, including pressure-sensitive walkways and automated gait analysis, provide more objective assessments (Van Hertem et al., 2016). Regular hoof inspections and routine trimming play a crucial role in early identification and prevention (Bicalho et al., 2007).

Mitigation and Management Strategies

Preventative measures focus on optimizing housing conditions, hoof care, and nutritional strategies. Proper barn design with comfortable bedding and non-slip flooring minimizes the risk of hoof injuries (Cook & Nordlund, 2009). Routine hoof trimming and the use of foot baths enhance hoof integrity (Solano et al., 2015). Nutritional strategies, including balanced diets rich in fiber and essential minerals, support overall metabolic health and hoof quality (Bicalho & Oikonomou, 2013). Integrating these strategies is key to reducing lameness prevalence.

Effects of Waiting Time and Lameness

Waiting time before milking is a crucial factor influencing cow welfare, milk yield, and the prevalence of lameness. Studies indicate that extended pre-milking waiting times can negatively impact cow comfort, increase stress, and reduce productivity (Rodenburg, 2017). Long waiting periods can lead to excessive standing time, which is a known risk factor for lameness in dairy cows (DeVries, 2017). Lameness is a significant welfare concern in dairy farming, often associated with poor hoof health, discomfort, and reduced mobility. Increased waiting times exacerbate these issues by limiting the time cows spend resting and ruminating.

Lameness affects a cow's ability to voluntarily visit the milking station, leading to irregular milking intervals and potential production losses. Studies by DeVries et al. (2017) suggest that

AMS can help mitigate these issues by allowing cows to milk at their own pace, reducing competitive stress and minimizing forced standing periods. However, in systems where cows must queue for extended durations, lameness prevalence increases due to prolonged weight-bearing on compromised hooves.

Optimizing barn design, ensuring adequate resting areas, and implementing proper cow traffic management strategies can help alleviate these problems. Research indicates that providing comfortable flooring, reducing overcrowding, and improving cow selection algorithms in AMS can significantly enhance cow welfare and reduce lameness-related complications (Jacobs & Siegford, 2012). Future AMS developments should focus on refining cow movement within the milking facility to further minimize waiting times and promote better hoof health.

Moreover, studies indicate that AMS can improve the overall cow time budget by reducing unnecessary standing periods, allowing for more time spent lying and ruminating (Manriquez et al., 2022). An optimized time budget is crucial for maintaining high milk production, as cows require sufficient resting time to maximize rumination efficiency and metabolic processes. This relationship between AMS design, milking waiting times, and lameness mitigation should be a key focus for future dairy management strategies.

Impact of Robots on Lameness and Cow Behavior

The use of robotics in AMS has been shown to positively affect cow mobility and overall behavior. Lameness is a major welfare concern in dairy farming, often exacerbated by extended standing times and poor barn management (Van Nuffel et al., 2015). AMS helps mitigate this issue by promoting voluntary milking, reducing the need for cows to stand in holding pens for extended periods, thus lowering the risk of hoof diseases and lameness (DeVries, 2017).

Robotic milking systems also encourage more natural cow movement patterns, reducing stress and promoting better hoof health. Studies indicate that cows using AMS exhibit more evenly distributed activity throughout the day, as opposed to conventional milking systems, where cows often experience high-stress movement during scheduled milking times (Jacobs & Siegford, 2012). This reduction in stress contributes to better immune function, improved milk yield, and overall enhanced welfare.

Selection Behavior of Cows in Milking Parlors and Voluntary Milking Systems

Cow selection behavior in milking parlors and voluntary milking systems (VMS) is an important factor in optimizing milk production efficiency. Some cows readily adapt to voluntary milking, while others require training and encouragement. High-ranking cows often access AMS more frequently, while lower-ranking cows may exhibit reluctance due to competition and social stress.Lovendahl et al. (2016) examined cow traffic and voluntary participation in AMS, emphasizing that cows exhibit individual preferences for milking times, influenced by factors such as parity, social hierarchy, and previous milking experiences. Their study suggests that cows with higher social dominance tend to visit the milking station more frequently, while subordinate cows may require additional encouragement or strategic barn design to facilitate milking access.

Additionally, research indicates that selection behavior is linked to motivation factors such as udder pressure, feed incentives, and learned routines. Devries (2024) highlights that cows conditioned to associate AMS with positive reinforcement, such as concentrate feed, are more likely to voluntarily approach the milking unit. This reinforces the importance of consistent training and barn layout in ensuring optimal use of AMS facilities. Additionally, training young heifers to use AMS at an early age improves adaptation and long-term milking efficiency. Overall, understanding selection behavior in AMS can help farmers improve cow traffic flow, enhance milking efficiency, and promote animal welfare.

Understanding selection behavior also aids in reducing congestion at milking stations, preventing bottlenecks, and improving overall cow flow within the system. Strategic placement of entry and exit points, coupled with targeted incentives, can enhance voluntary participation and minimize stress, contributing to higher milk yields and improved cow welfare (Lovendahl et al., 2016).

Future of Automated and Automated Batch Milking Systems

Automated milking systems have significantly transformed dairy farming, offering numerous benefits while posing certain challenges. The integration of advanced technologies continues to improve AMS efficiency and usability. The introduction of ABMS may contribute to the further adaptation of robotic milking. Future research should focus on robot usage efficiency and design to promote cow performance and health to maximize the potential of ABMS in the dairy industry

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CHAPTER 2: EFFECT OF PRE-MILKING WAITING TIME ON MILKING BEHAVIOR AND PERFORMANCE OF COWS IN A BATCH MILKING SYSTEM WITH AUTOMATIC MILKING UNITS

Abstract

The objective was to test the effect of pre-milking waiting time (WT) on the milking behavior and performance during the following visit to the milking robot in cows managed in a batch milking system with automatic milking units. A secondary objective was to test the effect of WT on the diagnosis of lameness. The study used data from 333,285 milking events in 1,037 cows from May 2023 to September 2024 in a commercial organic grass-fed dairy in TX. Cows were moved twice per day to the milking barn where they could select their milking visits among 22 AMS units (DeLaval, Sweden). Visit information was collected to calculate pre-milking WT, defined as the time elapsed between the entrance of the cow to the milking barn, as indicated by pedometers attached to each cow that were read by sensors located at the parlor, and the entrance of each individual cow to the robot milking box. WT were categorized into quartiles within each parity group as Q1 $\leq$ 9 min, Q2 = 10 to 24 min, Q3 = 25 to 46 min and Q4 $\geq$ 47 mins for primiparous and Q1 $\leq$ 11 min Q2 = 12 to 30 min, Q3 = 31 to 51 min and Q4 $\geq$ 52 mins for multiparous. All analyses were conducted using R-Studio 4.4.1 (Posit Software, PBC, Boston, MA). Least square means (SE) for outcome variables by parity category and breed (HO, JE, and HJ) were calculated and compared using ANOVA for repeated measures, with cow ID as the repeated measure. Multivariable models included WT category, parity category, breed, season, and DIM at milking time, along with their interactions, as potential covariates. Breed and parity category had significant effects and were retained in the models. Consequently, analyses were conducted separately for each breed and parity category. To assess the association between lameness and WT, individual cow WT averages were calculated separately for primiparous and multiparous groups.

Lameness was treated as a categorical variable, where 1 indicated a cow diagnosed with lameness and 0 indicated non-lame cow. Logistic regression models were used to evaluate the relationship, with average waiting time and breed as predictor variables. However, breed was not a significant factor in either model (primiparous: $p = 0.31$; multiparous: $p = 0.19$) and was subsequently removed from the analysis.

The results show that the average waiting time for all milking events was 33.6 min (± SD = 28.5), 34.5 ± 28.9 for PP, and 30.7 ± 27.3 for MP. The means for each breed were 25.6 ± 15.2, 42.3 ± 16.8, and 42.3 ± 23.4, for HO, JE, and HJ, respectively. While significant differences in LSM were observed between breeds for most variables, there was little to no significant association between WT and the analyzed outcomes. Significant seasonal differences in LSM were observed for milk yield in both PP and MP cows. Additionally, significant seasonal effects were found for incomplete milking, milking duration, and milk flow duration in multiparous cows. Lastly, an increase of 10 minutes in WT was associated with a 23.7% increase in the odds of lameness in multiparous cows (95% CI: 10.2–39.0; $p < 0.001$). However, no significant association was found in primiparous cows (OR: 1.09, 95% CI: 0.85–1.38, $p = 0.462$).

Key words: Robot, waiting, time, performance, lameness

Introduction

Pre-milking waiting time is a critical factor influencing dairy cow welfare, milk production efficiency, and overall farm management. Extended waiting periods before milking have been associated with increased stress levels in cows, which can negatively affect milk letdown and overall yield. Research indicates that prolonged standing in holding areas elevates cortisol levels, potentially inhibiting oxytocin release, a hormone essential for efficient milk ejection (Rushen et al., 2001). Additionally, extended waiting times can lead to discomfort, increased competition, and altered social behaviors among cows, which may contribute to health issues such as lameness and mastitis.

The physiological impact of prolonged waiting times is well-documented, particularly in relation to stress responses and hormone regulation. Elevated cortisol levels, a key indicator of stress, can suppress oxytocin release, delaying milk letdown and reducing overall milk yield (Bruckmaier & Wellnitz, 2008). Studies have also shown that cows subjected to longer waiting periods exhibit increased heart rates and behavioral agitation, further suggesting heightened stress levels (Gygax et al., 2008). This stress can also compromise immune function, making cows more susceptible to infections and reducing overall herd health (Sutherland et al., 2012).

From a behavioral perspective, extended waiting times can alter cow interactions and increase aggressive behaviors. In confined waiting areas, cows experience higher stocking densities, leading to greater competition for space and resources (Cook & Nordlund, 2004). This increased competition can result in displacement behaviors, where dominant cows push subordinate cows away from preferred positions, creating further stress and disrupting social stability within the herd. Over time, these disruptions can lead to chronic stress, which has long-term implications for cow well-being and productivity.

