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An economic evaluation of sensor-assisted health monitoring in dairy farming using the example of a rumen bolus

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ABSTRACT

The study investigates the economics of sensor-assisted dairy health management and indicates a certain economic potential in the use of a commercial rumen bolus capable of tracking activity and core body temperature. The economic evaluation was performed applying a stochastic model with the net return (NR) of investment of the sensor system as the target variable. The calculated NR considers the gross margin (GM) for both sensor-assisted and visual health monitoring, time savings through sensor-assisted monitoring, additional time spent addressing false positive messages from the sensor system, labor costs, and all costs associated with the investment in the sensor system. The analysis relies on a dataset acquired from a dairy research and demonstration farm on which 65 dairy cows were equipped with the sensor system. A comparison of health-related messages issued by the rumen bolus with disease diagnoses shows that the sensor system issued a message in 7 of 11 cases of retained placenta (sensitivity = 64%), in 19 of 31 cases of clinical hypocalcemia (sensitivity = 61%), in 30 of 70 cases of mastitis (sensitivity = 43%), in 6 of 24 cases of metritis (sensitivity = 25%), and in 2 of 42 cases of diseases of the locomotor system (sensitivity = 5%) in a defined observation period, in many cases several days before the visual diagnosis. SimHerd (A/S Viborg, Denmark) was applied to determine the GM as a function of incidence, SCC, risk of a mild case of disease, and days of milk withdrawal. In a workshop, veterinarians (n = 9) used the dataset to assess the effect of using the sensor system on these parameters. The empirical distributions given by the veterinarians' individual assessments were used to model the parameters considered in the calculation of the "sensor-assisted" GM. For the modeled Holstein herds with a milk yield of 9,000 kg, simulation results show that average NR of investment ranges from +€23 to +€119/cow per year for a herd of poor health, from −€12 to +€84/cow per year for a herd of average health, and from −€33 to +€63/cow per year for a herd of good health, depending on the scenario. The assumptions made regarding changes in labor had a strong influence on the calculated NR of investment. For a full economic evaluation of the sensor system, other functions (estrus detection, calving detection) and functional extensions (e.g., monitoring rumination) have to be considered.

Key words: digital, Monte Carlo method, sensitivity, net return, SimHerd

INTRODUCTION

Wearable sensor systems are being used on dairy cows to simplify and improve health management on dairy farms (Rutten et al., 2013). By recording parameters such as activity, core body temperature, rumination, feeding time, and pH in the reticulum, these sensor systems derive indications of the presence of estrus, a health problem, or imminent calving (Bewley, 2010; Saint-Dizier and Chastant-Maillard, 2015). In health management, wearable sensor systems offer the hope of detecting diseases earlier and, by starting treatment at an early stage, achieving milder disease outcomes and reducing the spread of infectious diseases, thereby reducing performance losses and treatment costs. Optimizing herd health is crucial due to the high costs associated with diseases such as mastitis (Halasa et al., 2007; Hagnestam-Nielsen and Østergaard, 2009; Nielsen et al., 2010), metritis (Mahnani et al., 2015; Pérez-Báez et al., 2021), clinical hypocalcemia (Liang et al., 2017; Yildiz, 2018; Mekonnen et al., 2022), retained placenta (Mahnani et al., 2021; Kamel et al., 2022), or diseases of the locomotor system (Willshire and Bell, 2009; Olechnowicz and Jaskowski, 2011; Ózsvári, 2017). Although numerous sensor systems have been developed for use in dairy farming, only a small number have undergone external validation with respect to their potential for health monitoring (Stygar et al., 2021). Studies on the

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economics of wearable sensor systems have primarily focused on estrus detection (van Asseldonk et al., 1999; Rutten et al., 2014; Bekara et al., 2017; Pfeiffer et al., 2020a) rather than health monitoring. Michaelis et al. (2013) conducted a survey of dairy farmers (n = 219) and found that 54% reported saving money and 18% reported reduced veterinary costs after investing in an automated activity monitoring system. However, as the focus of the survey was on changes in reproductive management, it was not possible to draw specific conclusions on the economic impact of the health management function of the sensor system. Steeneveld et al. (2015a) analyzed the impact of investing in different sensor systems for herd management (e.g., sensor systems for mastitis detection, estrus detection sensors, and other sensor systems such as weighing platforms, rumination time sensors, fat and protein sensors, temperature sensors) on performance parameters, based on data from 414 dairy farms. Considering all these sensor systems, the investment was associated with an increase in milk production per cow on farms with automatic milking systems and a decrease in milk production per cow on farms with conventional milking systems in the following years. An investment in sensor systems for mastitis detection resulted in a decrease in SCC, regardless of the milking system (Steeneveld et al., 2015a). In a later study, Steeneveld et al. (2015b) calculated the Malmquist total factor productivity index using farm accounting data from 217 Dutch dairy farms to measure changes in farm productivity over time. On average, they found no change in farm productivity after investing in a sensor system.

In summary, the existing literature on sensor systems in dairy farming primarily focuses on the technical and economic evaluation of estrus detection. This study aims to demonstrate the potential of a commercial rumen bolus (1) in improving herd health and (2) its resulting economic potential.

MATERIALS AND METHODS

Although assessing all the effects associated with the use of the sensor system is difficult, the study presents a comprehensive methodology that combines different sources of information. The net return (**NR**) of investment in a sensor system to support health monitoring was calculated based on several data sets and methodological steps. Figure 1 illustrates the applied methodological approach. A dataset obtained from a dairy research and demonstration farm where 65 animals were equipped with a health monitoring sensor system was analyzed. The sensitivity of disease case detection was evaluated by comparing health-related messages issued by the sensor system with disease diagnoses. In a workshop setting, veterinarians used the aforementioned results and their own specialized knowledge to assess the parameterization of SimHerd, a simulation model designed to determine the gross margin (**GM**). A stochastic model was used to perform the economic evaluation, with the target variable being the NR of investment in the health monitoring sensor system (see Figure 1).

Stochastic NR Model

The stochastic NR model incorporates the GM for both sensor-assisted and visual health monitoring. It also considers the potential time-saving benefits of sensor-assisted health monitoring, as well as the potential additional time spent on false positive messages from the sensor system. The model also takes into account all costs associated with investing in the sensor system. The GM was determined using the simulation model SimHerd (SimHerd A/S, Viborg, Denmark) and was expressed as a function of incidence, risk of a mild case of disease, days of milk withdrawal, and SCC (depending on the disease):

$$NR\left(SHM\right) = \left[\sum_{i=1}^{9} GM_{SHM} f\left(disease\ parameter\right) - GM_{VHM} f\left(disease\ parameter\right)\right] + \left(LC \times TS_{SHM}\right) - \left(LC \times TFP_{SHM}\right) - investment\ cost, \qquad [1]$$

where NR = net return, SHM = sensor-assisted health monitoring, VHM = visual health monitoring, GM = gross margin, f = as a function of, LC = labor costs, TS = time saving in health monitoring, TFP = time spent on false positive messages, and the following disease parameters i:

- 1 = mastitis: incidence
- 2 = mastitis: risk of a mild case of disease
- 3 = mastitis: days of milk withdrawal
- 4 = mastitis: somatic cell count
- 5 = metritis: risk of a mild case of disease
- 6 = metritis: days of milk withdrawal
- 7 = hypocalcemia: risk of a mild case of disease
- 8 = retained placenta: risk of a mild case of disease
- 9 = retained placenta: days of milk withdrawal

Dataset: Analysis of the Sensitivities of Disease Case Detection

The economic evaluation assumptions are based on a dataset obtained from the dairy research and demonstration farm for cattle feeding "Staatsgut Achselschwang" in Bavaria, Germany. In July 2018, 65 animals from

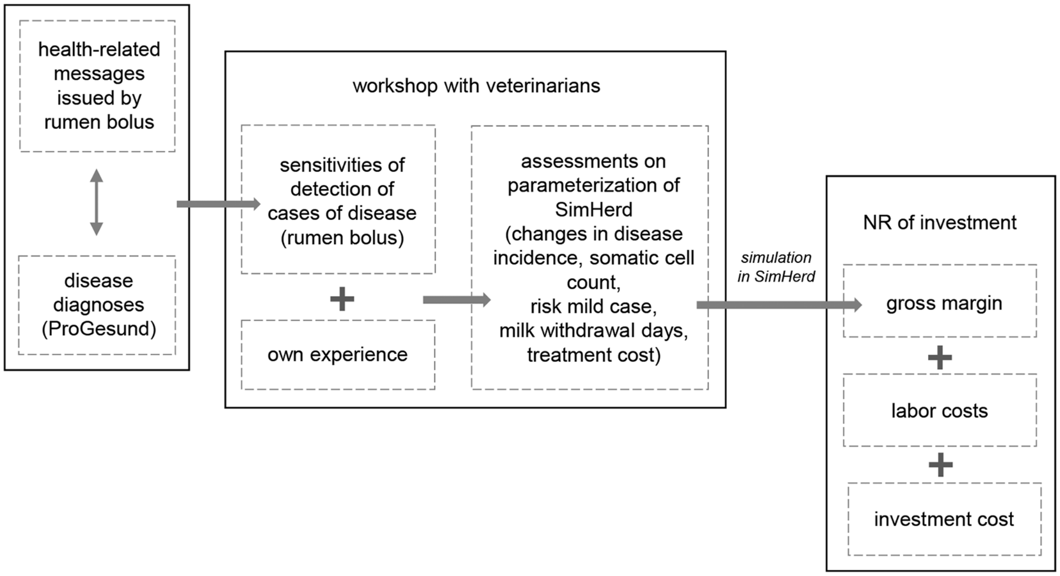

Figure 1. Schematic representation of the procedure for calculating the net return of investment of a sensor system used to assist in health monitoring (Pfrombeck et al., 2024, modified).

the herd were equipped with a smaXtec Classic bolus, a commercially available sensor system that is orally administered into the reticulorumen (smaXtec, 2023). The study included animals of various breeds, primarily Simmental, but also Brown Swiss and Holstein, and of different lactations. The dataset covered the period from July 2018 to June 2020, with 35 animals equipped with rumen boluses still in the herd at the end of this period. The sensor system recorded animal activity on a scale of 1 to 100 using a 3-dimensional accelerometer, core body temperature, and indirectly, the number of drinking cycles. Based on the manufacturer's proprietary algorithms, animal-specific estrus, health, and calving messages were issued. Health-related messages included changes in core body temperature, drinking cycles, or activity. The smaXtec bolus only indicated deviations in the parameters and did not provide concrete indications of possible disease diagnoses. Additionally, it has been developed to record rumination (smaXtec, 2023), which may also indicate changes in the presence of a disease (Calamari et al., 2014; Schirmann et al., 2016; Paudyal et al., 2018). However, the economic evaluation of this study only refers to the classic bolus as it was functioning at the time of data collection. Therefore, it does not include information on rumination.

