ABSTRACT

Suboptimal mobility (SOM) is a costly health condition in dairy production. Current SOM management is based on visual SOM detection by farm staff. This often leads to cows with severe SOM being detected and promptly treated, whereas the detection and subsequent treatment of cows with mild SOM is delayed or nonexistent resulting in prolonged cases of mild SOM being treated only at half-year routine hoof trimming. Using automatic SOM detection sensors may improve early detection of mild SOM allowing for improved SOM management. However, the economic value of these sensors used for sensor-based SOM management are not well known. The objective of this study was to evaluate the added economic value of automatic SOM detection sensors. A recently developed bioeconomic simulation model was extended to simulate a farm without and with automatic SOM detection sensors and farm economic performance comparisons were drawn. Moreover, for the farm with sensors, novel sensor-based SOM management strategies were designed. Within these sensor-based management strategies multiple scenarios with different sensor performance in terms of sensitivity, specificity, and mobility score detection were simulated. A new alert prioritization method was also introduced. Results from this study provide insights on the economic tradeoffs in production losses and additional labor costs for the different sensor-based management strategies, sensor performances, and alert prioritization. Simulations show that the added economic value of automatic SOM detection sensors are sensitive to the sensor-based management strategies, sensor performance, and the introduced alert prioritization method. Thirty-nine of the 80 simulated scenarios obtained a positive mean net economic sensor effect: the highest was €6,360 per year (€51/cow per yr). Based on evidence from our scenarios we suggest that twice-yearly routine hoof trimming should be replaced with cow specific hoof trimmer treatments following SOM detection by the sensor. Earlier detection and subsequent treatment of mild SOM resulted in economic gains when the alert prioritization method was introduced. Implementing automatic SOM detection sensor systems allows for many options to alter SOM management where improvements in farm economic performance can be achieved in combination with improved cow mobility. The implications for future research are discussed.

Key words: suboptimal mobility, lameness, precision livestock farming, sensors, automatic detection

INTRODUCTION

Suboptimal mobility [SOM; mobility score ≥2 where mobility score 1 = optimal mobility and mobility score 5 = severely impaired mobility (Sprecher et al., 1997)] is a costly health condition in dairy farming largely due to the associated milk production losses, premature culling, negative reproduction effects, and treatment related expenditures (Dolecheck and Bewley, 2018; Edwardes et al., 2022). Farmers generally underestimate the economic effect and prevalence of SOM (Leach et al., 2010; Bruijnis et al., 2013) meaning that cows with severe SOM are mostly detected visually and treated shortly afterward, whereas the detection and subsequent treatment of cows with mild SOM is often delayed (Alawneh et al., 2012). The associated mild SOM production losses contribute significantly to the total direct cost of SOM (Edwardes et al., 2022). Detecting and treating cows with mild SOM sooner may significantly reduce the total direct cost of SOM. Moreover, it will also reduce the risk of mild SOM transitioning to severe SOM (Leach et al., 2012) and additional treatments (Reader et al., 2011) with an altogether reduction in significant costs associated with severe SOM (Edwardes et al., 2022).

Detecting cows with mild SOM can only be achieved by increasing the detection frequency and performance coupled with increased farmer awareness of SOM. Doing this by means of visual detection is expected to incur additional costs due its subjective and time-
consuming nature. To circumvent these visual detection limitations, many automatic SOM detection sensors are being researched and developed to objectively, continuously, and autonomously monitor the mobility of cows (Schlageter-Tello et al., 2014; Alsaaod et al., 2019). Despite the growing body of literature on automatic SOM detection, their detection performance varies, due to differences in algorithms (Schlageter-Tello et al., 2014; Alsaaod et al., 2019), and only a few of these sensor systems are available in practice. The farmers’ willingness to implement these sensors in practice depends, among others, on whether their added economic value is clear (Steeneveld and Hogeveen, 2015). This results in a need to quantify the economic value of automatic SOM detection sensors to support farmers’ investment decisions with respect to better and economically feasible SOM management.

To date, only Van De Gucht et al. (2018) and Kaniyamattam et al. (2020) investigated the economic value of these sensors. Although both studies found that an added economic value is obtainable with these sensors, the studies possess limitations. For example, Van De Gucht et al. (2018) considered changes in SOM management but not sensor system costs, whereas Kaniyamattam et al. (2020) considered sensor system costs but not changes in SOM management. This demonstrates the need to combine multiple aspects such as changes in SOM management, sensor system costs, and performance to realize a better understanding of the added economic value of automatic SOM detection sensors.

With respect to SOM management, it is expected that management is required to change when automatic SOM detection sensor systems are implemented. Such a change in SOM management will require a change in farmer perception toward SOM so that cows detected with mild SOM are treated promptly. Thus, it is expected that farmers will need to react to sensor generated alerts more frequently. More frequent reaction to alerts will increase the associated labor costs of SOM management, especially if the performance of an automatic SOM detection sensor is poor. Including the additional opportunity costs of labor, to check alerts will provide a better estimate of the economic value with regard to the automatic SOM detection sensor systems. These labor costs were not considered by Van De Gucht et al. (2018) and Kaniyamattam et al. (2020) and should be considered, given that a high frequency of alerts could be generated depending on SOM prevalence and sensor performance.

