J. Dairy Sci. 108:9861–9875
https://doi.org/10.3168/jds.2025-26455

What information counts when detecting mastitis in automatic milking systems? A mixed methods approach from a Swedish perspective

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ABSTRACT

The increasing adoption of automatic milking systems (AMS) in modern dairy farming has shifted mastitis detection from traditional human-animal interactions to technologically mediated processes. This study used a mixed methods design, combining a quantitative survey of Swedish dairy farmers (n = 246) with in-depth qualitative interviews (n = 9). The survey explored the use of AMS data for mastitis detection across herds varying in size, AMS brand, and technological features. The interviews provided rich insights into farmers' practices, challenges, and decision-making processes regarding udder health management. Our findings revealed that AMS brands and tools create distinct working environments, influencing farmers' behaviors around mastitis detection. A common practice used to detect cows with udder health problems was to monitor the behavior of animals, for example, examine cows that are late for milking, rather than following the more direct udder health parameters, such as SCC or electrical conductivity. Farmers emphasized SCC as the key indicator of udder health. Integration of AMS data into broader herd health strategies, including collaboration with veterinarians, remains underused. Enhanced training in AMS customization and closer integration with advisory systems could optimize the use of available data. These insights offer a foundation for refining mastitis management and improving udder health in AMS-managed herds.
Key words: dairy cows, milking robot, sensor systems, udder health

INTRODUCTION

Clinical and subclinical mastitis are significant problems in modern dairy production, causing economic losses, use of antibiotics, and reduced animal welfare (Halasa et al., 2007; Hagnestam-Nielsen and Ostergaard, 2009; Hogeveen et al., 2019). In addition to having a direct negative effect on the affected farm, mastitis has a negative effect on the environmental performance of dairy production (Özkan Gülzari et al., 2018; Mostert et al., 2019). To achieve sustainable dairy production, it is essential to find strategies that improve udder health, where early mastitis detection is one important factor for effective treatment (Milner et al., 1997).

In 2021, ~50% of Swedish dairy cows were milked in automatic milking systems (**AMS**; Växa, 2022). The increased use of AMS in modern dairy production has led to substantial changes and needs related to mastitis detection—from animal-human interaction to animal-technology-human interaction. Prestripping and preparing the udder for milking in conventional milking systems is a convenient way of discovering abnormal milk or other symptoms of clinical mastitis, such as a swollen, tender udder. Subclinical mastitis detection has traditionally depended on manual routine investigations of the milk, such as the California Mastitis Test (**CMT**; Sargeant et al., 2001; Bhutto et al., 2012), or DHI test milkings in herd health programs. With AMS, all types of mastitis detection become largely dependent on the milking robot's sensor abilities, and the human interpretation of the sensor data. At every milking, data such as milk yield, milk flow, electrical conductivity (**EC**), milk color, and milk SCC can be measured. Based on these data, several udder health parameters and mastitis risk from data-based algorithms are presented to the farmer as cow and herd information in the management program (e.g., DelPro [DeLaval] or Horizon or T4C [Lely]); these are then often used in combination with mobile applications.

Although AMS has the potential to improve mastitis detection by frequently and continuously measuring dif-

Received February 11, 2025.
Accepted June 26, 2025.
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The list of standard abbreviations for JDS is available at adsa.org/jds-abbreviations-25. Nonstandard abbreviations are available in the Notes.

ferent indicators that are not visible to the human eye, there are no unambiguous signs of improved udder health in herds with AMS. There are indications of deteriorating udder health as a result of introducing AMS that may last for up to 1 yr, although the long-term effects are unknown (Hovinen and Pyörälä, 2011; van den Borne et al., 2021).

There is clear indication that AMS can improve the working situation for farmers but also that it may have negative aspects, such as information overload (Hansen, 2015; Lundström and Lindblom, 2021; de Assis Lage et al., 2024). Several studies address the adoption of AMS and other technology in dairy production (Borchers and Bewley, 2015; Pathak et al., 2019; Ahmed et al., 2024). However, few studies have examined farmers' practices around using technology-derived data in their everyday work.

To optimize udder health strategies on AMS farms, there is a need for increased understanding of these practices—how the AMS data are used by farmers today. In line with Shove et al. (2012), we consider a practice as something consisting of several interconnected elements, including 3 key elements: (1) materials, (2) competence, and (3) meanings. The practices of mastitis detection and decision-making could thus be understood as an integrated process of (1) existing tools and technical equipment on the farm, (2) farmer understanding and knowledge on how to use them, and (3) farmers' experienced meanings and underlying social structures affecting the adoption and use of these tools.

In this study, we applied a mixed methods approach with the aim to describe how Swedish farmers use data from AMS and udder health–related on-farm technology for detection of cows with udder health problems.

MATERIALS AND METHODS

Study Design

In this study, we sought to identify critical factors influencing the integration of AMS technology into udder health management strategies. Given the complexity of mastitis detection, we employed a sequential explanatory mixed methods design (Creswell and Clark, 2017), combining the quantitative breadth of a national survey with the qualitative depth of in-depth interviews. The study consisted of 2 phases: (1) a cross-sectional survey to explore the availability of udder health technologies and patterns of mastitis detection across Swedish dairy farms using AMS, and (2) semistructured interviews to capture farmers' lived experiences, interpretations, and practices around udder health management and AMS data. To integrate and synthesize the quantitative and qualitative findings, we adopted the Scott (2007) critical realism perspective, wherein ontology (the way things are) determines epistemology (the way things are known), embracing both inductive and deductive analytical approaches. This perspective allowed us to analyze quantitative and qualitative data jointly, combining broad national trends with detailed, contextualized insights to uncover relationships and diverse perspectives in the multifaceted challenge of mastitis detection. Quantitative data provided a demographic overview and identified key patterns, while qualitative analysis delved into the contextual factors shaping decision making. By synthesizing these approaches at the ontological level, we generated a nuanced interpretation of how AMS technology is used for mastitis detection, offering practical insights to support more effective data utilization on dairy farms. From a critical realist perspective, we acknowledge that reality exists independently of our understanding (realist ontology), but our access to it is always mediated through social, contextual, and subjective lenses (relativist epistemology).

Ethical Statement

In consultation with the ethics and legal department at the Swedish University of Agricultural Sciences University, in agreement with the Swedish Ethical Authority, the study did not require a special provision or permit according to Swedish law (SFS 2003:460). Nonetheless, a strict code of conduct as set out by the Swedish Research Council (Swedish Research Council, 2017) was followed, including gaining informed consent from all the participants and guaranteeing the pseudonymization of their responses and herd registry data. Furthermore, no sensitive personal information was discussed or collected during the process. No financial incentive was offered to farmers in exchange for their participation.