The database includes not only messages from the sensor system but also documentation of visual disease diagnoses made by the farm veterinarian or hoof trimmer of this dairy research and demonstration farm as part of the "Pro Gesund" project. Definitions of the diseases considered in the study can be found in Chase et al. (2017). "Pro Gesund" (http://www.progesundrind.de/) has been funded by the Bavarian State Ministry of Food, Agriculture and Forestry since 2009. The objective of the program is to facilitate the identification of health-related developments within a dairy herd by dairy farmers and veterinarians. This is achieved through the collection of data on milk yield, observations made by the farmer or hoof trimmer, and veterinary diagnoses. "Pro Gesund" integrates separate modules for fertility, udder health, and metabolic health, in addition to evaluating claw health and calf health, and uses all of these data to estimate the health breeding value of insemination bulls (Zeiler et al., 2013). The "Pro Gesund" program employs visual representations of animal health to assist farmers in identifying animals with an elevated risk of disease. On the dairy research and demonstration farm, the cows were subjected to a daily visual inspection in the milking parlor, with particular attention paid to the udder for any indications of abnormalities. In the event of an elevated core body temperature indicated by the rumen bolus, the initial procedure was to ascertain the rectal temperature of the affected animal and to examine the udder for any alterations. Subsequently, a California Mastitis Test was conducted. This procedure was repeated on subsequent days. In the event of a positive result on the California Mastitis Test or the emergence of symptoms indicative of mastitis, a rapid diagnostic test and a milk bacteriological test were conducted to ascertain the precise nature of the infection. In instances where the rumen bolus indicated a reduction in activity or the number of drinking cycles, a comprehensive examination of the hooves and the animal's overall condition was conducted. Any abnormalities in gait, such as lameness, were monitored on a regular basis across all animals. Hoof trimming was performed as necessary, with a minimum of 3 times per year. It is important to note that there was no additional systematic daily veterinary examination of all animals in the herd. Therefore, the absence of a diagnosis in the context of the "Pro Gesund" project does not necessarily exclude the presence of disease, whether clinical or subclinical. This study specifically focuses on mastitis, clinical hypocalcemia, retained placenta, metritis, and diseases of the locomotor system, as the dataset provides a sufficient sample for these diseases.

To assess the algorithm's sensitivity in the sensor system, we compared the visual diagnoses documented with the health-related messages generated by the sensor system:

$$sensitivity\,of\,detection\,of\,a\,specific\,disease\left(\%\right) = \frac{number\,of\,correct\,positives\left(sensor\,system\right)}{number\,of\,all\,diagnoses\left(Pro\,Gesund\right)} \times 100. \quad [2]$$

This step involved assessing the proportion of disease cases for which the sensor system issued a message during the period from 6 d before (d −6) to 1 d after (d +1) the documented visual diagnosis (d 0). The observation period for clinical hypocalcemia was shortened to d −2 to d +1, and for retained placenta to d −1 to d +1. It was assumed that the message assigned to a disease case as a correct positive was issued due to the disease and not due to any other unknown cause. The day of the visual diagnosis and the day of the first correct positive message issued by the sensor system (if multiple messages were issued) were considered for each disease case. To be counted as 2 independent diagnoses, 2 diagnoses of the same diagnostic group in one animal had to be at least 14 d apart (see Kim et al., 2019). However, this rule was not applied to diagnoses of different diagnostic groups.

The smaXtec Classic Bolus also issues notifications of imminent calving based on the recorded core body temperature (smaXtec, 2023), which is known to decrease toward calving (Burfeind et al., 2011; Rutten et al., 2017). In the defined calving window, which extends from 14 d before to 14 d after the target calving date set in the software, the sensor system issues a message indicating imminent calving instead of a health problem if the core body temperature declines to a specified threshold (until the actual calving event is documented in the software). The notifications of imminent calving were not included in the sensitivity calculations. Furthermore, in calculating the sensitivity for retentio secundinarum, only those health-related messages that were issued subsequent to the event of calving were included. It is not possible to definitively determine whether some of the health-related messages included in the analysis were prompted by disease or by calving. As these messages were issued as indications of a health problem in the smaXtec system, they were classified as such when determining the sensitivities.

Determination of GM using SimHerd

SimHerd (Østergaard et al., 2005) is a stochastic, dynamic and mechanistic dairy herd simulation model developed at Aarhus University in Denmark. The model simulates the production and state changes in the dairy herd, including young stock. The states are characterized by actual milk production, BW, reproductive status, and health status. SimHerd predicts the current status for each cow and heifer in the herd on a weekly basis. The individual animal's status is updated, and the herd's production and input usage are calculated. Discrete events, such as estrus detection, abortion, individual inherent and lactation milk yield potential, disease, and death, are triggered by drawing random numbers from relevant probability distributions. Therefore, simulating the production and change in status of individual cows and heifers indirectly determines herd production and development. The model includes diseases such as mastitis, hypocalcemia, dystocia, retained placenta, metritis, displaced abomasum, and diseases of the locomotor system. Risk factors for these diseases, including lactation stage, parity, and yield level, have been defined. The direct and indirect effects and interrelationships of these diseases have also been established (see Østergaard et al., 2003, 2005; Hernandez et al., 2007; Ettema et al., 2010). The behavior of the model can be regulated by a set of decision variables that define specific production systems and management strategies. By default, the model is parameterized to represent a conventional Holstein herd. It includes several parameters that determine the risk, course, and financial impact of a disease.

SimHerd provides the capability to simulate diverse herd scenarios, allowing the modeling of herds exhibiting a range of health statuses, including poor, average, and good. Differences between these herds may be attributable to genetic or management-related factors, for instance. A significant distinction between the 3 herds of different health statuses is the assumption of elevated disease incidence in those of poorer health. To illustrate, the standard incidence of mastitis is 49.9 for herds of poor health, 36.6 for herds of average health, and 21.6 for herds of good health. Furthermore, the SCC of these 3 herds exhibits notable differences (poor health: 290,000/mL, average health: 245,000/mL, good health: 180,000/mL). The herds of poor and good health represent herds in which the levels of mastitis and SCC correspond to the 75th and 25th percentiles, respectively, as registered for Holstein herds in the national cattle database in Denmark (SEGES Innovation, 2022). The average herd represents a herd in which the values are the average of the 25th and 75th percentiles from the same database. As SimHerd is a dynamic model, a positive influence on other factors is simulated in the model when the herd is in better health. For instance, a herd that is in good health will exhibit a greater number of productive years per cow, a higher lifetime production (in kg ECM), and a higher conception rate.

The economic analysis was conducted on 3 herds of poor, average, and good health, and a milk yield of 9,000 kg each. To calculate the GM using SimHerd, producer prices for milk, slaughter cows, and heifers for sale were adjusted to reflect the current market situation in Bavaria, Germany, based on a 3-yr average from August 2019 to August 2022 (refer to Table 1). The SimHerd runs were replicated 300 times.

To simulate scenarios for sensor-assisted health monitoring, the parameters incidence, risk of a mild case of disease, days of milk withdrawal, SCC, and treatment costs per case of disease were parameterized in SimHerd. The risk of a mild case of disease describes the frequency of occurrence in clinical cases of disease. SimHerd assumes that a mild case of disease has a default factor of 0.1 compared with a normal case. For example, the decrease in milk yield in a mild case is only 10% compared with the decrease in a normal case. SimHerd has been used to simulate GM for different levels of incidence, SCC, risk of a mild case, and days of milk withdrawal. In SimHerd, these parameters are not interdependent. For instance, a change in mastitis incidence does not necessarily lead to a change in SCC. Therefore, we analyzed the parameters individually and added them up in the NR formula. We varied the parameters in steps of 5% for incidence, 10% for the risk of a mild case, 1 for days of milk withdrawal, and 5,000 for SCC within a certain range to determine their respective influence on GM. The linear equations describing the relationships between the parameters and the GM were used for further calculations.