Another critical aspect of prolonged waiting times is its impact on cow health and milk production. Dairy cows naturally divide their time among essential activities, including lying, feeding, social interactions, and milking. Excessive waiting times before milking can disrupt this balance, leading to reduced resting and feeding periods, which are crucial for optimal milk production and cow health. Research has shown that prolonged standing in holding areas reduces the time available for lying and ruminating, potentially leading to lameness and other health issues (Cook & Nordlund, 2009). Manriquez et al. (2022) demonstrate that cows experiencing extended pre-milking waiting times exhibit changes in lying behavior pos t-milking. Extended standing periods have been linked to a higher incidence of lameness, which in turn affects cow comfort and mobility (Chapinal et al., 2013). Poor udder health not only reduces milk yield but also affects milk composition, potentially leading to higher somatic cell counts and lower milk quality.

With the growing adoption of automated milking systems (AMS), efficient cow traffic management has become essential in minimizing waiting times and improving milking efficiency. AMS allows cows to be milked voluntarily, reducing the need for prolonged waiting periods and optimizing milking schedules based on individual cow preferences. Well-designed barn layouts and strategic use of real-time data can significantly reduce waiting times, enhancing both productivity and cow welfare.

In addition to voluntary milking systems, batch voluntary milking systems (Batch VMS) have been developed by DeLaval as an alternative solution for larger dairy herds. Unlike traditional AMS units that operate on a continuous voluntary milking basis, Batch VMS organizes cows into groups that are milked at scheduled intervals. This system allows for more structured herd management while still reducing labor compared to conventional parlors. This means transitioning from a conventional milking routine to a Batch VMS system may be a smoother transition for producers as it is a hybrid of both. (DeLaval, 2024).

Batch VMS may not provide the same level of flexibility as fully voluntary AMS, where cows have the freedom to choose when they are milked. However, one key advantage of Batch VMS is its ability to maintain better cow flow and reduce idle time by grouping cows based on their expected milking times. This approach may minimize down periods and ensure that cows have a balanced daily routine, optimizing their time budget. Batch VMS could increase overall system efficiency by reducing congestion at milking stations, particularly in high-production herds (DeLaval, 2024).

Cows in a Batch VMS system may experience higher stress levels due to the imposed schedule compared to fully voluntary systems, and pre-milking waiting time may be a variable to explore in this relatively new technology. We hypothesized that pre-milking waiting time would have an effect on cow performance and cow health in a multibreed dairy farm with a batch milking system with automatic milking units. Therefore, the objective was to test the effect of pre-milking waiting time (WT) on the milking behavior and performance during the following visit to the milking robot in cows managed in a semi-voluntary batch milking system. A secondary objective was to test the effect of WT on the diagnosis of lameness.

Materials and Methods

Study farm and surveyed population

All research procedures were approved by the Colorado State University IACUC Waiver Subcommittee (protocol #4907). This retrospective observational study analyzed data from cows in a commercial, organic-certified, grass-fed herd located in Central TX, USA, utilizing an automated batch milking system (**ABMS**). The herd consisted of three breeds: Holstein (**HO**; 39.9%), Jersey (**JE**; 48.5%), and Holstein × Jersey crossbred (**HJ**; 11.6%), all managed under the same conditions. The analysis included data from 333,285 milking events recorded between May 2023 and September 2024, involving 1,037 HO (n=484), JE (485) and HJ (68) cows.

In compliance with organic grass-fed regulations, cows had access to grazing for at least 150 days per year. The grazing season extended from February to October, with individual days skipped due to adverse weather conditions such as heavy rain or extreme heat. During this period, cows were managed in multibreed groups of 250. The pasture primarily consisted of Coastal Bermuda grass, supplemented with a summer forage mix that included cowpea (*Vigna unguiculata*), Sunn hemp (*Crotalaria juncea*), organic Japanese millet (*Echinochloa esculenta*), BMR hybrid pearl millet (*Pennisetum glaucum*), organic buckwheat (*Fagopyrum esculentum*), kale (*Brassica oleracea var. sabellica*), and forage collards impact (*Brassica oleracea*). The winter forage mix contained Austrian winter peas (*Pisum sativum*), Balansa clover viper (*Trifolium michelianum*), organic winter rye (*Secale cereale*), organic soft red winter wheat (*Triticum aestivum*), organic winter barley (*Hordeum vulgare*), and organic winter triticale (*Triticosecale*). Throughout the grazing season, pasture contributed to 60% of the cows' dry matter intake (DMI).

During the non-grazing season, groups of 250 cows were housed in dry lots with shade provided at the center of the pens. On days without grazing access, cows were fed a grass-based mixed ration that contained no grain and had ad libitum access to water. Feed bunks were monitored throughout the day, and refusals were assessed to make daily adjustments based on DMI. The bedding and patio were turned and scraped daily, with a full cleaning and removal performed once per year.

Cows were moved to the milking barn twice daily, at 6:00 AM and 6:00 PM, starting with group 1 (fresh cows) followed by seven additional groups. Within the milking barn, cows had the flexibility to select their milking visits among 22 DeLaval VMS V300 units (Figure 2.1), which were equipped with DeLaval liners VMS 20M-LS (DeLaval International AB, Tumba, Sweden). When the fresh group (group 1) was nearing completion of milking, with fewer than 15–20 cows remaining, farm personnel guided the remaining cows toward the north end of the parlor and directed them toward the milking robots. Subsequent groups were brought to the milking parlor once the previous group had fewer than 50 cows remaining. Unlike group 1, cows from group 2 onwards were not actively guided toward the robots and were free to choose when to enter the milking units. Although this system allowed for some group mixing, cows returned to their respective groups through a series of sorting gates (Figure 2.1). Alfalfa pellets were provided at the automated milking system (AMS) in amounts ranging from 0.5 kg to 5 kg, depending on lactation stage and expected milk yield.

Data collection and waiting time calculation

Data on robotic milking station use per cow and milking event were collected from the AMS units via the parlor management software (DelPro Farm Manager; DeLaval International AB, Tumba, Sweden) and transferred to Excel spreadsheets (Microsoft Corp.). Demographic and health information, including breed, calving date, parity number, and lameness incidence was extracted from PCDART herd management software (Dairy Records Management Systems, NC, USA). The DelPro dataset was then cross-referenced with the PCDART database to ensure the accurate import of demographic information.

The CowAlert database (Peacock Technologies, UK) was analyzed to obtain entry times into the milking parlor. These times were recorded when pedometers attached to cows triggered a group of sensors positioned along the wall adjacent to the parlor entrance (Figure 1). Each entry time was matched to its corresponding milking event, and the pre-milking waiting time in the holding pen was defined as the difference between entry time and the start of milking. Pedometers at the farm were checked daily for faulty devices that may have been damaged or had battery issues. Any pedometer that did not trigger a signal in the last 48 hours and was assigned to a cow that was confirmed to have been at the milking parlor, was deemed faulty and a replacement was ordered.

All times were recorded in mm/dd/yyyy hh:mm format, with waiting times rounded to full-minute integers. Of the 333,287 milking events recorded, 77,516 (23%) were excluded due to missing entry times. This data loss was likely caused by high cow traffic at entry, which may have interfered with pedometer signal detection in addition to faulty devices.

Statistical Analysis

The databases were subdivided by parity into primiparous (PP) and multiparous (MP) groups. Within each parity group, subgroups were created based on quartiles of pre-milking waiting time. The shortest 25% were classified as Q1, while the longest 25% were classified as Q4. The quartile distributions were the following: Q1 ≤ 9 min, Q2 = 10 to 24 min, Q3 = 25 to 46 min and Q4 ≥ 47 mins for PP. And Q1 ≤ 11 min Q2 = 12 to 30 min, Q3 = 31 to 51 min and Q4 ≥ 52 mins for MP.

All analyses were conducted using R-Studio 4.4.1 (Posit Software, PBC, Boston, MA). Least square means (SE) for outcome variables by parity category and breed (HO, JE, and HJ) were calculated and compared using ANOVA for repeated measures, with ID as the repeated measure. Multivariable models included waiting time category, parity category, breed (HO, JE, HJ), season, and DIM at milking time, along with their interactions, as potential covariates. Breed and parity category had significant effects and were retained in the models. Consequently, analyses were conducted separately for each breed and parity category. For all outcome variables, significant predictors were determined at P-value < 0.05; interaction terms and controlling variables remained in the models at P-value ≤ 0.10.

To assess the association between lameness and waiting time, individual cow waiting time averages were calculated separately for PP and MP groups. Lameness was treated as a categorical variable, where 1 indicated a cow diagnosed with lameness and 0 indicated a non-lame cow.

Logistic regression models were used to evaluate the relationship, with average waiting time and breed as predictor variables. However, breed was not a significant factor in either model (PP: p = 0.31; MP: p = 0.19) and was subsequently removed from the analysis. A total of 112 of lameness cases (24 PP and 88 MP) were used in analysis in 787 cows with a calculated average waiting time (247 PP and 540 MP).

Results and Discussion

The distribution of waiting times for all milking events included in the analysis is presented in Figure 2.2. The results show that the average waiting time for all milking events was 33.6 min (± SD = 28.5), 34.5 ± 28.9 for PP, and 30.7 ± 27.3 for MP. The means for each breed were 25.6 ± 15.2, 42.3 ± 16.8, and 42.3 ± 23.4, for HO, JE, and HJ, respectively. The typically larger frame of Holstein cows compared with JE and HJ (Heins et al., 2008; Gibson et al., 2022) could play a role in having shorter WT, as their size could facilitate more competitive and dominant behaviors in herd settings with multiple breeds. Previous research has indicated that larger cows often display more dominant behaviors in herd dynamics, influencing space utilization and priority access to resources (Bouissou et al., 2001). Holsteins, being larger, may have an easier time displacing smaller cow, such as Jerseys, thereby reducing their own WT. Future studies investigating the behavioral interactions among different breeds in mixed herds could further clarify the impact of dominance on milking efficiency.