Eckelkamp and Bewely (2020) found that farmers tend to completely ignore alerts if too many are generated in a single day. Reducing the number of generated alerts to stimulate farmer reaction calls for alert prioritization methods. These methods have not been investigated with regard to automatic SOM detection sensors (Dominiak and Kristensen, 2017). However, alert prioritization methods should only be considered if they add economic value to the sensor, which also depends on sensor performance, SOM severity, and sensor-based SOM management strategy.

Therefore, the objective of this study is to contribute further to the limited literature concerning the economic value of automatic SOM detection sensors through economic analysis by addressing the multiple aspects of sensor-based SOM management in combination. An economic analysis was conducted to include changes in labor-related costs associated with sensor-based SOM management that would not have been addressed through a financial analysis. An economic analysis ultimately leads to a better economic valuation of automatic SOM detection sensors used in sensor-based SOM management. Very few automatic SOM detection sensors are commercially available making data from practice scarce. To overcome this data scarcity, we quantify the economic value of these sensors via bioeconomic simulation modeling. A variety of sensor-based SOM management scenarios were simulated. Based on these results, the considerations for future research are discussed.

**MATERIALS AND METHODS**

No human or animal subjects were used, so this analysis did not require approval by an Institutional Animal Care and Use Committee or Institutional Review Board.

To quantify the economic value of automatic SOM detection sensors we used a recently developed bioeconomic simulation model (Edwardes et al., 2022). We updated necessary model parameter values and extended the model by including sensor-based SOM management scenarios, so that our objective could be met. The economic objective was to quantify the mean net economic sensor effect by comparing a with- and without-sensor scenario. This was done for 5 sensor scenarios, each with 16 subscenarios that included differences in SOM management, sensor performance, and alert generation intervals. Components of this study are described in the subsequent sections in the following order: simulation model in brief, model extensions, economic analysis, simulation scenarios, sensitivity analysis, and last, sensor classification parametrization.

**Simulation Model in Brief**

The developed stochastic, mechanistic, and time-discrete bioeconomic simulation model [extensively described in Edwardes et al. (2022)] simulates a typical
Dutch dairy herd of 125 cows. The model was parameterized for a system where cows have access to pasture for >6 h per day during the spring and summer months (pasture period) and are housed in cubicle housing with concrete slatted floors during the autumn and winter months (housing period). Cows are either lactating or dried-off and are subject to removal by culling decisions on the premise that a replacement heifer is available on the following day.

The model simulates the actual SOM situation of the cows. This is done by simulating the infection dynamics of hoof disorders at the hoof-level as the underlying mechanisms responsible for the dynamics of SOM expressed at cow-level. Eight hoof disorders are included in the model: digital dermatitis, interdigital hyperplasia, interdigital dermatitis or heel-horn erosion, interdigital phlegmon, overgrown hoof, sole hemorrhage, sole ulcer, and white-line disease. Cow mobility is modeled by a 5-point ordinal mobility scoring method (1 = optimal mobility, 5 = severely impaired mobility; Sprecher et al., 1997), and we define a cow with SOM when she is scored with a mobility score ≥2. We define a cow as SOM as opposed to lame because the term lame often varies in its definition when using the same mobility scoring method. For example, a cow with mobility score ≥3 is typically defined as lame (Amory et al., 2006; Randall et al., 2018; Somers et al., 2019), whereas a cow with mobility score ≥2 (Olechnowicz and Jaśkowski, 2015) or ≥4 (Kovács et al., 2015) has also been defined as lame. By avoiding the term lameness, we can specifically focus on varying levels of mobility as defined by the mobility scoring method used in this study. More recently, other studies have focused on specific mobility scores (i.e., O’Connor et al., 2020). Furthermore, mild forms of SOM are represented by grouping mobility scores 2 and 3, whereas severe forms are represented by grouping mobility scores 4 and 5.

Preventative treatment of hoof disorders is routinely done by the hoof trimmer twice a year: at the start of the pasture and housing period, respectively. Hoof trimming when cows are dried is not performed. All cows have their hind hooves trimmed at routine hoof trimming, and front hooves are trimmed if a hoof disorder is present and responsible for a mobility score ≥3. Between the routine hoof trimming, cows with mobility scores 3, 4, and 5 are visually detected by farm personnel with increasing probabilities, respectively. Cows detected with mobility score 3 are treated at routine hoof trimming. Cows detected with mobility score 4 are treated by the farmer, whereas cows detected with mobility score 5 are treated by a veterinarian, uniformly distributed 1–21 (based on Alawneh et al., 2012) and 1–3 d after detection, respectively. Treatment efficacy depends on the underlying hoof disorder and agent performing the treatment. All hoof disorders are treated regardless of clinical sign. It was assumed that farmer-related treatment is less effective than the hoof trimmer and veterinarian due to varying skillsets. Cows are treated with antibiotics for interdigital phlegmon and have their milk withdrawn for 5 d in total. Cows with SOM are subject to a SOM culling probability per mobility score. Additionally, cows with severe SOM are culled if they required a fourth treatment.