Workshop with Veterinarians: Assumptions on Disease Incidence, Risk of a Mild Case of Disease, Days of Milk Withdrawal, SCC, and Treatment Costs

In July 2022, a workshop was conducted online with the participation of 9 veterinarians to assess the impact of using the sensor system on the parameters incidence, risk of a mild case of disease, days of milk withdrawal, SCC, and treatment costs per case of disease. The use of a sensor system to support the health management of a dairy herd is usually associated with positive effects on animal health and farm profitability (e.g., Bewley, 2010). However, detailed empirical evidence is scarce. Many influencing factors, such as individual courses of disease, make it difficult to generalize how incidence or treatment costs, for example, will change if individual cases of disease in the herd are detected early. For example, there may be cases of mastitis that can be treated differently and have a milder course of disease if detected early, but other cases of mastitis will not. The objective of the workshop was for the veterinarians to quantify the average effects on disease-relevant parameters, with the aim of incorporating these individual assessments into the calculation of the NR using Monte Carlo simulation. All participating veterinarians had prior experience with the sensor system on dairy farms. The workshop did not consider diseases of the locomotor system due to the low sensitivity of the sensor system in detecting them obtained in the dataset. It is possible that a use of the sensor system could reduce the incidence of infectious diseases by detecting cases early and preventing further spread within the herd. Because this potential is only relevant for mastitis among the diseases considered in the study (Gussmann et al., 2019), the parameterization of disease incidence was performed only for mastitis.

During the workshop, veterinarians were presented with the dataset comprising the sensitivity of disease detection and the timing of health-related messages issued by the sensor system, as well as default values for incidence, risk of a mild case, days of milk withdrawal, SCC, and treatment costs for poor, average, and good health herds in SimHerd. The group then discussed potential changes in the default values of these parameters resulting from the application of the sensor system. All veterinarians used an online form (Appendix Figures A1 and A2) to enter their individual assessment of a potential change in each of the default values. The online form was completed partly in groups, resulting in 6 completed online forms. A plausibility check of the re-

Table 1. Producer price-related assumptions for the calibration of SimHerd (€)

Parameter	Price[1] (€)
ECM, per kg	0.38
TMR of lactating cows, per kg DM	0.17
Cull cow, per kg of live weight	1.24
Springing heifer	1,443
Nonpregnant heifer	894
Bull calf, sold at 14 d	76
First-parity cow, sold for life	1,681
Milk replacer, per kg of powder	2.13
Price per feeding unit (6.9 MJ) for concentrates, heifers	0.27
Price per feeding unit (6.9 MJ) for roughage, heifers	0.15
Breeding, unsexed proven bull semen	22

[1] Net prices (average for Bavaria for the period from August 2019 to August 2022) according to Bayerische Landesanstalt für Landwirtschaft gross margin calculator (LfL, 2022).

Table 2. Scenario assumptions for health monitoring time requirements[1]

Parameter	Scenario 1 (sensitivity <100%, specificity <100%)	Scenario 2 (sensitivity <100%, specificity = 100%)	Scenario 3 (sensitivity = 100%, specificity <100%)	Scenario 4 (sensitivity = 100%, specificity = 100%)
Time savings through sensor-assisted health monitoring, h/cow per year	0	0	Minimum: 0.7 Mode: 1.5 Maximum: 3.0	Minimum: 0.7 Mode: 1.5 Maximum: 3.0
Time expenditure for false positives issued by the sensor system, h/cow per year	Minimum: 0.9 Mode: 1.3 Maximum: 1.7	0	Minimum: 0.9 Mode: 1.3 Maximum: 1.7	0

[1] Assumptions on minimum, mode, and maximum are based on analyzed dataset and authors' own expertise.

sponses led to the deletion of 8 individual entries from 3 completed forms.

To facilitate the work of the veterinarians, they should estimate the change in the risk of a mild case of disease among all cases of disease correctly detected by the sensor system (correct positives). As the estimated risk of a mild case of disease for the whole herd was required for further analysis, the proportion estimated by the veterinarians was then multiplied by the respective sensitivity identified in the dataset:

$$\begin{aligned}&\textit{estimated risk of a mild case of disease in herd}\left(\%\right)=\\&\textit{estimated risk of a mild case of disease for}\\&\textit{sensor - detected cases of disease}\left(\%\right)\times \textit{sensitivity}\left(\%\right).\end{aligned} \qquad [3]$$

The authors calculated the values for the entire herd based on the estimates provided by the veterinarians regarding the potential change in milk withdrawal days in relation to all cases of disease correctly detected by the sensor system:

$$\begin{aligned}&\textit{estimated milk withdrawal days in herd}=\\&\textit{default value milk withdrawal days}\times\left[100-\textit{sensitivity}\left(\%\right)\right]\\&+\textit{estimated milk withdrawal days for sensor detected cases}\\&\textit{of disease}\times\left[\textit{sensitivity}\left(\%\right)\right].\end{aligned} \qquad [4]$$

The veterinarians who participated in the workshop differed in their assessment of the influence of the sensor system on the parameters incidence, SCC, risk of a mild case of disease, and days of milk withdrawal. It is also expected that the sensor system's potential is used differently on different farms. To address the heterogeneity in the economic model, we used the Monte Carlo method in @RISK (Palisade Corporation, Ithaca, NY) to model these parameters for calculating the GM "sensor-assisted." The NR model integrated the veterinarians' individual assessments using the RiskCumul function in @Risk, based on the respective cumulative probability of these parameters.

The veterinarians provided estimates of potential changes in treatment costs for mild cases of disease. SimHerd calculates treatment costs per case of disease, which includes veterinary labor costs, medication costs, and farmer labor costs. It is important to note that a change in the parameter risk of a mild case of disease does not lead to a corresponding change in treatment costs in SimHerd. However, the veterinarians' estimates suggested that a mild course of the disease could lead to a reduction in treatment costs. Therefore, the authors adjusted the treatment costs when calculating GM based on the risk of a mild case of disease in SimHerd:

$$\begin{aligned}&\textit{mean treatment costs } (\text{€})_{\textit{certain risk of a mild case}} = \textit{certain}\\&\textit{risk of a mild case } (\%) \times \textit{mean treatment costs for a}\\&\textit{mild case of disease } (\textit{estimation of veterinarians}) \; (\text{€}) +\\&(100 - \textit{certain risk of a mild case}) \; (\%) \times \textit{treatment costs}\\&\textit{for a normal case of disease } (\textit{default value}) \; (\text{€}).\end{aligned} \qquad [5]$$

The equation calculates the average treatment costs per case of disease, taking into account the proportion of cases with a normal course of disease and those with a mild course of disease. The GM was determined for each disease based on the risk of a mild case of disease in 10% increments. Mean treatment costs were then calculated for each 10% increment (10%, 20%, ..., 90%, 100%) using Equation 5. The calculated treatment costs per case of disease did not differentiate between herds of good, average, and poor health.

Annual Cost of Investing in the Sensor System

The annual cost of investing in the sensor system, Classic bolus from smaXtec animal care GmbH, was calculated based on the time of purchase in July 2018. The cost includes the sensors, basic equipment, monthly fee per sensor, and implementation costs. The implementation costs include the time spent on initial information (estimated at 5 h), learning and installation

Table 3. Sensitivities and respective day of first health-related messages issued by the sensor system for detected cases of disease (correct positives)

Item	d −6	d −5	d −4	d −3	d −2	d −1	d 0 (visual diagnosis)	d +1
Retained placenta (n = 11) Sensitivity[1] = 64%	—[2]	—	—	—	—	xxxxx	xx	
Clinical hypocalcemia (n = 31) Sensitivity = 61%	—	—	—	—	xx	xxxx xxxx	xxx xxx	xxx
Mastitis[3] (n = 70) Sensitivity = 43%	xx	xxx	x	xxx	xxxxx	xxx	xxxxx xxxx	xxxx
Metritis (n = 24) Sensitivity = 25%		x	x	x	x	x		x
Diseases of the locomotor system[4] (n = 42) Sensitivity = 5%	x					x		

x = each "x" represents one health-related message issued by the sensor system (in each case of disease, only the first health-related message [correct positive] in the respective observation period is considered; messages issued at a later day in the case of disease are not shown).

[1] Sensitivity [%] = number of correct positive diagnoses/number of all diagnoses × 100 (in respective observation period).

[2] — indicates period not considered.

[3] Pathogen: *Escherichia coli,* CNS*, Streptococcus spp*., and others (see Table 4).

[4] Dermatitis digitalis, sole ulcer, panaritium, tyloma, paralysis, and others.

(estimated at 10 h), and equipping the cows (10 min per cow). An interest rate of 4% was assumed. The sensor system's useful life was assumed to be 4 yr, which is a conservative estimate considering that the basic equipment may have a longer lifespan. Repair costs were not factored in as the monthly fee per sensor covers free replacements in case of defects. Additionally, it was assumed that 2 extra repeaters would be purchased for a herd size of 210 animals, compared with 70 animals. With labor costs of €15/h, the annual cost of investment amounted to approximately €51 (70 animals) and €46 (210 animals) per cow per year, and with labor costs of €30/h to approximately €52 (70 animals) and €47 (210 animals) per cow per year.

Time Spent on Health Monitoring

The time spent on health monitoring in the NR model refers to checking whether animals in the herd are ill, rather than the time spent on treating ill animals. Treatment costs in SimHerd have already accounted for the latter. Empirical data on changes in the time spent on herd health management due to investment in sensor systems is scarce. Most studies do not differentiate between the time spent on the functions of estrus detection, health monitoring, and calving detection. For instance, Michaelis et al. (2013) surveyed 219 dairy farmers after an investment in an automated activity monitoring system, with 82% reporting time savings. However, Michaelis et al. (2013) focused on reproduction rather than health management. Steeneveld et al. (2015b) found no significant differences in labor costs (contract labor, paid labor, and own labor) on farms after investing in a sensor system. Therefore, the time spent on health monitoring is assumed based on the analyzed dataset and the authors' expertise. As health monitoring is often conducted simultaneously with other activities, such as milking and estrus control, it is challenging to accurately quantify the time spent solely on health monitoring. To account for the heterogeneity present on farms, we modeled the time spent on health monitoring (both sensor-assisted and visual) using triangular distributions and the Monte Carlo method in @RISK (Palisade Corporation, Ithaca, NY; see Table 2).