Survey Development and Methodology

The national survey was developed during October 2020 to January 2021. The development process involved an evaluation by an expert on survey design and 2 test runs on 3 independent farmers. The evaluation and test runs resulted in some minor changes to increase interpretability and remove redundant questions. Moreover, the initial test run made it clear that asking general questions about mastitis management was challenging. To account for different understandings of mastitis definitions or classifications (e.g., chronic, acute, subclinical, and clinical mastitis), as well as the complexity of decision making around cows with mastitis (e.g., dependence on cow and herd factors, such as severity of symptoms, lactation status, milk yield, genetic value, availability of recruitment heifers), we introduced 3 different mastitis

Table 1. Description of mastitis scenarios presented to respondents in a survey about udder health management targeting Swedish dairy farmers with automatic milking systems

Scenario	Described symptom
1. Severe clinical mastitis	Cow in first lactation, 8 DIM: Fever, anorexia, tender and swollen udder. Uncomplicated calving.
2. Subclinical mastitis	Cow in fourth lactation: High SCC,[1] no visible changes in milk or udder. Slightly decreased milk yield. History of mastitis in previous lactation and fluctuating cell count in this lactation.
3. Moderate clinical mastitis	Cow in second lactation, 21 DIM: Abnormal milk, somewhat swollen, red udder. Substantially decreased milk yield (from being one of the highest yielding cows in the herd). No systemic symptoms. History of high SCC and dry-cow treatment in previous lactation.

[1]SCC level was not defined in the description but left open to interpretation.

scenarios instead of asking general questions about mastitis. In that way, some of the uncertainty and individual factors could be aligned among the respondents. The mastitis scenarios are thus an approach to "set the stage" to make the respondents think about how they would act in a certain situation, as well as how information from the AMS would be used, whereas the specific differences for detecting different types of mastitis cases are not the main focus of this study. Supplemental Table S1 (see Notes) gives a detailed overview of the survey. The full survey is available from the authors upon reasonable request. The respondents were given 3 different scenarios with cases of mastitis, with symptoms and cow characteristics described according to Table 1. For each scenario, the respondents were asked to choose the alternative by which it was most likely that they would detect that the cow in the scenario had an ongoing udder health problem. The respondents had a list of 7 predefined detection alternatives to choose from (manual discovery in the freestall, routine examination of udder or milk, mastitis warning from the AMS, warning/flag for abnormal behavior, warning/flag for decreased milk yield, warning/flag for abnormal milk, and information from DHI test milking results) and could also add their own alternative in free text. It was possible to choose several response alternatives, although respondents were asked to choose the one alternative that would most likely be the first way to alert them about the cow in the scenario.

Study Population and Data Collection

The survey was distributed in February 2021 via Netigate (Netigate online survey, Netigate AB, Stockholm, Sweden). To determine the minimum number of subjects required for adequate study power, we performed a sample size estimation based on the total population of active Swedish dairy farms registered using AMS (data provided by the Swedish Official Milk Recording Scheme [**SOMRS**]) in 2020 (n = 709). The estimation was conducted using a 95% CI and a 5% margin of error, resulting in a required sample size of at least 228 participants to draw statistically valid conclusions from the questionnaire to achieve adequate power and precision for generalizing questionnaire results to the target population. The sample size was calculated to ensure that we collected enough observations to make valid inferences about the population. The calculation was based on the CI equation, where the margin of error (ε) represents the maximum acceptable deviation from the true population value. By rearranging the equation to solve for sample size (n), we determined the required number of participants. Additionally, according to the central limit theorem, the sampling distribution of the mean follows a normal distribution when the sample size is sufficiently large ($n \geq 30$). Because our estimated sample size (n = 228) exceeded this threshold, we assumed a normal distribution of sample means, allowing for reliable statistical inferences. Because the study was based on a descriptive survey rather than hypothesis testing for a continuous outcome, our focus was on achieving a representative sample size to make valid inferences about proportions within the population, rather than detecting a specific effect size between groups.

Expecting a response rate of 20% to 30%, drawing from experience from previous similar studies (Lind et al., 2020, 2023), we decided to send the invitation by email to all farms that met the inclusion criteria, that is, affiliation to the SOMRS with an available email address and AMS registered as the primary milking system on the farm (n = 709). Distribution reached 697 email addresses, reasons for not reaching all 709 were that some addresses had previously "opted-out" from Netigate surveys (n = 11) and nonfunctioning email addresses (n = 1). The survey was open for 4 wk after distribution, and 3 reminders were sent out to nonresponders during that time, with ~1 wk intervals. The invitation email asked for the person responsible for the udder health in the herd to fill out the survey. We received 246 answers to the questionnaire, 244 responded to all 3 mastitis scenarios (effective response rate 35%). For herds that gave consent and herd ID, additional herd data were obtained from the SOMRS, including average production of ECM per cow and year and herd-level SCC based on monthly DHI test milking data.

Statistical Analyses of the Survey

An initial data cleaning was performed, where obvious inaccurate answers were corrected or changed to missing (e.g., birth year given as age). In addition, free-text answers that largely corresponded to one of the given categories were included in that category. Survey responses were imported to STATA (StataCorp. 1985–2021. Stata Statistical Software: Release 17.0. College Station, TX) and merged with data from the SOMRS by using the individual herd ID given in the survey. The respondent population was compared with the whole population of dairy herds with AMS affiliated with the SOMRS in the aspect of herd size, production level, SCC, proportion of herds with organic production, and breed. To explore the data and identify differences in mastitis detection for different herds, the herds were divided into subgroups based on respondent age and sex, production system (organic or conventional), number of AMS units (1, 2, or ≥3 units), AMS brand (DeLaval or Lely), and having an SCC sensor (**SCCS**, yes or no). Associations between these subgroups were investigated with chi-squared tests for categorical variables and linear regression for continuous variables. To compare the subgroups' responses to the mastitis scenarios, univariable mixed effect logistic regression analyses were performed separately for each of the 7 response alternatives for mastitis detection (manual discovery in the freestall, routine examination of udder or milk, mastitis warning from the AMS, warning/flag for abnormal behavior, warning/flag for decreased milk yield, warning/flag for abnormal milk, and information from DHI test milking results), with response alternative as the dependent variable and subgroup as the explanatory variable. In these models, each respondent's answers to all 3 scenarios were included, meaning that the respondents contributed with 3 observations each, and respondent ID was included as random factor to account for the inclusion of all 3 scenarios in the same model. As a second step, if a response alternative was associated with more than one respondent subgroup, a multivariable mixed effect logistic regression model was built with that response alternative as dependent variable. The significant subgroups were included as explanatory variables and respondent ID as random factor. Before running the multivariable models, Spearman rank correlation tests were used to check for collinearity. If the test indicated collinearity ($r \geq 0.7$) between variables, the variable with the lowest *P*-value was kept.

Finally, for response alternatives where significant ($P < 0.05$) associations with respondent subgroups were found, we compared each of the 3 different scenarios separately using logistic regression models. Due to a strong association between AMS brand and having an SCCS, the analyses of SCCS and the response alternatives were performed separately for each AMS brand for improved clarity of the results.

