

**Management and Investment: Two Pillars of Automatic Milking
Systems Efficiency**

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ABSTRACT

Fetch cows, dairy cattle that do not voluntarily enter automated milking systems (**AMS**), increase labor costs, and decrease efficiency. The objective of this study was to describe fetch cows based on fetch lists and herd-management software data. This study was conducted on a commercial dairy farm ($n = 510$ cows) using 8 AMS from October 1, 2021, to May 10, 2022. Data were collected via PCDART, DairyComp, and a proprietary interface. Two fetch categories by cow, EverFetch (**EF**) and NeverFetch (**NF**), and three status groups by cow by day, True Fetch (on fetch list and fetched; **TF**), False Fetch (on fetch list and not fetched; **FF**), and No Fetch Required (not on list; **NFR**), were created. The impact of health events (no event, reproduction, general health, and scheduled events), parity (1, 2, 3, and 4+ lactations) and AMS variables (milk visit outcome, production, and components; feed intake, etc.) on fetch category and status were analyzed using the GLIMMIX procedure of SAS 9.4 ($P \leq 0.05$). The sections were evenly divided by fresh or in-training (≤ 25 days in milk (**DIM**)) and lactation (> 25 DIM). The lactating group was divided into three sections (early, mid, and late lactation) based on total cow-day observation quartiles. The sections were ≤ 25 DIM (fresh), > 25 and ≤ 86 DIM (early lactation), > 86 and < 214 DIM (mid-lactation), and ≥ 214 DIM (late-lactation).

Decision support tools have provided end-users with options for decision-making under different scenarios. The objective of this decision tool was for Southeastern USA producers considering an automatic milking system to input their information and determine AMS investment impact. Data were sourced from sixty-two farm observations across Tennessee, Kentucky, and North Carolina through the University of Tennessee

Dairy Gauge Program (2021 and 2022). Median data across years included farm incomes and expenses. Investment in AMS was modeled to determine net present value (**NPV**), internal rate of return (**IRR**), and payback period (**PP**). Across all scenarios, retrofitting was the most profitable construction style. Future research is needed to test the models and find benchmarks for determining fetch cow status and economic.

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CHAPTER I

REVIEW OF LITERATURE

Introduction

Precision technology has supported higher productivity and efficiency within the dairy industry. With an ever-increased population, the demand for the animal industry has increased. Demographic and dietary changes have contributed to increased animal product demand (Fontana et al., 2015). Increased demand required agriculturists to maximize productivity with efficient crop and livestock management practices (Monteiro et al., 2021). Through precision livestock farming, individual animals were monitored for growth, milk production, and disease detection (Banhazi et al., 2012). Precision technology improved animal comfort through monitoring and controlling building environment. Automatic milking systems (AMS) have provided a choice to the animal and improved human-animal interactions (Rutter, 2014, Van Erp-van der Kooij, 2020) . Automatic milking systems were used to minimize labor costs and maximize milk production. Since the AMS introduction, research has investigated milk quality and quantity, labor aspects, nutrition cost, training scenarios, and economic feasibility (Hogeveen and Van Der Voort, 2021). However, research was limited at the time of this literature review on identifying fetch cows based on records and AMS data. This review highlighted development, fetch cow research, and economic impact and considerations around AMS investment.

Precision Technology in Dairy Milking

Automated milking systems, voluntary milking systems, and robotic milkers have all been used to describe a stand-alone system using technology to milk dairy cattle with minimal to no human intervention. These systems included laser sights, udder mapping technology, individual teat attachment systems, feed delivery systems, and individual

cow identification with record-keeping capabilities (Castro et al., 2012, Hansen et al., 2020). Cows were enticed by concentrate feed to enter the AMS, where the milking robot cleaned the teats, attaches the teat cups, milks the udder on a quarter-basis and detaches the teat cups (Butler et al., 2012). After AMS introduction, cow-specific information was recorded including udder shape, expected production per quarter, expected milking time, and milk temperature (Schulte and Tranel, 2013).

Automatic Milking System History

Automatic milking machines were introduced in the mid-20th century (Sharipov et al., 2021). In the 1950s, exploratory studies for full process automation and implementation were conducted (Sharipov et al., 2021). In the 1970s, theoretical concepts were put into practice. From the 1970-1990s, universities in Western Europe determined the correct position of the teats and created a device to automatically attach the milking clusters (Figure 1.1; Rossing and Hogewerf), 1997. In 1992, after many changes and improvements, the first purchase of an AMS was conducted (Sharipov et al., 2021).

Automatic milking systems have been used in Canada (Rodenburg and House, 2007) since 1999 and in the United States since 2000 with continued growth worldwide as shown in Figure 1.2 (Koning, 2010). In 2010, over 9,000 AMS were installed around the globe, responsible for 1.2 million milkings per day (Greenaway, 2010). As of 2014, over 2,500 AMS units were installed in North America on $\geq 1,000$ farms (Rodenburg, 2017). In 2017, the first AMS was installed on a Tennessee dairy farm. In 2022, Tennessee had 28 AMS units across 8 AMS dairies (a mean of 3.5 AMS per dairy; Palmer, 2022).

Automatic Milking System Types

Several AMS companies existed at this time of this literature review including BouMatic, Galaxy, GEA, Lely, and DeLaval. The two primary robotic companies used in the Southeast United States were Lely and DeLaval (Rodenburg, 2002). All AMS had similar functions but may have design-specific differences or stated company goals that appealed to producers. From a design perspective, DeLaval AMS used a central teat cup to prepare teats before milking whereas Lely AMS had a rotating preparation brush. Automatic milking systems were manufactured as single-box or multi-box units (Figure 1.3). Single-box systems allowed one cow to be milked at a time while multi-box systems allowed two cows to be milked at a time (Sharipov et al., 2021). Single-box systems have a maximum of milking 60 to 70 cows per day (Sharipov et al., 2021). Multi-box systems consisted of two parallel milking boxes and a maximum of milking 160 cows per day (Andrews et al., 2016).

Automatic Milking System Functionality

Automatic milking systems provided cows with a choice of when to eat, drink, rest, or be milked (Butler and Holloway, 2016). The fundamental working element of an AMS was the multifunctional robot arm designed in the image of a human hand (Sharipov et al., 2021). The AMS was capable of three-dimensional movement to clean teats, attach the milking clusters onto the teats, detach the milking clusters, and disinfect the teats after milking. The robot arm was powered by hydraulics, pneumatics, or electric and located to the side or behind the cow's udder and remained underneath the cow during the entire milking process (Sharipov et al., 2021). The arm moved with the cow to provide freedom of movement in the box for cow comfort (Sharipov et al., 2021). Radio

Frequency Identification (**RFID**) tags were used for cow identification and to monitor each cow as an individual (Butler and Holloway, 2016). Captured data through AMS yielded large amounts of data on management-related information such as productivity and health (Butler and Holloway, 2016). A study by Cooper and Parsons (1999) showed the mean time a cow was in the stall (Table 1.1) and was one of the first studies to quantify time spent in the AMS. They reported mean time of 108 seconds for cows to travel from the gate to the AMS stall, 120 seconds for udder preparation, 60 seconds of arm movement, and 15 seconds to exit the AMS for a total of 5 minutes and 5 seconds per cow for an AMS milking (Cooper and Parsons, 1999). Armstrong and Quick (1986) found the total time spent in the parlor per 16 cows was 15.12 minutes.

Automatic Milking System Milk Production

While all automatic milking systems had the same overall goal, research outcomes focused on milk production, somatic cell count (**SCC**), and milk contents with AMS were varied. Automatic milking systems provided cows with more opportunities to visit the AMS (milking) when compared to 2x conventional parlors (Koning, 2010). Farms that moved from a 2x conventional parlor to AMS saw a 6 to 25% increase in milk production (Erdman and Varner, 1995, Koning, 2010). However, farms that moved from a 3x conventional parlor to AMS saw a 5 to 10% decrease in milk production (Koning and Rodenburg, 2004).

The relationship between the number of milkings and milk production has been examined. A milk production study was completed in Spain on 29 AMS dairy herds (Castro et al., 2012). Castro et al. (2012) used multilinear regression to find that the AMS

produced 3% more milk production per AMS with a mean of 2.4 to 2.6 milkings per cow per day. Another study by Tremblay et al. (2016) determined increased milkings was associated with increased milk production. Hogeveen et al. (2001) found shorter (short = ≤ 1 h, long = ≥ 17 h) milking intervals gave a higher milk production per cow hour. However, it was dependent on the total milk production of the cow (Hogeveen et al., 2001). He also found that milk flow-rate was lowered to 0.2 to 0.8 kg per minute for milking with a short interval compared to 1.2 to 1.6 kg per minute for the long interval (Hogeveen et al., 2001).

Producer surveys have also been completed to determine AMS milk production. A survey of Canadian AMS farms found eighty-one percent of respondents agreed that their milk production increased after the transition with a median of three milkings per day (Tse et al., 2018b). Most AMS surveys and studies have been conducted in Europe, including the comparison of automatic milking systems versus conventional milking systems (**CMS**) by Steeneveld and Hogeveen (2015). The results of their study showed automatic milking systems had a 189 kg higher yearly mean milk production per cow (after the investment; Steeneveld and Hogeveen, 2015). Those results were consistent with a previous research study finding that milk production increased 3.0 kg per day with automatic milking systems (Kruip et al., 2002).

However, while milk production quantity increased, the quality reportedly decreased especially in the first six months after the transition (Vorst et al., 2002). After the transition to AMS, several studies reported freezing point, free fatty acids (**FFA**), and total bacterial counts were higher (Klungel and Slaghuis, 2000, Rasmussen et al., 2002,

Vorst et al., 2002, Wiking et al., 2006, Tse et al., 2018b). A study found freezing point before the installation of AMS was -0.525°C (Rasmussen et al., 2002). Three months after the transition to AMS the freezing point was -0.518°C and after nine months the freezing point was -0.518°C ($P < 0.001$; Rasmussen et al., 2002). The AMS freezing point was close to the minimum limit of -0.516°C (Rasmussen et al., 2002). The Rasmussen et al. (2002) study showed that freezing point increased after AMS transition which indicated the milk increased in water solubility (Zagorska and Ciprovica, 2013).

Free fatty acid and bacteria counts could be higher due to the increased opportunity for microorganisms to enter during the milking process (Rotz et al., 2003). While unwanted due to off-flavor or the inhibited fermentation for cheese coagulation (Woodhouse and Kelton, 2023), increased frequency of milking was correlated with increased FFA (Wiking et al., 2006). Wiking et al. (2006) found that with 2x milking the FFA was 1.14 mEq/100g of fat and with 4x milking the FFA was 1.49 mEq/100g of fat ($P < 0.01$). Klungel and Slaghuis (2000) found that before the transition to AMS the total bacterial plate count (**TPC**) mean was 9,100 cfu/mL and after the AMS transition it was a mean of 18,000 cfu/mL ($P < 0.05$; Klungel and Slaghuis, 2000).

Studies have investigated SCC before and after the installation of AMS. Contradicting results have shown no change (Salovuoto et al., 2005, Helgren and Reinemann, 2006), an increase (Klungel and Slaghuis, 2000, Rasmussen et al., 2002, De Koning et al., 2003, Johansson et al., 2017), or a decrease (Shoshani and Chaffer, 2002, Tousova et al., 2014, Bentley et al., 2018) in bulk tank somatic cell count (Table 1.2). There were a number of factors that could account for the different SCC after using

AMS. These included changes in the environment, location of the study, the size of the herd under investigation, and so on. For instance, the studies that reported no changes in SCC levels were conducted on a small scale, with Salovuoto et al. (2005) worked on just three farms in Finland, and Helgren and Reinemann (2006) focused on a single farm in the United States. was located in the United States on one farm. Meanwhile, the studies that reported an increase in SCC levels were conducted on a much larger scale, with Klungel and Slaghuis (2000) investigated 77 Dutch farms, Rasmussen et al (2002) looked at 98 Danish farms, and Johansson et al (2017) investigated 104 Swedish dairies. The studies that reported a decrease in SCC levels were conducted on a smaller scale, with Shashani and Chaffer (2002) worked on a single farm in Israel, Bentley et al (2018) investigated six farms in the United States. De Koning et al. (2003) found that SCC increased a mean of 18,600 cells/mL from before the installation of AMS to after the installation of AMS. Salovuoto et al (2015) found an increase in SCC from 142,000 cells/mL to 208,000 cells/mL while Bentley et al. (2018) found a decrease from 257,000 cells/mL to 165,000 cells/mL. A survey of Canadian AMS farms reported a decrease in SCC (43% of respondents), no change in SCC (37% of respondents), or an increase in SCC (20% of respondents; Tse et al., 2018b).

Milk components such as fat and protein also have mixed results in research. A Canadian survey reported no change in milk fat content (56% of respondents) and milk protein content (79% of respondents; Tse et al., 2018b). However, Speicher et al. (1994) found that milk fat was lower in 3x milking per day in CMS for multiparous ($3.27 \pm 0.07\%$) and primiparous ($3.22 \pm 0.07\%$) when compared to 2x milking per day in CMS

for multiparous ($4.47 \pm 0.06\%$) and primiparous ($3.29 \pm 0.06\%$; $P < 0.05$, respectively). Similarly, milk protein was lower in 3x milking per day in CMS for multiparous ($3.07 \pm 0.02\%$) and primiparous ($3.01 \pm 0.02\%$) when compared to 2x milking per day in CMS for multiparous ($3.19 \pm 0.03\%$) and primiparous ($3.11 \pm 0.03\%$; ($P < 0.01$; Speicher et al., 1994).

Automatic Milking System Labor

After the start-up process, AMS farms reported reduced hours spent milking in a parlor and more time on other job responsibilities, including new AMS maintenance tasks, reproductive management, health management, calf and youngstock management, free time, flexibility in hours worked, time off, or fewer workers hired (Tse et al., 2018a). Labor requirements were reduced with AMS because teat cleaning, milking, and separation of abnormal milk were integrated into the AMS (Schewe and Stuart, 2015, Tse et al., 2018b). For example, in CMS 2 or 3 workers were needed in the parlor 2 or 3 times a day. After the transition, only 1 or 2 were needed to monitor the AMS (Schewe and Stuart, 2015). However, the workers must have knowledge and understanding of the AMS during and after the initial start-up (Kimpel, 2016). The initial start-up process was very labor intensive and required introduction of each cow to the system with someone there to help guide the AMS arm to the udder. Employees that possessed technological skills or developed them resulted in higher labor salaries (Tse et al., 2018a). Labor was also modified with AMS and required workers to be on-call for alarms for fetch cows, AMS maintenance, and utilize data-based methods for identifying health and welfare issues rather than working in the parlor (Tse et al., 2018a).

Tse et al. (2018a) reported labor savings with AMS in both Europe and the United States ranged from 18% to 46%. Another study by Tse et al. (2018b) showed a decrease of 20% in employees after transitioning to AMS. Employee's time devoted to milking-related activities, cleaning the parlor, and moving cows also decreased after the transition to AMS (Tse et al., 2018b). Other labor benefits to AMS included milking consistency through less error and adherence to the same milking procedure each time (Kimpel, 2016).

Automatic Milking System Nutrition

Traditionally, pelleted feed was used to encourage cows to come to the AMS. Feed has been attributed with positive impacts, such as enticing cows that were skeptical of the AMS, and negative impacts, such as causing cows to take up box time and increase milking rejections (Schewe and Stuart, 2015). Pellet amount and type were both controlled by individual producers (Schewe and Stuart, 2015). In a study by Schewe and Stuart (2015), the maximum number of times individual cows should be milked per day was a mean of 5 to 6 visits per day with high concentrate feed.

A common feeding strategy with AMS has been to start with a low level of concentrates at calving, with an equal and steady increase during the first weeks of lactation (Kokkonen et al., 2004). At peak lactation (week 3 to week 14), concentrate supply increased as milk yield increased (Andre et al., 2010). Once milk yield declined, then concentrate supply also declined (Andre et al., 2010). The ideal AMS concentrate amount has not been made clear, but cows did not consume all concentrate when the allotment was > 4 kg per cow per day (Bach and Cabrera, 2017). The amount of

unconsumed concentrates increased as the concentrate allowance increased as seen in Figure 1.4 (Bach and Cabrera, 2017). Cows typically consumed pelleted concentrate between 250 and 400 g per minute (Kertz et al., 1981). The mean time spent in the AMS per milking was around 7 minutes (Castro et al., 2012), and the cows were able to consume a maximum 2.8 kg of concentrate per milking (Bach and Cabrera, 2017). Based on the milking frequency of 3 times per day, a cow would be able to consume a maximum of 8.4 kg of concentrate per day (Bach and Cabrera, 2017).

Automatic Milking System Cow Flow

Within AMS, the two main forms of cow movement were guided and free flow. Movement, or flow, referred to how cows interacted with the AMS and their environment. Guided flow required the cow to pass through the AMS to either eat or lie down through 1) feed first or 2) milk first (Rodenburg, 2017). In feed first, cows had access to the feed alley but traveled through sort gates and the AMS to the resting area. In milk first, cows had access to the resting area but traveled through the AMS to reach the feed alley. With free flow, cows had access to feed, rest area, and the AMS continuously (Rodenburg, 2017).

Each flow system had potential benefits and limitations. Public perception was concerned with guided flow because cows were routed through the barn and did not have the freedom to fully choose their behavior (Rodenburg, 2017). Tremblay et al. (2016) reported that milk production per cow and milk production per AMS were 0.5 and 67.0 kgs per d higher, respectively, with free flow than with guided flow (Tremblay et al., 2016). In free flow, the cows ate more meals (8.6 per day) than guided flow (6.6 per day),

which increased feed intake (Harms et al., 2002). More milkings were seen on AMS with guided flow (2.6 per day) compared to free flow (2.3 per day; Harms et al., 2002). Harms et al. (2002) completed a study comparing the two different systems and the percentage of time the cows completed certain activities over 72 hours (Hermans et al., 2003). In a side-by-side comparison, cows ate less, stood longer, laid less, spent less time in the waiting area, and spent less time in the AMS in a guided flow system compared to the free flow system ($P < 0.001$; Table 1.2).

Automatic Milking System Fetch Cows

Fetch cows have been one of the biggest issues in AMS. They were determined by how long they were away from the AMS (i.e. time since the last milking; Rodenburg, 2017). Fetch lists informed the operators to “fetch” the cow that needed to be milked and physically bring them to the AMS. Fetching required labor that could be spent on other duties and responsibilities. Although the act of fetching the cow required minimal effort, the time spent identifying, finding, and herding the cows into the AMS took several hours each day (Rodenburg, 2017). Fetched cows have been defined as lame, injured, or infected by mastitis, but other factors like improper training, behavior, and personality also led to fetched cows (Rodenburg, 2017).

In 2001, Canadian producers recorded that 10 to 15% of the herd did not voluntarily milk in the AMS, and an mean of 19.2% of cows were fetched by the producer (Rodenburg and House, 2007). A survey showed that $14.6 \pm 10.3\%$ of cows were fetched at least once to two times a day (Table 1.3; Rodenburg and House, 2007). Tse et al. (2018b) found that AMS was occupied 77% of the day and had a median of

three fetch cows per AMS per day. The AMS study equated to fetching 4% of the herd per AMS per day (Tse et al., 2018b). Jacobs and Siegford (2012) completed a study on fetch cow status during the transition to AMS and found that fetch cow numbers decreased by day 30 after the transition to AMS (Figure 1.5). At the time of this publication, research was limited on when cows should be fetched, the financial impact of fetch cows, and if the time away from the AMS should be a main indicator of success.

An Automatic Milking System Training and Challenges Survey

Precise training has been known to prevent fetch cows. Research showed that it took one week of training for individuals and 30 days for a whole herd to adapt to AMS (Tse et al., 2018b). A mean of 2% of the herd was culled for not adapting, or not voluntarily milking while they were physically and behaviorally normal (Tse et al., 2018b). A 2018 survey was conducted on producers converting from CMS to AMS with 42% of producers training heifers, cows, or both before first milking and 58% of producers only fetching cows during the introduction of the AMS (Tse et al., 2018b). Likewise, 18% trained the cows before calving and no significant difference was seen (Tse et al., 2018b). Supervising the cow's first experience with the AMS was done by 99% of the producers. A majority of the farms, 63% of producers, trained with groups of ≤ 20 while 37% of farms trained with groups of ≥ 20 (Tse et al., 2018b). Both heifers and cows had a mean of 7 days to train while the whole herd took about 30 days to train. Training was twice a day for the first and second week after installation. The producers allowed for more time away from the AMS before fetching the cows during the first two

weeks of training (Tse et al., 2018b). Feed was used as an incentive for bringing the cow into the AMS (Tse et al., 2018b).

Challenges from transitioning included: learning AMS, training cows, feed changes, trusting the system, the demanding first few days, and the health management changes. Other less-seen challenges were general maintenance, cow traffic, too much milk, needing more AMS, and overall, a dislike of the technology (Tse et al., 2018b). It should be noted that these Canadian producers were on a quota system, but the potential issue of needing more milk storage and ensuring a market for any excess milk should be addressed. Of the surveyed producers, 86% recommend transitioning to AMS, 13% recommend transitioning depending on how technologically savvy the producer was, and 1% did not recommend transitioning to AMS (Tse et al., 2018b).

Overall, AMS had a positive impact on producers time and stress, employee management, and the quality of the producer and cow's lives (Tse et al., 2018b). The goal was to reduce the amount of fetch cows at the farm by improving training methods, healthier animals, and culling recurring fetch cows.