To account for the uncertainties associated with the time spent on health monitoring, the calculation of the NR of investment included 4 scenarios (see Table 2). Throughout the analysis period of this dataset, the sensor system issued a total of 665 health-related messages, of which 146 (22%) could be attributed to a Pro Gesund diagnosis (= positive predictive value). For the remaining 519 messages (78%), possible causes such as heat stress (THI ≥71), near-calving period, cell count ≥200,000/mL in the last milk content analysis (conducted 11 times per year) as a possible indication of subclinical mastitis, estrus, or vaccination were identified. Scenario 1 assumed that visual health monitoring is necessary, as the sensor system's disease detection sensitivity is below 100%. Therefore, investing in the sensor system does not save any time in health monitoring. False positive messages result in additional work for dairy farmers. This includes checking the message based on the animal's individual history in the software, searching for the animal in the barn, visually identifying possible signs of disease, and conducting follow-up checks the next day. It was hypothesized that a resulting daily time expenditure of 15 min on average (minimum 10 min and maximum 20 min) would be required for a herd of 70 animals, and 45 min on average (minimum 30 min and maximum 60 min) for a herd of 210 animals. This equates to a mode of 1.3 h/cow per year, which was assumed to account for the additional time expenditure for health-related messages from the sensor system that could not be assigned to a Pro Gesund diagnosis. Scenario 2 assumed that adopting the sensor system does not save any time in health monitoring. However, it also simulated that the sensor system would have a specificity of 100%, meaning that no additional time would be needed to check for false positives. Scenarios 3 and 4 assumed that the sensor system would have a sensitivity of 100% and would therefore detect all cases of disease in the herd. This could potentially save time in health monitoring by eliminating the need for routine visual observation of animals. A study on the organization of work on Bavarian dairy farms (n = 52, average 104 cows) revealed an average working time expenditure of 5.1 man-hours per cow and year for the category “barn management work,” which encompassed animal inspections, animal treatments, animal traffic, insemination, and calving assistance (Haidn and Mačuhová, 2009). Applying these findings to a herd of 70 animals yields a time expenditure of ~60 min/d for “barn management work.” It was assumed that, on average, one-third of the requisite working time required is attributable to health management, which corresponds to 20 min/d for a herd of 70 animals. It was hypothesized that the implementation of a sensor system with a disease detection sensitivity of 100% would result in a time saving of 85%. Consequently, a mode of 1.5 h/cow per year (minimum 0.7 h/cow per year and maximum 3.0 h/cow per year) was assumed for working time savings in scenarios 3 and 4.

Modeled Scenarios

The economic evaluation simulated different scenarios for a Holstein herd with an annual milk yield of 9,000 kg. The scenarios included herd sizes of 70 and 210, and labor costs of €15/h and €30/h for herds of good, average, and poor health, respectively. Four scenarios regarding potential time savings through sensor-assisted health monitoring and time expenditure for false positives were included. A total of 48 scenarios was analyzed, with each scenario undergoing 10,000 iterations in @RISK. The integration of probability distributions for some of the parameters allowed to model a probability distribution for the NR of investment of the sensor system for health monitoring.

Table 4. Microbiological diagnosis of milk samples obtained from clinical mastitis cases (n = 70) occurring in dairy cows of the dataset

Microbiological diagnosis	n	Percentage (%)
CNS (and others)	22	31
Streptococci esculine	5	7
Streptococcus uberis	3	4
Escherichia coli	2	3
Klebsiella spp.	2	3
Enterobacter spp.	2	3
Staphylococcus aureus	2	3
Serratia marcescens	2	3
Streptococcus dysgalactiae	1	1
No growth	6	9
Acute mastitis[1]	22	31
Chronic mastitis[1]	1	1
Total	70	100

[1] No further information available, the authors assume that no pathogen detection was carried out.

RESULTS AND DISCUSSION

Sensitivities of Detection of Cases of Disease

The calculated sensitivities together with the respective day of the first health-related message for detected disease cases (correct positives) are shown in Table 3 (see Pfeiffer et al., 2020b; Pfeiffer and Gandorfer, 2022, for preliminary analysis). The dataset included 219 disease diagnoses for the entire period of analysis, consisting of mastitis (see Table 4 for pathogens), diseases of the locomotor system (such as dermatitis digitalis, sole ulcer, panaritium, limax, paralysis, and others), clinical hypocalcemia, metritis, retained placenta, and other diseases (such as teat and udder injury, colic, indigestion, and cycle disorders). Sensitivities were calculated for all diseases except the latter group due to their small sample sizes. During the entire period of analysis, the sensor system issued a total of 665 health-related messages. The system issued a health-related message for retained placenta in 7 out of 11 cases (sensitivity = 64%), for clinical hypocalcemia in 19 out of 31 cases (sensitivity = 61%), for mastitis in 30 out of 70 cases (sensitivity = 43%), for metritis in 6 out of 24 cases (sensitivity = 25%), and for diseases of the locomotor system in 2 out of 42 cases (sensitivity = 5%). Extending the observation period for determining sensitivities of detecting cases of mastitis, metritis, and diseases of the locomotor system from d −6 to d +1, to d −10 to d +5 resulted in similar results for sensitivities. This demonstrates the robustness of the NR results with respect to the selection of the observation period.

In the interpretation of results from studies on the potential of sensor systems with regard to sensitivities and early detection of cases of disease, it is essential to consider the design of the study in a differentiated manner. The majority of studies analyzed recorded param-

Table 5. Default values for mastitis given in SimHerd and veterinarians' (vet1–vet6) estimates for considered parameters in herds of poor, average, and good health

Mastitis	Poor health	Average health	Good health
Incidence, cases per 100 cows/yr			
Default (SimHerd): in herd	49.9	36.6	21.6
vet1: in herd	45	33	20
vet2: in herd	40	28	18
vet3: in herd	40	25	12
vet4: in herd	45	32	18
vet5: in herd	—	—	—
vet6: in herd	45	33	20
Ø, n (%)	43 (−14)	30 (−18)	18 (−19)
Risk of mild case, %			
Default (SimHerd): in herd	0	0	0
vet1: in herd[1]/for detected cases[2]	22/50	22/50	30/70
vet2: in herd[1]/for detected cases[2]	30/70	26/60	26/60
vet3: in herd[1]/for detected cases[2]	17/40	22/50	37/85
vet4: in herd[1]/for detected cases[2]	17/40	26/60	34/80
vet5: in herd[1]/for detected cases[2]	22/50	26/60	34/80
vet6: in herd[1]/for detected cases[2]	22/50	22/50	30/70
Ø	22/50	24/55	32/74
Days of milk withdrawal			
Default (SimHerd): in herd	7	7	7
vet1: in herd[3]/for detected cases[2]	7/7	7/7	7/7
vet2: in herd[3]/for detected cases[2]	6/5	6/5	6/5
vet3: in herd[3]/for detected cases[2]	7/7	7/7	7/7
vet4: in herd[3]/for detected cases[2]	7/7	7/6	6/6
vet5: in herd[3]/for detected cases[2]	6/5	7/6	7/7
vet6: in herd[3]/for detected cases[2]	7/7	7/7	—
Ø, n/n (%/%)	6.7/6.3 (−4/−10)	6.7/6.3 (−4/−10)	6.7/6.3 (−4/−10)
SCC, ×1,000/mL			
Default (SimHerd): in herd	290	245	180
vet1: in herd	270	230	150
vet2: in herd	250	220	170
vet3: in herd	200	200	170
vet4: in herd	200	190	120
vet5: in herd	—	—	—
vet6: in herd	250	200	150
Ø, n (%)	234 (−19)	208 (−15)	152 (−16)

[1] Related on entire herd, calculated based on Equation 3. Calculated values are rounded.

[2] Related on all cases of disease detected by the sensor system.

[3] Related on entire herd, calculated based on Equation 4.

eters for changes in the case of disease or developed new, multiple parameters comprising models for automated disease detection, into which data from sensor systems were fed. This approach allowed for the evaluation of the "theoretical" potential. In our study, however, the potential of a sensor system was evaluated based on messages generated by the manufacturer's algorithm. For example, Kim et al. (2019) developed an algorithm that detected 93% of all cases of mastitis using body temperature data collected via rumen bolus. Similarly, Adams et al. (2013) demonstrated an increase of at least 0.8°C above baseline in 67% of cases of mastitis by applying temperature-sensing rumen bolus. Therefore, both studies (Adams et al., 2013; Kim et al., 2019) achieved higher sensitivity in detecting mastitis by considering temperature compared with the present study (43%). However, the present study highlights the importance of temperature as a crucial parameter for detecting mastitis. In 28 out of 30 detected cases (correct positives), an increase in temperature was the first message issued by the rumen bolus. De Mol et al. (2001) applied a model that resulted in sensitivities of mastitis detection ranging from 55% to 80%, based on sensor data of activity, milk yield, milk temperature, and electrical conductivity of milk. The application of the model revealed considerable differences in sensitivity on the 4 farms studied, indicating that a detection model may perform differently under field conditions (De Mol et al., 2001). Hogeveen et al. (2010) conducted a review study of 15 studies to identify clinical mastitis based on milk-related parameters, including SCC, electrical conductivity, color, milk yield, milk temperature, and milk flow. Sensitivities ranged from 32% to 100%, with only 4 of the 15 studies showing a sensitivity below 50%. The literature suggests that automatically collected sensor