Interview Process

The lead authors (GOA, LE, DA, and IG) developed the interview guidelines collaboratively in dialogue with the overarching project research team, integrating insights from the quantitative survey phase. Survey responses, including free-text answers, were used to define what aspects of the routine greatly affected mastitis detection. In that way, these findings aided in identifying whom to include to further explore and contrast farmers' experiences around mastitis detection. To minimize confounding factors between brand and SCCS presence, the qualitative phase focused on farmers using the most used AMS brand in Sweden (DeLaval). Based on initial survey results, the interviews focused on 5 areas: (1) the definition and perception of udder health, (2) the use of AMS and other technologies for mastitis detection, (3) challenges and needs related to AMS data utilization, (4) the integration of AMS data with other information sources such as DHI test milkings, and (5) collaboration with veterinarians in udder health strategies. Interviews were conducted in Swedish and led by IG, a female veterinarian who had prior training in AMS systems in Sweden and no prior relationship to the interviewees. Interviewees were chosen by convenience, based on previous knowledge within the research group, and first contact was made by email, where they were informed about the study and its purpose. In total, 19 farmers were contacted, of which 10 declined to participate, mainly due to lack of time. For the first 3 interviews, IG was accompanied by LE and GOA to fine-tune the process and to set the scene for those involved later in the analysis. The interviews (n = 9, see Table 2 for a description of the interviewees) were conducted on-farm face-to-face (n = 2), via video conference (n = 6), or over the phone (n = 1) during September and October 2021. All 9 interview participants used DeLaval AMS to facilitate isolation of the influence of having an SCCS within one specific brand and thus maintaining consistency in brand-related system design. Each interview adhered to a semistructured agenda built around 5 key thematic areas identified from survey responses to ensure coverage of all topics while maintaining flexibility to explore themes significant to each interviewee (see interview guide in Supplemental Table S3, see Notes). The interviews had an average duration of 45 min (30–60 min). All interviews were voice-recorded and transcribed verbatim in Swedish by a professional transcription service and revised and analyzed by the leading coauthors (LE, IG, DA, and GOA). Initial reflections and notes were taken during and postinterview to aid in later analysis. Representative excerpts were translated into English for reporting purposes.

Table 2. Farmers participating in interviews for a deeper understanding of farmers' experiences of mastitis detection in dairy herds with automatic milking systems (AMS) with or without SCC sensor (SCCS)

Farm no.	Participant's role on-farm	Cow (n)	AMS unit (n)	Production system	SCCS
1	Manager	60	1	Conventional	Yes
2	Owner	61	1	Organic	Yes
3	Owner	126	2	Conventional	No
4	Owner	65	1	Conventional	No
5	Owner	100	2	Conventional	No
6	Owner	103	2	Organic	Yes
7	Owner	780	12	Conventional	Yes (not in use)
8	Owner	100	2	Organic	Yes
9	Owner	120	2	Organic	No

Qualitative Analysis and Mixed Methods Integration

The transcriptions, field notes, and memoing (i.e., qualitative data) were open-coded using Dedoose (version 9.0.17; Los Angeles, CA: SocioCultural Research Consultants, LLC). A reflexive thematic analysis (Braun and Clarke, 2019, 2022) was employed to analyze the qualitative dataset, prioritizing an inductive-deductive continuum that emphasized farmer meanings and contextual experiences. Thus, coding was primarily inductive, allowing themes to emerge from farmers' narratives. However, deductive elements were also used, particularly in relation to key words and concepts from the survey results, which informed some initial coding categories (e.g., SCCS). This approach facilitated identifying central themes aligned with the research questions while going beyond descriptive coding to capture underlying assumptions, practices, and decision-making processes around AMS data utilization and mastitis management. The final themes were iteratively developed by leading coauthors (IG, GOA, LE, and DA) in interactive discussions, with additional input from NL and NF.

Mixed Methods Integration

Integration of the qualitative findings with the quantitative survey results followed a critical realism metatheoretical perspective (Scott, 2007). This framework allowed for synthesizing qualitative themes with quantitative trends at the ontological level, ensuring an enriched interpretation of mastitis detection practices. The qualitative findings added depth and contextual nuance to the survey results, enabling a comprehensive understanding of farmer behavior and decision making around the detection of udder health problems. This integration of data across methodologies, led by GOA, LE, and NL, ensured consistency with the mixed methods framework and provided a robust foundation for addressing the study's objectives.

Authors' Positionality Statement

All authors bring interdisciplinary expertise in dairy cattle health, welfare, and the agriculture sector in Sweden and internationally. Authors LE, IG, NF, and GOA have veterinary degrees, while NL has graduate and postgraduate degrees in psychology and a docentship in business studies. The author NF holds a professorship in veterinary epidemiology with a particular emphasis on data-driven decision making in livestock systems. The author LE has a shared research and development post between Swedish University of Agricultural Sciences and Växa Sverige, the Swedish dairy advisory group, which actively engages in research focused on improving herd health and advancing sustainable practices in the dairy sector. The author GOA has a graduate degree in applied animal behavior and welfare. She has additional training in social science, connecting traditional epidemiological research with qualitative approaches to enhance understanding of stakeholders' decision making related to animal welfare issues. The author NL brings a robust understanding of animal welfare science, farmer decision making, and sustainability, fostering a holistic approach to research that bridges biological sciences with socioeconomic contexts. The author IG is a clinical veterinary practitioner in Sweden. The author DA complements the team's expertise with her focus on stakeholder engagement, sustainability strategies, and innovative approaches to agricultural systems management. The author DA is a research and development expert in udder health at DeLaval and has a graduate degree in animal science and machine learning. The authors emphasize the importance of integrating scientific evidence with the perspectives of those directly involved in animal care. They prioritize cocreating knowledge and solutions that resonate with stakeholders' lived experiences and practical realities. The team shares a common commitment to fostering sustainable improvements in animal health and welfare through interdisciplinary research and collaboration and an unwavering belief that understanding the needs and motivations of farmers and animal caretakers is central to achieving meaningful progress in the field.

RESULTS

Survey Demographics

The mean respondent age was 49 yr (SD 10, range 21–74) and 55% of the respondents were male, whereas 45% were female. The respondents had between 2 and 60 yr of experience working with dairy cows (mean 28, SD 10). Descriptive data of the respondent herds in comparison to the national average Swedish dairy herd is presented in Table 3. The most common AMS brand was DeLaval (n = 158) followed by Lely (n = 83), whereas very few herds had another AMS brand (GEA, n = 3).

Comparisons Between Subgroups

As herds with AMS systems other than DeLaval or Lely were few (n = 3), they were excluded from the statistical analyses, leaving 239 respondents contributing with 3 observations each (1 for each scenario, n = 717). When investigating associations between subgroups, it became evident that there was a strong association ($P < 0.001$) between AMS brand and having an SCCS, where more Lely herds (70.7% n = 58) had an SCCS compared with DeLaval herds (33.1%, n = 52).

A weak association ($P = 0.063$) between the AMS brand and the number of AMS units was also observed. Out of respondents with 3 or more AMS units, 50% used DeLaval and 50% Lely, whereas this distribution was 71% with DeLaval and 29% with Lely for respondents with 1 AMS unit. No other associations were observed between the subgroups.