Economic Benefits of Using Precision Technology

Dairy Industry Economics

The decline of the dairy industry took an economic toll on dairy producers over the last few decades. Of 1.1 million dairy farms in 1965, only 97,560 were present in 2002 (Wolf, 2003). As of 2012, only 53,000 licensed dairies existed in the U.S. (Blayney, 2004). The decrease of dairy farms come from the increased cost (labor, feed, etc.) and the decreased demand (Mosheim and Lovell, 2009, Nehring et al., 2009). The threat of small farms leaving due to large-scale operations was also a concern (Nehring et al.,

2009). Between 1993 and 2012, the number of farms with ≤ 100 cows decreased by over 75% (Dong et al., 2016). One-way producers have been combating the issues with labor costs was with automatic milking systems.

Automatic Milking System Economics

Automatic milking systems overtime were meant to reduce labor costs and increase profit; however, the initial investments in the AMS were costly. In 2002, an AMS cost \$192,056 (Hyde and Engel, 2002). In 2017, for a 120-cow confinement operation, the AMS investment cost was \$375,000 $\pm$ \$46,000 (for two units; Salfer et al., 2017). Over time, investment costs rose with inflation and rapid demand growth. As of 2016, over 35,000 AMS were installed worldwide with an 8% increase in sales from 2013 to 2014 (Kimpel, 2016) with the payback period for the AMS was a mean of seven to ten years (Schulte and Tranel, 2013).

Multiple studies looked into the comparison of CMS and AMS (Table 1.4). Dijkhuizen et al. (1997) found AMS increased milk production and milk profit by 12.5% and increased labor savings by \$9,986 per year while Rotz et al. (2003) found AMS increased milk production and milk profit by 5\$ and increased labor savings by \$13,140 per year. Hyde and Engel (2002) compared CMS vs AMS) and reported that CMS has a maintenance cost of 3% of purchase price and AMS have 6% maintenance cost of the purchase price.

In 2018, Iowa State University completed a partial budget for a 216-cow herd. Their basis was for installing three AMS at a cost of \$250,000 per unit including AMS housing and yearly maintenance cost of \$7,000 per AMS. The expected usefulness of

each AMS was around 15 years and can be resold for ~\$35,000 each (Feuz and Feuz, 2020). Dijkhuizen et al. (1997) found the useful life was 12 years and can be resold for 5% of the initial cost after the 12 years.

Decision Modeling Automatic Milking System Economics

Decision support systems were tools that supplied users with options for decision-making under different scenarios (Gargiulo et al., 2022). Most decision tools included three elements: the data, a model that helps to understand how a real-world system operates, and a user interface that facilitates the interaction between the tool and the end user (Gargiulo et al., 2022). Previous studies have used decision support tools to look at parlor layout, milking time, calving pattern, and number of milking stalls (Cooper and Parsons, 1999); herd size, the number of AMS, milk yield, and total labor (Gargiulo et al., 2022); and parlor price, milk price, useful life for AMS (years), feed cost (\$ per 45.4 kg) maintenance cost (\$ per year), depreciation, tax rate, salvage value, and discount rate (Hyde and Engel, 2002).

Cooper and Parsons (1999) decision tool identified the optimal number of hours the AMS was available for milking was 21 hours per day. The profitability of the AMS on these farms related to current systems varied widely from farm to farm up to \$7,478.94 per year with the AMS open for 21 hours per day (Cooper and Parsons, 1999). Galindo et al. (2000) determined that decision support tools could be accurate. The physical performance model showed only a 2 to 8% difference between observed versus predicted values and proved to be highly correct when they tested predictive outcomes and current outcome of AMS farms (Galindo et al., 2000). This study showed these

decision support tools were accurate when comparing simulations to real-world data.

Hyde and Engel (2002) decision tool concluded breakeven information regarding labor costs, milk production, parlor costs, and useful life of the AMS.

Hyde and Engel found that the mean breakeven value (in 2002) for an AMS was \$125,000 to \$150,000 per AMS (Hyde and Engel, 2002). Each added dollar in labor costs increased the breakeven by \$4.10 to \$4.30. Greater milk production lowered the breakeven value by \$9.91 to \$10.64 per kg per unit. Increasing parlor costs by one dollar increased breakeven between \$0.45 and \$0.56. For each additional year of life from the AMS, breakeven decreased between \$5,000 to \$6,000.

Conclusion

While automatic milking systems were first introduced twenty-three years ago and much research has been conducted, novel information is constantly generated. Automatic milking systems research explored milk quality and production, labor savings, nutrition costs, and financial feasibility. Research has shown mixed results regarding milk quality with SCC, fat, and protein and an increase in freezing point, FFA, TPC, and milk production. Decreased labor cost and increased time for the producer have been seen with the transition of automatic milking systems in producer surveys and research studies. Nutrition cost increased with AMS due to the increase in milking and milk production. Lastly, AMS generated increased total economic returns with high net present values and internal rate of returns and shorter payback periods. However, with the amount of previous research, the AMS industry is continuing to generate more research with fetch cows and the economics of the AMS.

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Appendix



Figure 1.1. A 1995 automatic milking system at work (Lely, 2020).

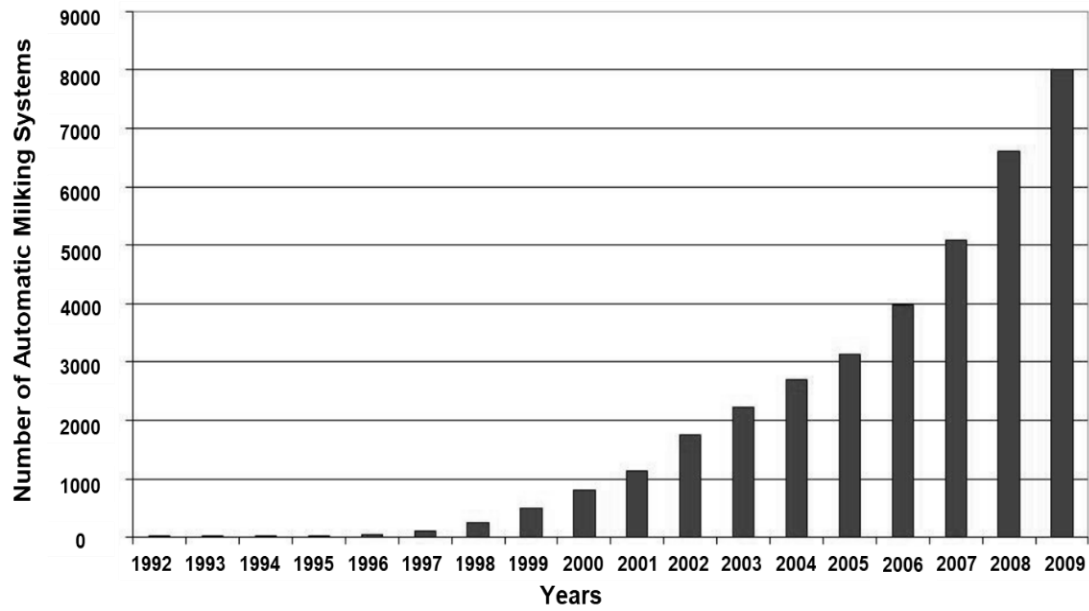


Figure 1.2. Growth of automatic milking system farms world-wide since the first introduction in 1992 (adapted from Koning, 2010).

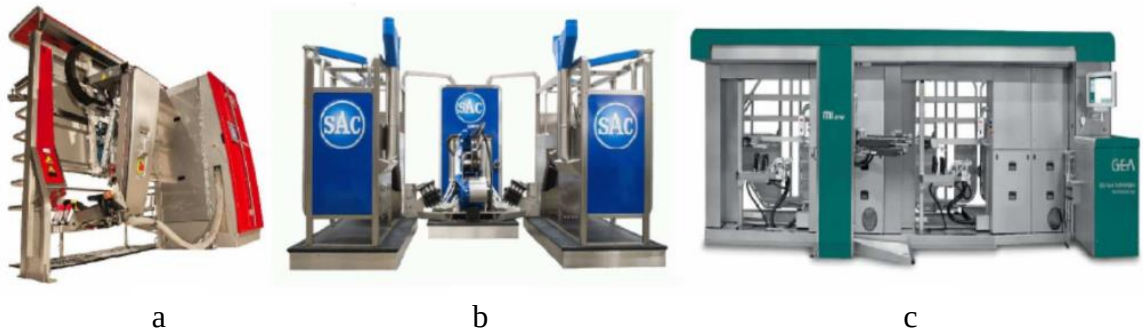


Figure 1.3. Common automatic milking systems designs: a) single-box; b) multi-box with two parallel milking boxes; c) multi-box with several milking boxes located in one row (Sharipov et al. , 2021).

Table 1.1. Suggested time benchmarks for automatic milking system activities (Cooper and Parsons, 1999).

Operation	Mean time, s/cow
Selection gate to milking stall	108
Udder preparation and cluster attachment	120
Robot arm movement, milking stall > 1	60 / stall
Time to exit	15

Table 1.2. Research regarding somatic cell count, milk production, and milk components before and after automatic milking system (**AMS**) transition.

Variable	Source	Change	Number Results	Significant
Somatic cell count (cells/mL)	Helgren and Reinemann, 2006	No change		No
	Saluvuo et al., 2015	Increase	142,000 to 208,000	No
	Klungel and Slaghuis, 2000	Decrease	233,000 to 217,000	No
	Bentley et al., 2018	Decrease	257,000 to 165000	Yes
	Tousova et al., 2014	Decrease	222,000 to 163,000	Yes
Milk production (total kgs.)	Koning et al., 2003	Increase		Yes
	Bentley et al., 2018	Increase	31.3 to 35.2	No
Milk components (fat %)	Saluvuo et al., 2015	Increase	3.9 to 4.0	No
	Tousova et al., 2014	Increase	4.1 to 4.2	Yes
	Jahansson et al., 2017	Decrease		No

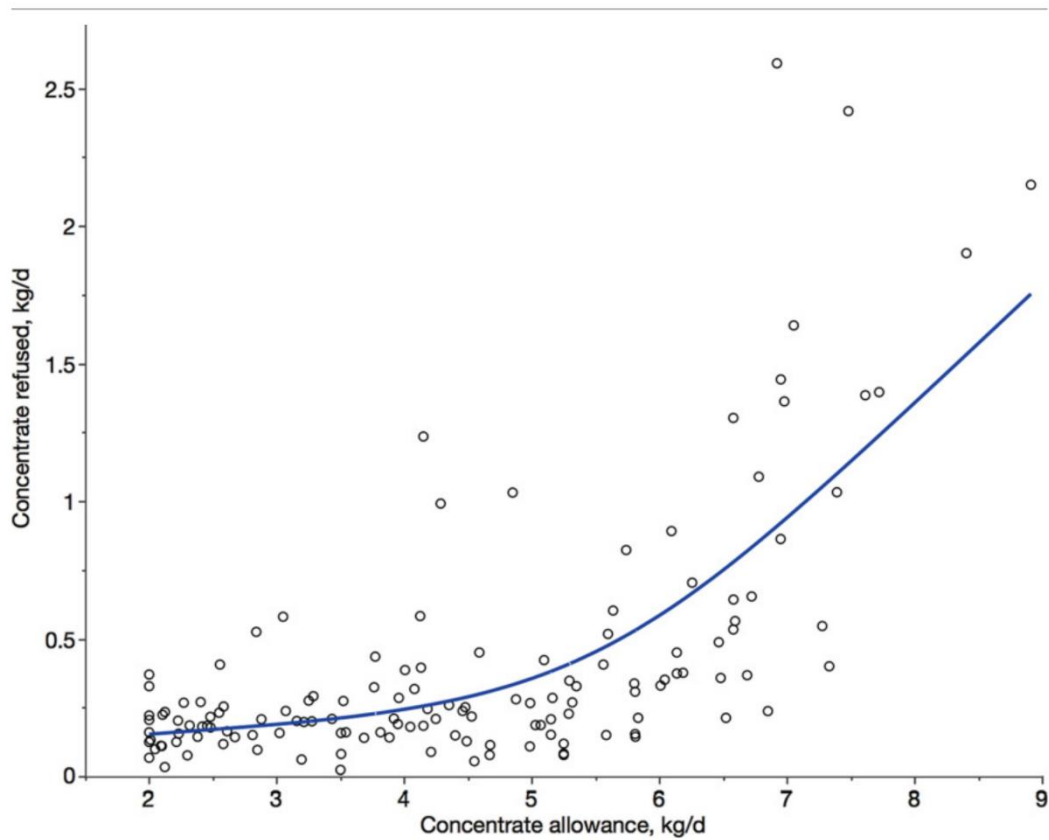


Figure 1.4. The amount of concentrate refused (left uneaten reported as mean over an 8-d period) relative to the amount of concentrate offered (mean over a 7-d period) in an automatic milking system (Bach and Cabrera, 2017).

Table 1.3. Automatic milking systems (**AMS**) activities timed in guided flow versus free flow (Hermans et al., 2003).

AMS Activities	Guided Flow	Free Flow
Eating, %	16.7	17.0
Standing in free stalls, %	12.9	9.7
Standing on floor, %	51.8	50.0
Lying, %	18.7	23.2
Waiting area, %	5.3	6.1
In AMS, min/d	43	55

Table 1.4. Reported reasons for fetching cows for milking across 43 survey herds

(Rodenburg and House, 2007).

Reason	Cows fetched, %	Total cows, %
Fresh or inexperienced cow (< 14 days experience)	11.0	1.6 ± 1.8
Milked manually due to teat placement	4.5	0.7 ± 1.2
Milked manually for other reasons	2.3	0.3 ± 1.0
Cow was visibly lame	19.0	2.8 ± 9.0
Cow has clinical mastitis or teat injury	5.7	0.8 ± 1.7
No identifiable reason for no-attendance	57.6	8.5 ± 9.9
Total fetched cows	100.0	14.6 ± 10.3

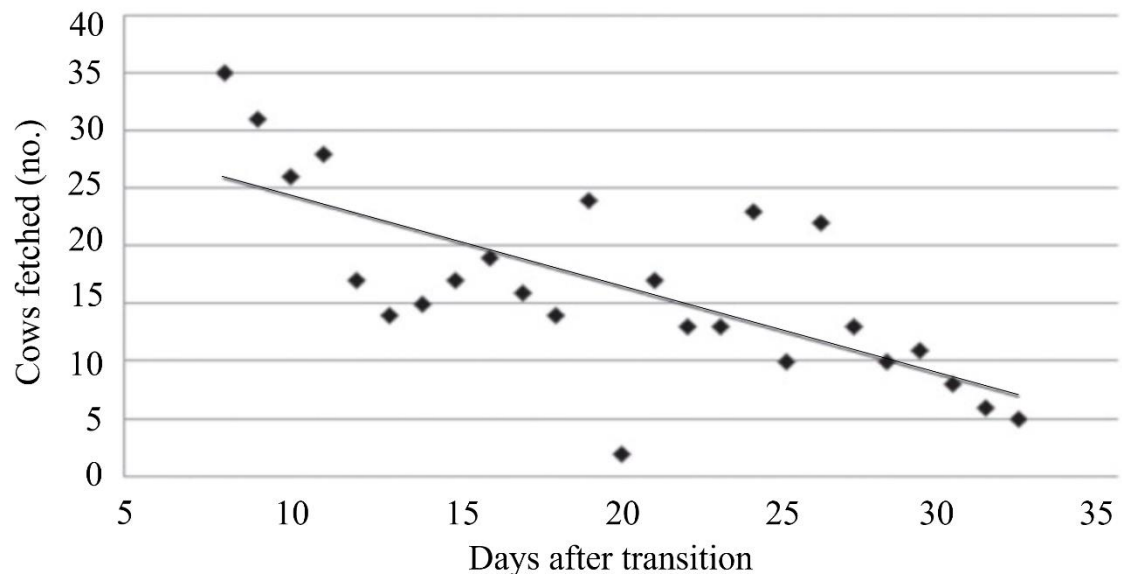


Figure 1.5. Number of cows fetched over a 35-day period after transition to automatic milking systems (Jacobs and Siegford, 2012).

Table 1.5. Assumptions on automatic milking systems (**AMS**) simulations (Salfer et al., 2017)

Variables	Dijkhuizen et al. (1997)	Hyde and Engel (2002)	Rotz et al. (2003)
Baseline:			
Milk baseline production, kg/cow	7,000	8,165	10,900
Annual increase in baseline, %	0.0	2.0	0.0
Finance:			
Parlor investment cost, \$	90,000	175,000	135,000
Interest rate, %	8	8	6
Inflation of milk and feed process, %	3.6 to 4.5	0	0
Depreciation periods, yr	5	7	10
Marginal tax rate, %	44	33	0
Labor wage rate, \$/h	7.6	NA	9.0
Annual production impact:			
Milk price, \$/45.4kg	12.5	14.0	13.2
AMS increased milk production, %	12	12.7	5
AMS decrease milk price, %	0.7	1	2
AMS increase feed cost, \$	12,600	4,441	2,040
AMS labor savings, \$	9,986	6,200	13,140
Life, repair, and salvage:			
Parlor economic life, yr	12	10 to 15	10
AMS economics life, yr	7	7 to 12	10
Parlor maintenance, % of purchase \$	3	3	3
AMS maintenance, % of purchase \$	6	6	4.6
Insurance cost, % of purchase price	0	0	0.5
Salvage value, % of purchase price	5	5	30

CHAPTER II
PREDICTING FETCH COW LIKELIHOOD FROM INDIVIDUAL
ANIMAL PERFORMANCE METRICS

A version of this chapter was originally published by Abby McCalmon:

Abby McCalmon, Yang Zhao, Charley Martinez, and Elizabeth Eckelkamp.
“Impact of parity and days in milk on fetch cow status in automatic milking systems.”
Journal of Animal Science

Abstract

Fetch cows, dairy cattle that do not voluntarily enter automated milking systems (**AMS**), increase labor costs, and decrease efficiency. The objective of this study was to describe fetch cows based on fetch lists and herd-management software data. This study was conducted on a commercial dairy (n = 510 cows) using 8 AMS from October 1, 2021, to May 10, 2022. Data were collected via PCDART, DairyComp, and a proprietary interface. Two fetch categories, EverFetch (**EF**) and NeverFetch (**NF**), and three status groups, True Fetch (on fetch list and fetched; **TF**), False Fetch (on fetch list and not fetched; **FF**) and Fetch Not Required (not on list; **NFR**), were created. The impact of health events (no event, reproduction, general health, and scheduled events), parity (1, 2, 3, and 4+ lactations), and AMS variables (milk visit outcome, production, and components; feed intake, etc.) on fetch category and status were analyzed using the GLIMMIX procedure of SAS 9.4 ($P \leq 0.05$). The sections were evenly divided by fresh or in-training (≤ 25 days in milk (**DIM**)) and lactation (> 25 DIM). The lactating group was divided into three sections (early, mid, and late lactation) based total cow-day observation quartiles. Across EverFetch and NeverFetch, cows that experienced ≥ 1 event during their lactation (Yes event) accounted for 94.9% of EverFetch and 96.2% of NeverFetch cows. Cows who experienced an event were more likely to show up on the fetch list. For fresh cows, results showed that PCDART compared to DCOMP; 1st and 2nd lactation cows compared to 3rd lactation cows; decreased milk fat, milk protein, daily max milk temperature, and feed intake; and an increased number of milkings increased

the likelihood of TF vs NFR. For fetch outcome early lactation cows, decreased milk production, failures, and feed intake and increased number of milkings, number of refusals, milk speed, and milk time led to a TF vs an NFR. For mid-lactation cows, decreased milk production, number of milkings, and number of refusals and increase in milk speed, milk time, and feed intake were more likely a TF than an NFR. For late lactation cows, PCDART compared to DCOMP; 3rd lactation cows compared to 1st and 4+ lactation cows; decrease in milk production, number of milkings, and number of refusals; and increase in failures and daily max milk temperature led to a TF vs an NFR. Cows that were more willing to enter the robot (greater milking and refusals per day) in early lactation cows were more likely to be coded as a TF when a fetch event occurred compared to cows that had experienced failures at the milking robot. Future research is needed to test the models and find benchmarks for determining fetch cow status.

Introduction

Automated milking systems (AMS), voluntary milking systems (VMS), and robotic milkers are analogous for stand-alone systems that use robotics to milk dairy cattle with minimal to no human intervention. These systems employ laser sights, udder mapping technology, individual teat attachment systems, feed delivery systems, and individual cow identification with record-keeping capabilities. These complex and costly machines can be advantageous for both labor and management. Automated milking systems were developed in Europe in the early 1990s to assist with labor issues on dairy farms (Rodenburg, 2017). Since March 1999, AMS have been used in Canada (Rodenburg and House, 2007) and since July 2000 in the United States (Lely, 2020), with

continued growth worldwide (Koning, 2010). As of 2014, there were > 2,500 AMS units in North America on $\geq 1,000$ farms (Rodenburg, 2017).

The two primary drivers of adopting AMS were (1) labor or labor costs reduction and (2) more time for farmers (Kimpel, 2016). After the start-up process, the AMS reduced hours in a parlor and allowed for more time on other job responsibilities like new AMS maintenance tasks or reduced total employees. However, employees should have or must acquire AMS knowledge which could lead to greater costs per employee (Kimpel, 2016). Surveys have shown improvement in farmer quality of life after adopting AMS. A quality-of-life survey conducted by Tse et al. in 2018 was sent to 530 AMS Canadian farms with a 41% response rate ($n = 217$). Their survey showed AMS provided 97% of the farmers with increase in time for family, meetings, sleep, other chores and crop duties (Tse et al., 2018). Another survey in 2013 showed similar results that 88% of respondents agreed that AMS provided more time for family and friends and 70% agreed that it decreased a need for hired employees (Bergman and Rabinowicz, 2013).