(Re)Production events are milking, feeding, culling, estrus detection, insemination, and calving, all simulated in daily time-steps. These (re)production events are affected per mobility score of 1 to 5. Economic calculations are based on production events (unaffected and affected by SOM), and management actions in non-SOM specific situations (i.e., inseminations) and SOM specific situations (i.e., treatment). Production and production loss input parameters and respective values are found in Appendix Table A1.

**Model Extensions**

For brevity of this manuscript, we omit the description of simulation processes already described in Edwardes et al. (2022). The following sections describe only the model extensions with regard to simulation processes and inputs.

**Automatic Mobility Score Classification**

The model was adapted to include a module that simulates sensors that have the ability to classify a cow with one of the 5 mobility scores as per Sprecher et al. (1997). In each time-step, each cow is subject to the probability of being correctly classified by the sensor with her actual mobility score. The outcome of a correct mobility score classification is predicted by a binomial distribution,

\[ \phi_{i,s,t} = B(1, P_s), \]

where \( \phi_{i,s,t} \) is the logical classification outcome for cow \( i \) being correctly classified by the sensor with a probability \( P_s \) for mobility score \( s \) in time-step \( t \). If a cow is not correctly classified with her mobility score (i.e., \( \phi_{i,s,t} = 0 \)), an incorrect mobility score is assigned to the cow by the sensor according to a weighted random sample. The sensor classification of cows with SOM is dependent on the mobility score threshold value for SOM inherent to the sensor. For example, the sensor classifies a cow with a mobility score ≥3 as a cow with SOM.

\[ \phi_{i,s,t} = B(1, P_s), \]

where \( \phi_{i,s,t} \) is the logical classification outcome for cow \( i \) being correctly classified by the sensor with a probability \( P_s \) for mobility score \( s \) in time-step \( t \). If a cow is not correctly classified with her mobility score (i.e., \( \phi_{i,s,t} = 0 \)), an incorrect mobility score is assigned to the cow by the sensor according to a weighted random sample. The sensor classification of cows with SOM is dependent on the mobility score threshold value for SOM inherent to the sensor. For example, the sensor classifies a cow with a mobility score ≥3 as a cow with SOM.
Economic Calculations

The economic calculations in this study were as in Edwardes et al. (2022). We briefly summarize the important economic calculations described in Edwardes et al. (2022). The respective parameter inputs are found in Appendix Table A2. Refer to Edwardes et al. (2022) for the full description of economic calculations.

Gross milk production per cow was calculated on a daily basis using a Wilmink lactation curve (Wilmink, 1987). Actual milk production per cow was calculated with a milk production loss factor of gross milk production per mobility score. Milk production loss factors per mobility score 1 to 5 were 0, 0, 0.05, 0.48, and 0.53, respectively. These factors were estimated as the ratio between the quotient of an average 305 d yield production loss per mobility score reported in O’Connor et al. (2020) and the median duration of a SOM episode of a maximum mobility score output by the model in the baseline scenario (scenario 0). Mobility scores according to the mobility scoring method used in O’Connor et al. (2020) were adjusted to match the mobility scores used in this current study. The daily cost of milk production loss per cow was calculated by multiplying the milk price and the difference between daily gross and actual milk production.

Daily feed energy requirements per cow were modeled as a function of daily kilograms of fat- and protein-corrected milk production and expressed as feed unit lactation (VEM; 1 VEM = 1.65 kcal of NE₃; van Es, 1978). Additional VEM were included for cows in parity ≤2 and pregnancy stage (van Es, 1978; Remmelink et al., 2015). The daily cost of VEM per cow was calculated as the product of VEM and price per kVEM (1,000 VEM).

Culling costs were calculated using a depreciation method. If a cow was culled before the end of the expected number of lactations the cull value of the cow was not realized and resulted in a culling cost, which reflects a capital loss. If the cow exceeded the number of expected lactations, no culling cost was incurred. The culling cost per culled cow was calculated as the salvage value (i.e., replacement heifer price less cull cow price) of the culled cow multiplied by the remaining lactations before completing the number of expected lactations.

In this current study, the economic calculations as in Edwardes et al. (2022) are extended with the following components.