Results of Univariable Logistic Regression Analyses

The univariable logistic regression analyses showed several associations between subgroups and response alternatives (Supplemental Table S2, see Notes). The response alternative, “Routine examination of udder/milk” was more common among farms with DeLaval AMS compared with farms with Lely (OR 16.6 [CI: 2.3–119.3], $P = 0.005$). On the contrary, the response alternative “Warning/flag for abnormal behavior” was more common among herds with Lely AMS compared with DeLaval (OR 2.2 [CI: 1.2–3.9], $P = 0.008$). Also, the response alternative “Warning/flag for decreased milk yield” was significantly more common in herds with more than 3 AMS units than herds with 1 AMS unit (OR 2.2 [CI: 1.2–5.2], $P = 0.01$). The response alternative “Manual discovery in the free-stall” was not associated with any of the investigated subgroups.

Results of Multivariable Mixed Effect Logistic Regression Analyses

Out of the 7 response alternatives, 3 were significantly associated with several subgroups and thus further investigated in multivariable logistic regression models, presented in Table 4 and in Supplemental Table S2. Spearman rank correlation tests did not indicate multicollinearity between variables in any of the models.

“Mastitis warning from the AMS” showed an association with 3 subgroups: the number of AMS units on the farm, AMS brand, and having an SCCS. When investigated in the multivariable model, the association with AMS brand was the only variable that remained significant. Respondents with Lely as AMS brand responded that they would detect the cow through a mastitis warning from the AMS to a higher extent than respondents with DeLaval (OR 6.5 [CI: 2.3–18.1], $P < 0.001$).

In the univariable analysis, “Warning/flag for abnormal milk” was positively associated with organic production system and having an SCCS, where only having an SCCS remained significant in the multivariable model (OR 6.5 [CI: 3.1–13.5], $P < 0.001$).

“Information from DHI test milkings” was associated with both AMS brand and having an SCCS. In the multivariable analyses, having an SCCS was negatively associated with the response alternative to detect the cow through test milking results (OR 0.4 [CI: 0.24–0.70], $P = 0.001$).

Table 3. Description of respondent population (n = 246) in comparison with the national Swedish dairy herd population (n = 2,955) for the same year as the survey was distributed

Variable	Respondent population	National population 2021
Mean herd size (n cows [SD])	112 (70.1)	102[1]
Proportion with organic production (%)	32	18[1]
Production (kg ECM/cow per yr [SD])	11,081 (1,103)	11,009[2]
Bulk tank SCC (cells/mL [SD])	240,000 (58,000)	248,000[2]
Proportion Swedish Holstein (% [SD])	51 (32)	57[2]
Proportion of Swedish Red (% [SD])	25 (23)	33[2]

[1]Based on data from the Swedish Board of Agriculture.

[2]Based on data from the Swedish Official Milk Recording Scheme (SOMRS).

Table 4. Associations between response alternatives to how a cow with udder health problems would first be detected in 3 different mastitis scenarios by farmers with different farm characteristics (production system; conventional or organic), number of automatic milking systems (AMS) units, AMS brand, and having an SCC sensor (SCCS), investigated in 3 multivariable mixed effect logistic regression models with respondent ID included as random factor[1]

Included variable	B[2]	SE	OR[2]	95% CI	*P*-value
Model 1: Detection by mastitis warning from the AMS[3]					
1 AMS unit	Referent				
2 AMS units	0.41	0.49	1.51	0.57–3.94	0.41
≥3 AMS units	1.09	0.65	2.99	0.84–10.62	0.092
AMS brand DeLaval	Referent				
AMS brand Lely	1.87	0.52	6.51	2.34–18.11	**0.0003**
Without SCCS	Referent				
With SCCS	0.69	0.47	1.99	0.79–4.98	0.14
Model 2: Detection by warning/flag for abnormal milk[4]					
Conventional	Referent				
Organic	0.55	0.37	1.74	0.84–3.62	0.14
Without SCCS	Referent				
With SCCS	1.88	0.37	6.52	3.15–13.52	**<0.0001**
Model 3: Detection by information from DHI test milking					
AMS brand DeLaval	Referent				
AMS brand Lely	−0.30	0.29	0.74	0.42–1.31	0.30
Without SCCS	Referent				
With SCCS	−0.97	0.37	0.41	0.24–0.70	**0.001**

[1]Variables for each model were chosen based on results from univariable analyses. Significant results are indicated in bold ($P < 0.05$).

[2]β = regression coefficient; OR = odds ratio.

[3]Explanation given in the survey: "For example, based on Mastitis detection index (MDi) or Milk quality control (MQC-C)."

[4]Explanation given in the survey: "For example related to elevated cell count or lactate dehydrogenase (LDH)."

The distribution of responses in the 3 different scenarios in relation to AMS brand and having an SCCS are presented in Figure 1. As SCCS and AMS brand were closely associated, the responses are shown for 4 separate groups, based on AMS brand and having an SCCS or not. In summary, respondents with SCCS did not respond that they would identify cows based on the DHI test results to the same extent as herds without SCCS, regardless of the AMS brand. However, respondents with Lely AMS more often chose the response alternatives "mastitis warning from the AMS" and "warning/flag for abnormal behavior," whereas DeLaval farms with SCCS more often chose "warning/flag for abnormal milk."

Qualitative and Quantitative Results Integration

From the analytical integration of quantitative and qualitative results, 3 themes summarized the key patterns from the survey in the context of farmers' experiences around detecting mastitis in AMS (i.e., in-depth interviews). These themes address tensions across (1) the practical use of AMS data in identifying udder health issues, (2) the influence of technology adoption and available resources on detection, and (3) the integration—or lack thereof—of AMS data into broader herd health management frameworks. These results are expanded upon in the subsequent sections, highlighting their implications for improving mastitis detection and management practices.

The Practical Use of AMS Data in Identifying Udder Health Issues

Udder health was primarily assessed through SCC, where "good" udder health is defined by "low SCC" values, often benchmarked against dairy plant contracts. A challenge was the ambiguity around what qualifies as "low" SCC and how effectively AMS data could be standardized across farms for practical decision making. The technical description of the AMS equipment as presented by AMS manufacturer (DelPro Farm Manager software version 5.9, DeLaval International AB, Tumba, Sweden) shows that the data reports could offer a far more profound and complex application than the behavior described in conversations. This indicates that farmers, depending on their interest in technology, mainly prefer straightforward decision support from the AMS output for identifying deviant cows, that is, cows that need further observation or veterinary care, including cows with udder problems. Regarding udder health, farmers preferred indicators or information related to SCC status at the herd or individual level.