However, fetch cows negatively impacted labor cost and flexible time for the farmer. When a cow does not voluntarily enter the AMS according to farm-specific criteria, they appear on a fetch list. This list informs the operators to “fetch” the cow and bring her to the AMS for milking. This requires labor (cost and time) which could be spent on other duties. Fetching the cow requires minimal effort but, the time spent on identifying and bringing cows to the AMS can take many hours each day. Fetched cows have been defined as lame, injured, or infected by mastitis, but other factors like improper training, behavior, and personality can also lead to a fetch cow (Rodenburg and

House, 2007). In 2001, Canadian farmers recorded that 10 to 15% of the herd did not voluntary milk in the AMS and $19 \pm 13\%$ of cows were fetched by the farmer (Rodenburg and House, 2007). The same study indicated $15 \pm 10\%$ of cows were fetched at least one to two times per day (Rodenburg and House, 2007). Rodenburg and House (2007) found most fetch cows in their study had no identifiable reason to not use the AMS.

Tse et al. (2018) reported that 4% of the herd per AMS ended up as fetch cows while Jacobs and Siegford (2012) found a higher percentage (12.5%) of the herd ended up as fetch cows. Castro et al. (2012) found that labor increases 55 ± 33 minute per day per AMS. At the time of this study, research was lacking in regard to fetch cows and their impact on AMS dairy farms.

Hypothesis

This study investigated the ability to determine fetch cow status based off data collected from dairy herd records management software (PCDART and DairyComp), AMS data, and the fetch list. We hypothesized that fetch cows could be categorized based on milk production, days in milk, parity, and overall health.

Material and Methods

Data were collected from October 1st, 2021, to May 10th, 2022, on a Holstein $1,510 \pm 51$ herd commercial dairy farm in East Tennessee. The farm had two Lely AMS units across the four pens for a total of eight AMS units. One hundred and twenty to one hundred and forty cows were in each pen throughout the study.

Record Management Reports

Data were collected from PCDART (Dairy Records Management Systems, Raleigh, NC USA) and DairyComp (Valley Agricultural Software, Tulare, CA USA). PCDART was used for the first six months (October 2021 – March 2022) and DairyComp was used the last two months (April - May 2022). Data collected from PCDART and DairyComp included: cow identification, breed, parity, reproduction status, calving date, and dry-off date. Additional information included disease events (abscess, digit issues, foot rot, general lameness, warts, retained placenta, ketosis, subclinical ketosis, left displaced abomasum, metritis, milk fever, respiratory issues, mastitis, and general sickness); reproductive events (breeding, synchronization, abortions breeding, and estimated breeding date); and scheduled health events (vaccinations, veterinary checks, and hoof trimming) that occurred.

Fetch List Reports

Fetch lists were collected every six hours (four times a day) at 7:00am, 12:30pm, 6:00pm, and 11:00pm EST from October 1, 2021, to May 11, 2022. Screenshots of the fetch list were taken 30 minutes before fetching to include all cattle who showed up on the list but may have not been fetched. Cows ≤ 25 days in lactation (**DIM**) were considered in the fresh group by the producer and those > 25 DIM were considered in the lactating group by the producer. Cows on the fresh group list were reviewed every six hours (four times a day) and cows on the lactating group list were reviewed every 12 hours (twice a day). The fresh cows fetching criteria were (1) not visiting the AMS in the last 3 hours and (2) < 4 milkings a day. The lactating cows fetching criteria were (1) not visiting the AMS for the last 6 hours and (2) an expected milk yield > 13.6 kg.

Automatic Milking System Reports

Data were collected from the automatic milking systems using a proprietary database. Data collected included: daily milk production (kg), milk fat and protein percentage (%), milk speed (total and each quarter; seconds/milking), dead milk time (total and each quarter; seconds/milking), box time (minutes/milking), mean daily conductivity for each quarter (millisiemens (**mS**)/cm), milk temperature (C°/milking), total feed intake (g/day), total feed allowed (g/day), and milking outcomes (success, failure, or refusal). Dead milk time was defined as seconds cows were in the AMS but not milking, and box time was defined as the total time the cow was in the AMS. The three visit statuses were defined as: success, a milking visit that was completed with no issues; refusal, a milking when a cow entered the AMS more times than her milking limit and was dismissed without milking; and failure, a milking that was not completed from inability to attach the teat cups to the udder.

Statistical Analysis

Data were collected for 4,873 cows over 1,078,536 cow-days. Cow-days referred to the number of calendar days an individual cow was in the herd. These cow and cow-day numbers came from the total herd of the farm including non-AMS cows. Exclusions were sequentially applied as follows:

- 1) Dry cow-days and days after a cow left the herd were removed based on herd management software records (n = 4,384 cows and 1,048,576 cow-days remaining in the data set).

- 2) The herd data were limited to the four AMS groups (n = 528 cows and 103,720 cow-days remaining in the data set). This removed cows in temporary groups, cows milked conventionally, and non-lactating heifers.
- 3) Cows with missing calving, DIM, parity, or AMS data were removed (n = 510 cows and n = 73,664 cow-days remaining in the data set).

The final data for this project included 510 cows and 73,664 cow-days. Cows were divided into two overall fetching groups: appeared on the fetch list at least once (**EverFetch**; n = 484) and never appeared on the fetch list (**NeverFetch**; n = 26). The cows were also divided into two overall groups based on ever experienced an event (**EverEvent**; n = 500) and never experienced an event (**NeverEvent**; n = 10). Three by cow by day fetch status categories were also created: True Fetch (**TF**; on fetch list and fetched), false Fetch (**FF**; on fetch list and not fetched), and Fetch Not Required (**NFR**; not on list).

The events were divided into four different groups by cow by day. The first category was no events occurred (**NE**; n = 71,297). The second category was reproduction events (**RE**; n = 668) including abortions, breeding, synchronization, and estimated breeding date. The third category was general health (**GE**; n = 81) issues including abscesses, digit issues, foot rot, general lameness, warts, retained placenta, ketosis, subclinical ketosis, left displaced abomasum, metritis, and milk fever, respiratory issues, mastitis, and general sickness. The final category was scheduled health intervention (**SE**; n = 550) included vaccinations, veterinary checks, and hoof trimming.

The frequency procedure with a χ^2 of SAS 9.4 (SAS Inst. Inc., Cary, NC) was used to determine significance between the categorical variables (parity, events, day of the week, and system) across FetchStatus and EventStatus. The GLIMMIX procedure with an odds ratio output was used to determine significance ($P \leq 0.05$) of categorical variables and AMS variables (daily milk production, milk fat and protein percentage, milk speed, dead milk time, box time, mean daily conductivity for each quarter, milk temperature, total feed intake, total feed allowed, and milking outcomes) against FetchStatus and fetch outcome.

The reports were then divided by DIM for more accurate models. The sections were divided into fresh group (≤ 25 DIM) and lactation group (> 25 DIM). The lactation group was divided into three sections (early, mid, and late lactation) based on total cow-day observation quartiles. The lactation sections were ≤ 25 DIM (fresh), > 25 and ≤ 86 DIM (early lactation), > 86 and < 214 DIM (mid-lactation), and ≥ 214 DIM (late lactation). Cows could be in multiple sections during the study as they moved through their lactation.

The GLIMMIX procedure of SAS 9.4 was used to determine univariable model significance between fetch outcomes and 21 variables from management reports and the automatic milking systems (Table 2.1). The CORR procedure of SAS 9.4 was used to determine the correlation between significant variables ($P \leq 0.05$) from the univariable GLIMMIX models. Significant variables with a < 0.6 correlation were combined into a multivariate GLIMMIX procedure. Stepwise backward elimination was used to

determine the final models across fetch group (EverFetch and NeverFetch) and DIM models (fresh, early, mid, and late lactation) focused on fetch outcome (TF, FF, or NFR).

Results

This study was conducted on 510 commercial Holstein cows (Table 2.2). Cows were 1st (n = 84), 2nd (n = 197), 3rd lactation (n = 137), or 4+ lactations (n = 87). Days in milk (**DIM**) ranged from fresh (n = 306), early lactation (n = 101), mid-lactation (n = 96), and late lactation (n = 7). While 94.8% of cows in the herd were on the fetch list at some point during study, $9.7 \pm 3.0\%$ of the herd appeared on the fetch list on a given day. Of that $9.7 \pm 3.0\%$, only $8.2 \pm 2.5\%$ were fetched by the producer. Recorded events occurred for 98.0% of the herd at least once during the study. By cow-day, cows experienced events less than 1% of the time during the study.

Fetch Status

Across EverFetch and NeverFetch, cows that experienced an event at some point during their lactation (Yes event) accounted for 94.9% of EverFetch and 96.2% of NeverFetch cows. The greatest number of cows (n = 475) were in the EverFetch groups and experienced at least one event during their lactation ($P < 0.001$; Table 2.3). No event, reproduction, general health events, and scheduled health event groups across fetch list outcomes (TF, FF, or NFR) were significantly different ($P < 0.001$; Table 2.4). Fetched cows (TF and FF) experienced reproduction (n = 48), general health (n = 21), and scheduled intervention (n = 53) events in conjunction with fetching $\leq 1\%$ of the time. The majority of observations came from cows that had no event (TF = 98.4%, FF = 97.8%, and NFR = 98.2%) while the least number of observations came from the general health event categories (TF = 0.31%, FF = 0.19%, and NFR = 0.09%). All variables used for

Fetch outcome and fetch status were described in Table 2.5 and Table 2.6, respectively with fetch status univariate results in Table 2.7.

Fetch Outcome

Milk contents such as milk production, milk fat percent, milk protein percent, milk temperature, and milk speed were significant across DIM groups (Table 2.8, 2.9, 2.10, and 2.11). Milk production was significant in the early, mid, and late lactation cows. Milk protein and milk fat were significant only with the fresh cows. Milk speed was significant in the early and mid-lactation cows. Milk time was significant only in the mid-lactation cows. Daily max milk temperature was significant across all four DIM groups. Milking visits (milking, refusals, and failures), conductivity, and feed intake were significant across all groups. The number of milkings and refusals were significant in all DIM groups. The number of failures were only significant in the late lactation cows. Conductivity was significant in the fresh and early lactation cows. Feed intake was significant in the fresh, early, and mid-lactation cows.

Behavior and production responses for True Fetch versus No Fetch Required

Fresh cow model. For the fresh cows regarding TF vs NFR, significance was associated with system, parity milk protein, milk fat, daily max milk temperature, milkings, refusal, conductivity, and feed intake. Under the PCDART system, fetch events were more likely to be TF compared to DCOMP (OR, CI = 3.2, 1.7 to 6.1, $P = 0.01$). Events occurring in 1st and 2nd lactation cows were more likely to be TF than NFR (OR, CI = 16.9, 6.0 to 47.4; 6.1, 2.3 to 15.9, respectively, $P < 0.01$). Milk protein percentage significantly impacted all fetch outcomes. Cows with decreased milk protein were more

likely to be a TF (OR, CI = 0.2, 0.01 to 0.7, $P < 0.01$). Cows with greater milk fat content were also more likely to be a TF (OR, CI = 1.0, 1.4 to 2.2, $P < 0.01$). A decrease in daily max milk temperature increased the chance a cow was a TF (OR, CI = 0.6, 0.4 to 0.8, $P < 0.01$). The number of milkings was significant in all three categories A cow more likely to be a TF if the number of milkings increased (OR, CI = 1.7, 1.4 to 1.9, $P < 0.01$). As milkings refusals decreased, TF likelihood increased (OR, CI = 0.7, 0.6 to 0.8, $P < 0.01$). Across all quarter conductivity, only left rear (**LF**) quarter conductivity was significant. An increase in LR conductivity meant cows were more likely to be a TF (OR, CI = 0.9, 0.9 to 0.9, $P = 0.01$). A decrease in feed intake associated with a cow that was more likely to be a TF (OR, CI = 0.6, 0.5 to 0.7, $P < 0.01$).

Early lactation model. For early lactation cows regarding TF versus NFR, significance was associated with milk production, milkings, refusals, failures, milk speed, milk time, and feed intake. Decreased milk production increased TF likelihood (OR, CI = 0.9, 0.9 to 0.9, $P < 0.01$). True Fetch events were more likely with increased milkings and failures per day (OR, CI = 2.2, 1.6 to 3.0; 2.9, 1.9 to 4.5, respectively, $P < 0.01$). However, decreased refusals per day were increased TF likelihood (OR, CI = 0.6, 0.5 to 0.7, $P < 0.01$). An increase in milk speed and time associated a cow that was more likely to be a TF (OR, CI = 1.1, 1.0 to 1.2; 1.0, 1.0 to 1.0, respectively, $P < 0.02$). A decrease in feed intake reported a cow that was more likely to be a TF (OR, CI = 0.5, 0.4 to 0.5, $P < 0.01$).

Mid-lactation model. For mid-lactation cows regarding TF versus NFR, milk production, milkings, refusals, milk speed, milk time, and feed intake were significant. A

decrease in milk production associated with a TF (OR, CI = 0.90, 0.9 to 0.9, $P < 0.01$).

An increase in the number of milkings and the number of refusals led to a cow less likely to be a TF (OR, CI = 0.1, 0.1 to 0.2; 0.8, 0.7 to 0.9, respectively, $P < 0.01$). An increase in milk speed and milk time associated with a cow less likely to be a TF (OR, CI = 1.0, 1.0 to 1.0; 1.1, 1.1 to 1.2, respectively, $P < 0.01$). An increase in feed intake led to a cow more likely to be a TF (OR, CI = 1.3, 1.1 to 1.6, $P = 0.01$).

Late lactation model. For late lactation cows regarding TF versus NFR, significance was associated in system, parity, health category, milk production, milkings, refusals, failures, and daily max milk temperature. PCDART was less likely to be a TF than DCOMP (OR, CI = 0.4, 0.3 to 0.5, $P < 0.01$). For parity, 1st lactation cows were less likely to be a TF than 3rd lactation cows (OR, CI = 0.3, 0.1 to 0.6, $P < 0.01$) and 3rd lactation cows were less likely to be a TF than 4+ lactation cows (OR, CI = 2.0, 1.2 to 3.6, $P < 0.01$). An illness event was more likely to be a TF than a no event (OR, CI = 1.7, 1.2 to 2.4, $P = 0.02$). A decrease in milk production associated with a cow more likely to be a TF (OR, CI = 0.9, 0.9 to 0.9, $P < 0.01$). A decrease in the number of milkings and the number of refusals led to a cow more likely being a TF (OR, CI = 0.3, 0.2 to 0.3; 0.8, 0.8 to 0.9, respectively, $P < 0.01$) while increase in the number of failures led to a cow more likely to be a TF (OR, CI = 3.2, 2.5 to 4.5, $P < 0.01$). An increase in daily max milk temperature associated with a cow more likely to be a TF compared to a NFR (OR, CI = 1.4, 1.2 to 1.8, $P < 0.10$)

Behavior and production responses for False Fetch versus No Fetch Required

Fresh cow model. For fresh cows regarding FF versus NFR, significance was seen in system, parity, health category, milk protein, milkings, refusals, daily max milk temperature, and feed intake. PCDART was more likely to be an FF than a NFR (OR, CI = 0.36, 0.26 to 0.50, $P = 0.01$). Third lactation cows were less likely to be an FF than fourth lactation cows (OR, CI = 0.2, 0.1 to 0.9, $P < 0.01$). An illness event was more likely to be an FF than a no event (OR, CI = 0.2, 0.1 to 0.9, $P < 0.01$). Milk protein percentage significantly impacted all fetch outcomes. A decrease in milk protein increased the chance of the cow being an FF (OR, CI = 0.2, 0.03 to 0.5, respectively, $P < 0.01$). An increase in the number of milkings led to cows more likely to be an FF (OR, CI = 1.6, 1.4 to 1.9, $P < 0.01$) while increase in refusals led to cows less likely to be an FF (OR, CI = 0.7, 0.6 to 0.8, $P < 0.01$). A decrease in daily max milk temperature associated with cows more likely being an FF (OR, CI = 0.5, 0.3 to 0.9, $P < 0.01$). A decrease in feed intake increased a cow's likelihood to be an FF than a NFR (OR, CI = 0.7, 0.6 to 0.8, $P < 0.01$).

Early lactation model. For early lactation cows regarding FF versus NFR, significance was associated with failures, daily max milk temperature, and feed intake. An increase in failures led to an FF compared to NFR (OR, CI = 2.4, 1.4 to 4.1, $P < 0.01$). A decrease in daily max milk temperature and feed intake associated with a cow more likely to be an FF (OR, CI = 0.7, 0.6 to 0.9; 0.7, 0.5 to 0.9, respectively, $P < 0.02$).

Mid-lactation model. For mid-lactation cows regarding FF versus NFR, significance was associated with milk production, milkings, milk speed, milk time, and daily max milk temperature. A decrease in milk production and milkings led to a cow that

was more likely to be an FF (OR, CI = 0.9, 0.9 to 0.9; 0.1, 0.1 to 0.1, respectively, $P < 0.01$). An increase in milk speed and milk time associated with a cow more likely to be an FF (OR, CI = 1.1, 1.0 to 1.2; 1.0, 1.0 to 1.0, respectively, $P < 0.01$). A decrease in daily max temperature led to a cow more likely being an FF compared to a NFR (OR, CI = 0.7, 0.6 to 0.9, $P < 0.01$).

Late lactation model. For late lactation cows regarding FF and NFR, significance was associated with system, milk production, refusals, and failures. PCDART was less likely to be an FF than DCOMP (OR, CI = 0.4, 0.2 to 0.5, $P < 0.01$). A decrease in milk production led to a cow more likely to be an FF (OR, CI = 0.9, 0.9 to 0.9, $P < 0.01$). A decrease in the number of refusals associated with a cow more likely to be an FF (OR, CI = 0.9, 0.9 to 0.9, $P < 0.01$) while increase in failures led a cow to more likely be an FF (OR, CI = 3.1, 2.3 to 4.2, $P < 0.01$).

Behavior and production responses for True Fetch versus False Fetch

Fresh cow model. For fresh cows regarding TF versus FF, significance was associated with parity, health category, milk protein, milk fat, milkings, and conductivity. First and 2nd lactation cows were less likely to be a TF than 3rd lactation cows (OR, CI = 0.3, 0.1 to 0.5; 0.4, 0.2 to 0.7, respectively, $P < 0.01$). For health category, an illness event was more likely to be a TF than a no event (OR, CI = 0.2, 0.1 to 0.4, $P < 0.01$). A decrease in milk protein and milk fat were more likely to be a TF (OR, CI = 0.3, 0.1 to 0.8; 0.8, 0.6 to 0.9, $P < 0.01$). An increase in milking showed cows more likely to be a TF (OR, CI = 1.1, 1.0 to 1.3, respectively, $P < 0.01$). Conductivity was only significant in the

left rear quarter of the udder. An increase in LR conductivity led to a more likely chance of a TF than an FF (OR, CI = 1.0, 1.0 to 1.1, $P < 0.01$).

Early lactation model. For early lactation cows regarding TF versus FF, significance was associated with milkings, refusals, daily max milk temperature, conductivity, and feed intake. A decrease in the number of milkings led to a cow more likely to be a TF (OR, CI = 0.6, 0.4 to 0.9, $P < 0.01$) while increase in the number of refusals led to a cow less likely to be a TF (OR, CI = 1.4, 1.1 to 1.8, $P < 0.01$). A decrease in daily max milk temperature associated with a TF than an FF (OR, CI = 0.7, 0.5 to 0.9, $P = 0.2$). Conductivity was only significant in the left rear quarter of the udder. An increase in LR conductivity reported a cow more likely to be a TF (OR, CI = 1.0, 1.0 to 1.0, respectively, $P < 0.01$). An increase in feed intake led to a TF (OR, CI = 1.2, 1.0 to 1.5, $P < 0.01$).

Mid-lactation model. For mid-lactation cows regarding TF versus FF, significance was associated with milk production, refusals, and daily max milk temperature. An increase in milk production associated with a cow more likely being a TF (OR, CI = 1.1, 1.1 to 1.1, $P < 0.01$). An increase in the number of refusals led to a cow more likely to be a TF (OR, CI = 1.3, 1.1 to 1.4, $P < 0.01$). A decrease in daily max milk temperature associated with a cow more likely being a TF (OR, CI = 0.7, 0.5 to 0.8, $P < 0.01$).

Late lactation model. For late lactation cows regarding TF versus FF, significance was associated with milkings, refusals, and daily max milk temperature. A decrease in milkings led to a cow more likely to be an FF (OR, CI = 0.6, 0.5 to 0.9, $P <$

0.01) while increase in refusals led to a cow more likely to be an FF (OR, CI = 1.2, 1.0 to 1.3, $P < 0.01$). A decrease in daily max milk temperature reported a cow to more likely be an FF (OR, CI = 0.7, 0.6 to 0.9, $P < 0.01$).

Discussion

Across the study period, most cows experienced ≥ 1 fetch event. However, the daily herd percent fetched was 9.7% in our study. This was less than the 19% reported by Rodenburg and House (2007) but higher than a study by Tse et al. (2018) (4%). The differences across studies were likely because both Rodenburg and House (2007) and Tse et al. (2018) conducted surveys asking producers for their impression of fetch percentages. In our study, fetch reports were collected multiple times each day, but were only reflective of fetch patterns in our herd. More studies across individual herds with detailed fetch reports should be done to improve our understanding of fetch percentages across herds.