The levels of significance for each of the variables included in the calculation of LSM of outcome variables are presented in Table 2.2. The effects of WT category and breed were significant for almost all variables, while the interaction between the two was significant in most cases. For season and DIM, there was significance for all the variables in analysis. And for the interaction between season and DIM with WT category, the interactions were significant for all except for 1 and 3 variables, respectively.

The least-square means (SE) for each WT category and breed for all outcome variables are shown in Tables 2.3 and 2.4. While significant differences in LSM were observed between breeds for most variables, there was little to no significant association between WT and the analyzed outcomes. The only notable finding was an increased incidence of incomplete milkings in PP cows, which correlated with higher WT categories. This finding aligns with previous research suggesting that younger or less experienced cows, particularly those in their first lactation, may exhibit greater hesitation or stress in milking environments, leading to an increased likelihood of incomplete milkings (Svennersten-Sjaunja & Pettersson, 2008; Jacobs & Siegford, 2012). Longer WT could exacerbate stress levels, potentially reducing milk let-down efficiency due to heightened cortisol responses and disrupted oxytocin release (Bruckmaier & Wellnitz, 2008).

Delayed access to milking may lead to udder overfilling, which can negatively affect milk flow dynamics and increase the likelihood of milking interruptions. While the current analysis did not identify strong associations between WT and other performance outcomes, further research could explore individual cow behaviors, stress responses, and adaptation patterns to automated milking systems. The ABMS setting may provide an environment where cows are exposed to less stimulation and/or stress. Understanding these dynamics may help optimize herd management strategies to improve milking efficiency and overall cow welfare.

The least-square means (SE) for seasonal differences in all outcome variables are presented in Table 2.1. Significant seasonal differences in LSM were observed for milk yield in both PP and MP cows. Additionally, significant seasonal effects were found for incomplete milking, milking duration, and milk flow duration in multiparous cows.

Seasonal fluctuations in milk production are well-documented and often attributed to variations in environmental conditions, including temperature, humidity, and forage availability (Kadzere et al., 2002). Heat stress, particularly in warmer months, has been shown to negatively impact milk yield by reducing feed intake, altering endocrine responses, and increasing energy expenditure for thermoregulation (Collier et al., 2006). These effects may be more pronounced in MP cows, as they generally have higher milk production demands and may experience greater metabolic stress compared to PP cows (Baumgard & Rhoads, 2013).

Lastly, an increase of 10 minutes in WT was associated with a 23.7% increase in the odds of lameness in multiparous cows (95% CI: 10.2–39.0; $p < 0.001$). However, no significant association was found in primiparous cows (OR: 1.09, 95% CI: 0.85–1.38, $p = 0.462$). The increased risk of lameness in MP cows with prolonged WT may be attributed to extended periods of standing on hard surfaces, which has been shown to contribute to hoof disorders and joint stress (Cook & Nordlund, 2009; Chapinal et al., 2013). MP cows, which generally have higher body weights than PP cows, may experience greater mechanical strain on their hooves and limbs when forced to stand for extended durations, further increasing their susceptibility to lameness (Bicalho et al., 2007). Additionally, prolonged standing in holding pens can exacerbate discomfort and fatigue, leading to altered gait patterns that may increase the risk of claw lesions and locomotion issues over time (Randall et al., 2015).

The lack of a significant association in PP cows suggests that younger cows may be more resilient to extended standing periods due to their lower body weight and potentially healthier hoof conditions compared to older, higher-parity cows (Alsaaod et al., 2019).

These findings highlight the importance of reducing unnecessary standing time in dairy cows, particularly for MP cows, to mitigate lameness risk. Strategies such as improving cow flow efficiency, optimizing flooring conditions with softer surfaces, and providing adequate resting opportunities can help alleviate the negative effects of prolonged standing (Cook et al., 2009). Future research should focus on individual cow responses to WT and explore precision dairy technologies for early lameness detection and prevention.

Conclusions

In our analysis, pre-milking waiting time in ABMS did not have a significant impact on milking performance. However, further investigation with an expanded database may be necessary to explore potential effects in greater detail. Additionally, lameness concerns should be considered, as prolonged waiting times were associated to increased lameness in multiparous cows.

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Table 2.1: Milking events, Mastitis Index (MDi) and performance data presented as relative frequencies (%) and averages by season of milking in primiparous and multiparous cows.

	Season of milking							
	Primiparous				Multiparous			
	Spring	Summer	Fall	Winter	Spring	Summer	Fall	Winter
Incomplete (%)	3.60	2.77	4.18	4.82	3.37[ab]	2.75[a]	3.30[ab]	4.10[b]
Kick-off Milkings (%)	6.37	6.20	6.54	6.81	4.43	4.71	4.26	3.69
MDi	1.27	1.33	1.35	1.14	1.33	1.32	1.36	1.35
Milk Duration (sec)	336	316	326	334	353[b]	329[a]	347[b]	362[b]
Milk Flow Duration (sec)	235	215	224	238	259[b]	236[a]	251[b]	267[b]
Mean Flow (lb/min)	1.94	1.97	1.99	2.30	2.21	2.11	2.09	2.19
Peak Flow (lb/min)	2.79	2.83	2.85	3.02	3.12	3.00	2.97	3.09
Milk yield (lb)	15.5[b]	13.4[a]	14.3[ab]	24.5[c]	20.8[c]	17.6[a]	18.7[b]	20.7[d]

*Different superscripts within rows indicate P <0.05

Table 2.2: Level of significance for each of the variables included in the calculation of outcome variables in the LSM calculation.

Variable	Parity category	WT Quartile	Breed	Season	DIM	WT*Breed	WT*Season	WT*DIM
Incompletes	Primiparous	< 0.001	0.40	< 0.001	< 0.001	0.412	N.A.	N.A.
	Multiparous	0.022	< 0.001	< 0.001	< 0.001	0.141	N.A.	N.A.
Kick-offs	Primiparous	0.004	0.379	0.407	< 0.001	0.145	N.A.	N.A.
	Multiparous	0.353	0.042	< 0.001	< 0.001	0.509	N.A.	N.A.
MDi	Primiparous	0.946	0.162	< 0.001	< 0.001	0.003	0.002	< 0.001
	Multiparous	< 0.001	0.002	< 0.001	< 0.001	0.677	< 0.001	0.126
MDi >1.4	Primiparous	< 0.001	0.002	< 0.001	< 0.001	0.005	N.A.	N.A.
	Multiparous	< 0.001	0.002	< 0.001	< 0.001	0.794	N.A.	N.A.
Milk Duration	Primiparous	< 0.001	0.387	< 0.001	< 0.001	0.59	0.08	0.022
	Multiparous	< 0.001	0.088	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Milk Flow Duration	Primiparous	< 0.001	0.036	< 0.001	< 0.001	0.293	< 0.001	0.152
	Multiparous	< 0.001	0.093	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Mean Flow	Primiparous	< 0.001	< 0.001	< 0.001	< 0.001	0.479	< 0.001	< 0.001
	Multiparous	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Peak Flow	Primiparous	< 0.001	< 0.001	< 0.001	< 0.001	0.307	< 0.001	< 0.001
	Multiparous	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Milk Yield: Current	Primiparous	< 0.001	< 0.001	< 0.001	< 0.001	0.18	< 0.001	< 0.001
	Multiparous	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Milk Yield: Next	Primiparous	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
	Multiparous	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

Table 2.3: Milking events and Mastitis Index (MDi) data presented as frequencies, relative frequencies (%) and averages by waiting time category and breed (HO = Holstein, HJ =Holstein × Jersey crossbred, and JE = Jersey) in primiparous and multiparous cows.

		Waiting Time Category							
		Primiparous				Multiparous			
		Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Milkings (n)									
	HO	15,009	14,864	12,558	9,232	28,020	22,161	12,946	10,540
	HJ	260	402	423	375	2,588	3,507	4,579	4,894
	JE	807	1136	3,484	6,383	15,895	21,878	30,722	33,108
Incomplete (%)									
	HO	3.80^{a}	3.89^{ab}	4.05^{ab}	4.72^{b}	4.96	4.65	4.63	4.96
	HJ	1.94	5.14	5.00	7.12	3.26	3.74	4.06	3.75
	JE	2.28^{a}	2.87^{ab}	3.20^{ab}	3.89^{b}	2.28	1.99	1.95	2.26
Kick-off Milkings (%)									
	HO	5.73	5.96	5.49	6.09	5.03	5.10	5.04	5.68
	HJ	8.31	10.08	11.26	9.49	3.42	3.55	3.74	3.92
	JE	5.05	4.31	4.12	5.96	4.19	3.94	4.00	4.06
MDi									
	HO	1.25	1.24	1.25	1.25	1.24	1.25	1.25	1.27
	HJ	1.09	1.24	1.22	1.16	1.35	1.37	1.36	1.39
	JE	1.40	1.39	1.38	1.38	1.38	1.39	1.40	1.41
MDi > 1.4 (%)									
	HO	8.35	8.11	6.80	6.90	7.56	7.78	8.06	9.15
	HJ	12.1	4.32	7.81	8.62	19.9	21.6	22.6	24.3
	JE	27.6	29.1	26.1	20.5	15.4	15.6	17.4	18.7

*Different superscripts within rows indicate $P < 0.05$

Table 2.4: Milking performance data presented as averages by waiting time category and breed (HO = Holstein, HJ =Holstein × Jersey crossbred, and JE = Jersey) in primiparous and multiparous cows.