Table 6. Default values for metritis given in SimHerd and veterinarians'(vet1–vet6) estimates for considered parameters in herds of poor, average, and good health

Item	Poor health	Average health	Good health
Risk of mild case, %			
Default (SimHerd): in herd	0	0	0
vet1: in herd[1]/for detected cases[2]	5/20	5/20	8/30
vet2: in herd[1]/for detected cases[2]	8/30	5/20	5/20
vet3: in herd[1]/for detected cases[2]	3/10	3/10	3/10
vet4: in herd[1]/for detected cases[2]	5/20	6/25	7/27
vet5: in herd[1]/for detected cases[2]	13/50	10/40	8/30
vet6: in herd[1]/for detected cases[2]	13/50	13/50	13/50
Ø	8/30	7/28	7/28
Days of milk withdrawal			
Default (SimHerd): in herd	6	6	6
vet1: in herd[3]/for detected cases[2]	6/6	6/6	6/6
vet2: in herd[3]/for detected cases[2]	6/4	6/5	6/5
vet3: in herd[3]/for detected cases[2]	6/4	6/4	6/4
vet4: in herd[3]/for detected cases[2]	6/5	6/5	6/4
vet5: in herd[3]/for detected cases[2]	6/4	6/5	6/5
vet6: in herd[3]/for detected cases[2]	6/4	6/4	6/4
Ø, n/n (%/%)	5.6/4.5 (−6/−25)	5.7/4.8 (−5/−21)	5.7/4.7 (−6/−22)

[1] Related on entire herd, calculated based on Equation 3. Calculated values are rounded.

[2] Related on all cases of disease detected by the sensor system.

[3] Related on entire herd, calculated based on Equation 4.

data has a higher potential for detecting mastitis, which was not found to the same extent in the present study. It is important to note that the course and symptoms of mastitis depend not only on the individual animal but also on the particular pathogen (Oliveira et al., 2013). Stangaferro et al. (2016b) developed a model that combined rumination and activity data and detected 58% of all cases of mastitis. In differentiating all cases of mastitis by their pathogen, a comparatively high sensitivity of 81% was found for cases caused by *Escherichia coli* (Stangaferro et al., 2016b).

Literature on the detection of lameness includes studies that have applied models demonstrating higher sensitivities than in the present study, depending on the parameters considered. O'Leary et al. (2020) conducted a review study on the detection of lameness based on accelerometer data. It has been documented that some studies have demonstrated a sensitivity of 80% or higher for the detection of lameness based on the analysis of activity and additional parameters, including milking and feeding data (e.g., De Mol et al., 2013; Garcia et al., 2014; Grimm et al., 2019). O'Leary et al. (2020) also concluded that behavior measures alone are not reliable indicators of lameness. They discussed the analysis and future development of sensor systems for automatic detection of gait measures as a more promising approach for automatic lameness detection. This is because a cow's gait changes during claw disease to relieve painful limbs (O'Callaghan, 2002; Gleerup et al., 2015). Many of the studies included in the review (O'Leary et al., 2020) analyzed gait measures to detect lameness and reported good performance. For example, Mangweth et al. (2012) found a sensitivity of 94%, whereas Beer et al. (2016) reported a sensitivity of 90%. Although Charlton et al. (2016) and Blackie and Maclaurin (2019) did not identify a definitive influence, the majority of studies indicated that lame cows spend more time lying down, with fewer but longer bouts (Ito et al., 2010; Westin et al., 2016; King et al., 2017; Weigele et al., 2018). Therefore, the low sensitivity (5%) found for diseases of the locomotor system in the present study may be due to the fact that only overall activity was recorded by the sensor system, without specific lying parameters.

Of the 6 correct positive cases of metritis, the sensor system detected an increase in core body temperature in 4 cases and a decrease in activity in 2 cases. Subsequent messages were also related to an increase in core body temperature. The messages from the sensor system therefore indicated symptoms that are commonly associated with metritis. Animals with metritis may have a fever (Benzaquen et al., 2007; Palenik et al., 2009; Wenz et al., 2011); however, not all cases of metritis are accompanied by a fever (Palenik et al., 2009; Adams et al., 2013). This may be a possible reason for the low sensitivity of metritis detection in the present study (25%). Metritis can cause a decrease in activity, resulting in fewer steps and longer lying time, as reported in the literature (Steensels et al., 2017; Tsai et al., 2021; Rial et al., 2023). This decrease in activity may also lead to cows spending less time at the feeding table (Urton et al., 2005) and ruminating (Steensels et al., 2017; Rial et al., 2023). Stangaferro et al. (2016c) developed a model to detect metritis in

Table 7. Clinical hypocalcemia: Default values given in SimHerd and veterinarians' (vet1–vet6) estimates for considered parameters in herds of poor, average, and good health

Item	Poor health	Average health	Good health
Risk of mild case, %			
Default (SimHerd): in herd	0	0	0
vet1: in herd[1]/for detected cases[2]	12/20	12/20	12/20
vet2: in herd[1]/for detected cases[2]	55/90	55/90	55/90
vet3: in herd[1]/for detected cases[2]	31/50	37/60	49/80
vet4: in herd[1]/for detected cases[2]	43/70	37/60	37/60
vet5: in herd[1]/for detected cases[2]	55/90	49/80	49/80
vet6: in herd[1]/for detected cases[2]	43/70	31/50	21/35
Ø	40/65	37/60	37/61

[1] Related on entire herd, calculated based on Equation 3.

[2] Related on all cases of disease detected by the sensor system calculated values are rounded.

animals based on rumination and activity parameters, resulting a sensitivity of 53% for animals with metritis only and 78% for animals with metritis and another disorder. Stangaferro et al. (2016c) also found that the model predominantly detected severe cases of metritis.

This study found that the sensor system had the highest sensitivities of detecting clinical hypocalcemia (61%) and retained placenta (64%). In cases of clinical hypocalcemia, the sensor system primarily issued messages due to a decrease in activity, a decrease in the number of drinking cycles, and a decrease in core body temperature. Several studies have reported typical symptoms of the disease, including decreased activity such as prolonged lying time (Melendez 2017; Hendriks et al., 2020; Tsai et al., 2021), decreased body temperature (Venjakob et al., 2016; Melendez 2017; Arechiga-Flores et al., 2022), and decreased rumination (Paudyal et al., 2018; Tsai et al., 2021). Retained placenta may be accompanied by an increase in body temperature and additional symptoms, such as weakness or cold extremities, which may indicate the development of metritis (Uhlig, 2009; Vickers et al., 2010; Momont and Checura 2017). In case of both retained placenta and clinical hypocalcemia, the messages issued by the sensor system reflected typical symptoms of the diseases, explaining the comparatively high sensitivities of detection of these 2 diseases.

The sensor system under examination in this study demonstrates the potential for the early detection of diseases. Table 3 displays the first health-related message issued by the sensor system for each detected case of disease (correct positive). Considering all correct positive cases, more than 50% of messages were issued one to 6 d before the visual diagnosis (d 0). However, determining the day of visual diagnosis (d 0) is subject to uncertainty as the herd managers had access to all messages issued by the sensor system during the entire study period due to the fact that the dataset was obtained from the dairy research and demonstration farm. This may have influenced the day of visual diagnosis (d 0). It can be assumed that if sensor messages had not been accessed, visual diagnosis would have taken place at a later date in some cases. This would have resulted in the sensor system being ascribed greater potential in terms of the early detection of diseases. Moreover, the observed effect may be intensified by the fact that the health management of the dairy research and demonstration farm, from which the dataset originates, can be classified as above average. However, the presence of a correct positive message does not necessarily result in an accurate diagnosis or treatment. This may be attributed to the existence of unspecific symptoms or poor herd management, which may limit the efficacy of a sensor system in terms of early disease detection. This discrepancy is also evident in the dataset analyzed, as there were up to 6 d between the first correct positive message from the sensor system and the diagnosis in some cases of disease, despite the fact that herd managers had access to the sensor messages. Previous research has demonstrated the potential for data recorded by wearable sensor systems to indicate the presence of a disease several days before visual diagnosis. Gusterer et al. (2020) found changes in activity and rumination data recorded by a 3-dimensional accelerometer in animals with health disorders during the early postpartum period, before a clinical diagnosis being made. Adams et al. (2013) monitored reticular temperature using sensor systems and detected cases of clinical mastitis and pneumonia based on a temperature increase within 4 d before diagnosis. Stangaferro et al. (2016a) developed an alert system that combined activity and rumination data resulting in the detection of displaced abomasum on average 3 d, ketosis on average 1.6 d, and digestive disorders on average 0.5 d before diagnosis by farm personnel. Edwards and Tozer (2004) focused on the diseases displaced abomasum, ketosis, and digestive disorders, detecting them by monitoring activity and milk yield within 5 to 6 d preceding clinical diagnosis. Mazrier et al. (2006) documented a decrease in activity, as recorded by pedometers, of 5% or more 7 to 10 d before the onset of clinical symptoms

Table 8. Retained placenta: Default values given in SimHerd and veterinarians' (vet1–vet6) estimates for considered parameters in herds of poor, average, and good health

Item	Poor health	Average health	Good health
Risk of mild case, %			
Default (SimHerd): in herd	0	0	0
vet1: in herd[1]/for detected cases[2]	0/0	0/0	0/0
vet2: in herd[1]/for detected cases[2]	13/20	10/15	6/10
vet3: in herd[1]/for detected cases[2]	32/50	32/50	26/40
vet4: in herd[1]/for detected cases[2]	6/10	3/5	3/5
vet5: in herd[1]/for detected cases[2]	13/20	6/10	6/10
vet6: in herd[1]/for detected cases[2]	32/50	32/50	32/50
Ø	16/25	12/22	12/19
Days of milk withdrawal			
Default (SimHerd): in herd	3	3	3
vet1: in herd[3]/for detected cases[2]	3/3	3/3	3/3
vet2: in herd[3]/for detected cases[2]	—	3/3	3/3
vet3: in herd[3]/for detected cases[2]	2/2	2/2	2/2
vet4: in herd[3]/for detected cases[2]	3/3	3/3	3/3
vet5: in herd[3]/for detected cases[2]	1/0	1/0	1/0
vet6: in herd[3]/for detected cases[2]	2/2	3/3	—
Ø, n/n (%/%)	2.4/2.0 (−21/−33)	2.6/2.3 (−14/−22)	2.5/2.2 (−17/−27)

[1] Related on entire herd, calculated based on Equation 3. Calculated values are rounded.