Alert Confirmation Costs. For each alert that was generated to notify the farmer of a cow with SOM, an alert confirmation cost is incurred and calculated with

\[
C_i^{(\text{confirm})} = \frac{N(\mu_{\text{confirm}}, \sigma_{\text{confirm}})}{60} \times C^{(\text{labor})},
\]

where \(C_i^{(\text{confirm})}\) is the alarm confirmation cost for cow \(i\), \(\mu_{\text{confirm}}\) is the mean alert confirmation duration in minutes, \(\sigma_{\text{confirm}}\) is the standard deviation of an alarm confirmation duration in minutes, and \(C^{(\text{labor})}\) is the farmer labor price per hour. We assumed 1 min for \(\mu_{\text{confirm}}\) 0.2 min for \(\sigma_{\text{confirm}}\), and the farmer labor price per hour is €30.70 (Blanken et al., 2017).

Hoof Trimmer Costs. Hoof trimmer cost calculations were calculated on a per treated hoof basis at a cost of €3.50 per hoof using an hourly rate of €47.95, assuming a hoof trimmer can attend to 7 cows per hour (8.6 min/cow; Blanken et al., 2017). In addition, a call out fee of €17.50 was incurred at every visit. Calculations and inputs were based on Blanken et al. (2017).

Sensor Costs. We based our cost estimates on the cost for a wearable Nedap Smarttag leg with heat detection and health monitoring sensor (Sleurink, 2018; Nedap, 2021) because few automatic SOM detection sensors are commercially available and Van De Gucht...
et al. (2017) report that farmers prefer wearable sensors. Sensor related costs were treated as a fixed annual overhead cost. Although it is treated as a fixed overhead, we include it in the model because it concerns the proactive management of SOM: incurring an annual cost of €1,553.75. This annual sensor cost is composed of an initial investment cost of €110 per unit per cow (Sleurink, 2018; Nedap, 2021), an annual depreciation of the sensor system initial investment cost depreciated over a 10-yr useful life, annual maintenance costs at 0.5% of the initial investment cost, and sensor replacement costs at a rate of one unit per year.

**Economic Analysis**

The primary objective was to obtain the mean net economic sensor effect, which reflects changes in individual cost factors, with the implementation of sensors. To obtain the mean net economic sensor effect, preliminary steps had to be performed. First the net economic results for each simulation in a 1-yr time horizon were computed. This was obtained with

\[ NER_{y,z} = \sum_{i=1}^{125} \sum_{t=1}^{365} R_{i,t,y,z}^{(milk)} - \sum_{i=1}^{125} \sum_{t=1}^{365} \sum_{k \in K} C_{i,t,y,z}^{(k)} - C_{y,z}^{(sensor)}, \]  

where \( NER_{y,z} \) is the net economic result for simulation \( y \) in scenario \( z \) and \( R_{i,t,y,z}^{(milk)} \) is the gross milk returns for cow \( i \) in time-step \( t \). For notational convenience, the cost factors for each cow \( i \) in the simulation model are denoted as \( C_{i,t,y,z}^{(k)} \), where \( k \in K = \{milk, discard, feed, insemination, culling, hoof trimmer, veterinarian, labor, treatment, confirm\} \). The (cost) elements of \( K \) associated with the cost factor \( C^{(k)} \) are briefly described: milk is the cost milk loss due to SOM, discard is the cost of discarded milk where a cow with SOM was treated with antibiotics, feed is the cost of feed, insemination is the cost of an insemination following the successful detection of estrus, culling is the net cost of culling, hoof trimmer is the cost of the professional hoof trimmer for the hoof trimming of a cow, veterinarian is the cost of the veterinarian for the treatment of a cow with severe SOM, labor is the cost of the farmer for the treatment of a cow with SOM, treatment is the cost of treating a cow with SOM, and confirm is the cost of confirming a sensor generated alert. Last, \( C_{y,z}^{(sensor)} \) is the annual cost of a sensor. The mean, 5th, and 95th percentiles were then calculated.

Once the net economic results were obtained, the mean net economic sensor effect for each sensor scenario was calculated by comparing the mean net economic results against the mean net economic results of the baseline without-sensor scenario \( (z = 0) \):

\[ NESE_z = \frac{1}{R} \left( \sum_{r=1}^{R} NER_{r,z} - \sum_{r=1}^{R} NER_{r,0} \right), \]  

where \( NESE_z \) is the mean net economic sensor effect for the with sensor scenario \( z \), and \( R \) is the number of replications required per scenario for model convergence. In addition, the mean totals for all the economic factors in the with-sensor scenarios \( (z = 1:80) \) were compared with those of the without-sensor scenario \( (z = 0) \) to gain insight on the composition of \( NESE_z \). To reduce the number of scenarios required for a detailed analysis on the compositions of the mean net economic sensor effect, we selected those with a mean net economic sensor effect in the (1) top 5%, (2) center 5%, and (3) bottom 5% of the mean net economic result distribution for the 80 sensor scenarios.

**Simulation Scenarios**

Several simulation scenarios were defined (Table 1). A baseline scenario was defined for a farm without an automatic SOM detection sensor system (scenario 0) so that a farm with an automatic SOM detection sensor system could be compared against it. Five scenarios were defined for a farm with an automatic SOM detection sensor system, each with primary differences in the mobility score threshold value for SOM classification by the sensor system and in the management of SOM with a sensor system.