		Waiting Time Category							
		Primiparous				Multiparous			
		Q1	Q2	Q1	Q2	Q1	Q2	Q3	Q4
Milk Duration (sec)									
	HO	316	319	319	327	325	344	346	351
	HJ	322	323	327	331	358	358	362	366
	JE	365	372	315	302	330	332	337	345
Milk Flow Duration (sec)									
	HO	213	216	216	222	242	245	248	252
	HJ	249	292	226	220	265	268	271	274
	JE	216	219	223	226	237	241	245	253
Mean Flow (lb/min)									
	HO	2.20	2.20	2.20	2.18	2.43	2.41	2.41	2.42
	HJ	1.91	2.14	2.07	2.21	2.04	2.03	2.03	2.03
	JE	1.89	1.89	1.87	1.86	2.00	2.00	1.99	1.98
Peak Flow (lb/min)									
	HO	3.10	3.10	3.10	3.09	3.41	3.38	3.38	3.39
	HJ	2.41	2.91	2.84	3.09	2.88	2.89	2.88	2.89
	JE	2.70	2.71	2.70	2.70	2.86	2.86	2.85	2.85
Milk yield: current milking (lb)									
	HO	16.21	16.43	16.66	16.79	20.41	20.61	21.01	21.71
	HJ	19.91	22.01	21.60	19.34	19.12	19.53	19.80	20.44
	JE	13.30	13.27	13.65	13.71	16.98	17.53	17.90	18.43
Milk yield: next milking (lb)									
	HO	16.65	16.75	16.55	15.82	20.94	20.94	20.67	20.23
	HJ	22.86	20.36	20.80	21.21	20.06	20.21	20.07	19.49
	JE	13.86	14.06	13.97	13.34	18.05	18.06	18.03	17.75

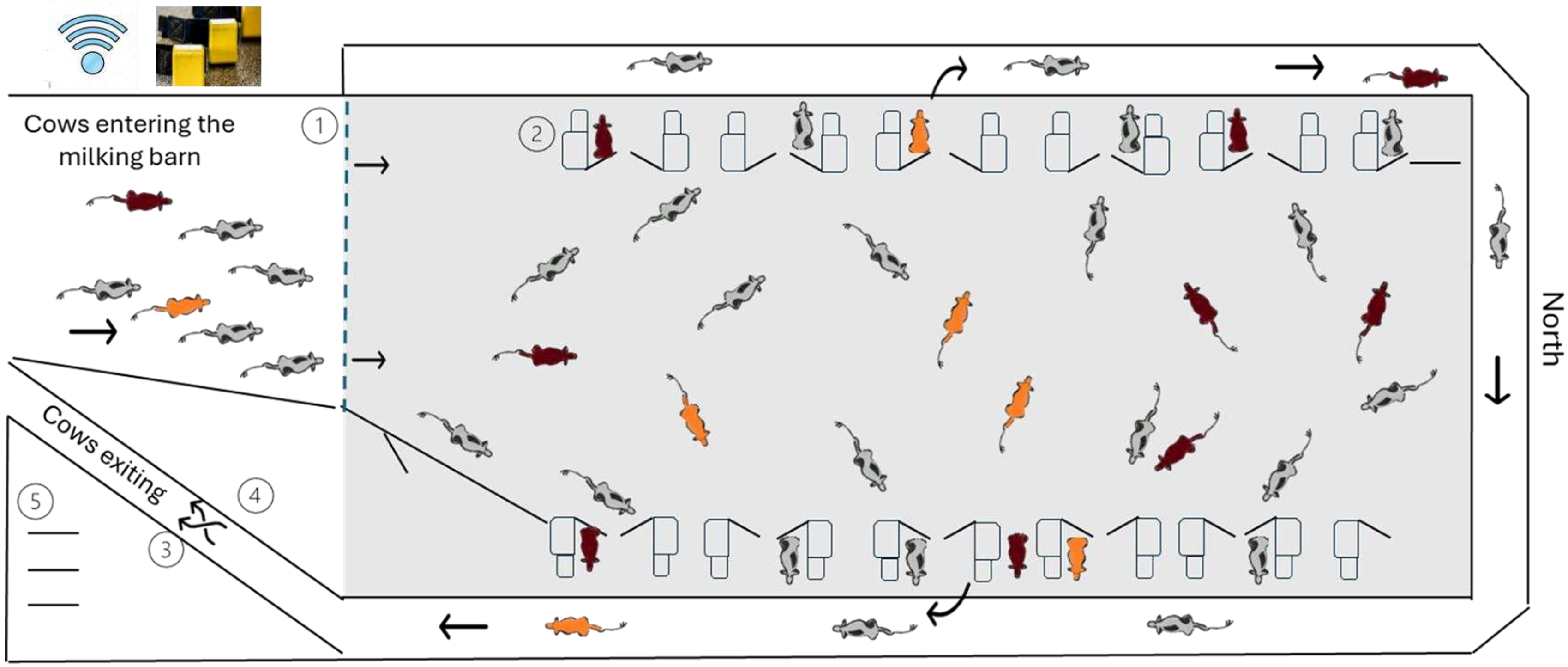

Figure 2.1: Diagram illustrating the milking barn layout. Cows were moved to the milking barn twice per day in groups including Holstein, Jersey, and Holstein x Jersey crossbred cows. A finger gate allowed the entrance of cows to the milking barn (1) where the entry time was registered through pedometer's signal to the receiver. They could select their milking visits among 22 DeLaval VMS V300 robots arranged in two rows (2). A gate was available to gather cows in the North section of the barn (3). A sorting gate (4) was used for redirecting cows to the milking barn (5) or to the cow processing area (6). A set of sorting gates allowed for guiding the cows to their respective groups after the milking (not shown). The West and East AMS lines (7) and left and right arm configuration (8) were considered for cow preference

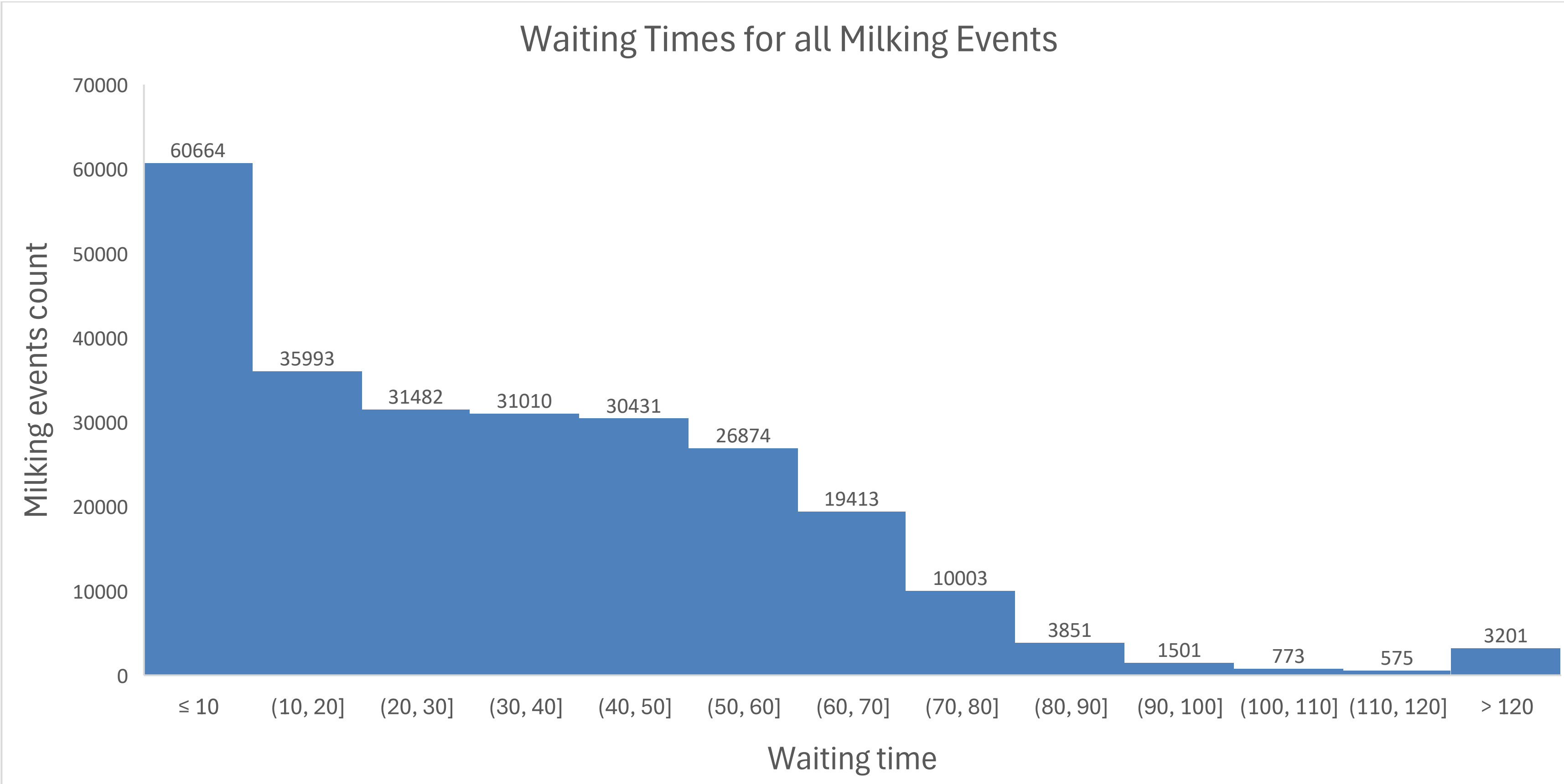

Figure 2.2: Waiting time distribution for all milking events.