[2] Related on all cases of disease detected by the sensor system.

[3] Related on entire herd, calculated based on Equation 4.

of lameness. Therefore, the results of the present study corroborate those of previous research, which have indicated that sensor systems have the potential to detect cases of disease at an early stage.

Workshop with Veterinarians: Assumptions on Disease Incidence, Risk of Mild Case, Days of Milk Withdrawal, SCC, and Treatment Costs

For further calculations with the NR model, veterinarians' assessments of possible changes in health parameters were obtained. It is important to note that the presented findings on the potential of the sensor system are based on the assessments of the veterinarians who participated in the workshop and pertain to a single dairy herd. As herd managers had access to all messages issued by the sensor system, the designation of the day of visual diagnosis (d 0) and the evaluation of the potential for early detection of disease cases were subject to some uncertainty. This raises the question of why the risk of a milder course of disease would increase despite the dairy farm's implementation of the sensor system. It seems reasonable to posit that the data set already contained cases of disease that had a milder course or lower treatment costs due to earlier detection, given that the herd managers had access to the sensor messages. However, as the analyzed dataset lacked information on disease courses, days of milk withdrawal, and treatment costs, default values from SimHerd were used as the basis for the veterinarians' assessments.

Tables 5 to 8 show the SimHerd default values, the estimates provided by the veterinarians following plausibility checks, and the resulting calculated values obtained through the application of Equations 3 and 4. Among the diseases considered, the use of the sensor system is only expected to result in changes in the parameters incidence and SCC for mastitis. The SimHerd model provides default values for the incidence of mastitis, which are 21.6 (good health), 36.6 (average health), and 49.9 (poor health). The veterinarians estimated that using the sensor system with the accuracy described in the dataset could lead to an average reduction in mastitis incidence of 14% in herds of poor health, 18% in herds of average health and 19% in herds of good health. The veterinarians' estimates indicated that the SCC, for which SimHerd stipulates the default values of 180,000/mL (good health), 245,000/mL (average health), and 290,000/mL (poor health) could be reduced by 16%, 15%, and 19%, respectively. The veterinarians also estimated that of the cases detected by the sensor system (correct positives), between 40% and 85% of the mastitis cases, 10% and 50% of the metritis cases, 20% and 90% of the clinical hypocalcemia cases, and 0% and 50% of the retained placenta cases could have a mild course of disease due to earlier treatment initiation. In terms of milk withdrawal days, the veterinarians estimated that the use of the sensor system could result in an average reduction in mastitis cases of 10%, metritis cases of 23%, and retained placenta cases of 27% in cases detected by the sensor system (correct positives).

Table 9. Treatment costs: Default values given in SimHerd (normal case of disease) and veterinarians' (vet1–vet6) estimates (mild cases of disease) in herds of poor, average, and good health

Item	Mastitis	Metritis	Clinical hypocalcemia	Retained placenta
Default (SimHerd): treatment costs for a normal case of disease, €	54	110	211	110
Individual estimates of veterinarians: treatment costs for a mild case of disease, €				
vet1	45	110	200	110
vet2	50	95	120	100
vet3	25	100	150	75
vet4	30	80	130	100
vet5	50	90	180	100
vet6	20	80	100	50
Ø, € (%)	37 (−31)	93 (−15)	147 (−30)	89 (−19)

The economic analysis also took into account the reduced treatment costs associated with mild cases of disease. Table 9 shows the default values for treatment costs for a normal case of disease in SimHerd, as well as the estimated treatment costs for a mild case of disease as perceived by the veterinarians. The determination of GM as a function of the risk of a mild case was based on the respective average of the estimated treatment costs for a mild case of disease. Based on the assessments provided by the veterinarians, a mild case could result in an average reduction in treatment costs of 31% for mastitis, 15% for metritis, 30% for clinical hypocalcemia, and 19% for retained placenta.

Gross Margin Depending on Incidence, SCC, Risk of Mild Case, and Days of Milk Withdrawal

A linear relationship was identified between GM and incidence, SCC, risk of mild case, and days of milk withdrawal in SimHerd. This relationship was observed in each of the 3 herds of poor, average, and good health. The model showed that improved health, indicated by lower incidence, a higher proportion of cases with a mild course of disease, lower SCC, and fewer days of milk withdrawal, resulted in fewer dead cows, a shift in herd demographics toward older cows, and a lower replacement rate. Therefore, an increase in GM due to improved health was mainly due to higher revenues from milk and heifers, as well as lower expenses for disease treatment. Table 10 shows the linear equations for GM as a function of incidence, risk of mild case, SCC, and days of milk withdrawal for the 3 modeled herds, based on the simulation results. In the NR model, the GM was calculated using these linear equations.

Net Return of Investment of a Sensor System to Assist in Health Monitoring

The use of @RISK to incorporate uncertainty in certain variables produced probability distributions for the NR of investment of the sensor system. For each scenario, 10,000 iterations are used to determine the possible combinations of variables, including incidence, SCC, risk of a mild case, days of milk withdrawal, time savings through sensor-assisted health monitoring, and time expenditure for false positives issued by the sensor system. The probabilities of these variables are based on the defined distributions.

Table 11 displays the NR of investment of the sensor system in simulated scenarios. The results indicate that the average NR of investment ranges from +€23 to +€119 for a herd of poor health, from −€12 to +€84 for a herd of average health, and from −€33 to +€63 for a herd of good health, depending on the scenario. The probability of a positive NR of investment (i.e., greater than €0 per cow per year) was found to range from 80% to 100% for a herd of poor health, from 25% to 100% for a herd of average health, and from 6% to 100% for a herd of good health. These discrepancies can be attributed to the veterinarians' assessments indicating that specific variables (such as incidence) demonstrate a greater potential for improvement in a herd of average or poor health compared with one of good health.

To illustrate probability distributions, cumulative representations such as those in Figure 2 are traditionally used, allowing a direct comparison of different scenarios. Figure 2 shows the cumulative probability of the NR of investment for scenarios with a herd size of 70 and labor costs of €15/h for herds of poor, average, and good health (scenario 1: no time savings through sensor-assisted health monitoring, but time expenditure for false positives). It can be observed that a herd of poor health can achieve a higher NR of investment at any probability level than is the case for herds of average or good health. Moreover, it is evident that the probability of a negative NR of investment in a herd of poor health is nearly zero, whereas in a herd of good health, an investment is not economically viable with a probability of 75%. A comparison of all analyzed scenarios shows that the NR of investment is higher for a herd size of 210 compared

Table 10. Estimated linear equations[1] for gross margin (€/cow per year) as a function of incidence, risk of mild case, SCC, and days of milk withdrawal for 3 herds of poor, average, and good health[2]

Item	Poor health	Average health	Good health
Mastitis			
Incidence	$y = -3.3967x + 1{,}769.1^{0;60}$ $(R^2 = 0.99)$	$y = -3.2564x + 1{,}824.7^{0;50}$ $(R^2 = 0.99)$	$y = -3.6227x + 1{,}896.8^{0;100}$ $(R^2 = 0.99)$
Risk of mild case	$y = 108.91x + 1{,}594.4^{0.1;1}$ $(R^2 = 0.99)$	$y = 78.303x + 1{,}708.9^{0.1;1}$ $(R^2 = 0.99)$	$y = 46.424x + 1{,}823.5^{0.1;1}$ $(R^2 = 0.99)$
Days of milk withdrawal	$y = -2.7939x + 1{,}617.9^{0;9}$ $(R^2 = 0.96)$	$y = -2.0364x + 1{,}721.2^{0;9}$ $(R^2 = 0.96)$	$y = -1.097x + 1{,}826.8^{0;9}$ $(R^2 = 0.82)$
SCC, ×1,000/mL	$y = -0.8284x + 1{,}841.5^{200;300}$ $(R^2 = 0.99)$	$y = -0.7402x + 1{,}887.7^{170;250}$ $(R^2 = 0.99)$	$y = -0.7021x + 1{,}944.9^{100;200}$ $(R^2 = 0.99)$
Metritis			
Risk of mild case	$y = 6.6061x + 1{,}598.1^{0.1;1}$ $(R^2 = 0.69)$	$y = 1.2121x + 1{,}713.5^{0.1;1}$ $(R^2 = 0.21)$	$y = 1.8182x + 1{,}825.4^{0.1;1}$ $(R^2 = 0.21)$
Days of milk withdrawal	$y = -0.7091x + 1{,}602.5^{0;9}$ $(R^2 = 0.76)$	$y = -0.697x + 1{,}710.2^{0;9}$ $(R^2 = 0.81)$	$y = -0.1212x + 1{,}820.3^{0;9}$ $(R^2 = 0.06)$
Clinical hypocalcemia			
Risk of mild case	$y = 14.121x + 1{,}598.3^{0.1;1}$ $(R^2 = 0.97)$	$y = 13.818x + 1{,}710.6^{0.1;1}$ $(R^2 = 0.91)$	$y = 10.667x + 1{,}823.3^{0.1;1}$ $(R^2 = 0.79)$
Retained placenta			
Risk of mild case	$y = 3.2121x + 1{,}598.9^{0.1;1}$ $(R^2 = 0.42)$	$y = 5.2727x + 1{,}710.6^{0.1;1}$ $(R^2 = 0.80)$	$y = 3.6364x + 1{,}822.8^{0.1;1}$ $(R^2 = 0.69)$
Days of milk withdrawal	$y = -0.2788x + 1{,}599.7^{0;9}$ $(R^2 = 0.28)$	$y = -0.2545x + 1{,}706.9^{0;9}$ $(R^2 = 0.39)$	$y = -0.1939x + 1{,}820.1^{0;9}$ $(R^2 = 0.26)$

[1] Linear equations were estimated based on simulation of gross margin as a function of incidence, risk of mild case, somatic cell count, and days of milk withdrawal with SimHerd. Function graph for mastitis incidence as example see Appendix Figure A3.