System. Within our study, management system (PCDART and DairyComp) significantly impacted the overall categories of EverFetch and NeverFetch, fresh cow fetch outcomes, and late lactation fetch outcomes. EverFetch were more likely to occur under the DairyComp system than PCDART system. The shorter time managed under DairyComp could have decreased the likelihood that cows never required a fetch (NeverFetch). Similarly, late lactation cows were more likely to be NFR compared to TF or FF on DCOMP than PCDART. The total time the herd was managed under PCDART (6 months) compared to DairyComp (2 months) could have impacted these results. The greater time managed under PCDART increased the total occurrence of TF, FF, and NFR recorded on the study herd. Therefore, the significance with the different management

system was expected. In a study by Eckelkamp and Bewley (2020b), a similar phenomenon was reported. As exposure to a system (use) increased, likelihood of evaluating system alerts decreased (OR = 1.40, 95% CI = 1.24 to 1.57; Eckelkamp et al., 2020). The increased likelihood of NFR under the DairyComp system (month 7 and 8) compared to PCDART (months 1 to 6) could have been influenced by producer exposure fatigue with fetching over time.

Conversely, fresh lactation cows were more likely to be coded as TF and FF compared to NFR. This indicated that producers were more likely to either bring cows to the AMS (TF) or cows appeared on the list and were not brought to the AMS (FF). The producer increased AMS visit allowance and decreased the acceptable time away (appeared on fetch list if ≥ 3 hr. since last milking). The fresh period (three wk. pre- and three wk. post-parturition) has the highest risk for dairy cattle (Ito et al., 2010)(LeBlanc, 2010). Because of this, producers were more likely to pay attention to health alerts (Eckelkamp and Bewley, 2020a). Producers may also be more likely and willing to evaluate fresh fetch cow status and bring them to AMS because of concern during that stage of a cow's life.

Parity. Within our study, parity (1st, 2nd, 3rd, and 4+ lactations) significantly impacted the overall categories of EverFetch and NeverFetch, fresh cow lactation fetch outcome, and late cow lactation fetch outcomes. First lactation cows were more likely to be on the fetch list at least once during lactation than 3rd lactation cows. First lactation cows were new to the AMS as well as milking in general while 3rd lactation cows could have used the AMS in previous lactation due to the farm owning the AMS for over three

years. Second lactation cows were more likely to be EverFetch than 1st and 3rd lactation cows. Third lactation cows were considered more mature than 2nd lactation cows and more likely to be EverFetch; however, the opposite was seen with 1st lactation cows. Fourth+ lactation cows were more likely to be EverFetch than 1st, 2nd, and 3rd lactation. Difference between parity have been seen in other scientific works such as Neave et al. (2017) found differences in feed, social, and exploratory behavior amongst primiparous (1st lactation) and multiparous (2+ lactations) during their fresh cow stage. While fresh cows were understanding the AMS, the different parity behavior such as exploratory behavior could lead to increased fetching outcomes. During the fresh period, 1st and 2nd lactation cows were more likely to be TF than NFR compared to 3rd lactation cows. First and second lactation cows were still learning the AMS while 3rd lactation cows could have used the AMS in previous lactations which may explain the differences across parities. In late lactation, 3rd lactation cows were more likely to be FF than NFR than 4th lactation. Third lactation cows were more likely to be on the fetch list and not fetch by the producer than 4th lactation cows.

Milk production and contents. Within our study, milk production significantly impacted the overall categories of EverFetch and NeverFetch, early lactation cow fetch outcomes, mid-lactation cow fetch outcomes, and late lactation cow fetch outcome. For the fetch status model, a decreased milk production increased EverFetch likelihood. Early lactation cows were more likely to be TF than NFR when milk production decreased. Decreased milk production could have led to a cow not going to the AMS which would cause the producer to fetch the cow.

Mid and late lactation cows were more likely to be TF and FF than NFR when milk production decreased while an increase in milk production for mid-lactation cows was more likely to be TF than FF. The increased milk production when comparing TF versus FF followed the farms protocol that cows would have been a TF if their milk production was > 13.6 kg. Our study found an increased milk production in early and mid-lactation cows. Milk production increased biologically in the early and mid-lactation cows (Ferris et al., 1985) and was considered peak lactation. Cows in peak lactation may have been listed as a NFR rather than a TF or FF due to that biological increase.

Milk protein significantly impacted the overall categories of EverFetch and NeverFetch and fresh lactation cow fetch outcomes. Fresh lactation cows were more likely to be TF and FF than NFR and TF than FF when milk protein decreased. Cows were more likely to be an EverFetch when milk protein decreased. Milk fat significantly impacted the overall categories of fresh lactation cow fetch outcomes. Fresh lactation cows were more likely to be TF than FF and NFR when milk fat decreased. It was reported by de Vries and Veerkamp (2000) that large decreases in milk fat percentage were related to high initial fat percentages in fresh lactations and found that decreased fat percentage during fresh lactation might serve as an indicator of energy balance.

Compared to our study, we found significance in fat percent only in the fresh group and showed a greater milk fat led to more of an appearance in the fetch list. Milk components such as fat and protein also have mixed results in research. A Canadian survey reported no change in milk fat content (56% of respondents) and milk protein content (79% of respondents; Tse et al., 2018b). However, Speicher et al. (1994) found that milk fat was

lower in 3x milking per day in CMS for multiparous ($3.27 \pm 0.07\%$) and primiparous ($3.22 \pm 0.07\%$) when compared to 2x milking per day in CMS for multiparous ($4.47 \pm 0.06\%$) and primiparous ($3.29 \pm 0.06\%$; $P < 0.05$, respectively). Similarly, milk protein was lower in 3x milking per day in CMS for multiparous ($3.07 \pm 0.02\%$) and primiparous ($3.01 \pm 0.02\%$) when compared to 2x milking per day in CMS for multiparous ($3.19 \pm 0.03\%$) and primiparous ($3.11 \pm 0.03\%$; $P < 0.01$; Speicher et al., 1994). Milk fat and milk protein decreased as the number of milkings increased and vice versa, therefore decreased milk fat and milk protein increased TF likelihood.

Milking outcome. Within our study, milking outcome (milking, refusal, and failure) significantly impacted the overall categories of EverFetch and NeverFetch, fresh lactation cow fetch outcomes, early lactation cow fetch outcomes, mid-lactation cow fetch outcomes, and late lactation cow fetch outcome. Cows were more likely to be an EverFetch when milkings, refusals, and failure visits decreased. Cows appeared on the fetch list based on farm protocols regarding time away from the AMS, number of milkings, and expected milk production. Cows with low milking visits (< 2) appeared on the fetch list and were fetched based on farm protocols. Wagner-Storch and Palmer (2003) found that increased in milk yield was a contributor to increased milking frequency. Refusal and failure visits showed that the cow was willing to go in the AMS but either an issue or refusal occurred. Producers could have seen this as the cow would try again later without human intervention and as a result would not fetch her (FF or NFR).

Fresh lactation cows were more likely to be TF and FF than NFR and a TF than FF when the number of milking visits increased. When the number of refusals decreased, cows were more likely to be TF and FF than NFR. Fresh lactation cows were still in training therefore, the number of milking outcome visits could be due to training visits. Early lactation cows were more likely to be TF than NF and FF than TF when the number of milkings increased. When refusals decreased, cows were more likely to be TF than NFR and FF than TF. When failures increased cows were more likely to be a TF and FF than an NFR. Failures could have occurred due to improper head position, poor teat attachment, or excessive kicking. Producers could have seen this as the cow would try again later without human intervention and as a result would not fetch her (FF or NFR). Regarding the number of milkings, milk production following a milking failure was 26% lower than with non-failed milkings (Bach and Busto, 2005). Decreased milk production due to failures was more severe as DIM increased (Bach and Busto, 2005). Mid-lactation cows were more likely to be TF and FF than NFR when the number of milkings decreased. When refusals increased, cows were more likely to be NFR than TF and TF than FF. Increased refusals were more likely to not be on the fetch list compared to being on the fetch list and fetched or not fetched. Refusals occurred when cows attempted to enter the AMS before she was able (by the producer's time allotment) to milk again. Therefore, increased refusals were more likely to indicate NFR.

Late lactation cows were more likely to be TF than FF and NFR when the number of milkings decreased. When refusals decreased, cows were more likely to be TF than NFR and FF than TF and NFR. When failures increased, cows were more likely to be TF

and FF than NFR. Hogeveen et al. (2001) found that shorter milking intervals resulted in higher milk production per cow per hour; however, our research showed increase in fetch status with increased milk speed and decrease in milkings. Jacobs and Siegford (2012) found that a balance of time spent milking and time spent in the box was correlated with successful AMS visits. Therefore, milk speed and box time significance across models was expected.

Conductivity and health. Within our study, conductivity per quarter significantly impacted the overall categories of EverFetch and NeverFetch, fresh lactation cow fetch outcomes, and early lactation cow fetch outcomes. Decreased conductivity was more likely to be associated with EverFetch than Never Fetch. However, only LR conductivity significantly impacted fetch outcomes. Fresh lactation cows were more likely to be a TF than NFR and FF than TF when conductive decreased. Early lactation cows were more likely to be TF than FF when conductivity increased. Cows with greater LR conductivity were more likely to be fetch cows and fetched compared to appearing on the list or not being fetched. Conductivity could have been associated with somatic cell count and milking max temperature could have been associated with fever or infection in the cows (Tavman and Tavman, 1999). Both inform producers of possible diseases such as mastitis. Veissier et al. (2017) found that cows with illness were less active which could led to decrease in milkings. Therefore, cows with increased conductivity and increased temperature could be less likely to voluntarily walk into the AMS and will more likely be on the fetch list. Conductivity was significant in the models; however, on a biological level conductivity would not be a reliable predictive variable. Within our study, health

category significantly impacted the overall categories of fresh lactation cow fetch outcomes. Fresh cows were more likely to be TF than FF when a health event occurred. Cows did not go to the AMS when health events occurred, and the producer would have fetched her.

Feed intake and milk temperature. Within our study, feed intake significantly impacted the overall categories of EverFetch and NeverFetch, fresh lactation cow fetch outcomes, early lactation cow fetch outcomes, and mid-lactation cow fetch outcome. Cows were more likely to be EverFetch when feed intake decreased. Cows that did not go to the AMS would have a decreased feed intake since a portion of their daily feed intake was only provided at the AMS in the form of a concentrate pellet. Therefore, lower feed intake and greater fetch rate would be expected, as fetch cows had fewer overall visits per day.

Fresh lactating cows were more likely to be TF and FF than NFR when feed intake decreased. Early lactating cows were more likely to be TF and FF than NFR when feed intake decreased and TF than FF when feed intake increased. Increased feed intake correlated with increased milk production. This followed farm protocols when fetching only cows with < 13.6 kg of milk production. Additionally, feed intake for this metric was based on pelleted feed consumption at the AMS. If cows reduced visits, their feed intake would likely decrease as well. This particular metric should be interpreted with caution, as it could be a trailing indicator instead of a causal relationship with fetching. Mid-lactation cows were more likely to be TF than NFR when feed intake increased. This could be due to an increased milk production biologically during peak-lactation.

Within our study, daily max milk temperature significantly impacted the overall categories of fresh lactation cow fetch outcomes, early lactation cow fetch outcomes, mid-lactation cow fetch outcomes, and late lactation cow fetch outcomes. Fresh lactation cows were more likely to be TF and FF than NFR when daily max temperature decreased. Fresh cows could have been prone to hypocalcemia which can lower the cow's temperature. Oetzel (2000) found hypocalcemia was most common in fresh cows immediately following parturition. Cows with milk fever may have been less motivated to visit the AMS for milking, similar to the impact of health event mentioned in the previous section. Although health events did not impact TF compared to NFR like max milk temperature did, hypocalcemia could have been sub-clinical and not recorded by farm staff. This could explain the impact of max milk temperature on TF and FF compared to NFR that was not found in health events. Early and mid-lactation cows were more likely to be TF than FF and FF than NFR when the daily max temperature decreased. Hypocalcemia could still affect early lactation cows but not as prominently as fresh lactation cows. Late lactation cows were more likely to be TF than NFR and FF than TF when daily max temperature increased. The increased temperature could be due to an underlying disease or mastitis which would cause the cows to not go to the AMS and need to be fetched (Kim et al., 2019).

Limitations

Limitations occurred with this project being only on one farm for eight months. Incorrect or incomplete updated record keeping was a limitation as well as challenges like duplicate identification or missing data. The switch from PCDART and DairyComp

and the Astronaut 3 to the Astronaut 5 AMS units also complicated cow and data tracking.

Conclusion

Management decisions, DIM, and general health issues (illnesses) increased the likelihood of cows being fetched. Days in milk impacted fetch cow status when comparing the four sections for fetch outcome (fresh, early, mid, and late lactations). Health events also impacted fetch status and outcome like we hypothesized. Cows who experienced an event were more likely to show up on the fetch list. Days of the week did not impact fetch cow status. With the combined data, the models found will help predict fetch cow status based on DIM. Each model had different variables that led to unique DIM models. Cows that appeared on the fetch list and were fetch by the producer were termed as True Fetch, cows that appeared on the fetch list and not fetched by the producer were termed False Fetch, and cows that did not appear on the fetch list were termed No Fetch Required. The models were the beginning of predicting a fetch cow before she enters the AMS. Future research is needed to test the models and find benchmarks for determining fetch cow status.

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Appendix

Table 2.1. Variables used in fetch cow models with their definition and unit.

Variable	Unit
System	PCDART vs DairyComp
Day of week	Weekday vs weekend
Parity	1 st , 2 nd , 3 rd , and 4+ lactations
Health category	None, reproductive, health, scheduled
Milk production	kgs. per day
Milk fat %	% per day
Milk protein %	% per day
Milkings	Number of visits to the AMS a day
Refusals	Number of AMS rejections per day
Failures	Number of times the AMS is unable to attach per day
Milk speed sum	kgs. sum per minute
Milk speed mean	Mean kgs. per minute
Udder color number sum	Sum of daily udder color failures
LF conductivity	Millisiemens per cm per day
LR conductivity	Millisiemens per cm per day
RF conductivity	Millisiemens per cm per day
RR conductivity	Millisiemens per cm per day
Mean daily milk time	Mean daily milk time in seconds
Daily max milk time	Total daily max milk time in seconds
Daily max milk temperature	Max milk temperature in °C
Daily feed intake	Number of grams consumed

Table 2.2. Descriptive data for a commercial herd (n = 510 Holstein cows) utilizing automatic milking systems from October 1, 2021, to May 10, 2022.

	Total cows	Number of observations	% of observation (%)
Parity			
1 st lactation ¹	84	8,347	11.33
2 nd lactation ¹	197	28,906	39.22
3 rd lactation ¹	137	21,719	29.48
4+ lactation ¹	87	14,713	19.97
DIM			
Fresh ²	387	4,312	5.85
Early ²	387	18,198	24.70
Mid ²	385	33,848	45.96
Late ²	207	17,306	23.50

¹The parity category grouped lactations into 1st lactation, 2nd lactation, 3rd lactations, and 4+ lactations.

²DIM group sections were ≤ 25 DIM (fresh), > 25 and ≤ 86 DIM (early), > 86 and < 214 DIM (mid), and ≥ 214 DIM (late).

Table 2.3. Relationship between fetch and event status from 510 cows utilizing automatic milking systems monitored from October 1st, 2021, to May 10th, 2022 ($P \leq 0.001$).

	EverFetch ¹ # (%)	NeverFetch ¹ # (%)
Yes event ²	475 (94.9%)	25 (96.2%)
No event ²	9 (1.9%)	1 (3.9%)

¹EverFetch = cow appeared on fetch list at least once during the; NeverFetch = cow did not appear on fetch list at least once during the study.

²Yes event = cow experienced a health event during the study; No event = cow did not experience a health event during the study.

Table 2.4. Relationship between fetch outcome and event categories from 510 cows monitored from October 1st, 2021, to May 10th, 2022 ($P \leq 0.001$).

	True Fetch ¹ # (%)	False Fetch ¹ # (%)	NFR ¹ # (%)
No event	5,956 (98.4%)	1025 (97.8%)	65,216 (98.2%)
Reproduction ²	35 (0.6%)	13 (1.2%)	620 (0.9%)
General health ³	19 (0.3%)	2 (0.2%)	60 (0.1%)
Scheduled health ⁴	45 (0.7%)	8 (0.8%)	497 (0.8%)

¹True Fetch = cows on the list and fetched; False Fetch = cows on the list and not fetched; No Fetch Required (NFR) = cows not on the list and not fetched.

²The reproduction (n = 668) category included abortions, breeding, synchronization, and estimated breeding date.

³The general health (n = 81) event included abscesses, digit issues, foot rot, lameness, warts, retained placenta, ketosis, displaced abomasum, metritis, milk fever, respiratory issues, mastitis, and general sickness.

⁴The scheduled health category (n = 550) included vaccinations, veterinary checks, and hoof trimming.

Table 2.5. Variables used in univariable GLIMMIX analyses to determine relationship to fetch outcome by days in milk. Significant variables ($P \leq 0.05$) were included in multivariable GLIMMIX analyses.

Categorization and risk factor	P-Value	Categorization and risk factor	P-Value
Fresh		Early	
System	< 0.01	System	0.08
Day of week	0.85	Day of week	0.62
Parity	< 0.01	Parity	< 0.01
Health category	< 0.01	Health category	< 0.01
Milk production, kg	< 0.01	Milk production, kg	< 0.01
Milk fat, %	< 0.01	Milk production, kg	< 0.01
Milk protein, %	0.28	Milk fat, %	0.60
Milkings, #/d	< 0.01	Milkings, #/d	0.02
Refusals, #/d	< 0.01	Refusals, #/d	< 0.01
Failures, #/d	< 0.01	Failures, #/d	0.20
Milk speed sum, s	< 0.01	Milk speed sum, s	< 0.01
Milk speed mean, s	0.004	Milk speed mean, s	< 0.01
Udder color number, #/d	0.32	Udder color number, #/d	0.82
LF conductivity, mS	< 0.01	LF conductivity, mS	< 0.01
LR conductivity, mS	< 0.01	LR conductivity, mS	< 0.01
RF conductivity, mS	0.16	RF conductivity, mS	0.91
RR conductivity, mS	0.07	RR conductivity, mS	0.07
Mean daily milk time, s	0.67	Mean daily milk time, s	0.26
Daily max milk time, s	< 0.01	Daily max milk time, s	< 0.01
Daily max milk temperature, °C	< 0.01	Daily max milk temperature, °C	< 0.01
Daily feed intake, kg	< 0.01	Daily feed intake, kg	< 0.01
Mid		Late	
System	0.05	System	0.04
Day of week	0.10	Day of week	0.30
Parity	0.15	Parity	0.05
Health category	0.23	Health category	< 0.01
Milk production, kg	< 0.01	Milk production, kg	< 0.01
Milk production, kg	< 0.01	Milk production, kg	< 0.01
Milk fat, %	< 0.01	Milk fat, %	< 0.01
Milkings, #/d	< 0.01	Milkings, #/d	< 0.01
Refusals, #/d	< 0.01	Refusals, #/d	< 0.01
Failures, #/d	< 0.01	Failures, #/d	< 0.01
Milk speed sum, s	< 0.01	Milk speed sum, s	< 0.01
Milk speed mean, s	< 0.01	Milk speed mean, s	0.51
Udder color number, #/d	0.12	Udder color number, #/d	0.27
LF conductivity, mS	< 0.01	LF conductivity, mS	0.49
LR conductivity, mS	< 0.01	LR conductivity, mS	< 0.01
RF conductivity, mS	0.10	RF conductivity, mS	0.13
RR conductivity, mS	0.01	RR conductivity, mS	0.01
Mean daily milk time, s	< 0.01	Mean daily milk time, s	0.07
Daily max milk time, s	< 0.01	Daily max milk time, s	0.35
Daily max milk temperature, °C	< 0.01	Daily max milk temperature, °C	0.35
Daily feed intake, kg	< 0.01	Daily feed intake, kg	< 0.01

Table 2.6. Variables used in univariable GLIMMIX analyses to determine relationship to fetch status¹ and fetch outcome². Significant variables ($P \leq 0.05$) were included in multivariable GLIMMIX analyses.

Categorization and risk factor	P-Value	Categorization and risk factor	P-Value
NeverFetch vs EverFetch ¹		Fetch Outcome ²	
System ³	< 0.01	System ³	< 0.01
Day of week ⁴	0.89	Day of week ⁴	0.16
Parity ⁵	< 0.01	Parity ⁵	< 0.01
Health category ⁶	0.06	Health category ⁶	0.09
DIM ⁷	< 0.01	DIM ⁷	< 0.01
Milk production, kg	< 0.01	Milk production, kg	< 0.01
Milk production, kg	< 0.01	Milk production, kg	< 0.01
Milk fat, %	< 0.01	Milk fat, %	< 0.01
Milkings, #/d	< 0.01	Milkings, #/d	< 0.01
Refusals, #/d	< 0.01	Refusals, #/d	< 0.01
Failures, #/d	< 0.01	Failures, #/d	< 0.01
Milk speed sum, s	< 0.01	Milk speed sum, s	< 0.01
Milk speed mean, s	0.22	Milk speed mean, s	< 0.01
Udder color number, #/d	0.14	Udder color number, #/d	0.14
LF conductivity, mS	< 0.01	LF conductivity, mS	< 0.01
LR conductivity, mS	< 0.01	LR conductivity, mS	< 0.01
RF conductivity, mS	< 0.01	RF conductivity, mS	0.06
RR conductivity, mS	< 0.01	RR conductivity, mS	0.05
Mean daily milk time, s	< 0.01	Mean daily milk time, s	0.06
Daily max milk time, s	< 0.01	Daily max milk time, s	< 0.01
Daily max milk temperature, °C	< 0.01	Daily max milk temperature, °C	< 0.01
Daily feed intake, kg	< 0.01	Daily feed intake, kg	< 0.01

¹EverFetch = cow appeared on fetch list at least once during the; NeverFetch = cow did not appear on fetch list at least once during the study.

²Yes event = cow experienced a health event during the study; No event = cow did not experience a health event during the study.

³The system was grouped into the old (PCDART) and new (DairyComp).