Most automatic SOM detection sensors being developed use the Sprecher et al. (1997) mobility scoring method as classification method, where mobility score ≥3 is the threshold value for SOM classification by the sensor (Alsaad et al., 2019). Therefore, scenarios 1–3 incorporate mobility score ≥3 as the threshold value for SOM classification by the sensor. Scenarios 4–5 include mobility score ≥2 as the threshold value for SOM classification by the sensor, because this score can be considered as the onset of SOM, can cause economic losses (Edwardes et al., 2022), and may be of interest in detecting to prevent a case of severe SOM.

In respect to SOM management with a sensor system, scenario 1 simulated a situation where the sensor system was an addition to current SOM management (i.e., twice a year hoof trimming by a professional). Alerts generated for cows with mobility score 3 were checked by the farmer, perceived as false due to SOM awareness under current SOM management (Leach et al., 2010; Bruijnis et al., 2013), and these detected cows were
treated at twice-yearly routine hoof trimming. Cows
detected with mobility scores 4 and 5 were treated by
the farmer (mobility score 4) or veterinarian (mobility
score 5). Hence, cows detected with severe SOM were
immediately treated after detection.

Different SOM management were introduced in sce-
narios 2–5. First, routine hoof trimming at the start of
the pasture and housing period no longer occurred. This
was to incorporate more precise intervention for cows
that were detected with SOM that cannot be achieved
with twice-yearly hoof trimming. An increase in treat-
ment intensity for cows detected with mild SOM, as per
the mobility score threshold value for SOM classification
by the sensor, was also introduced. This proxied an
increased farmer awareness toward SOM that is
required for better (sensor-based) SOM management.
Cows that had true-positive alerts for mobility score 3
(scenario 2) and mobility scores 2–3 (scenario 4) were
treated by the farmer. Cows that had true-positive alerts
for mobility score 3 (scenario 3) and mobility
scores 2–3 (scenario 5) were treated by a professional
hoof trimmer. Cows that had true-positive alerts for
mobility scores ≥4 in scenarios 2–5 were treated as in
scenario 1. Due to the increased treatment intensity in
scenarios 2–5, the decision rule to cull a cow with severe
SOM if the cow required a fourth treatment for SOM
in the same lactation, as in Edwardes et al. (2022), was
removed.

In addition, subscenarios for each scenario 1–5 were
simulated. The subscenarios included changes in the
performance of the sensor in terms of sensitivity and
specificity and the ability of the sensor system to dis-
tinguish between mild and severe SOM by means of
the alert notification interval. For example, a daily
notification interval entails that the sensor system can-
not distinguish between mild and severe SOM, whereas
a notification interval of more than one day for mild
SOM entails that the sensor system can distinguish be-
tween mild and severe SOM. Changes in sensor perfor-
ance and mild SOM notification intervals respectively
occurred at 4 levels. Including mild SOM notification intervals help address tradeoffs between alert confirmation costs and additional production losses incurred, considering potential mobility score transitions, during the interval.

A full factorial of 16 subscenarios for each scenario 1–5 were simulated. A total of 81 scenarios were simulated: 1 for the baseline without-sensor system scenario (scenario 0) and 80 for the with sensor scenarios. 500 replications (i.e., \(R = 500\)) for each of the 81 scenarios were required for model convergence.

### Sensitivity Analysis

A sensitivity analysis was performed to assess the sensitivity in mean net economic sensor effect due to different values of farmer labor and hoof trimmer price per hour. We performed a sensitivity analysis with regard to these 2 parameters because of their economic uncertainty regarding changes in SOM management as per the simulated scenarios previously described.

Farm labor price may vary between farmers based on the required time to perform on-farm activities that they value most within their time budget due to behavioral, emotional, and intuitive reasons. For example, the disutility of giving up an additional time unit may be valued more than the utility in commensurate gains, such as reduced production losses, and vice versa (Tversky and Kahneman, 1992). This idea is encapsulated in the endowment effect (Kahneman et al., 1991). Thus, the labor price to perform SOM related management activities may vary based on the farmers perception toward SOM management, and respective changes in SOM management. Hoof trimmer fee structures may also change due to changes in the frequency of hoof trimming visits. To account for these uncertainties and the resulting sensitivity in mean net economic sensor effects, the default farm labor and hoof trimmer price per hour values were increased and decreased by €10 and €20, respectively. Changes in the hoof trimmer call out fee were omitted because preliminary simulations with a smaller number of replications showed insignificant effects on the mean net economic sensor effect. The hoof trimmer price per hour was not adjusted for scenario 1 because the frequency of hoof trimming remained unchanged. The sensitivity analysis was limited to the top, center, and bottom 5% selected subscenarios.