CHAPTER 3: ROBOTIC MILKING STATION PREFERENCE IN HOLSTEIN, JERSEY, AND HOLSTEIN X JERSEY CROSSBRED COWS IN A BATCH MILKING SYSTEM WITH AUTOMATIC MILKING UNITS

Abstract

The efficiency of automatic milking systems (AMS) depends on the continuous flow of cows, which may be affected by specific cow behaviors, including robotic milking station preferences. The objective of this study was to analyze the robotic milking station selection behavior of three breeds including Holstein, Jersey, and Holstein × Jersey crossbred cows in a multibreed dairy farm with a batch milking system with automatic milking units. The study used data from 1,762,461 milking events in 3705 HO (n=1355), JE (1876) and HJ (475) cows from May 2023 to September 2024 in a commercial organic grass-fed dairy in TX. Cows were moved to the milking center twice per day, where they could select their milking visits among 22 robot units (DeLaval, Sweden). For the analysis, robots were also classified by barn location [East (n=11); West] and arm configuration [left (n=11); right]. Milking visit information was collected to determine the frequency of specific robot usage per cow during the study period. Subsequently, the frequencies of selection for the top 1, 3, and 5 robotic milking stations, top barn location, and top arm configuration were calculated for each cow. Preference consistency scores (PCS) were calculated considering the frequency of access to each robotic milking station, barn side, and arm configuration in 30 days periods. Least square means (SE) for PCS were calculated by parity category and breed by 30-day periods and compared using ANOVA for repeated measures analysis. Preference consistency scores were different from those expected by random selection in robotic milking station, barn location, and arm configuration, indicating different levels of cow preference behavior. Overall, multiparous and HO cows evidenced more consistent behaviors in

milking station preference. Dairy cow selection behavior should be considered when analyzing the efficiency of milking procedures.

Key words: Milking, robot, preference, automatic milking

Introduction

Dairy cows undergo numerous repetitive procedures daily throughout their productive lives. These procedures affect the cows' behavior and determine their time budgets, which should be in harmony with adequate resting, drinking, and eating time, while providing opportunity for satisfying social interactions.

As milking is the core of the daily routine of dairy cows and one of the most consistent activities completed in dairy operations, the behavior of cows during this process has received growing attention in recent decades (Rousing et al., 2004; Cerqueira et al., 2017). Potential cow preferences during the milking are of especial interest, as they can affect the efficiency of the milking procedure and have cow welfare and health implications. For example, milking order has been determined to be repeatable, and cows establish hierarchies in the milking order within the group, resulting in individual cows consistently exposed to longer waiting times (McVey et al., 2020; Hansson and Woudstra, 2023). This becomes relevant as post-milking behaviors, such as lying and eating time could be consistently affected by the differences in pre-milking waiting time (Manriquez et al., 2022).

Early studies identified milking parlor side preference of cows in herringbone (Gadbury, 1975) and parallel (Tanner et al., 1994) parlors. Subsequently, Hopster et al. (1998) reported that individual cows differed consistently in side preference in the milking parlor in 30-day periods, with a substantial proportion of the cows showing consistent side preference despite changes in their social environment or in other environmental factors. Furthermore, when cows that showed a parlor side preference were forced on their nonhabitual side, they evidenced an increase in heart rate as well as heart rate variability.

With the advent of automatic milking systems (**AMS**) the interaction of cows with people has decreased significantly (von Kuhlberg et al., 2020), which gives cows relative freedom to choose the time and frequency of milking throughout the day. Moreover, cows in AMS have more flexibility to manage other aspects of the milking process, such as the milking box to be used. It is plausible to envision that distinctive preference patterns of behavior may be identified in these more flexible systems, where cows might acquire a routine, that could imply a degree of consistency (Løvendahl et al., 2016).

Remarkably, some authors have indicated that when preferences are more consistent for some individuals compared with others, both an acquired and genetic components might contribute (Koolhaas et al., 1999; Løvendahl and Buitenhuis, 2022). In agreement, Løvendahl et al. (2016) determined a component of genetic variance in preference consistency of Holstein cows when selecting between 2 milking boxes. Aligned with this idea, in this study, we considered 3 breeds, Holstein Jersey and their crosses, kept under similar conditions, to investigate milking robot station preference and to determine whether variation across breeds exist.

We hypothesized that cows would have variable degrees of station preference when exposed to a large number of milking robots (n = 22) and the selection behavior will be associated with both the time exposed to the system and the cow's breed. In consequence, the objective of this study was to analyze the robotic milking station selection behavior of three breeds including

Holstein, Jersey, and Holstein × Jersey crossbred cows in a multibreed dairy farm with a batch milking system with automatic milking units.

Materials and Methods

Study farm and surveyed population

All the research procedures were approved by the Colorado State University IACUC Waiver Subcommittee (protocol #4907). This retrospective observational study used data from cows housed in a commercial organic-certified grass-fed herd in Central TX, USA using an automated batch milking system (**ABMS**). The herd included three breeds: Holstein (**HO**; 39.9%); Jersey (**JE**; 48.5%); and Holstein x Jersey crossbred (**HJ**; 11.6%) under the same management conditions and the analysis included information from 1,762,461 milking events in 3705 HO (n=1355), JE (1876) and HJ (475) cows from May 2023 to September 2024.

Following organic grass-fed regulations, cows had access to grazing for at least 150 d/year. The grazing period went from February to October and individual days were skipped depending on weather conditions, such as heavy rain or extreme heat. During grazing, cows were managed in multibreed groups of 250 cows. The base grass for the pasture was Coastal bermuda grass and a summer mix including cow pea (*Vigna unguiculata*), Sunn hemp (*Crotalaria juncea*), organic Japanese millet (*Echinochloa esculenta*), BMR hybrid pearl millet (*Pennisetum glaucum*), organic buckwheat (*Fagopyrum esculentum*), kale (*Brassica oleracea var. sabellica*), and forage collards impact (*Brassica oleracea*). The winter mix incorporated a seed variety with Austrian winter peas (*Pisum sativum*), Balansa clover viper (*Trifolium michelianum*), organic winter rye (*Secale cereale*), organic soft red winter wheat (*Triticum aestivum*), organic winter barley (*Hordeum *vulgare*), and organic winter triticale (*Triticosecale*). During the grazing season, 60% of their DMI originated from pasture.

In the non-grazing season, groups of 250 cows were housed in dry lots, where shade was provided in the center of the pens. On non-grazing days, cows were fed a grass-based mixed ration that excluded any grain component and had water *ad libitum*. Feed bunks were checked throughout the day and refusals were monitored to make day-to-day adjustments based on DMI. The bedding and patio were turned and scraped every day with full cleaning and removal completed once a year.

Calvings occurred in a maternity facility with a double 27 parallel milking parlor where cows started their lactation. Fresh cows were transferred to the AMS every week depending on space availability (mean ± SD = 15.1 ± 29.1 d). To allow for adjustment to the AMS routine, in this study cows were monitored starting on day 1 in the system.

Cows were moved to the milking barn twice per day, starting at 6:00 AM and 6:00 PM, with group 1 (fresh cows) followed by 7 groups. At the milking barn, cows could select their milking visits among 22 DeLaval VMS V300 units (Figure 1), equipped with DeLaval liners VMS 20M-LS (DeLaval International AB, Tumba, Sweden). However, when the fresh group (group 1) almost completed their milking (i.e. <15-20 cows remaining), farm personnel grouped the remaining cows towards the north end of the parlor guiding them towards the milking robots. Subsequent groups were brought to the milking parlor when the previous group had less than 50 cows. Cows from group 2 onwards were not guided towards the robots and could choose when entering the milking robots. Although this setting allows for group mixing, cows returned to their original groups as they went through a series of sorting gates (Figure 1). Alfalfa pellets were offered at the AMS in amounts that varied from 0.5 kg to 5 kg, according to lactation stage and expected milk yield.

Data collection and edits

Data including robotic milking station use per cow and milking event originated from the AMS units was collected from the parlor management software (DelPro Farm Manager software; DeLaval International AB, Tumba, Sweden) and transferred into Excel spreadsheets (Microsoft Corp.). Demographic information including breed, calving date, and parity number, among others, was extracted from PCDART herd management software (Dairy Records Management Systems NC, USA). Subsequently, the dataset from DelPro was cross referenced with the PCDART database to confirm that all the demographic information was imported correctly. Data were excluded from the analysis in cows with less than 20 visits within a 30-day period.

Preference consistency score calculation

A preference consistency score (PCS) was calculated according to Løvendahl and Buitenhuis (2022), considering the frequency of access to each milking station in a 30-days period. After arriving at the milking barn, cows had free access to the 22 milking stations, so it was assumed that the station visited most frequently was the preferred one. If all boxes were equally used, the frequency of first choice would be equal to 1/22 (0.045). The PCS was then calculated as a ratio between the excess frequencies of the first choice over the base frequency of "not first choice" (actual_frequency − expected frequency). This ratio was 0 if all choices were taken equally and became 1.0 if only the first choice was made in all events.

For comparison with previous references, PCS was adjusted for the number of choices as follows:

PCS = 1.00 × [actual_frequency – (1/number of choices)]/[1 − (1/number of choices)].

The PCS calculation was made in 30 days periods and a minimum of 20 visits/cow/period was required for cow inclusion in the calculation.

PCS were calculated considering the frequencies of robot station selection for the top 1, 3 and 5 stations, combining the frequency of visits to the 3 and 5 most chosen robots, out of the 22 choices. In addition, PCS were calculated for barn location (11 robots in west or 11 robots in east) and arm configuration is (11 left arm configuration 11 right arm configuration robots).

Statistical Analysis

All the analyses were conducted using SAS 9.4 (SAS institute Inc., Cary, NC). Initial data evaluation was completed by building frequency tables (PROC UNIVARIATE) and through visual assessment of robotic milking station use and PCS.

A chi-square test of independence was used to establish if robot selection was different from random (4.54% for robotic milking station; 50% for barn location and arm configuration). Least square means (SE) for PCS by parity category and breed (HO, JE, and HJ) were calculated by 30-d periods and compared using ANOVA for repeated measures analysis, considering ID as the REPEATED statement (PROC MIXED). Initial univariable models using only parity category and breed (HO, JE, and HJ) as explanatory variables were followed by multivariable models that considered DIM at introduction to the AMS and previous lactation experience in the AMS (yes, no) and their interaction as potential covariates. Only breed and parity category had significant effects and remained in the models. In consequence the analyses were completed by separate for each breed and parity category.