⁴Day of week was grouped by WD (Monday, Tuesday, Wednesday, Thursday, and Friday) and WE (Saturday and Sunday).

⁵The parity category grouped lactations into 1st lactation, 2nd lactation, 3rd lactations, and 4+ lactations.

⁶Events were divided into no events, reproduction events, general health events, and scheduled health events.

⁷DIM group sections were ≤ 25 DIM (fresh), > 25 and ≤ 86 DIM (early), > 86 and < 214 DIM (mid), and ≥ 214 DIM (late).

Table 2.7. Odds ratios and 95% confidence intervals for automatic milking system

(AMS) variables, parity, events, weekday, and system based on EverFetch and

NeverFetch on whole dataset. Variables marked with * indicate continuous variables.

Categorization and risk factor	Reference Group	Odds Ratio	95% CI ¹	P-Value
EverFetch vs NeverFetch ²				
DCOMP ³	PCDART ³	1.5	1.4 to 1.6	< 0.01
1 st lactation ⁴	3 rd lactation ⁴	1.4	1.3 to 1.5	< 0.01
2 nd lactation ⁴	1 st lactation ⁴	2.3	2.0 to 2.5	< 0.01
2 nd lactation ⁴	3 rd lactation ⁴	5.0	4.5 to 5.6	< 0.01
4+ lactations ⁴	1 st lactation ⁴	3.7	3.3 to 4.2	< 0.01
4+ lactations ⁴	2 nd lactation ⁴	1.7	1.5 to 1.8	< 0.01
4+ lactations ⁴	3 rd lactation ⁴	3.1	2.9 to 3.3	< 0.01
Fresh ⁵	Early ⁵	1.6	1.3 to 1.9	< 0.01
Fresh ⁵	Mid ⁵	2.5	2.1 to 2.9	< 0.01
Fresh ⁵	Late ⁵	2.5	2.1 to 3.0	< 0.01
Early ⁵	Mid ⁵	1.6	1.5 to 1.7	< 0.01
Early ⁵	Late ⁵	1.6	1.5 to 1.8	< 0.01
Milk production*, kg		0.9	0.9 to 0.9	< 0.01
Milk protein*, %		2.0	1.7 to 2.4	< 0.01
Milkings*, #/d		0.7	0.6 to 0.7	< 0.01
Refusal*, #/d		0.9	0.9 to 0.9	< 0.01
Failure*, #/d		2.2	1.1 to 1.4	< 0.01
LFConductivity*, mS		0.9	0.9 to 0.9	< 0.01
LRConductivity*, mS		0.9	0.9 to 0.9	< 0.01
RFConductivity*, mS		0.9	0.9 to 0.9	< 0.01
RRConductivity*, mS		1.0	1.0 to 1.0	< 0.01
Milk speed*, s		0.9	0.9 to 0.9	< 0.01
Feed intake*, kg		0.8	0.8 to 0.9	< 0.01
Milk time*, s		1.0	1.0 to 1.0	< 0.01

¹Confidence intervals (CI) overlapping the null value (Odds Ratio = 1) were not reported.

²Fetch status was categorized by EverFetch (cow on the fetch list at least once during the study) and NeverFetch (cow never on the fetch list during the study).

³The system was grouped into the old (PCDART) and new (DairyComp).

⁴The parity category grouped lactations into 1st lactation, 2nd lactation, 3rd lactations, and 4+ lactations.

⁵DIM group sections were ≤ 25 DIM (fresh), > 25 and ≤ 86 DIM (early), > 86 and < 214 DIM (mid), and ≥ 214 DIM (late).

Table 2.8. Odds ratios and 95% confidence intervals for automatic milking system

(AMS) variables, parity, events, weekday, and system based on fetch outcome for fresh model. Variables marked with * indicate continuous variables.

Categorization and risk factor	Reference Group	Odds Ratio	95% CI ¹	P-Value
True Fetch vs No Fetch Required				
PCDART ²	DairyComp ²	3.2	1.7 to 6.1	0.01
1 st lactation ³	3 rd lactation ³	16.9	6.0 to 47.4	< 0.01
2 nd lactation ³	3 rd lactation ³	6.1	2.3 to 15.9	< 0.01
Milk protein*, %		0.2	0.01 to 0.7	< 0.01
Milkings*, #/d		1.7	1.4 to 1.9	< 0.01
Daily max temperature*, °C		0.6	0.4 to 0.8	< 0.01
Feed intake*, kg		0.6	0.5 to 0.7	< 0.01
Refusals*, #/d		0.7	0.6 to 0.8	< 0.01
LR Conductivity*, mS		0.9	0.9 to 0.9	0.01
Milk fat*, %		0.9	1.4 to 2.2	< 0.01
True Fetch vs False Fetch				
1 st lactation ³	3 rd lactation ³	0.3	0.1 to 0.5	< 0.01
2 nd lactation ³	3 rd lactation ³	0.4	0.2 to 0.7	< 0.01
Health category ⁴		0.2	0.1 to 0.4	< 0.01
Milk protein*, %		0.3	0.1 to 0.8	< 0.01
Milkings*, #/d		1.1	1.0 to 1.3	< 0.01
LR Conductivity*, mS		1.0	1.0 to 1.1	< 0.01
Milk fat*, %		0.8	0.6 to 0.9	< 0.01
False Fetch vs No Fetch Required				
PCDART ²	DairyComp ²	3.1	1.4 to 6.6	0.01
3 rd lactation ³	4 th lactation ³	0.2	0.1 to 0.9	< 0.01
Health category ⁴		0.2	0.1 to 0.4	< 0.01
Milk protein*, %		0.2	0.03 to 0.5	< 0.01
Milkings*, #/d		1.6	1.4 to 1.9	< 0.01
Daily max temperature*, °C		0.5	0.3 to 0.9	< 0.01
Feed intake*, kg		0.7	0.6 to 0.8	< 0.01
Refusals*, #/d		0.7	0.6 to 0.8	< 0.01

¹Confidence interval overlapping the null value (Odds Ratio = 1) were not reported.

²The system was grouped into the old (PCDART) and new (DairyComp).

³The parity category grouped lactations into 1st lactation, 2nd lactation, 3rd lactation, and 4+ lactation. Parity was not significant amongst 2nd lactation and 3+ lactation.

⁴Events were divided into no events, reproduction events, general health events, and scheduled health events.

Table 2.9. Odds ratios and 95% confidence intervals for automatic milking system

(AMS) variables, parity, events, weekday, and system based on fetch outcome for the early model. Variables marked with * indicate continuous variables.

Categorization and risk factor	Reference Group	Odds Ratio	95% CI ¹	P-Value
True Fetch vs No Fetch Required				
Milk production*, kg		0.9	0.9 to 0.9	< 0.01
Milkings*, #/d		2.2	1.6 to 3.0	< 0.01
Failure*, #/d		2.9	1.9 to 4.5	< 0.01
Milk speed*, s		1.1	1.0 to 1.2	0.02
Feed intake*, kg		0.5	0.4 to 0.5	< 0.01
Refusal*, #/d		0.6	0.5 to 0.7	< 0.01
Milk time*, s		1.0	1.0 to 1.0	0.004
True Fetch vs False Fetch				
Milkings*, #/d		0.6	0.4 to 0.9	< 0.01
Daily max temperature*, °C		0.7	0.5 to 0.9	0.02
Feed intake*, kg		1.2	1.0 to 1.5	< 0.01
Refusal*, #/d		1.4	1.1 to 1.8	< 0.01
LR Conductivity*, mS		1.0	1.0 to 1.0	0.003
False Fetch vs No Fetch Required				
Failure*, #/d		2.4	1.4 to 4.1	< 0.01
Daily max temperature*, °C		0.7	0.6 to 0.9	0.02
Feed intake*, kg		0.7	0.5 to 0.9	< 0.01

¹Confidence interval overlapping the null value (odds ratio = 1) were not reported.

Table 2.10. Odds ratios and 95% confidence intervals for automatic milking system (AMS) variables, parity, events, weekday, and system based on fetch outcome for the mid model. Variables marked with * indicate continuous variables.

Categorization and risk factor	Reference Group	Odds Ratio	95% CI ¹	P-Value
True Fetch vs No Fetch Required				
Milk production*, kg		0.9	0.9 to 0.9	< 0.01
Milkings*, #/d		0.1	0.1 to 0.2	< 0.01
Refusal*, #/d		0.8	0.7 to 0.9	0.01
Milk speed*, s		1.1	1.1 to 1.2	< 0.01
Feed intake*, kg		1.3	1.1 to 1.6	0.01
Milk time*, s		1.0	1.0 to 1.0	< 0.01
True Fetch vs False Fetch				
Milk production*, kg		1.1	1.1 to 1.1	< 0.01
Daily max temperature*, °C		0.7	0.5 to 0.8	0.02
Refusal*, #/d		1.3	1.1 to 1.4	< 0.01
False Fetch vs No Fetch Required				
Milk production*, kg		0.9	0.9 to 0.9	< 0.01
Milkings*, #/d		0.1	0.1 to 0.1	< 0.01
Milk speed*, s		1.1	1.0 to 1.2	< 0.01
Daily max temperature*, °C		0.7	0.6 to 0.9	0.001
Milk time*, s		1.0	1.0 to 1.0	< 0.01

¹Confidence interval overlapping the null value (odds ratio = 1) were not reported.

Table 2.11. Odds ratios and 95% confidence intervals for automatic milking system (AMS) variables, parity, events, weekday, and system based on fetch outcome for the late model. Variables marked with * indicate continuous variables.

Categorization and risk factor	Reference Group	Odds Ratio	95% CI ¹	P-Value
True Fetch vs No Fetch Required				
PCDART ²	DairyComp ²	0.4	0.3 to 0.5	< 0.01
3 rd lactation ³	1 st lactation ³	0.3	0.1 to 0.6	< 0.01
3 rd lactation ³	4+ lactation ³	2.0	1.2 to 3.6	< 0.01
Health category ⁴		1.7	1.2 to 2.4	0.02
Milk production*, kg		0.9	0.9 to 0.9	< 0.01
Milkings*, #/d		0.3	0.2 to 0.3	< 0.01
Refusal*, #/d		0.8	0.8 to 0.9	< 0.01
Failure*, #/d		3.2	2.5 to 4.5	< 0.01
Daily max temperature*, °C		1.4	1.2 to 1.8	< 0.01
True Fetch vs False Fetch				
Milkings*, #/d		0.6	0.5 to 0.9	< 0.01
Daily max temperature*, °C		0.7	0.6 to 0.9	< 0.01
Refusal*, #/d		1.2	1.0 to 1.3	< 0.01
False Fetch vs No Fetch Required				
PCDART ²	DairyComp ²	0.4	0.2 to 0.5	< 0.01
Milk production*, kg		0.9	0.9 to 0.9	< 0.01
Refusal*, #/d		0.9	0.8 to 0.9	< 0.01
Failure*, #/d		3.1	2.3 to 4.2	< 0.01

¹Confidence interval overlapping the null value (Odds Ratio = 1) were not reported.

²The system was grouped into the old (PCDART) and new (DairyComp).

³The parity category grouped lactations into 1st lactation, 2nd lactation, 3rd lactation, and 4+ lactation. Parity was not significant amongst 2nd lactation and 3+ lactation.

⁴Events were divided into no events, reproduction events, general health events, and scheduled health events.

CHAPTER III
AUTOMATIC MILKING SYSTEM DECISION SUPPORT TOOL
FOR SOUTHERN DAIRY BUSINESSES

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Abstract

Decision support tools have provided end-users with options for decision-making under different scenarios. The objective of this decision tool was for Southeastern USA producers considering an automatic milking system (**AMS**) to input their information and determine AMS investment impact. Data were sourced from sixty-two farm observations across Tennessee, Kentucky, and North Carolina through the University of Tennessee Dairy Gauge Program (2021 and 2022). Median data across years included farm incomes and expenses. Investment in AMS was modeled to determine net present value (**NPV**), internal rate of return (**IRR**), and payback period (**PP**). Three sensitivity analyses were done as a research baseline of three construction styles (retrofitting, add-on, and a new construction barn) that contained a minimum, mean, and maximum labor increase (0.0, 0.075, and 0.15 percent, respectively) with a 20-year loan and a 50% down payment. Three additional sensitivity analyses were examined as an industry perspective of the three construction styles with a 7-year loan for the AMS and a 10-year loan for the facilities with a 0% down payment and a minimum, mean, and maximum labor increase (0.0, 0.05, and 0.10 percent, respectively). Across all mean scenarios, retrofitting was the most profitable construction style. However, the mean NPV and IRR across all 62 sub-scenarios were positive. The research perspective models were most favorable when farms purchased 4 to 8 AMS while the industry perspective models had greater economic return with 6 to 7 AMS were purchased. Between baseline scenarios, research

consistently had a greater NPV across construction style relative to industry. In most Southeast dairy scenarios, AMS investment positively impacted financial indicators.

Introduction

Over the last decade, the decline of the dairy industry has taken an economic toll on small and large dairy producers. Dairy cattle numbers decreased from 21.9 million in 1950 to 9.2 million in 2000, a 58% decrease (Wolf, 2003). Tennessee alone has had a 36% decline in the dairy farms over the past five years (Strasser, 2023). Increased costs (labor, feed, etc.) and decreased fluid milk demand (Mosheim and Lovell, 2009, Nehring et al., 2009) contributed to decreased dairy farm numbers. The threat of small farms leaving due to large-scale operations was also a concern (Nehring et al., 2009). Between 1993 and 2012, total number of farms with ≤ 100 cows decreased dramatically ($> 75\%$) (Dong et al., 2016). Many producers viewed automatic milking systems (**AMS**) as a way to combat challenges on the farm and provide a more comfortable lifestyle.

Automatic Milking System Economics

Automatic milking systems were meant to reduce labor costs and increase profit during their production use; however, the initial investments in the AMS were costly. In 2002, an AMS cost \$192,056 (Hyde and Engel, 2002). In 2017, for a 120-cow confinement operation, the AMS investment cost $\$375,000 \pm \$46,000$ (for two units; Table 3.1; Salfer et al., 2017). In 2022, the construction cost was a mean of \$400,000 per AMS, the installation cost was a mean of \$250,000 per AMS unit, and the AMS itself was a cost of \$250,000 per AMS unit (Palmer, 2022). Over time, investment costs have risen with inflation and rapid demand growth. As of 2016, over 35,000 AMS were in operations worldwide, which was an 8% increase in sales from 2013 to 2014 with the

payback period for the AMS a mean of seven to ten years (Schulte and Tranel, 2013, Kimpel, 2016). In 2018, Iowa State University completed a partial budget for a 216-cow herd. This budget consisted of installing three AMS for \$250,000 per unit including AMS housing. They came to a \$7,000 yearly maintenance cost per AMS. The expected usefulness of each AMS was around 15 years, and it was expected that each could be resold for ~\$35,000 after the completion of the useful life (Tranel, 2018).

Decision Modeling Automatic Milking System Economics

Decision support systems were tools that supplied users with options for decision-making under different scenarios (Gargiulo et al., 2022). Most decision tools included three elements: the data, a model that helps to understand how a real-world system operates, and a user interface that facilitates the interaction between the tool and the end user (Gargiulo et al., 2022). Previous studies have used decision support tools to look at parlor layout, milking time, calving pattern, and number of milking stalls (Cooper and Parsons, 1999); herd size, the number of AMS, milk yield, and total labor (Gargiulo et al., 2022); and parlor price, milk price, useful life for AMS (years), feed cost (\$ per 45.4 kg) maintenance cost (\$ per year), depreciation, tax rate, salvage value, and discount rate (Hyde and Engel, 2002). Cooper and Parsons (1999) decision tool identified the optimal number of hours the AMS was available for milking was 21 hours per day. The profitability of the AMS on these farms related to current systems varied widely from farm to farm up to \$7,478.94 per year with the AMS open for 21 hours per day (Cooper and Parsons, 1999). The study found that the hours of an open AMS were important for the operation efficiency of the AMS (Cooper and Parsons, 1999). Galindo et al. (2000)

determined that decision support tools could be accurate. The physical performance model showed only a 2 to 8% difference between observed versus predicted values and proved to be highly correct when they tested predictive outcomes and current outcome of AMS farms (Galindo et al., 2000). This study showed these decision support tools were accurate when comparing simulations to industry data. Hyde and Engel (2002) decision tool concluded breakeven information regarding labor costs, milk production, parlor costs, and useful life of the AMS. Hyde and Engel found that the mean breakeven value (in 2002) for an AMS was \$125,000 to \$150,000 per AMS (Hyde and Engel, 2002). Each added dollar in labor costs increased the breakeven by \$4.10 to \$4.30. Greater milk production lowered the breakeven value by \$9.91 to \$10.64 per kg per unit. Increasing parlor costs by one dollar increased breakeven between \$0.45 and \$0.56. For each additional year of life from the AMS, breakeven decreased between \$5,000 to \$6,000.

Hypothesis

The objective of this study's decision tool was for Southeastern producers considering an automatic milking system (**AMS**) to input their information and determine AMS investment impact. Specifically, this study tested the ability of the decision tool and compared research outcomes versus industry perspective for AMS. We hypothesized that decreased construction costs, increased milk production, labor savings, and useful life contributed to greater net present value. Moderate herd size, loan rates, and concentrate feeds will be associated with greater net present values. Additionally, the construction type will impact the net present values and reveal preferred scenarios for producers.

Materials and Methods

Data were sourced from 62 dairy farms across Tennessee, Kentucky, and North Carolina through the University of Tennessee Dairy Gauge Program (2021 and 2022). Median data across years included farm incomes and expenses, such as milk production, feed, and labor costs, hauling, and veterinary expenses. Investment in AMS was modeled to determine the net present value (**NPV**), internal rate of return (**IRR**), and payback period (**PP**). Net present value is the total value of an investment opportunity and shows the profitability of the investment. A higher NPV equals a better investment. Internal rate of return is the discount rate that makes NPV of all cash flow equal zero and is the expected future annual cash flow. A positive IRR is a sign of a good investment. The payback period is the time (in years) it takes to recover the cost of the investment. A total of six scenarios were run to find the best outcome for NPV from all 62 farm observations through stochastic simulation via Simetar (College Station, TX) in Excel (Redmond, WA) as followed: 1) research baseline retrofitted barn, 2) research baseline add-on to the current barn, 3) a research baseline new constructed barn, 4) industry perspective retrofitted barn, 5) industry perspective add-on to the current barn, and 6) an industry perspective new constructed barn.

Scenarios

- 1) Scenario one (research retrofit) considered the construction costs of a retrofitted barn that incorporated a minimum, mean, and maximum labor increase (0.0, 0.075, and 0.15 percent, respectively) with a 20-year loan and 50% down payment for both the AMS unit and facility cost. Retrofitted construction was defined as updating a current barn with the AMS technology.

- 2) Scenario two (research add-on) considered the construction costs of an add-on barn that incorporated a minimum, mean, and maximum labor increase (0.0, 0.075, and 0.15 percent, respectively) with a 20-year loan and 50% down payment for both the AMS unit and facility cost. Added-on construction was defined as adding a shed-like structure (which held the AMS) to the side of the current barn.
- 3) Scenario three (research new barn) considered the construction costs of a new barn that incorporated a minimum, mean, and maximum labor increase (0.0, 0.075, and 0.15 percent, respectively) with a 20-year loan and 50% down payment for both the AMS unit and facility cost. A brand-new barn construction was defined as a barn that was not in existence before the installation of the automatic milking systems.
- 4) Scenario four (industry retrofit) considered the construction costs of a retrofitted barn that incorporated a minimum, mean, and maximum labor increase (0.0, 0.05, and 0.1 percent, respectively) with a 7-year loan for the AMS, a 10-year loan for the facility cost, and a 0% down payment for both.
- 5) Scenario five (industry add-on) considered the construction costs of an add-on barn that incorporated a minimum, mean, and maximum labor increase (0.0, 0.05, and 0.1 percent, respectively) with a 7-year loan for the AMS, a 10-year loan for the facility cost, and a 0% down payment for both.
- 6) Scenario six (industry new barn) considered the construction costs of a new barn that incorporated a minimum, mean, and maximum labor increase (0.0, 0.05, and

0.1 percent, respectively) with a 7-year loan for the AMS, a 10-year loan for the facility cost, and a 0% down payment for both.

Construction Scenario

The prices set for each construction scenario came from personal communication with AMS specialists, Tennessee economist, and current AMS producers. The calculated construction cost for a retrofitted barn was \$200,000 per AMS unit, \$400,000 per AMS unit for an add-on to a current barn, and \$800,000 per AMS unit for a new construction. The installation cost was \$250,000 per AMS unit and a discounted rate of \$150,000 for every additional AMS unit (i.e., 4 AMS equaled \$250,000 + 3 AMS (\$150,000) = \$700,000 for total installation only). The AMS unit had a fixed purchase cost of \$250,000 per unit (Table 3.1). Automatic milking system unit cost had a separate location in the decision tool for user input ease. The calculations below were used to determine the construction cost with the installation cost (not including the AMS unit):

$$\text{Equation 3.1. Retrofitted Scenario: } (\$200,000 \times (\# \text{ of AMS})) + \$250,000 + (\$150,000 \times (\# \text{ of AMS} - 1))$$

$$\text{Equation 3.2. Add-On Scenario: } (\$400,000 \times (\# \text{ of AMS})) + \$250,000 + (\$150,000 \times (\# \text{ of AMS} - 1))$$

$$\text{Equation 3.3. New Barn: } (\$800,000 \times (\# \text{ of AMS})) + \$250,000 + (\$150,000 \times (\# \text{ of AMS} - 1))$$

Default Variables for All Scenarios

A total of twenty-three variables were available for data input within the decision support tool (Figure 3.1). Portions of the decision tool were presented in Figure 3.1 and

Figure 3.2. The constant variables were found from the Dairy Gauge or other data sources (Table 3.2) NPV discount Rate; loan interest rate; AMS salvage value (Hyde and Engel, 2002), cost/AMS (Lely, 2023), AMS useful life (Hyde and Engel, 2002), insurance rate per \$1,000 value, tax rate (Tennessee Tax), repair cost per AMS/year (Hyde and Engel, 2002), software value/cow/year, utilities/cow/year, facility useful life (Hyde and Engel, 2002), and facility salvage value.