#### Sensor Classification Parametrization

For subscenario (a) with regard to the sensor performance, \(P_s\) (Equation 1) was directly based on the mobility score classification sensitivity (Table 2) reported in Van Hertem et al. (2016) in their 4-tier mobility confusion matrix. The weights used in the weighted random sample to simulate incorrect mobility score classifications (i.e., when \(\phi_{i,t} = 0\)) was obtained by setting the diagonals of the Van Hertem et al. (2016) 4-tier confusion matrix to NA and estimating the remaining distribution of incorrect mobility score classification as percentages per observed mobility score (Table 3). The overall sensor performance in terms of specificity and sensitivity were then obtained by transforming the 4-tier confusion matrix into a binary scaled confusion matrix (SOM and non-SOM) according to the mobility score threshold value for SOM defined in the scenarios 1 to 5 (Table 1).

Other than the study by Van Hertem et al. (2016), current literature at the time of publication with regard to specific mobility score classification sensitivity does not exist. Thus, we hypothetically set the sensor performance \(P_s\) for each mobility score for subscenarios (b), (c), and (d; Table 2). In subscenarios (b) and (c), \(P_s\) were hypothetically set to achieve overall gains in sensitivity and losses in specificity compared with subscenario (a); a trade-off apparent in literature (Dominiak and Kristensen, 2017). In subscenario (d), \(P_s\) was hypothetically set to emulate a sensor with the highest performance in both sensitivity and specificity in comparison to subscenarios (b), (c), and (d; Table 2). In subscenarios (b) and (c), \(P_s\) were hypothetically set to achieve overall gains in sensitivity and losses in specificity compared with subscenario (a); a trade-off apparent in literature (Dominiak and Kristensen, 2017). In subscenario (d), \(P_s\) was hypothetically set to emulate a sensor with the highest performance in both sensitivity and specificity in comparison to subscenarios (a), (b), and (c); in practice, high performance in terms of sensitivity and specificity is a desirable sensor feature (Dominiak and Kristensen, 2017; Van De Gucht et al., 2017). Weights for the weighted random sample of incorrect mobility scores in subscenarios (b), (c), and (d) remained as

| Sensor performance subscenario | Probability \((P_s)\) of correct mobility score classification | Source |
|-------------------------------|--------------------------------------------------|--------|
| (a) | 0.54, 0.75, 0.50, 0.49 | Van Hertem et al. (2016) |
| (b) | 0.45, 0.55, 0.60, 0.65 | Hypothetical inputs |
| (c) | 0.50, 0.60, 0.70, 0.75 | |
| (d) | 0.85, 0.80, 0.80, 0.85 | |

Table 2. Sensor mobility score classification probabilities
per Table 3. Using the hypotheticals set for $P_s$ found in Table 2, the number of correct mobility score classifications were calculated in accordance with the row total per observed mobility score in the 4-tier confusion matrix. The remaining observations not correctly classified were then distributed along the incorrect mobility scores per the weights in Table 3. The overall sensor performance was then estimated through a binary scale transformation as described for subscenario (a).

### RESULTS

The mean net economic result was €279,209 per farm per year for the baseline scenario (scenario 0) and ranged between €268,214 and €285,569 per farm per year for the 80 sensor subscenarios (Figure 1). See Supplemental Table S1 in the supplemental material for the mean net economic results for the 80 with sensor scenarios (Supplemental Table S1; https://doi.org/10.5281/zenodo.6555977; Edwardes et al., 2021a). Overall, the mean net economic results for 39 of the 80 simulated subscenarios were greater than the mean net economic results for the baseline scenario 0. Of these 39 simulated subscenarios, most were either part of scenario 3 (16 subscenarios), had an alert notification interval of 7 or 14 d for mild SOM (12 subscenarios, respectively), or concerned a sensor system with an 88% sensitivity and 91% specificity (12 subscenarios). In contrast, the 41 subscenarios with a mean net economic result lower than the baseline scenario 0, most were either part of scenario 1 or scenario 4 (16 subscenarios, respectively), had an alert notification interval of 1 d for mild SOM (14 subscenarios), or concerned a sensor system with a 68% sensitivity and 88% specificity, or a 75% sensitivity and 79% specificity, or an 82% sensitivity and 81% specificity (11 subscenarios, respectively).

When sensors were used as an addition to current SOM management (scenario 1), none of the scenarios had a mean net economic result greater than the mean net economic result of the baseline scenario 0 (range between €272,984 and €278,610). Increasing SOM treatment intensity (scenario 2–5) resulted in increasing mean net economic results for most of the scenarios respective of sensor performance and alert notification interval. The mean net economic results were higher when the hoof trimmer treated cows detected with mild SOM (scenario 3 and 5) compared with the farmer treating cows detected with mild SOM (scenario 2 and 4). In scenario 2, when the threshold value for SOM classification by the sensor was mobility score 3, the mean net economic results were higher in comparison with scenario 4, when the threshold value for SOM classification by the sensor was mobility score 2. Increasing the alert notification interval for mild SOM from 1 to 7 d showed an increase in mean net economic results for all scenarios 1–5 respective of the sensor performance. A notification interval of 7 d for mild SOM resulted in the highest mean net economic result for most scenarios 1–5 respective of sensor performance. Compared with the sensor with a 68% sensitivity and 88% specificity and daily notification interval for mild SOM, the mean net economic results were lower in all scenarios 1–5 for sensors with a 75% sensitivity and 79% specificity or 82% sensitivity and 81% specificity and daily notification interval for mild SOM. Within scenarios 1–5, the mean net economic results between sensors were relatively constant for sensors with a notification interval of 7 d for mild SOM.