For all outcome variables, significant predictors were determined at P-value < 0.05; interaction terms and controlling variables remained in the models at P-value ≤ 0.10.

Results

The chi-square test of independence indicated that robot selection was different from random for robotic milking station ($P < 0.001$), barn location ($P < 0.001$), and arm configuration ($P < 0.001$).

The relative frequencies of primiparous and multiparous cows by category of top one selection for robotic milking unit are presented in Figure 2 and Figure 3, respectively. In both parity groups the distribution was positively skewed, indicating smaller cow frequencies towards the greatest selection categories. In both primiparous and multiparous cows, the greatest cow frequency corresponded to the > 0.1 to 0.15 greatest selection category, which was the group of cows that used their most selected milking unit >10% to 15% of the times.

Some differences in breeds for the greatest selection category for barn location (West - East) are evident in Figure 2 and Figure 3. The distribution of cows was also different between parity groups, with a distribution that seems more positively skewed in primiparous cows, which would be an indication of smaller selective behavior in this group. As for robotic milking station, the distribution of selection of arm configuration (left-right) was positively skewed, indicating greater frequencies of cows with low configuration preferences.

The least square means (SE) for preference consistency score (degree of use of the same robotic milking station) for the top 1, 3, and 5 robotic milking station in primiparous and multiparous cows by days in the automatic milking system are depicted in Figure 4. As expected, mean PCS scores increased from top 1 to top 5 station preference from relative frequencies close to 0.2 to frequencies around 0.55. Interestingly, there is an evident separation among breeds in multiparous cows, with greater selective behavior in HO, followed by HJ, and JE cows.

When PCS for are analyzed for preference consistency score for barn location (West vs. East; top panel) and arm configuration (left-right), values were similar for primiparous and multiparous cows (Figure 5). Nonetheless, similar to the findings in robotic milking station, multiparous cows evidenced differences among breeds, with greater selective behavior in HO, followed by HJ, and JE cows.

The levels of significance for each of the variables included in the calculation of preference consistency scores LSM are presented in Table 1. The effects of breed and DIM at introduction to the AMS were significant for all the preference variables in analysis, while the interaction breed by time was significant in most cases.

Discussion

An appropriate understanding of dairy cattle behavior is beneficial for developing efficient management practices. The behavior of animals and their reactions to husbandry practices, such as handling and transport, can be influenced by the environmental conditions, management, and various experiences they encounter throughout their lives and across different production systems (Grandin, 1997). The system in place in the study farm provides some unique opportunities for the analysis of behavioral and performance data originated from a batch milking system with automatic milking units, where cows were directed to the milking barn at fixed times of the day, but were free to select their robotic milking unit among a large number of stations. Moreover, the commingling of three breeds in this multibreed herd made it possible to compare the selective behavior among different genetic backgrounds.

Results from this study showed that a significant proportion of the study cows consistently used the same robotic milking unit and barn location with a small preference for a specific robotic arm configuration. In agreement with our results, Løvendahl and Buitenhuis (2022) highlight in their study that dairy cows in large herds using automatic milking choosing between 2 or more AMS were consistently preferring the same milking station, even when it required waiting. Individual preferences were exhibited for milking times, influenced by factors such as parity, social hierarchy, and previous milking experiences. This also goes in accordance with studies showing that cows tend to develop and maintain consistent behaviors during the milking routine (Gadbury, 1975; Tanner et al., 1994, Hopster et al. 1998).

Although in a different milking setting, cows have been reported to follow a consistent order of entry to milking parlors, also showing preferences to specific sides of the milking parlor (Hopster et al., 1998; Paranhos da Costa and Broom, 2001; Grasso et al., 2007; McVey et al., 2020).

Our results show selection differences between breeds, with Holstein cows showing higher PCS scores in all categories through the lactation in both primiparous and multiparous cows. The typically larger frame of Holstein cows compared with JE and HJ (Heins et al., 2008; Gibson et al., 2022) could play a role in these findings, as their size could facilitate more competitive and dominant behaviors in herd settings with multiple breeds. Moreover, in an ABMS environment, competitive behaviors may be favored and could translate into freedom of selection during the visits to the milking barn. Holsteins may be more aggressive in accessing the robot of their preference, potentially leading to increased competition among herd members. This competitive behavior can result in a “first-come, first-served” dynamic, where dominant animals secure their preferred milking slots.

Notably, previous research has demonstrated behavioral differences between breeds, with Holstein cows spending more time lying and eating than Jersey cows, whereas Jersey cows had greater numbers of steps (Munksgaard et al., 2019). In another study Henriksen et al. (2019) reported that Holstein and Jersey cows differed in their partial mixed ration eating rate, lying time, steps, and activity level. More relevant to the current study, as reviewed by Pacheco et al. (2024) and Brito et al. (2020), the estimated heritabilities for different AMS-derived traits range from 0.01 to 0.69, evidencing a genetic component for these behaviors.

The differences in milk yield among breeds could also have an effect on selection behavior. Research indicates a positive genetic correlation from 0.27 to 0.80 between milk yield and milking frequency, with high-yielding cows tending to visit AMS more frequently each day (Pacheco et al., 2025). As Holstein cows have greater milk yield thank Jersey and their crosses, it is plausible to infer that this high producing group may have a greater interest in accessing the milking units than the other two groups of cows.

The PCS for robotic milking unit tended to increase for HO and JE primiparous cows after 200 DIM but remained more constant for multiparous cows until the end of the lactation. These dynamics are in partial agreement with the results presented by Løvendahl et al. (2022) where cows had an increased their PCS during the early lactation and then declined.

Interestingly, the PCS for barn location (East - West) had a clear increase during the first 60 DIM to remain constant for the rest of the lactation. In the case of arm configuration, an increase in PCS was only noticeable in primiparous HO and HJ cows.

The observed differences in milking robot selection behavior between Holsteins, Jerseys and Holstein x Jersey crossbreds may have several practical implications for ABMS design and the overall herd management. Interestingly, crossbred cows showed an intermediate selection behavior when compared with Holstiens and Jerseys. Preference behaviors may have to be studied further as there may be benefits to including crossbred cows in ABMS to enhance cow traffic and overall system efficiency, increasing profitability and return of investment of ABMS. In the dairy sector economic margins tend to be small and historically large dairy operations implementing robotic parlors were found to be not as economically beneficial compared to conventional milking systems (Salfer et al, 2017; Örs et al., 2022).

Conclusions

The differences in milking robot selection behavior between breeds enforce the need for a nuanced approach to ABMS management. While Holsteins may leverage their competitive nature to maximize selection preference, Jerseys' behavioral traits may provide flexibility in system design and herd management to accommodate for best management practices that enhance milking efficiency and animal welfare. Integrating breed-specific strategies into ABMS design and daily management can enhance productivity while safeguarding animal welfare, ensuring that the benefits of robotic milking systems are fully realized across diverse dairy operations.

Acknowledgments

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Table 3.1: Number of cows assigned to each barn location (East; West) and arm configuration (left; right) based on their greatest selection category by parity and breed.

		Barn Location		Arm Configuration	
Group	n	East	West	Left	Right
Primiparous					
HO	279	159	120	130	149
HJ	130	76	54	73	57
JE	281	139	142	133	148
Total	690	374	316	336	354
Multiparous					
HO	1,076	588	488	554	522
HJ	344	174	170	189	155
JE	1,595	691	904	805	790
Total	3,015	1,453	1,562	1,548	1,467

Table 3.2: Level of significance for each of the variables included in the calculation of preference consistency scores LSM.

Variable	Parity category	Breed	Time period	Previous experience in AMS	DIM at introduction	Breed*Time
Top 1	Primiparous	< 0.001	< 0.001	N.A.	0.0322	0.08
	Multiparous	< 0.001	< 0.001	0.06	< 0.001	0.04
Top 3	Primiparous	< 0.001	< 0.001	N.A.	0.001	0.02
	Multiparous	< 0.001	< 0.001	< 0.001	0.49	0.02
Top 5	Primiparous	< 0.001	< 0.001	N.A.	0.001	0.007
	Multiparous	< 0.001	< 0.001	< 0.001	0.93	0.04
Barn location	Primiparous	< 0.001	< 0.001	N.A.	0.007	0.12
	Multiparous	< 0.001	< 0.001	0.0004	0.004	< 0.001
Arm configuration	Primiparous	< 0.001	0.01	N.A.	0.46	0.27
	Multiparous	< 0.001	0.02	< 0.001	0.007	0.07