Monte Carlo simulation through Simetar in Excel was used to determine realistic scenario outcomes for the Southern dairy industry. Minimum and maximum endpoints from Dairy Gauge or other sources (Table 3.3) milk production (12.5 and 37.0 kg/cow/day), milk price/CWT (Livestock Marketing Information Center, 2023), purchased feed (\$3.38 and \$13.92/CWT), raised feed (\$0 and \$10.82/CWT), labor rate (\$0 and \$1,123.29/cow/year), herd size (60/AMS unit; Lely, 2023), number of AMS (1 thought 12), and facility costs (calculated above) were used as model inputs across all scenarios.

Milk Production

Milk production and feed cost (purchased and raised) had a positive correlation; therefore, the decision tool was coded that simulations with high milk production had high feed cost and vice versa. The decision tool for this scenario was programmed so that when one of the two variables increased, the decision tool would randomly generate increased number for the other variable. The random numbers for feed costs came from Dairy Gauge. An additional 1.04 kg of milk was added to each year to simulate genetic milk production increases. The additional 1.04 kg of increased genetic milk production

came from 2003 to 2023 PCDART (Dairy Records Management Systems, Raleigh, NC USA) records from the University of Tennessee Little River Dairy Herd.

Milk Price

Milk price was modeled using simulation with multi-variable empirical distribution. Data came from mean milk prices in Florida, Georgia, and Virginia from January 2019 to February 2023 from the Livestock Marketing Information Center (LMIC, 2023). Milk prices were modeled as multivariate empirical for realistic revenue additions and milk price fluctuations.

Purchased and Raised Feed Cost

Feed cost was broken down into two categories: purchased feed and raised feed. Purchased feed was bought forage or grain that was ready for storage or consumption. Raised feed was forage or grain that was produced on the farm or from the producer on different land. Purchased and raised feed cost models were run using stochastic simulations with Simetar in Excel using all 62 farm observations from Dairy Gauge with endpoints at the minimum (\$3.38, \$0 per CWT for purchased and raised feed, respectively) and maximum (\$13.92, \$10.82 per CWT for purchased and raised feed, respectively) values with simulations being skewed towards the mean (\$8.76, \$2.87 per CWT for purchased and raised feed, respectively) and median (\$8.72, \$2.83 per CWT for purchased and raised feed respectively).

Labor Rate

Labor rate was calculated using simulation with multi-variable empirical distribution using all 62 farm observations from Dairy Gauge. The endpoints were set at

\$0 per cow to \$1,123.29 with a mean of \$532 per cow per year. Labor rate was determined by the total cost per cow per year.

Herd Size and Number of Automatic Milking Systems

Herd size and the number of AMS were based in Simetar with stochastic simulation in Excel using all 62 farm observations from Dairy Gauge with endpoints at the minimum (60 cows and 1 AMS) and maximum (720 cows and 12 AMS) values with simulations being skewed towards the mean (240 cows and 4 AMS). A large variety of herd sizes was chosen to look at the impact AMS had on small and large dairy farms. The first sub-scenario considered a small operation owning 1 AMS unit with a herd of 60 lactating cows. The second and third sub-scenarios considered 4 AMS units with a herd of 240 lactation cows and 8 AMS units with a herd of 480 lactating cows. Sub-scenario 2 and 3 were the average-sized farm in the Southeast and more of an expected input from producers for this decision tool. The last sub-scenario was a high AMS installation total that was uncommon in the Southeast. However, extreme herd size and AMS number were considered (sub-scenario 1 and 4) to provide information for all Southeastern operations. Milk production and feed cost had a positive correlation with herd size and the number of AMS; therefore, when the herd size increased so did the milk production and feed cost and vice versa. The decision tool was programmed so that when one of the three variables increased, the decision tool would randomly generate increased number for the other two variables. The random numbers for milk production and feed costs came from Dairy Gauge.

Research Baseline and Industry Perception Variable Differentiation

Loan rate, loan year, and labor reduction were the differentiation between the research baseline and industry perception scenarios. The research baseline created scenarios based on AMS data from previous research papers (Schulte and Tranel, 2013, Schewe and Stuart, 2015, Kimpel, 2016, Tse et al., 2018). The industry baseline scenarios modified loan rate, loan years, and increased labor percentage based on discussions with industry representatives familiar with AMS systems in the Southeast (Williams, 2023).

Results

Research Baseline Scenario

The three research analyses (retrofit, add-on, and new construction) were run with stochastic simulation in Simetar across AMS situations (1 to 12 units) for a total of 36 sub-scenarios. Five hundred iterations for each sub-scenarios were calculated to determine NPV (Figure 3.3), IRR (Figure 3.4), and PP (Figure 3.5) across sub-scenarios. Table 3.3 showed the level of NPV preference and determined which scenarios provided the best investment opportunity. Based on research assumptions, a 12-AMS retrofitted barn and a 1-AMS new construction barn had the highest and lowest NPV, respectively.

Retrofit had a mean and standard deviation NPV of \$9,048,854.31 ± \$3,391,413.67 with a minimum of -\$8,759,070.62 and a maximum of \$35,179,776.06 across the 12 scenarios. Add-on had a mean and standard deviation NPV of \$7,789,101.95 ± \$3,394,835.57 with a minimum of -\$11,359,431.35 and a maximum of \$32,673,159.95. New barn had a mean and standard deviation NPV of \$4,966,295.94 ± \$3,405,336.54 with a minimum of -\$16,590,789.10 and a maximum of \$27,659,927.71. All three outcomes increased NPV from 1 AMS to 12 AMS, however retrofit showed the

largest mean and standard deviation variation from 1 AMS (\$1,877,761.97 ± \$711,960.78) to 12 AMS (\$16,219,528.28 ± \$6,171,324.32). Although the NPV increased with the number of robots, the economic risk also increased. Retrofit had the highest mean NPV and was the most preferred scenarios related to NPV (Figure 3.6).

Across AMS units (1 to 12), retrofit construction consistently had the highest, NPV, IRR, and shortest PP compared to new construction or add-on construction (Figure 3.3, 3.4, and 3.5). Retrofit had a mean and standard deviation IRR of 0.30 ± 0.11 across the 12 scenarios. Add-on had a mean and standard deviation IRR of 0.22 ± 0.08 . New barn had a mean and standard deviation IRR of 0.13 ± 0.05 . All three outcomes decreased IRR from 1 AMS to 12 AMS, however new barn showed the lowest mean and standard deviation variation from 1 AMS (0.17 ± 0.07) to 12 AMS (0.12 ± 0.05). Retrofit had the highest IRR mean and therefore was the best construction scenario regarding IRR (Figure 3.7).

Retrofit had a mean and standard deviation PP of 6.82 ± 2.43 years during the 12 scenarios. Add-on had a mean and standard deviation PP of 8.63 ± 2.78 years. New barn had a mean and standard deviation PP of 11.94 ± 3.13 years. All three outcomes increased PP from 1 AMS to 12 AMS and had a variation of around 2 years. Retrofit had the lowest PP mean and therefore was the best construction scenario regarding PP (Figure 3.8).

Retrofit was the most profitable construction style for all three outcomes in the research perspective. However, all 36 sub-scenarios had high NPV and positive IRR. The research perspective results showed that all scenarios were applicable but depending on

the construction style and number of AMS the NPV, IRR, and PP had better results around 4 and 8 AMS.

Industry Perspective Scenario

The three industry perspectives (retrofit, add-on, and new construction) were run with stochastic simulation in Simetar against the number of AMS (1 to 12) yielded a total of 36 sub-scenarios. Each sub-scenarios was run 500 times to find the NPV (Figure 3.9), IRR (Figure 3.10), and PP (Figure 3.11). Table 3.3 showed the level of NPV preference and determined which scenarios provided the best investment opportunity. Results showed that, with industry perceptive input into the decision tool, a 12-AMS retrofitted barn was the most NPV preferred, and a 1-AMS new construction barn was the lowest NPV. A pattern of decreasing AMS numbers was seen in all their scenarios with overlap of 8 AMS or greater.

Across AMS units (1 to 12), retrofit construction consistently had the highest, NPV, IRR, and shortest PP compared to new construction or add-on construction (Figure 3.6, 3.7, and 3.8). Retrofit had a mean and standard deviation NPV of \$4,770,003.95 $\pm$ \$2,771,956.49 during the 12 scenarios. Add-on had a mean and standard deviation NPV of \$3,276,832.74 $\pm$ \$2,776,869.38. New barn had a mean and standard deviation NPV of \$286,259.32 $\pm$ \$2,790,397.54. All three outcomes increased NPV from 1 AMS to 12 AMS, however retrofit showed the largest mean and standard deviation variation from 1 AMS (\$708,062.46 $\pm$ \$432,972.49) to 12 AMS (\$8,831,896.03 $\pm$ \$5,114,909.99). While the NPV increased with the number of robots as did the economic risk. Retrofit had the

highest NPV mean and therefore was the best construction scenario regarding NPV while new barn had the lowest and was the least optimal choice (Figure 3.12).

Retrofit had a mean and standard deviation IRR of 1.04 ± 3.37 during the 12 scenarios. Add-on had a mean and standard deviation IRR of 0.88 ± 5.73 . New barn had a mean and standard deviation IRR of 0.15 ± 0.67 . All three outcomes increased and decreased throughout the increasing of AMS numbers. Retrofit had the highest IRR mean and therefore was the best construction scenario regarding IRR (Figure 3.13).

Retrofit had a mean and standard deviation PP of 7.47 ± 2.64 years during the 12 scenarios. Add-on had a mean and standard deviation PP of 9.37 ± 2.96 years. New barn had a mean and standard deviation PP of 12.79 ± 3.22 years. All three outcomes slightly decreased PP from 1 AMS to 12 AMS. Retrofit had the lowest PP mean and therefore was the best construction scenario regarding PPP (Figure 3.14).

Retrofit was the most profitable construction style for all three outcomes for the industry perspective. However, all 36 sub-scenarios had high NPV and positive IRR. The industry perspective results showed that all scenarios were applicable but depending on the construction style and number of AMS the NPV, IRR, and PP had better results around 6 and 7 AMS.

Comparing Research Baseline and Industry Perspective Scenarios

When compared, the industry perspective indicated retrofitting was a more viable option with the top four most preferred key output variables 8 to 12 number of AMS for a retrofitted barn. While the research baseline saw a higher number of AMS as a more viable option. Retrofitting was the most profitable option across baselines (Table 3.4).

The two perspectives reported different overall preferable outcomes which led to a difference in research and industry results.

Discussion

Construction styles. Across all models, retrofitted barns had the most desirable NPV, IRR, and PP compared to new construction or a barn addition specifically for the AMS. Tremblay et al. (2016) compared construction styles for a new barn to retrofitting a current barn. They found that there was no significant difference between a new barn and a retrofitted barn regarding initial cost. In our study, we modeled a lower overall initial cost associated with initial costs with the lowest being add-on, mid-range cost for retrofitting, and the greatest cost for new construction. Similar to Tremblay et al. (2016), mean responses across retrofit, add-on, and new construction were positive financial investments. However, greater returns were associated with retrofit compared to the other construction styles. This occurred regardless of the total number of AMS units. In applied settings, Siewert et al. (2018) found that 45% of farms in the Upper Midwest United States constructed retrofitted barns. No difference was found with new construction and retrofitted barns in milk production. Siewert et al., (2018) suggested retrofitting improved profitability, which supported our findings.

The decision to build a new barn, add-on, or retrofitted facilities will likely be influenced by other factors such as usability of facilities, labor efficiency, herd size, and building cost (Siewert et al., 2018). Jago and Kerrisk (2011) found that new barn construction often led to increased herd size. Our model did not account for changes in herd size depending on construction style, and the potential to overstock a new barn should be considered. If overstocking occurred, potential negative effects, such as

decreased production per cow (Baratta et al., 2017), could occur and invalidate our results.

While the retrofitted barn construction style showed the most preferred results on paper, it might not be an option in a real-world setting. Barn layout, structural integrity, or space per animal may not meet the needs of AMS barn flow. This may be particularly true if guided flow was used, as guided flow required specific pathways through the resting, feeding, and AMS areas. Therefore, considerations regarding real-world settings are needed.

Salfer et al. (2017) found that the cost of construction was \$7,000 per cow excluding the cost of the AMS. This was higher than our study where our mean cost of construction across all systems was \$6,666 per cow. A two AMS dairy with 120 cows would cost \$840,000 no matter the construction style (Salfer et al., 2017). That disagreed with our study. Our study incorporated additional details across multiple price points for different construction styles while Salfer et al. (2017) looked at construction cost as a whole regardless of construction style.

Labor costs. Labor costs for this study were collected via Dairy Gauge. The endpoints were set at \$0 per cow to \$1,123.29 with a mean of \$532 per cow per year. Labor rate was determined by the total cost per cow per year. The labor rate for the research perspective AMS labor offset incorporated a minimum, mean, and maximum labor increase (0.0, 0.075, and 0.15 percent, respectively). The labor rate for the industry perspective AMS labor offset incorporated a minimum, mean, and maximum labor increase (0.0, 0.05, and 0.1 percent, respectively). Salfer et al. (2017) found the

breakeven labor analysis of a 1,500-cow farm showed the breakeven labor rate was \$27.02/h for AMS investment assuming the labor rate increased 1% and daily milk production decreased by 0.91 kg/d. With similar milk production between the AMS and conventional milking systems, if the labor rate increased by 3% over a 30-yr time horizon, the breakeven labor rate decreased to \$17.11/h (Salfer et al., 2017). Management factors that determined the net annual impact were 1) milking labor cost changes and 2) milk production (Salfer et al., 2017). This supported our study in assuming that AMS had a labor-saving impact. Conversely, Heikkila et al. (2010) reported a decreased profit due to the increased labor salaries. However, the farms that did not experience a labor savings could have been due to other jobs or responsibilities that were being completed rather than working in the parlor.

Loan rate and downpayment. For this study, loan rate and down payment information came from Tennessee AMS loan specialist. The research perspective loan rate was set at a 20-year loan and 50% down payment for both the AMS unit and facility cost. The industry perspective loan rate was set at a 7-year loan for the AMS, a 10-year loan for the facility cost, and a 0% down payment for both. Salfer et al. (2017) used a loan interest rate of 5% for 20-years with the barn and 10-years for the AMS. Their simulations found AMS to be profitable with these loan rates and years (Salfer et al., 2017). Our study found that a mean of 7 to 10 years was needed to pay off the loans. Salfer's study doubled their years to pay back the loan which was not needed with our study. However, our study did report a lower NPV, IRR, and greater PP under industry assumptions. This was likely driven by the lack of downpayment and shorter years to pay

off the loan (7 and 10 yr in industry model compared to 20 yr in research model).

However, even with the larger total loan amounts and shorter loan-term, NPV remained positive on average across all industry models.

Limitations

No decision tool model can be 100% accurate (Bethard, 1997). The goal of an economic simulation is not to provide exact results, but rather to “highlight relative consequences of different strategies” (Lien, 2003). Several assumptions were made that could not be adequately defined in the model. Values that were pulled randomly from reasonable distributions improved model accuracy and allowed our study to report values based on 500 simulations. This meant 500 possible scenarios were run for each sensitivity analysis. Although these changes were based on research and were conservative, real-life situations rarely respond identically to a modeled scenario. Results should be interpreted with this limitation in mind while encouraging producers to input farm-specific values into a deterministic model.

Conclusion

Automatic milking systems are a permanent and expensive investment. This decision tool’s purpose was to aid current and potential Southern dairy producers to find their best AMS financial impact before the investment. The tool was tested using research and industry information. The comparison of the two outcomes differed in results. Retrofitting was most preferred in both outcomes. All 72 sub-scenarios showed a positive NPV with major variability.

Acknowledgements

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Appendix

Table 3.1. Outline for the number of cows, automatic milking systems (AMS) cost, and total construction cost based on the number of AMS.

Number of AMS	Number of Cows	AMS Cost, \$	Retrofitted Cost, \$	Add-on Cost, \$	New Barn Cost, \$
1	60	\$250,000	\$450,000	\$650,000	\$1,050,000
2	120	\$500,000	\$800,000	\$1,200,000	\$2,000,000
3	180	\$750,000	\$1,150,000	\$1,750,000	\$2,950,000
4	240	\$1,000,000	\$1,500,000	\$2,300,000	\$3,900,000
5	300	\$1,250,000	\$1,850,000	\$2,850,000	\$4,850,000
6	360	\$1,500,000	\$2,200,000	\$3,400,000	\$5,800,000
7	420	\$1,750,000	\$2,550,000	\$3,950,000	\$6,750,000
8	480	\$2,000,000	\$2,900,000	\$4,500,000	\$7,700,000
9	540	\$2,250,000	\$3,250,000	\$5,050,000	\$8,650,000
10	600	\$2,500,000	\$5,600,000	\$5,600,000	\$9,600,000
11	660	\$2,750,000	\$6,150,000	\$6,150,000	\$10,550,000
12	720	\$3,000,000	\$6,700,000	\$6,700,000	\$11,500,000

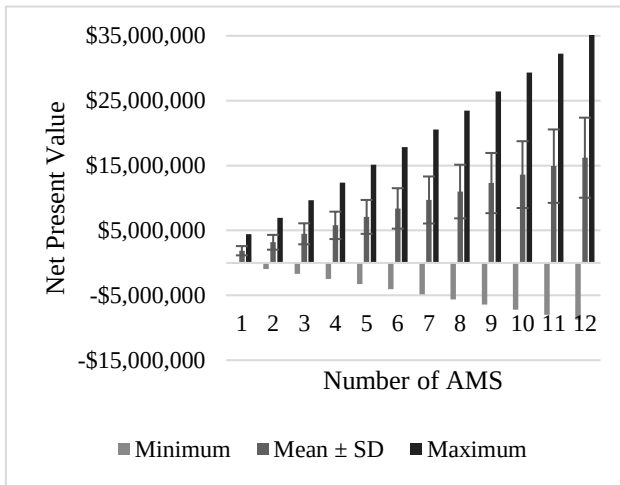
Table 3.2. Constant variables from used in the decision support tool with automatic milking system (**AMS**).

Constant Variables	Unit	Source
NPV discount rate	5%	Tranel, 2018
Loan interest rate	7%	Tranel, 2018
AMS salvage value	\$40,000	Hyde and Engel, 2002
Cost/AMS	\$250,000	Lely, 2023
AMS useful life	15 years	Hyde and Engel, 2002
Insurance rate/\$1,100 value	0.5%	Model Constant
Tax rate	9.25%	Tennessee tax rate
Repair cost/AMS/year	\$7,000	Hyde and Engel, 2002
Software value/cow/year	\$60	Tranel, 2018
Utilities/cow/year	\$6.75	Model Constant
Facility useful life	15 years	Hyde and Engel, 2002
Facility salvage value	15%	Hyde and Engel, 2002

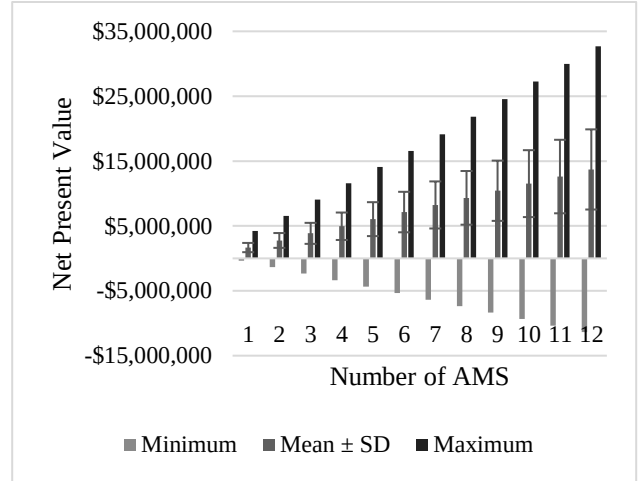
Table 3.3. The minimum, mean, median, and maximum numbers from Dairy Gauge for the stochastic variables with automatic milking system (**AMS**).

Variables	Minimum	Mean	Median	Maximum
Milk production, kg/cow/d	12.5	27.3	28.5	37.0
Purchased feed, \$/CWT	\$3.38	\$8.76	\$8.72	\$13.92
Raised feed, \$/ WT	\$0.00	\$2.87	\$2.83	\$10.82
Herd size, # of cows	60	240	240	720
Number of AMS	1	4	4	12
Facility costs, \$	\$450,000	\$2,300,000	\$2,300,000	\$11,500,000
Labor Rate	\$0.00	\$532	\$533	\$1,123.29
Loan rate, %	0%	50%	50%	100%
Loan years, years	10	15	15	20

a)



b)



c)

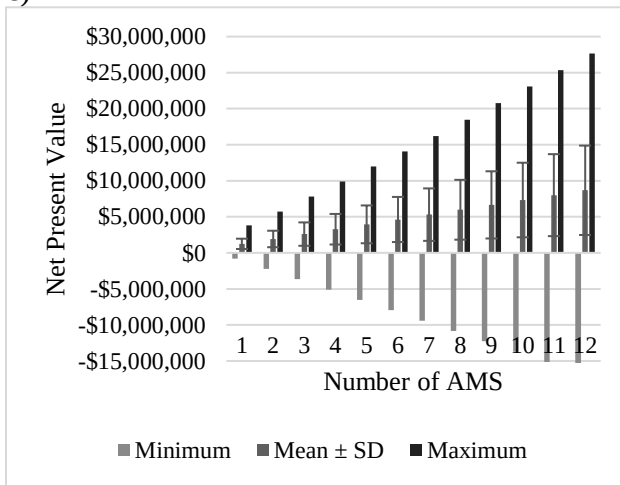


Figure 3.3. Net present value stochastic simulation outcomes based on research assumptions for investment in 1 to 12 automated milking robots across a 20-year investment horizon depending on construction style: a) retrofit construction, b) add-on construction, and c) new construction.