The AMS data were generally not used for a specific udder health purpose but rather as an integrated part of the animal monitoring, followed by manual investigations. A typical example of data usage was the farmer starting the day by checking the herd status in the farm management software program, and identifying cows in need of special attention, listed as "red cows," that

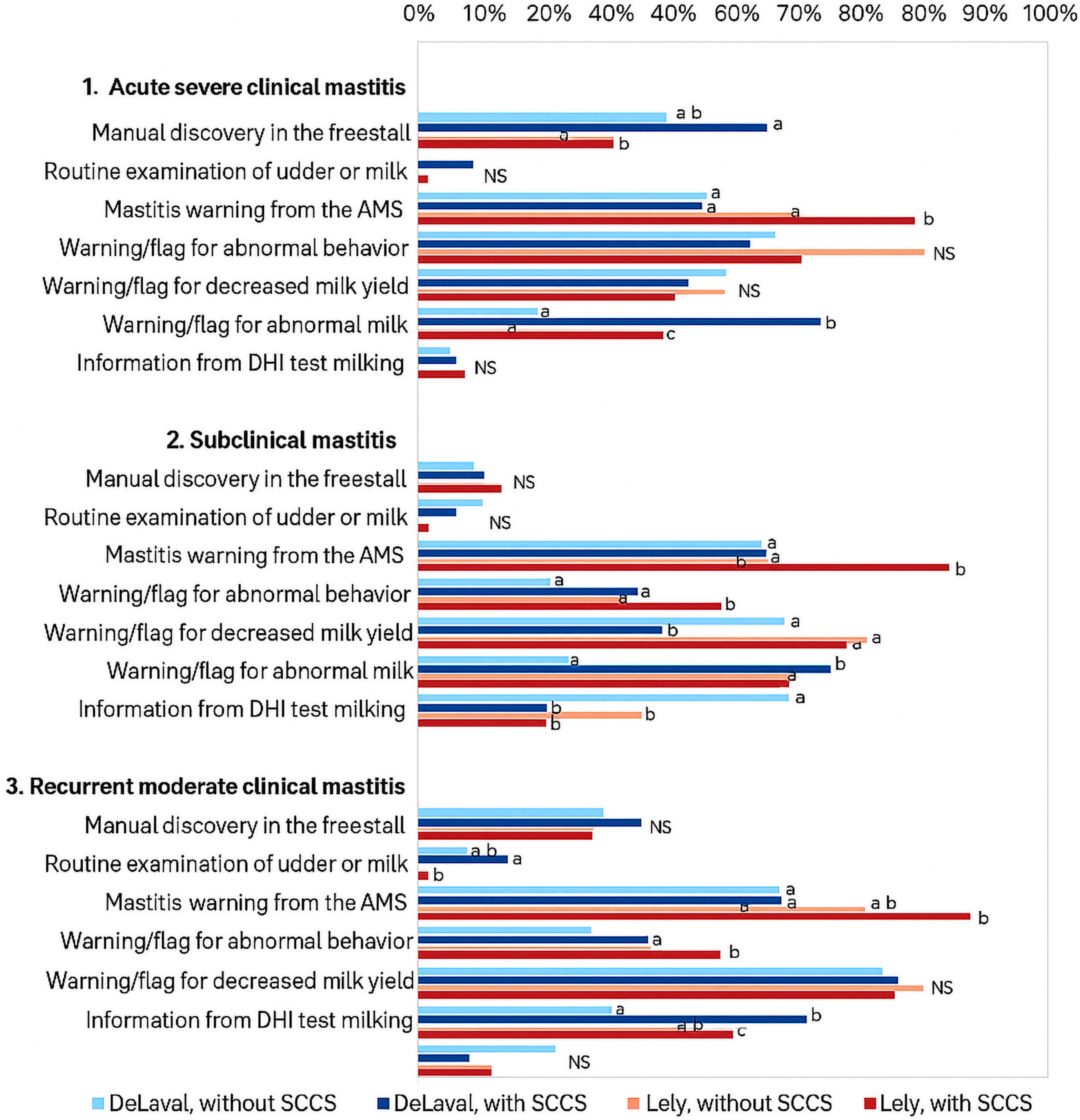

Figure 1. Response distribution on how respondents of a survey targeting Swedish dairy farmers thought they would detect a cow with udder health problems according to 3 different mastitis scenarios: (1) A primiparous cow with acute severe clinical mastitis, (2) an older (fourth lactation) cow with high cell count, no clinical symptoms, and (3) an older cow with a recurrent case of moderate clinical mastitis. Responses are divided into subgroups based on automatic milking systems (AMS) brand (DeLaval or Lely) and availability of an SCC sensor (SCCS). Different letters (a–c) for subgroups indicate a significant difference ($P < 0.05$) between subgroups for that response alternative when investigated with logistic regression. NS = model not overall significant ($P > 0.05$) for that response alternative.

is, cows that were overdue for milking according to the system settings in the farm management program.

"It is a quite good job when you have started up in the morning and checked that everything is okay, you sit down and have an apple and then you go through this whole list" (Farmer 9).

"Those that start the morning shift, it is a lot to get in, check milking lists and all that, get in cows that are late [for milking] and new cows so they learn to go [to the robot]. It is the first thing they do really. But then, later in the morning we check for conductivity and such, if there are any cows with deviated milk" (Farmer 7).

The cows on the daily list, including cows with the overdue milking intervals ("red" cows) but also those with incomplete milkings, were manually attended to and then brought to the AMS unit for milking. Although this routine was not mainly for mastitis detection, it would indirectly lead to the identification of cows with udder health problems.

"It is no high-tech solutions we're using. She doesn't show up for milking, that's how we see it" (Farmer 5).

Deviated milk, mentioned previously, constitutes one aspect of the AMS data usage where a decision was made without the farmer's active involvement but rather based on predefined values (possible to adjust by the farmer), such as color, EC thresholds, and, if available, SCC. In these predefined cases, the AMS automatically diverts the undesired milk from a specific cow, to avoid low-quality milk being delivered to the dairy plant.

Keeping the bulk tank milk hygienic with low SCC was also emphasized regarding the farmers' perception of good udder health in their herd. This was mainly addressed by herd-level SCC, where a low SCC equals good udder health. A satisfyingly low SCC level was considered at 200,000 cells/mL or below, which corresponded to the limit the dairy plant set for full milk payment.

"The aim with the udder health is to get the full payment, that is, full payment for the milk" (Farmer 7).

"But we can say that we want to be at 200 [200 000 cells/mL]. I don't have a goal to be super low, but there somewhere it is kind of stable" (Farmer 3).

"You should not deliver milk with higher quality than the dairy plant asks of you" (Farmer 9).

Udder health management is one part of the farm ecosystem that occurs in relation to all other tasks on the farm. It was clearly relevant at different levels to different farmers and that routines around udder health management varied between farms.

The Influence of Technology Adoption and Available Resources on Mastitis Detection

The process of mastitis detection on farms was shaped by the interplay of technological tools and the resources (time, skills, finance) available to farmers. Farmers described a tension between adapting the system to fit their context versus conforming their practices to the demands and limitations of the technology, in other words, solving a complex puzzle where pieces must align. In conversation, all farmers conveyed that SCC was the primary indicator, a "holy grail" to define udder health and udder health goals. However, the identification and further investigation of cows with udder health problems (i.e., deviant SCC) depended on which information the farmers received from their AMS system and how it was presented. Thus, farmers must combine different information to define if a cow needs attention concerning the overall herd health; how they did this varied between farmers, especially between farms with or without SCCS. In addition, the balance between getting enough or too much information (feeling overwhelmed) was a perceived challenge among the farmers. However, adapting the AMS management system's settings to cater to their needs was uncommon.