[2] Superscript values describe the range (minimum;maximum) in which the parameters were varied (incidence: 5%, risk of a mild case: 10%, days of milk withdrawal: 1, SCC: 5,000 steps); for R^2, only 2 decimal places are displayed.

with 70, which can be explained by cost degression effects. The simulation results demonstrate that the assumptions regarding the time savings of sensor-assisted health monitoring and the time spent on false positives have a considerable effect on the NR of investment. To make precise assertions regarding the NR of investment of a sensor system for health monitoring, it is essential to possess a deeper understanding of the sensitivities and specificities of existing commercial technologies and the resulting impact on workload. Further technological advances may result in sensitivity and specificity approaching 100%, as demonstrated in scenario 4. The results of scenario 4 indicate that the NR of investment is positive for almost all simulation runs performed in this study, making it a profitable investment.

The results indicate a positive effect of investing in a specific sensor system on farm profitability across the majority of analyzed scenarios. This finding is at odds with the results presented by Steeneveld et al. (2015b), which did not demonstrate any change in productivity following the investment in sensor systems. Additionally, Steeneveld et al. (2015b) did not observe a significant change in labor costs. In scenario 2 of our study, which assumes no change in labor costs, the majority of simulation runs indicate a positive NR of investment, with an average NR of investment ranging from +€7 to +€68 per cow per year. However, the Steeneveld et al. (2015a,b) studies included a considerable number of farms where the investment in a sensor system occurred concurrently with other significant changes at the farm, such as the introduction of a new milking system or barn. This makes it challenging to discern the effect of sensor systems in isolation. Our results suggest that the assumptions made about labor costs have a significant impact on the NR of investment, and thus, further empirical data are required to enhance comprehension of potential time savings and economic aspects of sensor systems for health monitoring.

The economic potential of the sensor system is not only derived from its health monitoring function but also from its ability to detect estrus and calving. Stein (2017) conducted a study on the performance of activity-based estrus detection using the smaXtec bolus and found a sensitivity of 92% (using blood progesterone as a reference) and a positive predictive value of 89%. Pfeiffer et al. (2020a) analyzed the economic potential of investing in activity sensors for estrus detection. The study analyzed different scenarios and found that the average NR of investment ranged from +€7 to +€46 per cow per year, with a probability of a positive NR ranging from 74% to 99%. The study by Pfeiffer et al. (2020a) study confirmed the economic potential of activity sensors for improved estrus detection, as previously identified in studies by van Asseldonk et al. (1999), Inchaisri et al. (2010), and Rutten et al. (2014). In addition, the calving detection function of the smaXtec rumen bolus offers

Table 11. Net return of investment (€ per cow per year) of sensor system for health monitoring under simulated scenarios[1]

	Time savings through sensor-assisted health monitoring[2]													
	None				None		Yes				Yes			
	Time expenditure for false positives[2]													
	Yes				None		Yes				None			
	Labor costs, €/h													
	15		30		15/30		15		30		15		30	
	Herd size													
Item	70	210	70	210	70	210	70	210	70	210	70	210	70	210
Poor health														
Minimum	−15	−12	−38	−33	7	10	−2	5	−11	−8	22	30	35	40
Maximum	87	90	69	75	102	106	120	129	146	152	139	145	184	186
Mean	43	48	23	28	63	68	69	74	75	80	89	94	114	119
Ratio net return >€0/cow per year, %	98	99	80	85	100	100	100	100	100	100	100	100	100	100
Average health														
Minimum	−29	−26	−55	−50	−8	−2	−14	−7	−24	−23	8	14	21	26
Maximum	41	48	29	30	58	63	83	87	106	109	101	102	143	144
Mean	9	14	−12	−7	28	33	35	40	40	45	54	59	79	84
Ratio net return >€0/cow per year, %	75	83	25	34	93	100	99	100	98	99	100	100	100	100
Good health														
Minimum	−47	−43	−73	−69	−24	−19	−33	−25	−49	−39	−10	−5	1	7
Maximum	33	39	19	23	50	55	74	77	104	101	90	96	132	138
Mean	−13	−8	−33	−28	7	12	13	18	19	24	33	38	58	63
Ratio net return >€0/cow per year, %	26	32	6	10	62	68	71	79	77	83	98	100	100	100

[1] 10,000 iterations of each scenario.

[2] According to Table 2.

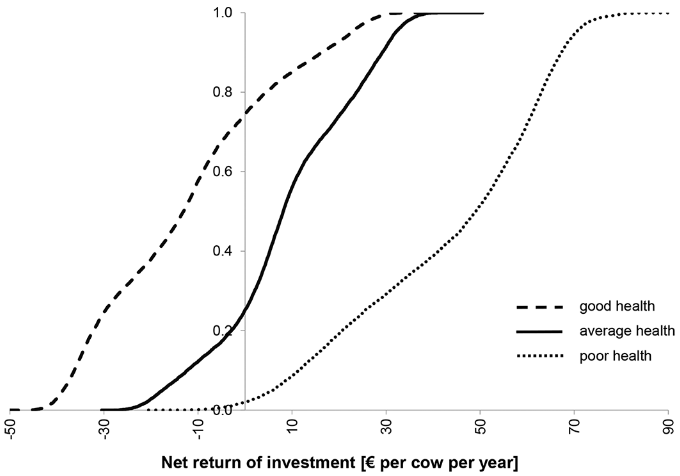

Figure 2. Cumulative probability of net return of investment (€/cow per year) of a sensor system for health monitoring for simulated herds of poor, average, and good health (herd size: 70; labor costs: €15/h; scenario 1: no time savings through sensor-assisted health monitoring, but time expenditure for false positives).

further economic potential. The sensor system can provide timely assistance, which can reduce the incidence of stillbirth and the risk of postpartum endometritis and uterine infections (Paolucci et al., 2010; Palombi et al., 2013). Pfeiffer et al. (2021) found a sensitivity of 85% and a specificity of 95% for the calving detection function of the smaXtec rumen bolus.

The implementation of such a sensor system on dairy farms may potentially give rise to rebound effects (see Berkhout et al., 2000, for definition of rebound effect), although currently, there is a paucity of empirical evidence to substantiate this hypothesis. The deployment of a sensor system has the potential to enhance the detection of additional instances of disease. However, this approach may also result in an increased number of false positive outcomes. It can be hypothesized that the occurrence of false positive messages may contribute to an increase in the prophylactic administration of medication. Furthermore, the identification of subclinical cases of disease may result in an increase in the administration of medication. However, the lack of reliable data on this topic meant that these factors were not quantified in the study and thus, not included in the calculation of the NR.

Limitations of the Study

The study focused on the 5 diseases mastitis, metritis, clinical hypocalcemia, retained placenta, and diseases of the locomotor system, as these were the only ones in the dataset with a sufficiently large sample size. The literature shows that sensor systems can contribute to the early detection of other diseases such as ketosis (Steensels et al., 2017; Antanaitis et al., 2020; Sturm et al., 2020), displaced abomasum (Edwards and Tozer, 2004; Stangaferro et al., 2016a), digestive disorders (Edwards and Tozer, 2004; Talukder et al., 2015; Stangaferro et al., 2016a), and pneumonia (Adams et al., 2013) at an early stage. Therefore, detection of diseases beyond the scope of this study could lead to further economic potential.

The detection of subclinical disease was not considered in this study, but such detection may have an economic impact (Sinha et al., 2014; Mekonnen et al., 2022). During the analysis of false positives, an SCC of >200,000 was found in individual animals in this dataset, which may indicate the presence of subclinical mastitis (Jadhav et al., 2018). Systematic daily veterinary examinations of all animals, along with additional blood and milk analyses, would provide insight into the potential of the sensor system to detect subclinical cases of disease.

Each parameter was modeled separately in SimHerd to determine its influence on GM. In this step, interactions could have been considered, such as the simultaneous variation of several parameters (e.g., 3 levels of incidence and 3 levels of risk of a mild case of disease). Further studies could investigate potential interactions in more detail. However, including them in the current study design would have made it too large.

The sensor system used in the data set of this study now includes rumination data (SmaXtec, 2023). As many studies have shown a decrease in rumination during disease (e.g., Paudyal et al., 2018; Gusterer et al., 2020; Tsai et al., 2021; Antanaitis et al., 2022), incorporating this parameter may lead to additional economic potential beyond that identified in this study. In addition, there is a version of the sensor system that measures pH in the stomach. This may help to detect subacute ruminal acidosis (AlZahal et al., 2007; Enemark, 2008) and increase the economic potential.