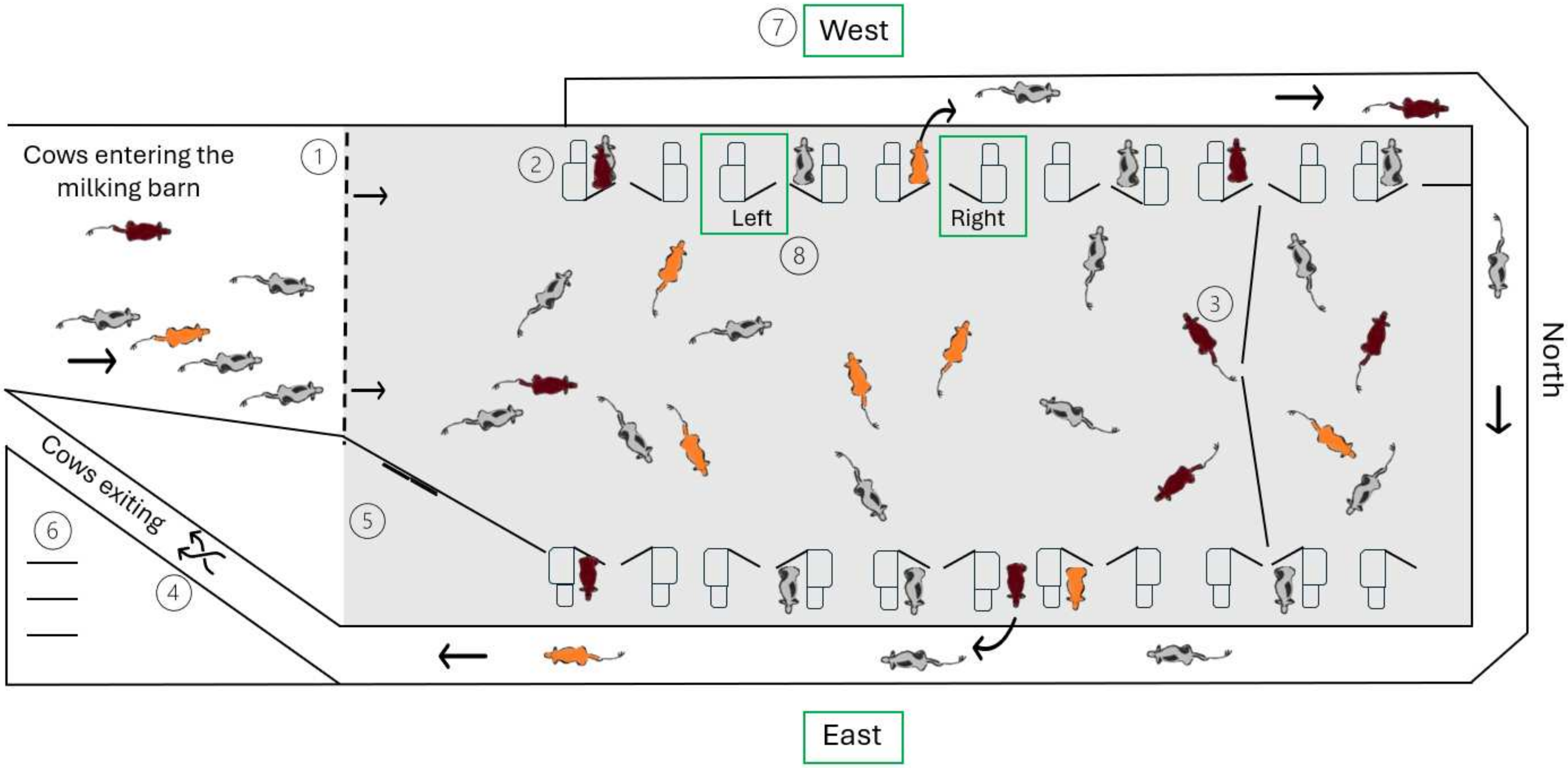

Figure 3.1: Diagram illustrating the milking barn layout. Cows were moved to the milking barn twice per day in groups including Holstein, Jersey, and Holstein x Jersey crossbred cows. A finger gate allowed the entrance of cows to the milking barn (1) where they could select their milking visits among 22 DeLaval VMS V300 robots arranged in two rows (2). A gate was available to gather cows in the North section of the barn (3). A sorting gate (4) was used for redirecting cows to the milking barn (5) or to the cow processing area (6). A set of sorting gates allowed for guiding the cows to their respective groups after the milking (not shown). The West and East AMS lines (7) and left and right arm configuration (8) were considered for cow preference

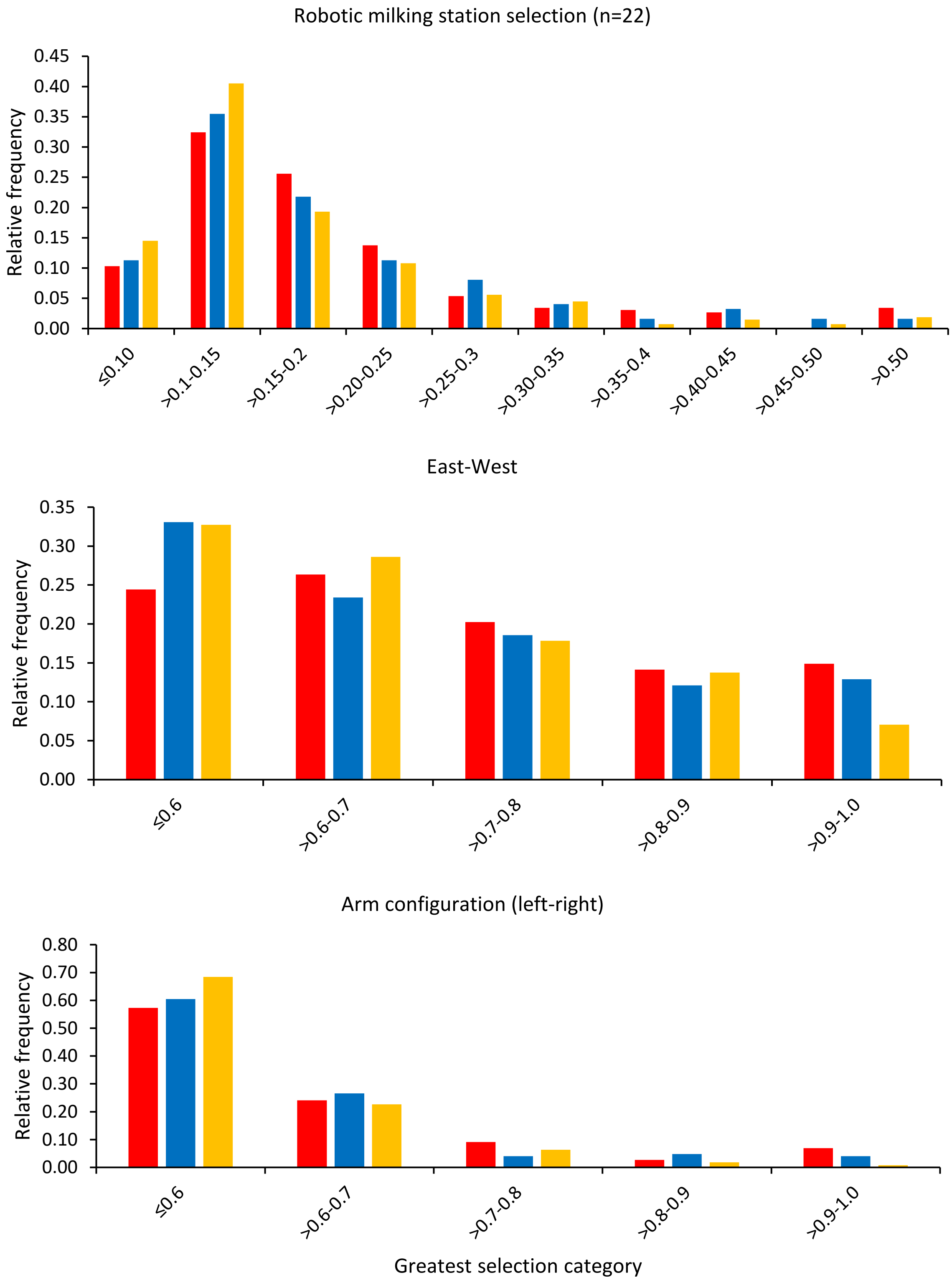

Figure 2: Relative frequencies of primiparous Holstein (red bars), Jersey (orange bars), and Holstein x Jersey crosses (blue bars) by category of top 1 selection for robotic milking unit, barn location, and arm configuration.

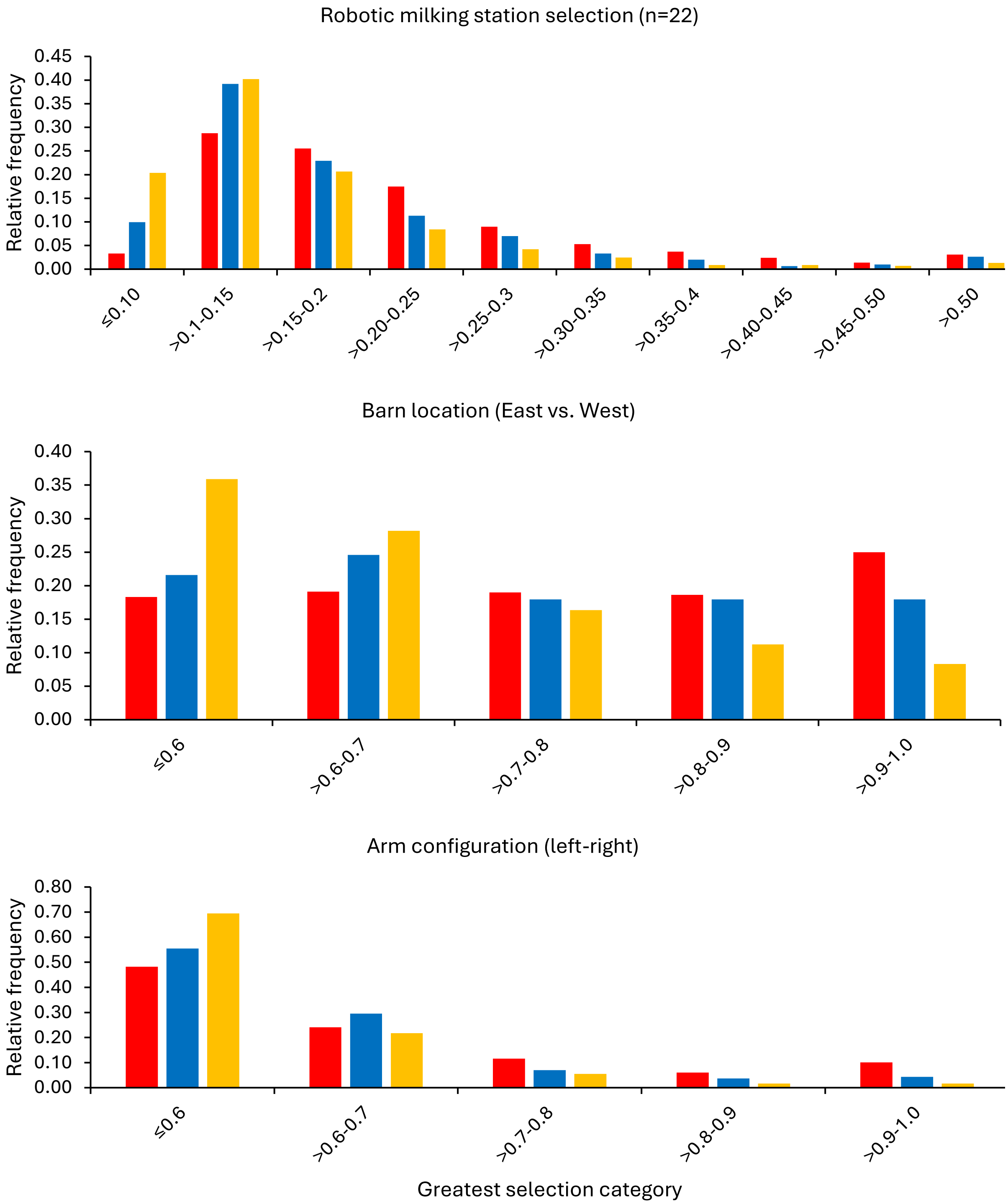

Figure 3: Relative frequencies of multiparous Holstein (red bars), Jersey (orange bars), and Holstein x Jersey crosses (blue bars) by category of top 1 selection for robotic milking unit, barn location and arm configuration.