In herds using SCCS, the cell count information was the primary (and sometimes only) basis for detecting udder health problems, making it the largest and most important piece of the puzzle. Additionally, EC or mastitis detection index (**MDi**) was used by farmers together with the SCCS information to determine which quarter was affected, as SCCS yields information on cow-level only.

"As I said, we use OCC very frequently and that's how we find out if they are sick or not. This means that the other functions are actually a bit superfluous" (Farmer 2).

Most farmers, with and without SCCS, described this system as a clear advantage that outlasted the cost and maintenance needed. The cost-benefit balance was, however, dependent on the farmer/farm context, where negative experiences could outweigh the potential benefits.

"Unfortunately, it is the case that they require quite a lot of maintenance from the staff, from me, for them to work all the time because it often malfunctions" (Farmer 6).

This meant that SCCS had an economic burden and could lead to increased workload, emphasizing the importance of working proactively with udder health within the herd and not only having the SCCS as a tool to aid in "putting out fires," which is not viable in the long run. Thus, a farmer may see no use in investing in an SCCS system if the udder health is good in the herd (i.e., if the herd-level SCC is low).

Farms without SCCS had found different ways to interpret their data, but most had a farm specific routine where the interplay of various parameters, such as EC or MDi (combined information of quarter EC, color, and milking interval), was used as key information. The DHI test milking was also mentioned as an important tool for finding and tracking cows with high SCC, that is, subclinical mastitis for farms without SCCS.

"I can't say we have much use for it [the MDi-value]. It doesn't guide us much; rather, the conductivity says more" (Farmer 9).

"Mastitis is almost always the general condition; you see that the cow is different from yesterday, and often, there are no changes in the milk at that point. But that's how I discover them; I spend much time in the barn, watching. . . . If you don't see it on the individual, you notice a long interval; maybe she hasn't gone to the robot in 14 hours, which never happens otherwise. . . . Then, even if we don't have OCC, we have the MDi on ours [robot]. We get an alarm if MDi is above 2. . . . So you can say that it's basically those 3 things" (Farmer 3).

In addition, other pieces of information, not directly linked to the milk or AMS data, were useful for the farmers to determine if a cow required further evaluation. These pieces included activity, feed intake, rumination, and how the cow had moved in the barn (gate passages). The need to look at the actual animal and not just the data were also emphasized—expressing that technology cannot replace a farmer's "djuröga," a Swedish term that refers to a person's expertise in knowing their animals and their behaviors that comes from sharing common spaces and life, developing the farmer's "animal eye."

Participants conveyed that the original settings from the installation of the AMS unit were generally used, even though there are ample possibilities to adapt different settings in the management system according to their interests and needs. Even so, some adaptations were reported, mainly the setting for diverting milk. Time restraint was one reason for not interacting more with the management program.

"Generally, we have those settings because they were there from the beginning" (Farmer 5).

"I don't have time for that. . . . I can't nerd out there [at the computer] because then the cows won't be taken care of " (Farmer 6).

Several participants pointed out that there is a lot of information available from the AMS and that it can be challenging to sort out relevant information,

"It's a bit like not seeing the forest for all the trees or so" (Farmer 5).

"You can't have all the stuff [visible on the screen], then it gets too much" (Farmer 4).

The wish for easy and effective decision support was evident, as was the want of early detection.

"We don't want to know that someone is sick, we want to know that someone is getting sick or that the risk is increasing" (Farmer 9).

Thus, the conversations emphasized the importance of timely and accurate decision support from their on-farm data, where balancing the amount of information and how it is presented constitutes a significant challenge.

The Integration—or Lack Thereof—of AMS Data into Broader Herd Health Management Frameworks

Another major challenge for utilizing AMS data and other technology on the farm was the lack of integration between different technological systems. Time constraints and competing priorities leave little room for deeper analysis and strategic use of AMS data, together with other on-farm apps and tools in holistic herd health planning. Farmers conveyed those constraints included the lack of integration of information from the AMS in the work of veterinarians and herd health advisors on the farm.

For example, herd health data from the SOMRS can be attained in one program, whereas other farm and cow data from the AMS are not available. Merging or transferring data between the SOMRS and the AMS was one expressed example of how to improve the on-farm technology use. Some farmers stated that they received so much information from their AMS that affiliation to the SOMRS was redundant. In contrast, others felt that being affiliated with the SOMRS provided a sense of security and control, as well as a sense of being part of a community.

"We talked about cell counters before and that it can be a way to finance the cell counter to leave Kokontrollen [SOMRS] so to speak. . . . At the same time, it feels a bit empty without Kokontrollen, it does" (Farmer 5).

The participating farmers attested that veterinarians visiting the farm, in acute cases in both acute and preventive animal health visits, rarely asked about the history of the cow from the AMS. A common perception among the participants was that veterinarians were used to looking at the data and figures from the SOMRS, and thus tended to use and trust that data rather than incorporating data from the AMS in their work.

"They [the veterinarians] look at the animal only, it is an examination of the individual for their part" (Farmer 1).

"She [the veterinarian] mainly looks at the SOMRS figures, that is how it is. Because she is comfortable with that" (Farmer 8).

Another perception was that the veterinarian probably did not have time to immerse themselves in the AMS data.

"That could be good in itself, but it means that they have time to dig in. They can't spend much time on that either" (Farmer 6).

In contrast, on one of the farms where they had regular veterinary visits every 14 d, the farmer stated that the vet sat down with them to look at AMS data.

"Yes, we do that, every 14th day he [the veterinarian] comes and goes through that [data]. We sit together and look through it" (Farmer 7).

DISCUSSION

This article investigated farmers' practices for detecting mastitis in Swedish dairy farms with AMS and yielded important insights on how farmers interact with, and use, data produced by their AMS.

The survey results highlighted that AMS brand and availability of cell count information were crucial elements that split the behavior of farmers in relation to what information aids in the mastitis detection process. Hence, during the in-depth interviews, we chose to focus on the aspects of AMS brand and the availability of an SCCS to enhance our understanding of the use of AMS data for mastitis detection. As a higher proportion of Lely herds had the SCCS equipment compared with DeLaval herds, the effect of having an SCCS versus the effect of having a specific AMS brand may be difficult to untangle. Also, the SCCS add-on systems differ between the brands, which may affect the farmer interpretation of the generated data. DeLaval provides an online somatic cell counter (**OCC**, DeLaval International AB, Tumba, Sweden), where the cell nuclei are dyed and counted using an image technique. Lely provides the milk quality control (MQC-C, Lely Industries N.V., Maassluis, the Netherlands), an automated CMT where the cell count is estimated through a gel formation in a milk sample. Lely recommends using the sample result as average over 24 h for interpretation of the trend, while with the DeLaval option, it is possible to use each measurement individually. The finding that the majority of respondents had DeLaval or Lely AMS was expected and aligns with their prominence in the Swedish AMS market.