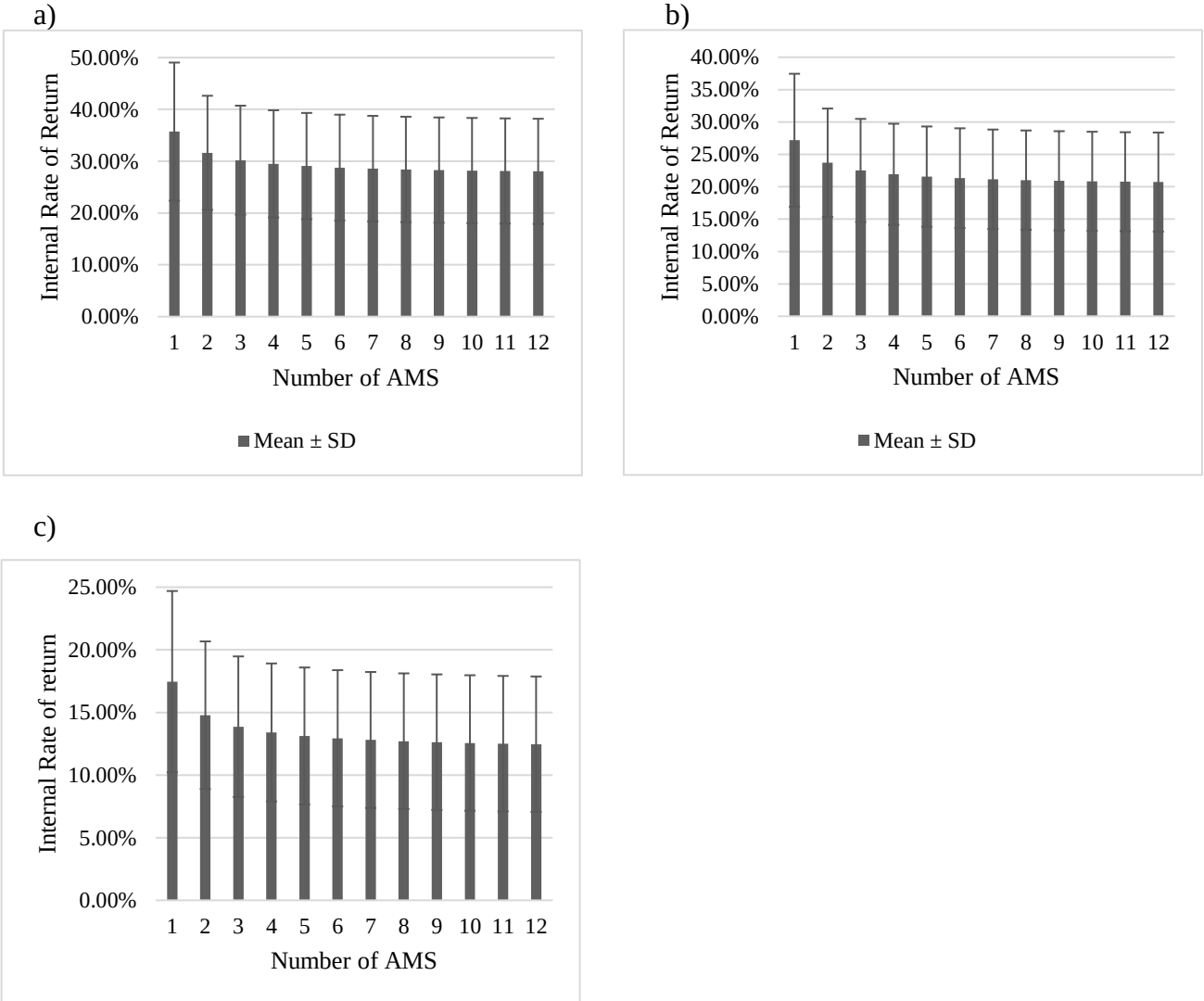


Figure 3.4. Internal rate of return stochastic simulation outcomes based on research assumptions for investment in 1 to 12 automated milking robots across a 20-year investment horizon depending on construction style: a) retrofit construction, b) add-on construction, and c) new construction.

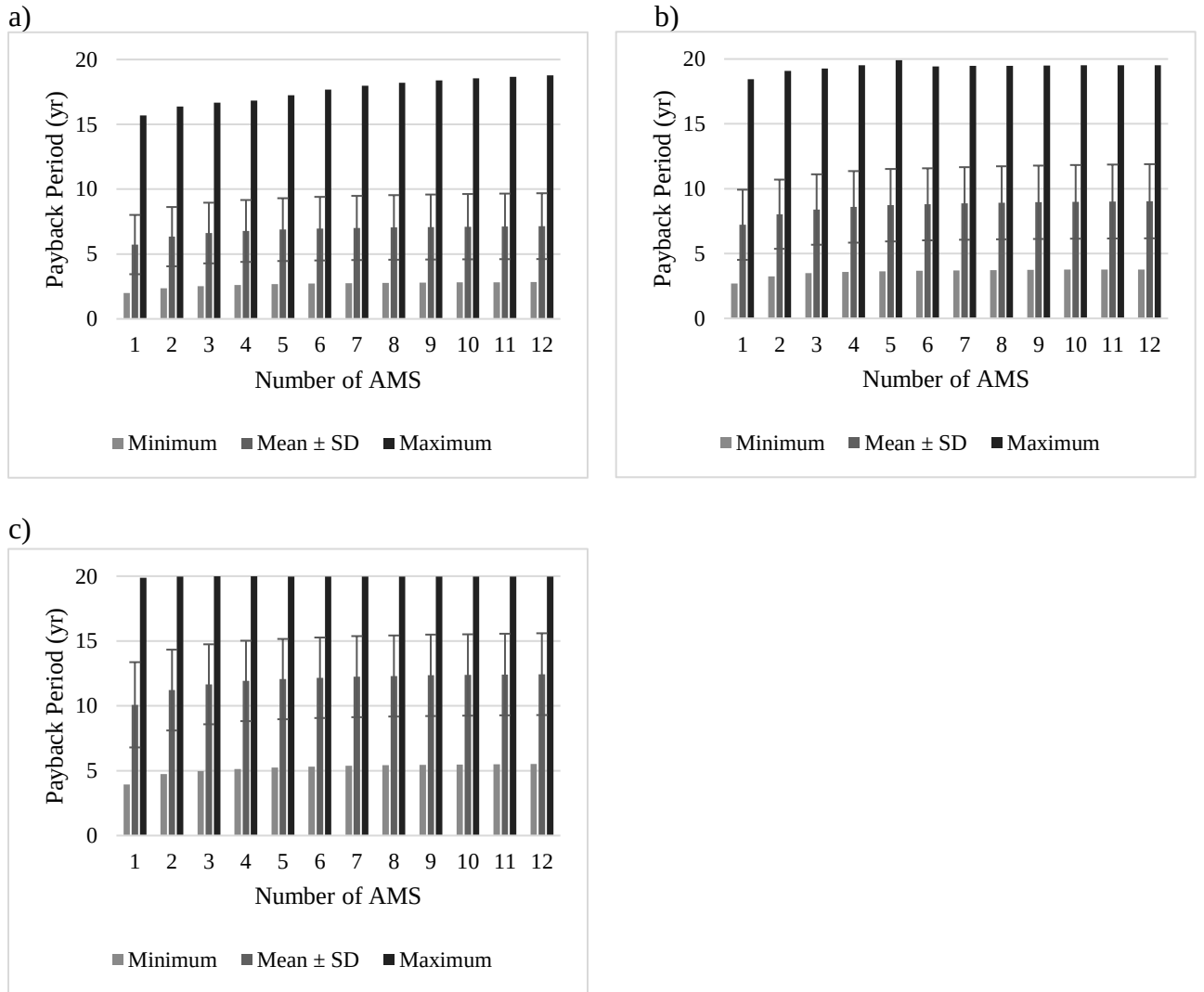


Figure 3.5. Payback period stochastic simulation outcomes based on research assumptions for investment in 1 to 12 automated milking robots across a 20-year investment horizon depending on construction style: a) retrofit construction, b) add-on construction, and c) new construction.

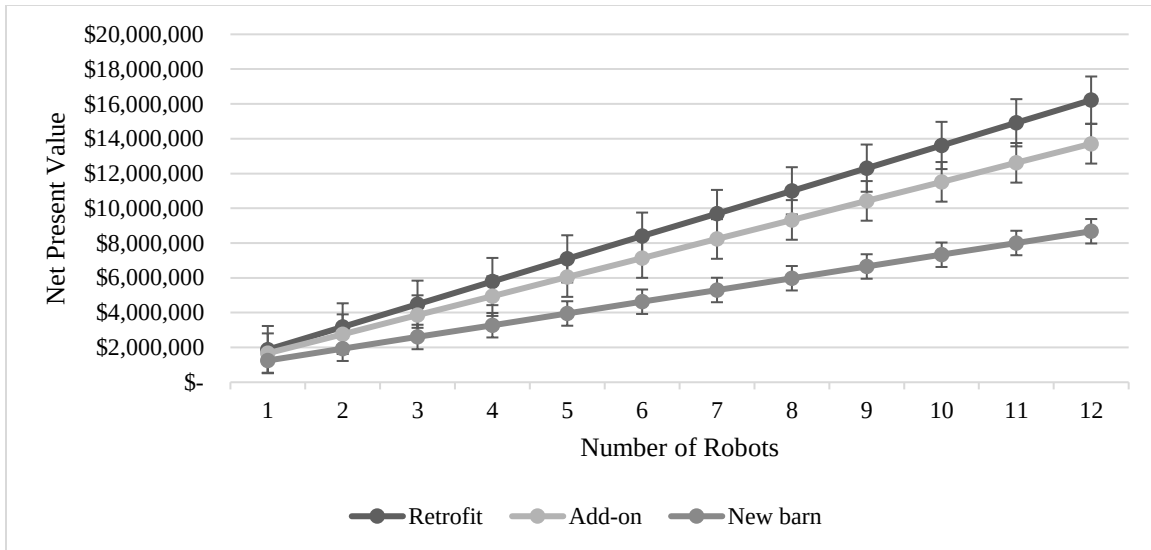


Figure 3.6. Net present value construction scenarios (retrofit, add-on, and new) and number of automatic milking system (**AMS**) under research assumptions.

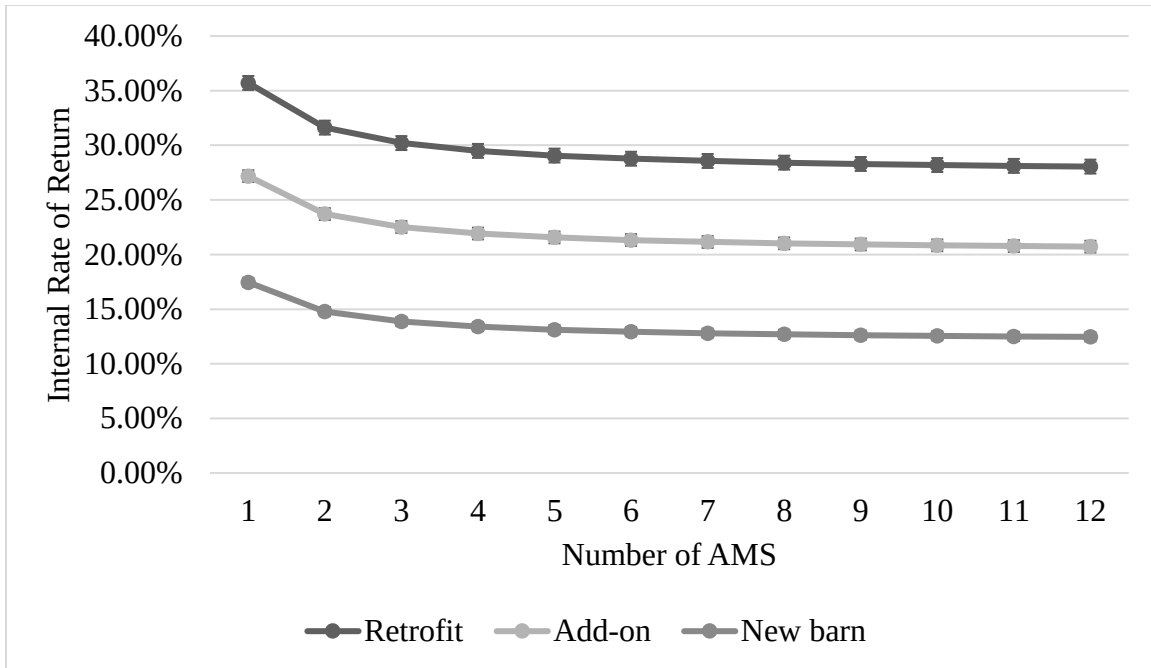


Figure 3.7. Internal rate of return construction scenarios (retrofit, add-on, and new) and number of automatic milking system (**AMS**) under research assumptions.

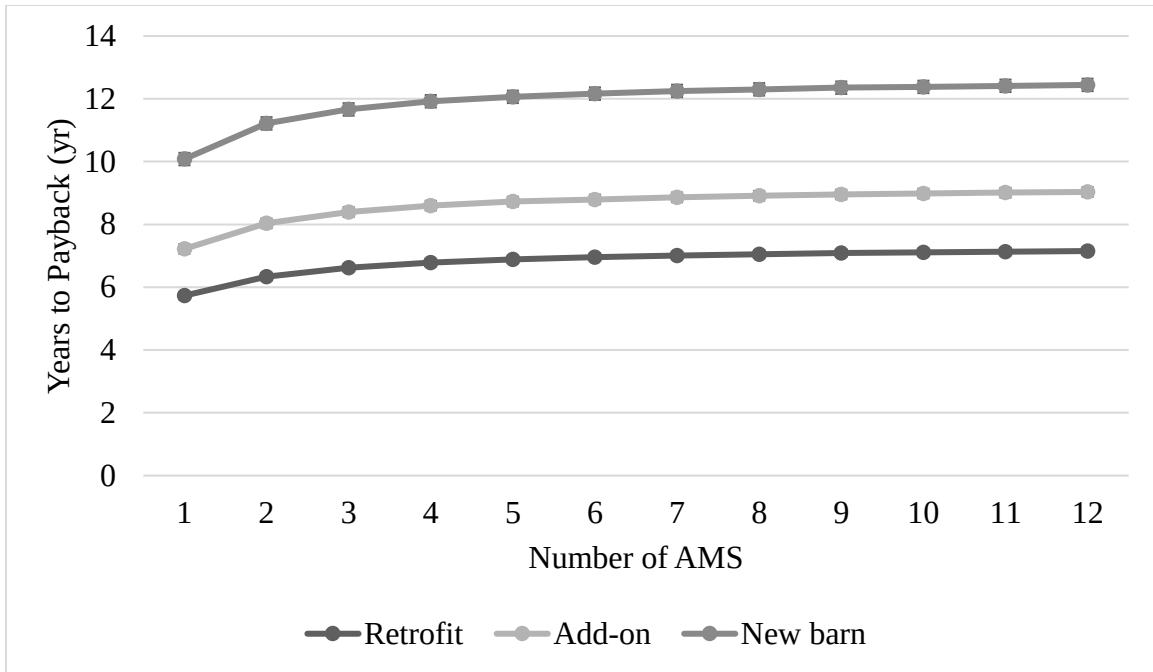


Figure 3.8. Payback period construction scenarios (retrofit, add-on, and new) and number of automatic milking system (AMS) under research assumptions.

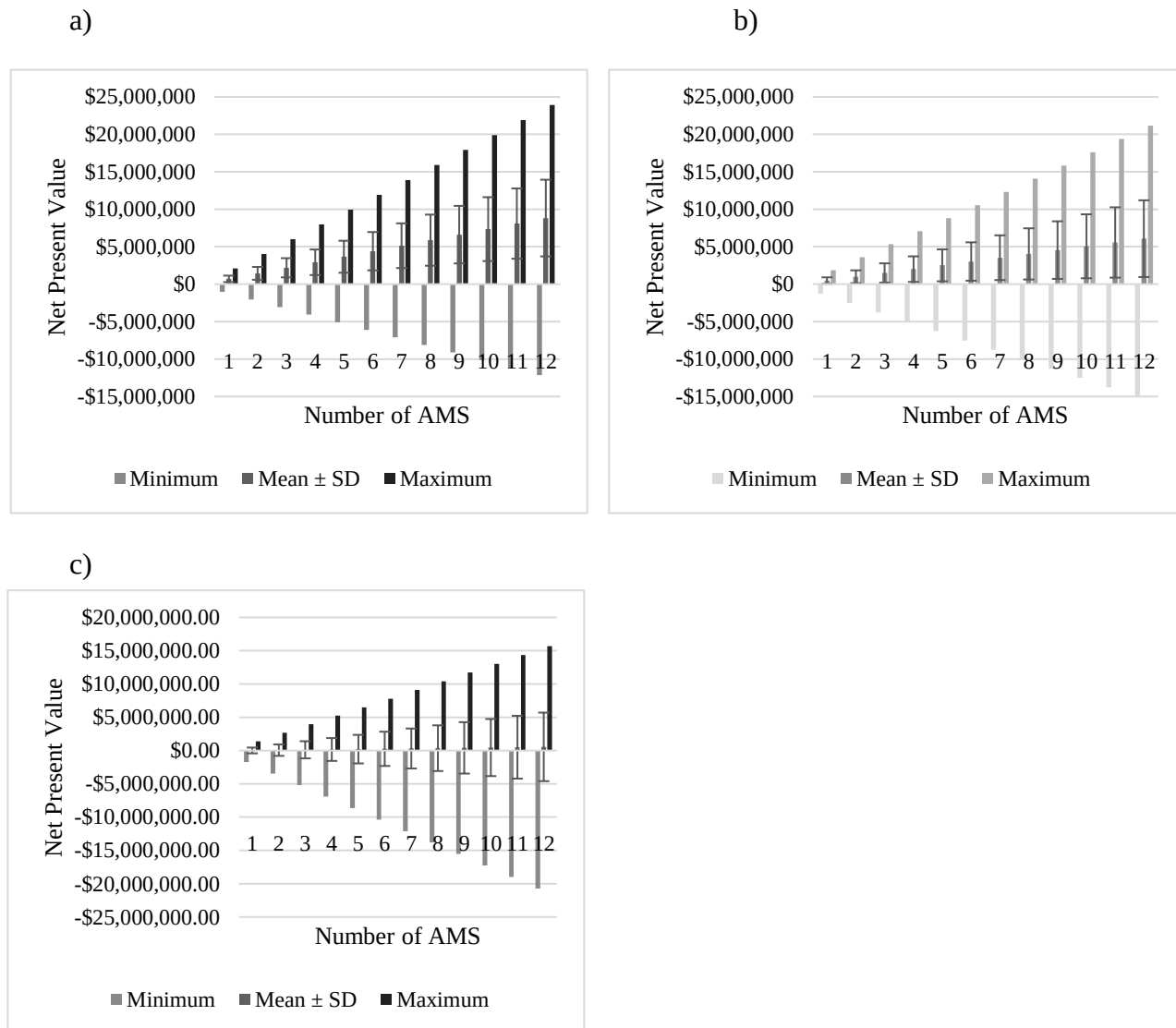


Figure 3.9. Net present value stochastic simulation outcomes based on industry assumptions for investment in 1 to 12 automated milking robots across a 20-year investment horizon depending on construction style: a) retrofit construction, b) add-on construction, and c) new construction.

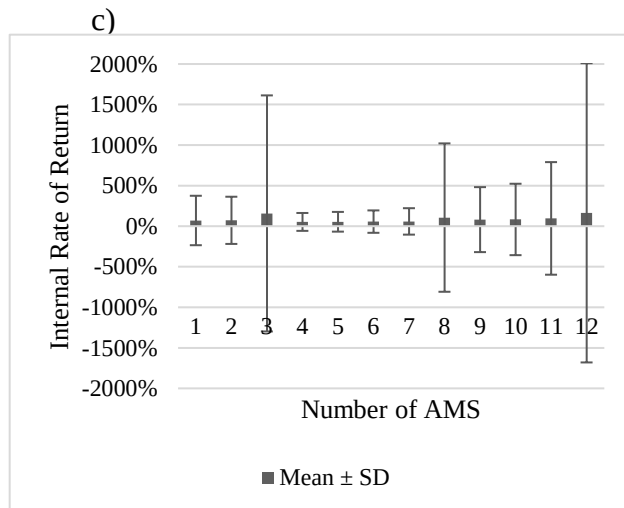
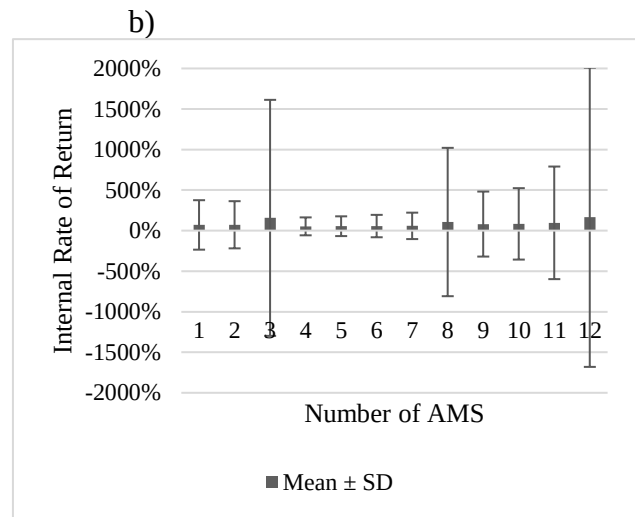
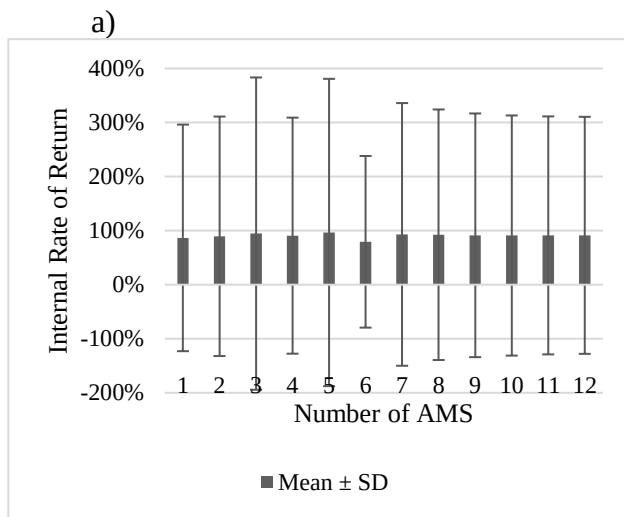


Figure 3.10. Internal rate of return stochastic simulation outcomes based on industry assumptions for investment in 1 to 12 automated milking robots across a 20-year investment horizon depending on construction style: a) retrofit construction, b) add-on construction, and c) new construction.