CONCLUSIONS

The findings of the study demonstrate the economic potential of a rumen bolus that records activity and core body temperature, with the objective of facilitating the health management of a dairy herd. The sensitivity of the sensor system's algorithm in detecting disease cases varies from 5% to 64% for the diseases under consideration. The results indicate that the sensor system has the potential to facilitate the early detection of disease. According to the assessments of veterinarians, this could lead to improvements in the incidence of disease, SCC, risk of mild disease, days of milk withdrawal (depending on the disease), and treatment costs. The assumptions regarding the potential time savings from sensor-assisted health monitoring and the time required for false positive messages have a significant impact on the calculated NR of investing in the sensor system. Based on calculated NR of investment for the estrus detection and health monitoring functions and potential improvements in calving management, it can be concluded that the investment in a sensor system for herd management would be profitable for many dairy farms.

NOTES

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Nonstandard abbreviations used: GM = gross margin; NR = net return.

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APPENDIX

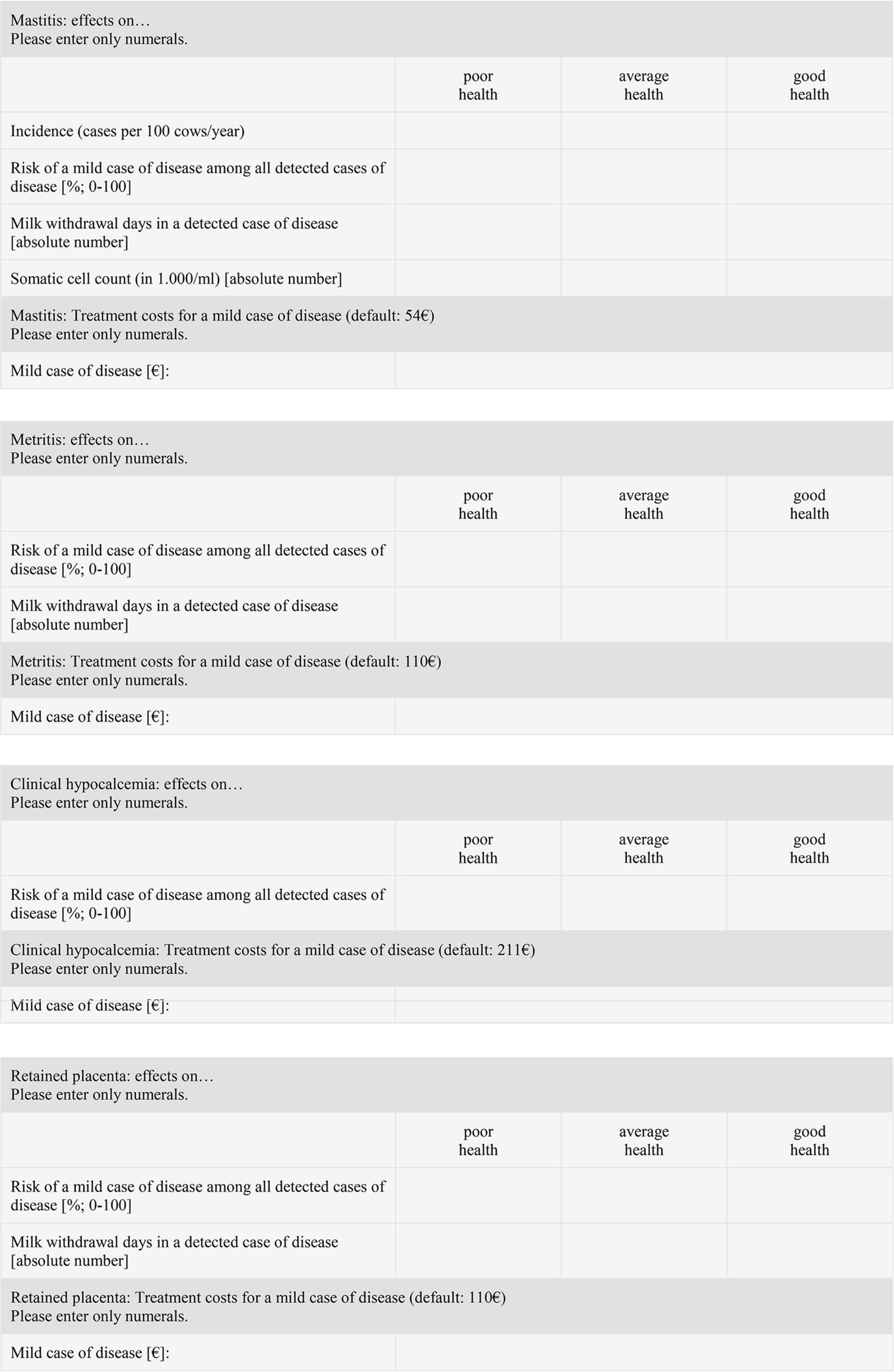
Mastitis: Auswirkungen auf… Bitte geben Sie nur Zahlen ein.			
	schlechte Gesundheit	durchschnittliche Gesundheit	gute Gesundheit
Inzidenz (Fälle je 100 Tiere/Jahr)			
Anteil milder Krankheitsverlauf unter den erkannten Fällen [%; 0-100]			
Tage weggeschüttete Milch bei erkanntem Erkrankungsfall [absolute Anzahl]			
Zellgehalt (in 1.000/ml) [absolute Anzahl]			
Mastitis: Behandlungskosten bei mildem Krankheitsverlauf (default: 54€) Bitte geben Sie nur Zahlen ein.			
milder Krankheitsverlauf [€]:			

Metritis: Auswirkungen auf… Bitte geben Sie nur Zahlen ein.			
	schlechte Gesundheit	durchschnittliche Gesundheit	gute Gesundheit
Anteil milder Krankheitsverlauf unter den erkannten Fällen [%; 0-100]			
Tage weggeschüttete Milch bei erkanntem Erkrankungsfall [absolute Anzahl]			
Metritis: Behandlungskosten bei mildem Krankheitsverlauf (default: 110€) Bitte geben Sie nur Zahlen ein.			
milder Krankheitsverlauf [€]:			

Klinische Hypokalzämie: Auswirkungen auf… Bitte geben Sie nur Zahlen ein.			
	schlechte Gesundheit	durchschnittliche Gesundheit	gute Gesundheit
Anteil milder Krankheitsverlauf unter den erkannten Fällen [%; 0-100]			
Klinische Hypokalzämie: Behandlungskosten bei mildem Krankheitsverlauf (default: 211€) Bitte geben Sie nur Zahlen ein.			
milder Krankheitsverlauf [€]:			

Nachgeburtsverhalten: Auswirkungen auf… Bitte geben Sie nur Zahlen ein.			
	schlechte Gesundheit	durchschnittliche Gesundheit	gute Gesundheit
Anteil milder Krankheitsverlauf unter den erkannten Fällen [%; 0-100]			
Tage weggeschüttete Milch bei erkanntem Erkrankungsfall [absolute Anzahl]			
Nachgeburtsverhalten: Behandlungskosten bei mildem Krankheitsverlauf (default: 110€) Bitte geben Sie nur Zahlen ein.			
milder Krankheitsverlauf [€]:			

Figure A1. Questionnaire that was given to the veterinarians as an online form for completion (German).



Mastitis: effects on… Please enter only numerals.			
	poor health	average health	good health
Incidence (cases per 100 cows/year)			
Risk of a mild case of disease among all detected cases of disease [%; 0-100]			
Milk withdrawal days in a detected case of disease [absolute number]			
Somatic cell count (in 1.000/ml) [absolute number]			
Mastitis: Treatment costs for a mild case of disease (default: 54€) Please enter only numerals.			
Mild case of disease [€]:			

Metritis: effects on… Please enter only numerals.			
	poor health	average health	good health
Risk of a mild case of disease among all detected cases of disease [%; 0-100]			
Milk withdrawal days in a detected case of disease [absolute number]			
Metritis: Treatment costs for a mild case of disease (default: 110€) Please enter only numerals.			
Mild case of disease [€]:			

Clinical hypocalcemia: effects on… Please enter only numerals.			
	poor health	average health	good health
Risk of a mild case of disease among all detected cases of disease [%; 0-100]			
Clinical hypocalcemia: Treatment costs for a mild case of disease (default: 211€) Please enter only numerals.			
Mild case of disease [€]:			

Retained placenta: effects on… Please enter only numerals.			
	poor health	average health	good health
Risk of a mild case of disease among all detected cases of disease [%; 0-100]			
Milk withdrawal days in a detected case of disease [absolute number]			
Retained placenta: Treatment costs for a mild case of disease (default: 110€) Please enter only numerals.			
Mild case of disease [€]:			

Figure A2. Questionnaire that was given to the veterinarians as an online form for completion (English translation).

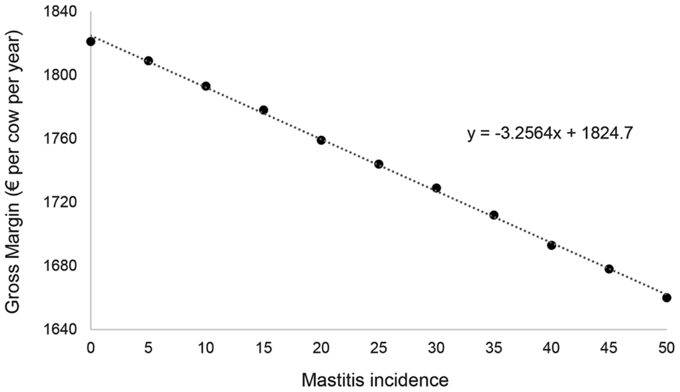


Figure A3. Example of a function graph for estimation of gross margin (here as a function of mastitis incidence for a herd of average health).