For these reasons, we focused on the experiences of farmers with SCCS or without SCCS using the same AMS brand and included only DeLaval herds, which is also the most common Swedish AMS brand. The identified differences in behavior between AMS brand do not imply a qualitative assessment of specific AMS brands or herd configurations but rather highlight observed associations between farm-level technology setups and reported mastitis detection strategies. In other words, it states that there are different farm ecologies that advisors and other stakeholders must recognize if they wish to improve mastitis detection on AMS farms. Considering that we only interviewed DeLaval AMS users, the interpretability of our qualitative insights is somewhat restricted: data routines probably differ on farms that operate other brands. Qualitative studies seek analytical, rather than statistical, generalization; so we treat the present results as a transferable mechanism that future, brand-specific work should test empirically. Replicating the interviews on Lely, GEA, and other AMS platforms will help clarify how brand-level interface design shapes udder health management.

The adoption of AMS in dairy farming not only changed the way cows were milked but the whole farm management (Butler et al., 2012; Hansen, 2015; Lundström and Lindblom, 2021).The detection of cows with udder health problems is the first step toward decision making and further measures to care for the cows, including contacting a veterinarian when necessary. Efficient detection is a key factor for successful treatment (Milner et al., 1997) and to improve animal welfare by reducing the time a cow suffers from mastitis. Although this is a widely recognized challenge, previous research has focused on the technology in itself, and the development of algorithms for detection of udder health problems, and less focus has been on the actual on-farm use of technology and user experience (reviewed by Rutten et al., 2013).

Farmers use AMS information for udder health management with 2 main objectives: (1) finding deviating cows in need of attention and check-up, and (2) deciding which milk that could go in the tank and which milk that needed to be deviated to ensure hygienic milk in the tank and full payment from the dairy plant.

The practices varied between farms, depending on available technology and perceived relevance of different pieces of information (farmer experience). Our results indicated that AMS brand (Lely or DeLaval), and having an SCCS or not, are key factors that affected the behavior related to mastitis detection. Respondents with Lely more often chose the response alternative "mastitis warning" when compared with respondents with DeLaval, who instead more often chose "warning/flag for changes in the milk." We argue that this reflects differences in how the management systems from DeLaval and Lely present information to the farmer. In a way, the brand of AMS and its related management system and functions set the basis for the daily work on the farm, including routines for mastitis detection and other animal health–related issues. However, farmers emphasized that there are a lot of data available to evaluate, whereas they wanted a simple decision support. Thus, many choose one, or a few, specific parameters to rely on, meaning all available data were often not used to their full potential. Despite an extensive amount of research on how to use and combine milking data from AMS, SCCS, and data from other sources to detect as well as to predict udder health problems with sufficient specificity and sensitivity (Anglart et al., 2020; Hogeveen et al., 2021; Bonestroo et al., 2022), udder health is not improving in herds with AMS, as mentioned in the Introduction (Hovinen and Pyörälä, 2011; van den Borne et al., 2021). The balance between getting the right amount of information in time with a minimum number of false alerts is truly a challenge due to the complexity of udder health and uniqueness of every farm (Hogeveen et al., 2010; Mollenhorst et al., 2012). Indeed, farmers in our interviews stated that there was a risk of "information overload" with all the available data, which has also been reported by Hansen (2015) and Butler et al. (2012). It could be speculated that this complexity and risk of information overload is one reason for not reaching the potential positive udder health benefits of having an AMS. We argue that this information overload actually means that a lot of the provided information is not interpreted as useful for decision making and subsequent actions, and thus redundant. One measure to achieve a more efficient use of AMS data could be to facilitate a deepened farmer understanding of their data from the AMS, for example, through training or education by technological companies or advisors (Butler et al., 2012; Lunner-Kolstrup et al., 2018). Training could also improve farmers' attitudes toward new technologies, as it not only introduces the technologies but also promotes the benefits of using them (Rehman et al., 2007).

The AMS management system provides certain opportunities to decide what information is visualized, or to create reports according to specific farm needs. Yet, farmers had limited use of tailored reports. It could be hypothesized that this low use of tailored settings indicates a mismatch between the developers of AMS functions (providing flexibility and complexity) and the farmers' practical needs (simplicity). These results emphasize the importance of how new technology must be codeveloped with the end-user and tested in diverse practical settings. Hansen (2015) found that Norwegian farmers in a region with a high AMS adoption rate modified the AMS settings to fit their work. Social networks and peer learning were mentioned as important factors for such adaptations (Hansen, 2015). One reason for not engaging in learning to adapt the system is lack of time. However, optimizing system settings could lead to long-term workload and overall time savings. Farmers also acknowledged that the AMS might contain valuable, yet unexplored, information. This represents a potential untapped resource for decision-making support, as the management system has the capacity to generate specific data points of particular interest to the farmer.

It was clear that farms with SCCS relied heavily on the information from that sensor. As milk SCC is a common metric of udder health and reflects the quality of the milk, the SCCS yields familiar and interpretable information, often seen as "the ground truth." Furthermore, because many dairies apply penalties for delivering milk with SCC above a certain threshold, it is also a direct economic indicator to the farm profit. This was also emphasized by the common viewpoint of farmers when relating the udder health in the herd to the average herd SCC and to receiving full payment for the milk.

The farmers had all made an active choice whether they had acquired SCCS or not. A previous Swedish study on mastitis control options showed that implemented control options were ranked as more beneficial than those that were not implemented at the farm (Lind et al., 2020). Similarly, it could be argued that the deliberate decision to invest in an SCCS may lead to an increased perceived importance of the information it provides. However, if the importance of SCCS is perceived so good that other provided information becomes redundant (as expressed by one farmer), there might be a risk of an SCC tunnel vision, where other information is overlooked. This further emphasizes the need of training and understanding of how to use and combine the AMS data.

We posit that there also could be an important untapped potential in the use of information from AMS in how data are integrated with other information systems and used by veterinarians and other herd health advisors. Our results indicate that the AMS data were used in isolation, with no, or little, integration with data from other systems, and primarily by the farmers themselves. It was unusual that veterinarians used data from the AMS when visiting the farm, especially in cases of acute clinical mastitis. It was somewhat more common when it came to regular herd health visits, although some farmers stated that the advisors were more familiar with the data from their own organization (such as the SOMRS) and thus rather used that data. Other potential reasons for veterinarians not using the on-farm data could be lack of training or software access issues. Further interviews with veterinarians and other dairy farm advisors would be interesting to investigate these reasons and potential barriers for utilizing AMS data. Farmers acknowledged that the AMS data could be useful to veterinarians and advisors at the farm, as well as for managing and following cows with mastitis. If veterinarians and other herd health advisors engaged in the use of data and possible reports and settings from different AMS brands, this could be a help both for their animal health work, as well as for the farmers. Time constraints have previously been shown to hamper successful veterinary herd health management (Svensson et al., 2022), which was also addressed in the conversations. The role of the cattle veterinarian is evolving toward more proactive herd health advisory services compared with the traditional role of treating sick animals (Hall and Wapenaar, 2012; Svensson et al., 2018). In this new role, communication skills become extremely important, as the relationship between the farmer and the veterinarian changes (Jansen et al., 2010; Svensson et al., 2020). If farmers think that the veterinarian does not have time to investigate AMS data, and vice versa, it would be an unfortunate misunderstanding. In addition, veterinarians and other advisors could face the same challenges as addressed by the farmers when interpreting the available data from the AMS, warranting training in the different systems available for their clients, that is, the farmers.