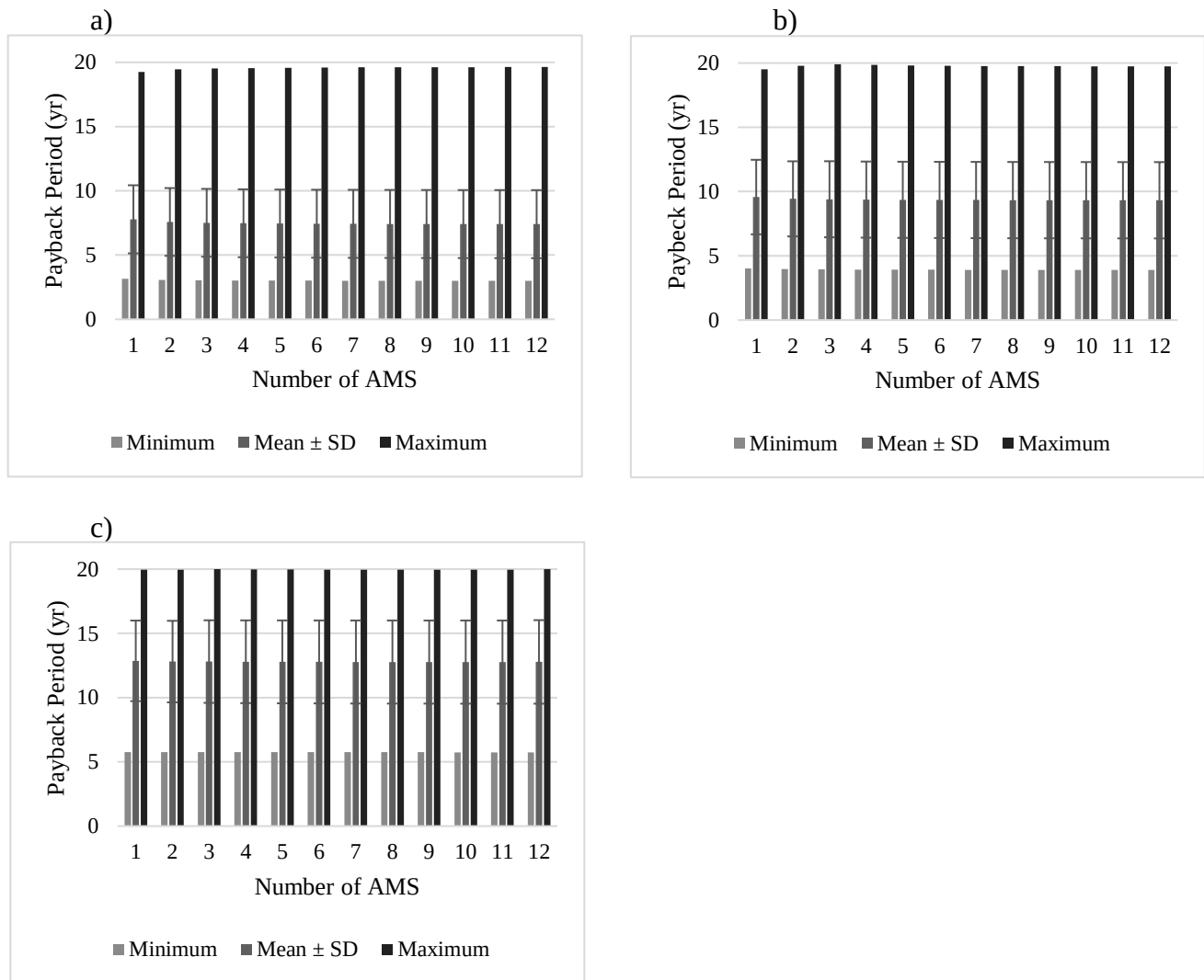


Figure 3.11. Payback period stochastic simulation outcomes based on industry assumptions for investment in 1 to 12 automated milking robots across a 20-year investment horizon depending on construction style: a) retrofit construction, b) add-on construction, and c) new construction.

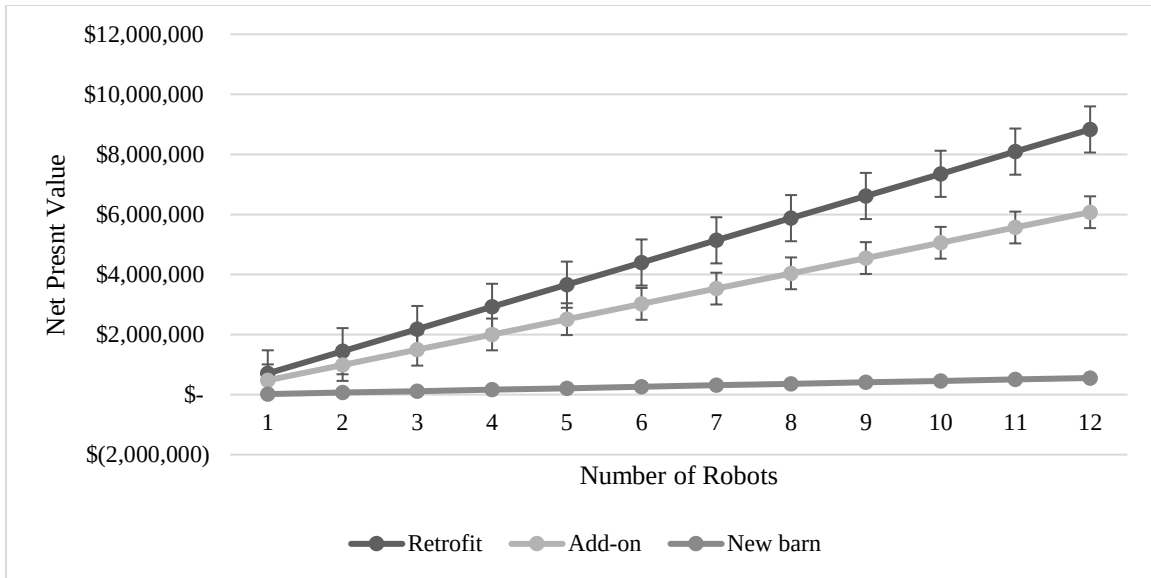


Figure 3.12. Net present value construction scenarios (retrofit, add-on, and new) and number of automatic milking system (AMS) under industry assumptions.

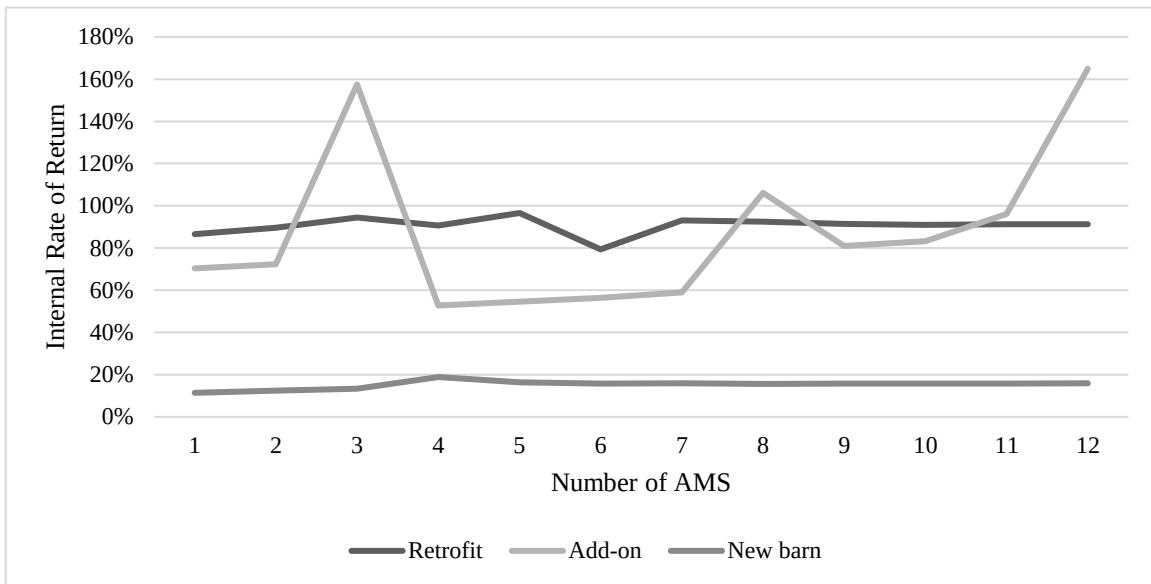


Figure 3.13. Internal rate of return construction scenarios (retrofit, add-on, and new) and number of automatic milking system (**AMS**) under industry assumptions.

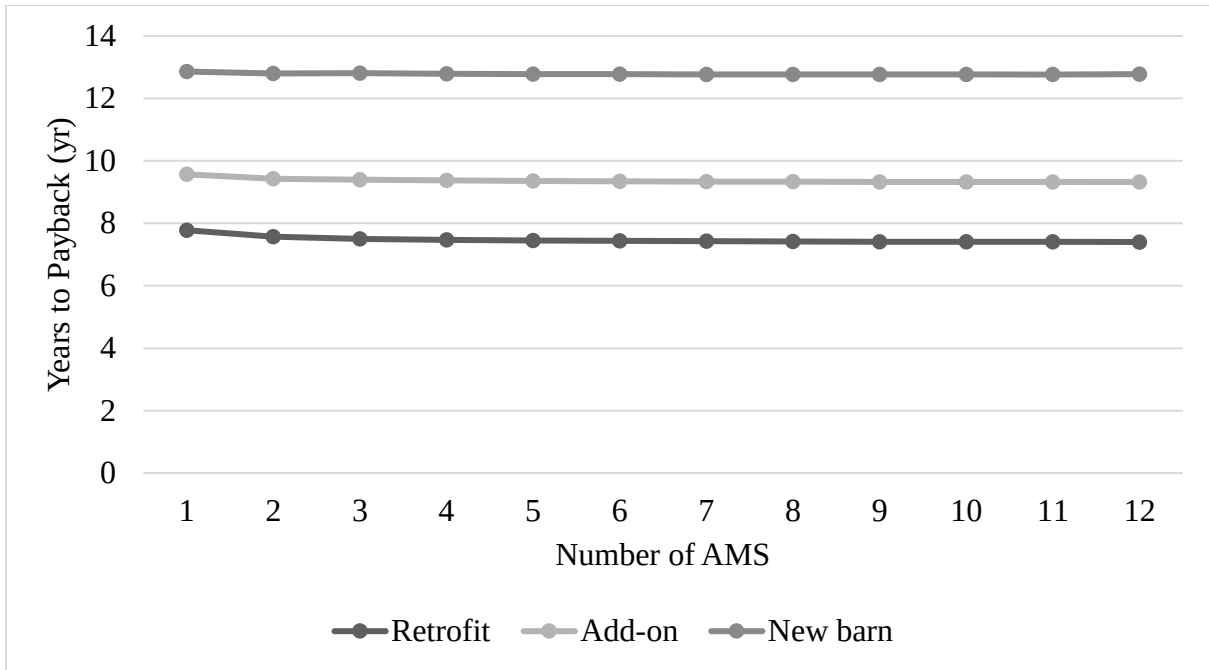


Figure 3.14. Payback period construction scenarios (retrofit, add-on, and new) and number of automatic milking system (**AMS**) under industry assumptions.

Table 3.4. Net present value preferences under research and industry model assumptions.

Research Baseline	Level of Preference	Industry Perspective
12-AMS Retrofit	Most Preferred	12- AMS Retrofit
11-AMS Retrofit	2nd Most Preferred	11- AMS Retrofit
12- AMS Add-On	3rd Most Preferred	10- AMS Retrofit
10- AMS Retrofit	4th Most Preferred	9- AMS Retrofit
11- AMS Add-On	5th Most Preferred	12- AMS Add-On
9- AMS Retrofit	6th Most Preferred	8- AMS Retrofit
10- AMS Add-On	7th Most Preferred	11- AMS Add-On
8- AMS Retrofit	8th Most Preferred	7- AMS Retrofit
9- AMS Add-On	9th Most Preferred	10- AMS Add-On
7- AMS Retrofit	10th Most Preferred	9- AMS Add-On
8- AMS Add-On	11th Most Preferred	6- AMS Retrofit
12- AMS New	12th Most Preferred	8- AMS Add-On
6- AMS Retrofit	13th Most Preferred	5- AMS Retrofit
7- AMS Add-On	14th Most Preferred	7- AMS Add-On
11- AMS New	15th Most Preferred	6- AMS Add-On
10- AMS New	16th Most Preferred	4- AMS Retrofit
6- AMS Add-On	17th Most Preferred	5- AMS Add-On
5- AMS Retrofit	18th Most Preferred	3- AMS Retrofit
9- AMS New	19th Most Preferred	4- AMS Add-On
5- AMS Add-On	20th Most Preferred	3- AMS Add-On
8- AMS New	21st Most Preferred	2- AMS Retrofit
4- AMS Retrofit	22nd Most Preferred	2- AMS Add-On
7- AMS New	23rd Most Preferred	1- AMS Retrofit
4- AMS Add-On	24th Most Preferred	12- AMS New
6- AMS New	25th Most Preferred	11- AMS New
3- AMS Retrofit	26th Most Preferred	1- AMS Add-On
5- AMS New	27th Most Preferred	10- AMS New
3- AMS Add-On	28th Most Preferred	9- AMS New
4- AMS New	29th Most Preferred	8- AMS New
2- AMS Retrofit	30th Most Preferred	7- AMS New
2- AMS Add-On	31st Most Preferred	6- AMS New
3- AMS New	32nd Most Preferred	5- AMS New
2- AMS New	33rd Most Preferred	4- AMS New
1- AMS Retrofit	34th Most Preferred	3- AMS New
1- AMS Add-On	35th Most Preferred	2- AMS New
1- AMS New	Least Preferred	1- AMS New

CHAPTER IV

CONCLUSION

Conclusion

While automatic milking systems were first introduced twenty-three years ago and much research has been conducted, new information is constantly generated. Automatic milking systems research explored milk quality and production, labor savings, nutrition costs, and financial feasibility. Researchers found mixed results regarding milk quality with SCC, milk fat, and milk protein and increase in freezing point, FFA, TPC, and milk production. Decreased labor cost and increased flexible time for producers were reported with the transition to automatic milking systems in producer surveys and research studies. Nutrition cost increased with AMS due to increased milkings and milk production. Lastly, AMS increased total economic returns with high net present values and internal rate of returns and shorter payback periods. However, with the amount of previous research, the AMS industry is continuing to generate more research with fetch cows and the economics of the AMS.

Fetch cows, dairy cattle that do not voluntarily enter automated milking systems (AMS), increase labor costs, and decrease efficiency. The objective of this study was to describe fetch cows based on fetch lists and herd-management software data. This study was conducted on a commercial dairy farm (n = 510 cows) using 8 AMS from October 1, 2021, to May 10, 2022. Data were collected via PCDART, DairyComp, and a proprietary interface. Two fetch categories by cow, EverFetch (**EF**) and NeverFetch (**NF**), and three status groups by cow by day, True Fetch (on fetch list and fetched; **TF**), False Fetch (on fetch list and not fetched; **FF**), and No Fetch Required (not on list; **NFR**), were created. The impact of health events (no event, reproduction, general health, and scheduled events), parity (1, 2, 3, and 4+ lactations) and AMS variables (milk visit outcome,

production, and components; feed intake, etc.) on fetch category and status were analyzed using the GLIMMIX procedure of SAS 9.4 ($P \leq 0.05$). The sections were evenly divided by fresh or in-training (≤ 25 days in milk (**DIM**)) and lactation (> 25 DIM). The lactating group was divided into three sections (early, mid, and late lactations) based total cow-day observation quartiles. The sections were ≤ 25 DIM (fresh), > 25 and ≤ 86 DIM (early), > 86 and < 214 DIM (mid), and ≥ 214 DIM (late). Across EverFetch and NeverFetch, cows that experienced an event at some point during their lactation (Yes event) accounted for 94.9% of EverFetch and 96.2% of NeverFetch cows. Cows who experienced an event were more likely to show up on the fetch list. For fetch outcome fresh model, results showed that PCDART compared to DCOMP; 1st and 2nd lactation cows compared to 3rd lactation cows; a decreased milk fat, milk protein, daily max milk temperature, and feed intake; and increased number of milkings increased the likelihood of a cow being a TF vs an NFR. In early lactation cows, decreased milk production, failures per day, and feed intake and increased milkings, refusals per day, milk speed, and milk time were more likely to be TF vs NFR. In mid-lactation, decreased milk production, milkings, and refusals per day and increase in milk speed, milk time, and feed intake were more likely to be TF than NFR. In late lactation, PCDART compared to DCOMP; 3rd lactation cows compared to 1st and 4+ lactation cows; decreased milk production, milkings per day, and refusals per day; and increased failures and daily max milk temperature were more likely to be TF cow vs NFR. Cows that were more willing to enter the robot (greater milking and refusals per day) in early lactation cows were more likely to be coded as a TF when a fetch event occurred compared to cows that had experienced failures at the milking robot.

Management decisions, DIM, and general health issues (illnesses) increased the likelihood of cows being fetched. Days in milk impacted fetch cow status when comparing the four sections for fetch outcome. Health events also impacted fetch status and outcome like we hypothesized. Cows who experienced an event were more likely to show up on the fetch list. With the combined data, the models found will help predict fetch cow status based on DIM. Each model had different variables that led to unique DIM models. The models were the beginning of predicting a fetch cow before she enters the AMS. Future research is needed to test the models and find benchmarks for determining fetch cow status so that the concept can be used for producers.

Decision support tools have provided end-users with options for decision-making under different scenarios. The objective of this decision tool was for Southeastern USA producers considering an automatic milking system to input their information and determine AMS investment impact. Data were sourced from sixty-two farm observations across Tennessee, Kentucky, and North Carolina through the University of Tennessee Dairy Gauge Program (2021 and 2022). Median data across years included farm incomes and expenses. Investment in AMS was modeled to determine net present value (**NPV**), internal rate of return (**IRR**), and payback period (**PP**). Three sensitivity analyses were done as a research baseline of three construction styles (retrofitting, add-on, and a new construction barn) that contained a minimum, mean, and maximum labor increase (0.0, 0.075, and 0.15 percent, respectively) with a 20-year loan and a 50% down payment. Three additional sensitivity analyses were examined as an industry perspective of the three construction styles with a 7-year loan for the AMS and a 10-year loan for the

facilities with a 0% down payment and a minimum, mean, and maximum labor increase (0.0, 0.05, and 0.10 percent, respectively). Across all scenarios, retrofitting was the most profitable construction style. It was found that as the number of AMS increased so did the NPV and the risk factor. The research perspective models were most favorable when farms purchased 4 to 8 AMS while the industry perspective models had greater economic return with 6 to 7 AMS were purchased. Between baseline scenarios, research consistently had a greater NPV across construction style relative to industry. In most Southeast dairy scenarios, AMS investment positively impacted financial indicators.

Automatic milking systems are a permanent and expensive investment. The decision tool's purpose was to aid current and potential Southern dairy producers to determine financial impact before investment. The tool was tested using research and industry information. The comparison of the two outcomes differed in results. Retrofitting was most preferred in both outcomes; however, the order of the three scenarios differed between the two outcomes. All seventy-two sub-scenarios showed a positive NPV with major variability.

Future research is needed to better predict fetch cows and the economics of automatic milking systems. The next step for project one would be completing the study on all the AMS farms in Tennessee for one year. The next step for project two would be to add more variables into the decision tool to test their economics and relationship with net present value, internal rate of return, and payback period.

VITA

Abby N. McCalmon was born and raised in Jackson, Tennessee. After high school, she attended the University of Tennessee and received her Bachelor's in Animal Science with a concentration in Pre-Veterinary Medicine and a minor in Biology in May of 2021. She continued her education by pursuing a Master's degree at the University of Tennessee in Animal Science. Her research focused on precision technology particularly with automatic milking systems and fetch cow status. She will continue her education by attending Ross University's College of Veterinary Medicine starting in January of 2024. She is grateful for the support and love of her family and friends as she continues her education and eventually a career improving the animal industry.