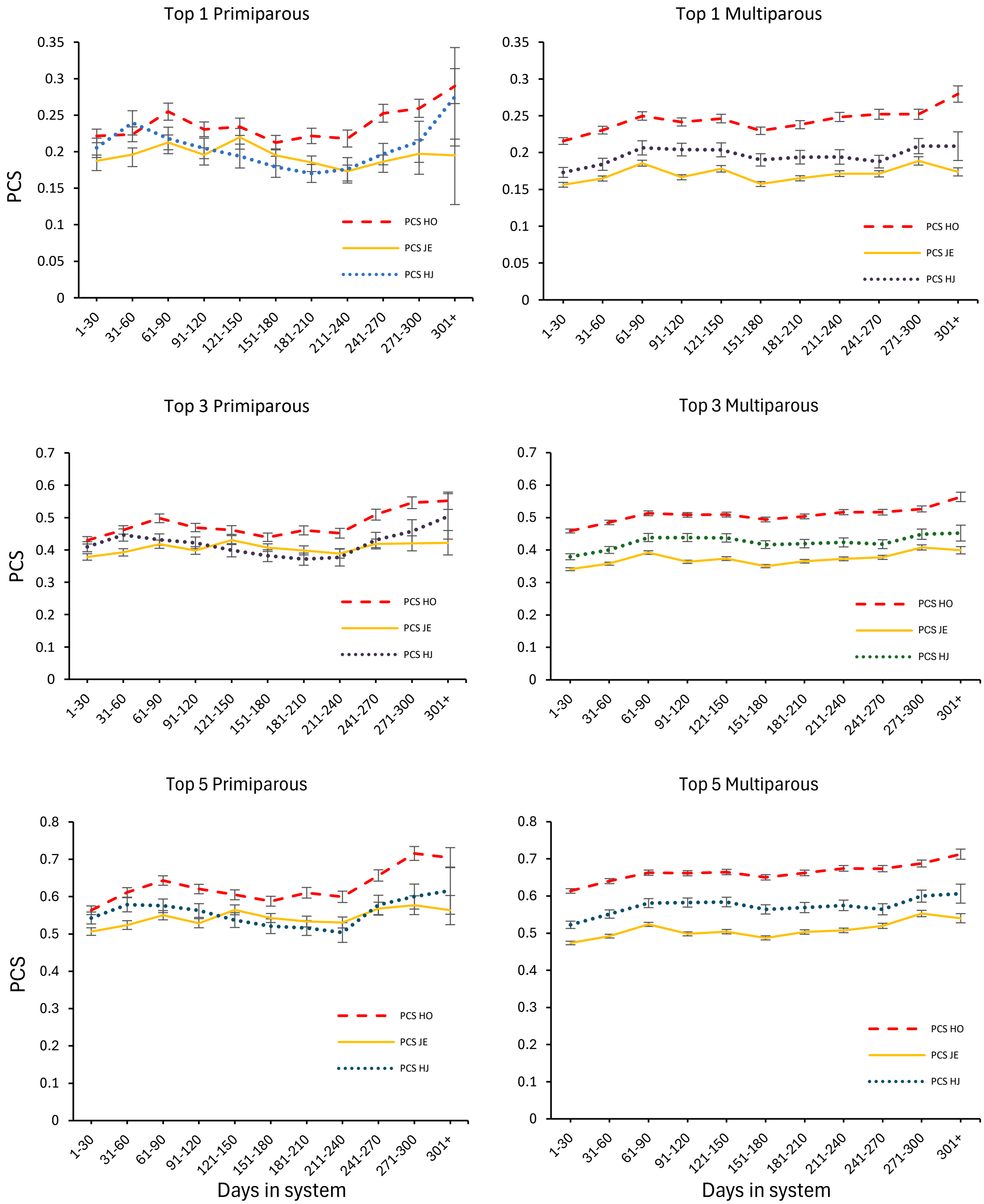

Figure 4: Least square means (SE) for preference consistency score (degree of use of the same robotic milking station) for the top 1, 3, and 5 robotic milking station in Holstein (red segmented line), Jersey (orange solid line), and Holstein x Jersey crosses (blue dotted line) in primiparous (left panel) and multiparous (right panel) cows by days in the automatic milking system. Models included DIM at introduction to the AMS and previous lactation experience in the AMS (yes, no in multiparous) and their interaction as covariates.

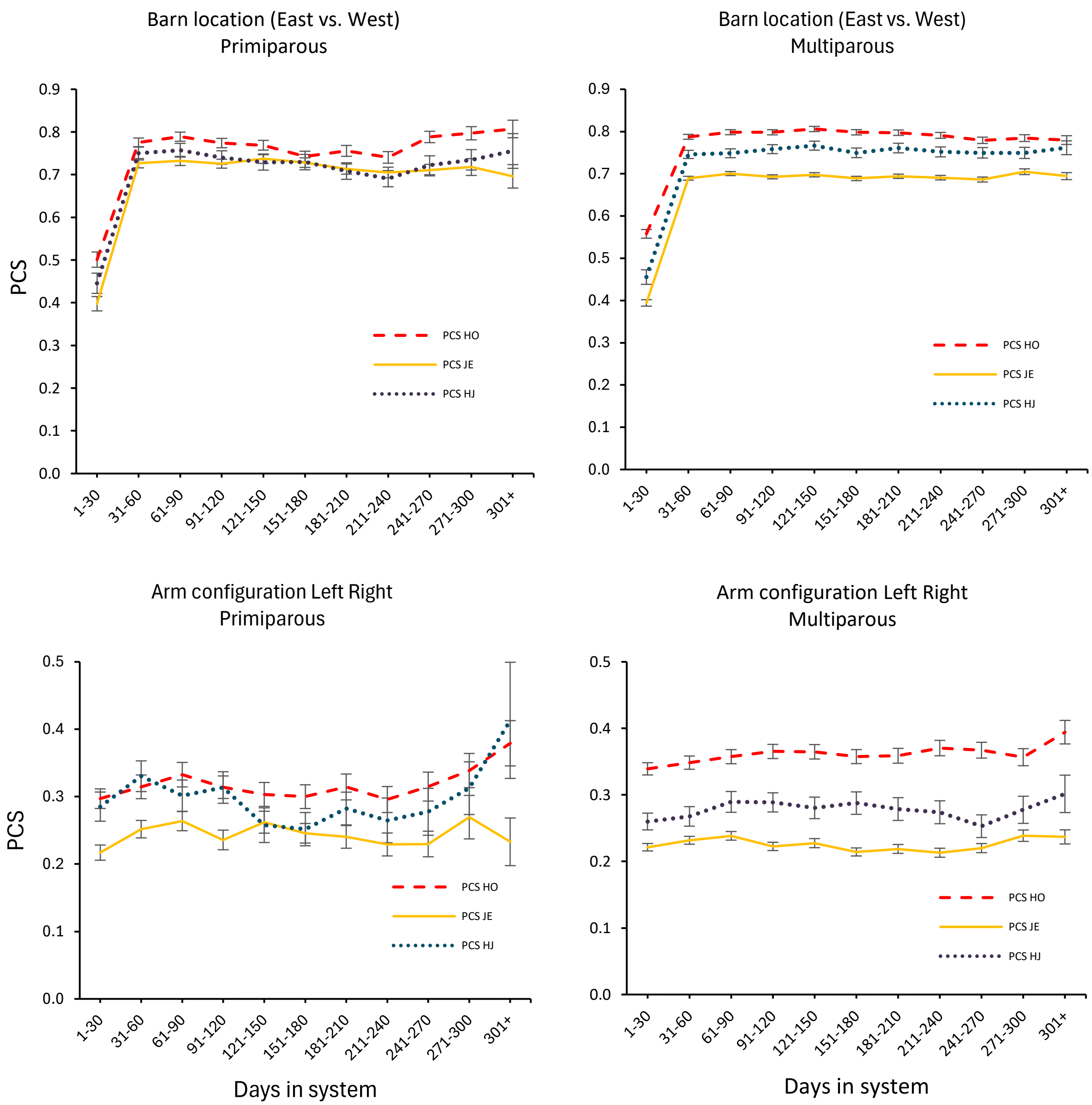

Figure 5: Least square means (SE) for preference consistency score for barn location (West vs. East; top panel) and arm configuration (left-right) in Holstein (red segmented line), Jersey (orange solid line), and Holstein x Jersey crosses (blue dotted line) for primiparous (left panel) and multiparous (multiparous) cows by days in the automatic milking system. Models included DIM at introduction to the AMS and previous lactation experience in the AMS (yes, no in multiparous) and their interaction as covariates.