During the last decades, the proportion of herds and cows affiliated to the SOMRS have declined (from ~85% of the Swedish dairy cow population enrolled in 2000 to 76% in 2021, Växa, 2022). The perception of receiving enough data from on-farm technology might play a role in the decrease. One of the interviewed farmers stated this very frankly in the terms that leaving the SOMRS could give financial space for investing in an SCCS. The lack of integration between the AMS and SOMRS data could potentially be one reason for farmers choosing one or the other, as they present similar information in 2 different interfaces to the farmer. Familiarity with the SOMRS data could be one reason for using that data instead, which was reported by a Norwegian farmer (Hansen, 2015). An advantage of the data from the SOMRS is that they include milk quality components such as fat and protein content of the milk for individual cows. On the contrary, as DHI test milking is performed 1 time a month, the use of AMS data, especially from an SCCS, can be a complement to assess an animal's daily udder health status, as well as SCC trends, which was mentioned in several interviews. If information from different systems could be integrated into the same management system, the final output of the combined information may become more useful. In addition, if veterinarians and advisors strive to combine data from both on-farm technology and SOMRS in their work, this could potentially promote continued affiliation to SOMRS and thus a national surveillance of udder health.

Although future work should directly interview veterinarians and farm advisors about how they use AMS data in day-to-day decisions, the present findings point to a practical next step: joint continuing-professional-development modules, codesigned and cotaught by AMS vendors and academic specialists, could equip advisors to translate these data into actionable herd health recommendations.

General Discussion and Methodology Discussion

This study had focus on udder health and thus asked specific questions around detecting cows with udder health problems. However, udder health work is not an isolated work task but rather one aspect, out of many, that farmers have to be constantly aware of and puzzle into their work.

For example, in the survey responses to how a cow with udder health problems probably would be detected, many respondents checked several of the proposed alternatives, although they were asked to choose one. One of the free-text answers made it clear that different pieces of information were used at the same time point: "I understand that I'm only allowed to give one answer, but on a fresh cow you check rumination, milk yield, health every day in T4C [their Lely management program]." The interviews conveyed the importance of finding cows in need of attention, whether they had an udder health problem or not. Here, the management system provided them with lists of "red" cows, which became a first step for detection.

The scenario approach used in the survey was an attempt to give the respondents a sense of a "real case" that worked fairly well. However, if the in-depth interviews had been conducted before the survey, a different approach would probably have been used, considering the holistic perspective of the work on the farm, and how the AMS management system is incorporated into the farm ecosystem. This exemplifies how we, as researchers, must evolve more holistic perspectives and adopt the "farmer's lens" to be able to truly understand how technology interacts with, and affects, the udder health work on dairy farms.

One challenge in the survey was to choose the appropriate response alternatives for detection. It is very possible that, for example, "mastitis warning" had a different meaning to different respondents, not just depending on how the management system presented the information but related to individual interpretations. Some information was not brought up in the survey, although the free-text answers as well as the interviews illustrated the importance of them, such as parameters related to cow activity, feed intake, rumination, and how the cow had moved in the stable (gate passages). However, these parameters were mainly used for further evaluation of deviating cows, not for the first way of detecting them. One aspect to consider is the balance between getting detailed information and making the survey too long, which may hamper the response rate.

In analyses of qualitative data, the subjectivity of the researchers is part of composing the analysis. We acknowledge that our interpretations of the data are colored by our experiences and prior knowledge, as veterinarians and researchers within dairy production.

CONCLUSIONS

This study framed mastitis detection and decision making as an integrated process involving tools, farmer knowledge, and the social context of their use. Our findings revealed that AMS brands and tools create distinct working environments, influencing farmers' behaviors around mastitis detection. A common practice used to detect cows with udder health problems was to monitor the behavior of animals, for example, examine cows that are late for milking, rather than following the more direct udder health parameters, such as SCC or EC. Farmers emphasized SCC as the key indicator of udder health, aligning with dairy plant standards. However, the practical use of AMS data for identifying udder health issues is shaped by various factors: the interplay between technology adoption and available resources (e.g., adapting the system vs. adapting to the system), and the integration—or lack thereof—of AMS data into herd health management frameworks, often constrained by time and labor availability. In addition, use of on-farm data from, for example, the AMS by veterinarians and other herd health advisors, as well as integration with other systems could be important untapped potentials that could further improve the utilization of on-farm data. These insights highlight knowledge gaps and opportunities to enhance mastitis management strategies, ultimately improving udder health and animal welfare.

NOTES

This study was fully funded by the research council Formas, Stockholm, Sweden (2019-00393). We thank all participating farmers for contributing their time and effort. We also acknowledge Anna Duse (Annas djurhälsa AB, Havdhem, Sweden) for valuable input to the survey development and Ulf Emanuelson (Department of Clinical Sciences, Swedish University of Agricultural Sciences, Uppsala, Sweden) for great support and advice during the manuscript preparation. Supplemental material for this article is available at https://osf.io/t4esk/files/osfstorage/68230edc1d341f4bf5c4c017. In consultation with the ethics and legal department at the Swedish University of Agricultural Sciences University, in agreement with the Swedish Ethical Authority, the study did not require a special provision or permit according to Swedish law (SFS 2003:460). Nonetheless, a strict code of conduct as set out by the Swedish Research Council (2017) was followed, including gaining informed consent from all the participants and guaranteeing the pseudonymization of their responses and herd registry data. Furthermore, no sensitive personal information was discussed or collected during the process. No financial incentive was offered to farmers in exchange for their participation. The authors declare no conflicts of interest. One coauthor (DA) is affiliated with DeLaval, a manufacturer of one of the AMS types under investigation. Additionally, one of the lead authors (LE) has a dual affiliation with SLU and Växa Sverige, an advisory organization for farmers. Both these coauthors contributed to survey design and analysis discussions, as part of a multidisciplinary team and contributed with specific insights on AMS technology (DA) and farmer experiences (LE). These affiliations did not influence the study design, data collection, analysis, or interpretation of results.

Nonstandard abbreviations used: AMS = automatic milking systems; CMT = California Mastitis Test; EC = electrical conductivity; MDi = mastitis detection index; OCC = online somatic cell counter; SCCS = SCC sensor; SOMRS = Swedish Official Milk Recording Scheme.

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