Table 4 shows 12 selected subscenarios including the baseline scenario 0 each with the composition of the mean net economic results. See Supplemental Table S2 in the supplemental material for the composition of net economic results for the 80 with sensor scenarios (Supplemental Table S2; https://doi.org/10.5281/zenodo.6555977; Edwardes et al., 2021b). Subscenarios in the top 5% of mean net economic results all included a changed SOM management strategy where the hoof trimmer treated cows with mild SOM, as defined per the mobility score threshold value for SOM classification by the sensor, after an alert for cows requiring treatment for mild SOM was generated every 7 or 14 d. On the other hand, subscenarios in the bottom 5% of the mean net economic results did not include the hoof trimmer in the changed SOM management strategy and alerts for mild SOM were generated daily. Sensors with the highest performance (Se: 88% and Sp: 91%) were
included in 3 of the 4 top 5% selected subscenarios. No other observable commonality with respect to sensor performance was clear in the 12 selected subscenarios. To illustrate the differences between the economic factors in the 12 selected sensor subscenarios in contrast to the without-sensor scenario a graphical representation of the mean absolute changes in the economic factors are shown in Figure 2 with the mean net economic sensor effect in the top-right corner of each subscenario panel. The mean net economic sensor effect was positive for all top 5% selected subscenarios. In the center 5% selected subscenarios, only 1 of 4 had a positive mean net sensor economic effect. Reductions in the milk production loss and culling costs were largest in the top 5% selected subscenarios. Similar reductions in the milk production loss and culling costs were observed in the center 5% selected subscenarios. But these reductions were offset by the increase in labor costs due to increased labor time required to treat cows with SOM or the increased time required to confirm alerts, and an increase in the total treatment costs incurred by the farmer. Conversely, the mean net economic sensor effect was negative for the bottom 5% of selected sensor subscenarios. This was largely due to the high costs incurred for confirming alerts daily. This especially held for subscenarios when the mobility score threshold value for SOM classification by the sensor was mobility score 2 (i.e., scenario 4) despite reductions in milk production loss and culling costs in these bottom 5% subscenarios being similar to those observed in the top 5% performing subscenarios.

Results from the sensitivity analysis showed that the mean net economic sensor effect remained positive due to changes in the farm labor and hoof trimmer price per hour in the top 5% subscenarios (Figure 3). The
Table 4. Composition of net economic results in €1000 (× €1,000; 5th and 95th percentiles shown in parentheses)

| Sensor performance | Sensitivity (Se) | Specificity (Sp) | Alert (d) | Return | Gross milk return | Milk production loss | Discarded milk | Inseminations | Feed | Culling | Treatment | Alert confirmation labor | Hoof trimmer | Vaccination | Treatments | Hoof health | Total costs | Net economic result |
|--------------------|-----------------|------------------|----------|--------|-------------------|---------------------|-----------------|-----------|--------|--------|----------|------------------------|-----------|-------------|-----------|-----------|-----------|---------------------|
| Scenario           | Top 5%          | Center 5%        | Bottom 5%|        |                   |                     |                 |            |        |        |         |                       |          |             |           |           |           |                     |
|                    | 0               | 5                | 2        | 3      | 5                 | 3                   | 1               | 4          | 4      | 4      | 4        |                       | 1         |             |           |           |           |                     |
| Sensor performance 1 |                  |                  |          |        |                   |                     |                 |            |        |        |         |                       |          |             |           |           |           |                     |
| Se                  | 88%             | 88%              | 88%      | 88%    | 88%               | 75%                 | 82%             | 68%        | 82%    | 68%    | 82%      |                       | 81%       | 88%         | 81%       | 79%       |           |                     |
| Sp                  | 91%             | 91%              | 91%      | 88%    | 91%               | 79%                 | 81%             | 88%        | 81%    | 88%    | 81%      |                       | 81%       | 88%         | 81%       | 79%       |           |                     |
| Alert (d)2          |                  |                  |          |        |                   |                     |                 |            |        |        |         |                       |          |             |           |           |           |                     |
| Sensor (fixed cost) | 0               | 1.55             | 1.55     | 1.55   | 1.55              | 1.55                 | 1.55             | 1.55        | 1.55   | 1.55   | 1.55     |                       | 1.55      | 1.55        | 1.55      | 1.55      |           |                     |
| Total costs         | 109.7           | 104.53           | 104.72   | 105.05 | 109.93            | 110.13              | 110.11           | 110.54      | 115.24 | 119.38 | 120.17   | 121.4                 |           |             |           |           |           |                     |
| Net economic result | 279.21          | 265.57           | 285.14   | 284.54 | 279.4             | 278.56              | 278.84           | 278.83       | 272.96 | 270.18 | 309.26   | 269.21                 |           |             |           |           |           |                     |

1Se = sensitivity; Sp = specificity.
2Alert notification interval (d).
mean net economic sensor effects were more sensitive to changes in the hoof trimmer price per hour compared with changes in the farm labor price per hour, especially for subscenarios in scenario 5. The mean net economic sensor effect for subscenarios in the center 5% were positive with a €10 reduction in the labor price. The mean net economic sensor effect for subscenario in the bottom 5% remained negative across all changes in the farm labor price.

The mean total number of alerts generated during the year varied considerably between the 12 selected subscenarios (Table 5). The highest number of alerts were generated in subscenarios from the bottom 5% where on average >98% of the alerts generated were false. Subscenarios from the bottom 5% all had a daily alert notification interval for cows with mild SOM and 3 of the 4 subscenarios included mobility score 2 as a threshold value for SOM (scenario 4). Increasing the notification interval from 1 to either 7, 14, or 30 d for mild SOM reduced the mean total number of generated alerts considerably. The fewest number of mean alerts was generated in the subscenario for a sensor with a 30-d alert notification interval and, 82% sensitivity and 81% specificity. Increasing the alert notification alert intervals from 1 d also reduced the false alert rate. False alert rates were on average >40% lower than the true alert rate in scenarios when mobility score 2 was included in the threshold value for SOM for sensors with a performance of 88% sensitivity and 91% specificity.

We report 1 subscenario from each scenario 1–5 to demonstrate the effect that changes in SOM management, in terms of increasing treatment intensity, with regard to the use of sensors on yearly mobility score prevalence trends in contrast to SOM management without sensors (Figure 4). Scenario 0 illustrates the trend with regard to SOM management without sensors. The mean prevalence for mobility score 1 increased twice during the year after routine hoof trimming occurred at the start of the pasture and housing period. Thereafter the mean prevalence for mobility score 1 decreased as the mean prevalence for mobility scores 2 and 3 increased. The mean prevalence for mobility scores 4 and 5 were lower due to lower incidence rates and faster intervention when compared with mobility scores 2 and 3. When sensors were implemented in addition to current SOM management (scenario 1) the mean prevalence for mobility scores 1, 2, and 3 were comparable to the prevalence trend for the same mobility scores compared with the without-sensor scenario. The mean prevalence for mobility scores 4 and 5 in scenario 1 were lower with less variation compared with the mean prevalence for the same scores in the without-sensor scenario as treatment in reaction to the detection of these mobility scores occurred earlier when compared with scenario 0. Changes in the mobility score prevalence were more apparent in scenario 2–5. In scenarios 2 and 3 when cows with a mobility score 3 were treated, either by the farmer (scenario 2) or hoof trimmer (scenario 3), after an alert was generated, the prevalence of mobility score 3 showed a decrease compared with scenarios 0 and 1. A lower mean prevalence for mobility score 3 was achieved when the hoof trimmer treated cows with this score after an alert was generated every 7 d for these cow (scenario 3) compared with when the farmer treated cows with a mobility score 3 after an alert was generated every 30 d for these cows (scenario 2). The mean prevalence of mobility score 2 increased and showed an increasing trend during the year in scenarios 2 and 3 in contrast to scenarios 0 and 1. This occurred because mobility score 2 was below the mobility score threshold value for SOM classification by the sensor (mobility score 3). Using mobility score 2 as the mobility score threshold value for SOM classification by the sensor in scenarios 4 and 5 considerably reduced the mean prevalence of mobility score 2 to below 10% in both these scenarios. Overall, this showed a beneficial effect with the highest prevalence of mobility score 1 being achieved during the year in scenarios 4 and 5. The prevalence of mobility score 1 varied more in scenario 5 because of a longer alert notification interval (7 d) meaning that some cows would be scored with a mobility score 2 or 3 for longer before an alert was generated, and subsequently treated, compared with the shorter notification interval (1 d) in scenario 4.

DISCUSSION

In light of the automatic SOM detection sensor systems documented in the literature (Schlageter-Tello et al., 2014; Alsaaod et al., 2019), a dearth in research quantifying their economic value exists. Information concerning their economic value is paramount in stimulating the uptake of these sensors by farmers [e.g., Steeneveld and Hogeveen (2015)]. We investigated the economic value of automatic SOM detection by simulating various scenarios with and without automatic SOM detection sensors and drew comparisons between them. Our scenarios are not exhaustive because differences within other important economic factors such as SOM prevalence, automatic SOM detection sensor cost, and type were excluded (Van De Gucht et al., 2018; Kaniyamattam et al., 2020). Including different sensor types may have been of interest because farmers have shown preferences for different sensor types (Van De Gucht et al., 2017). However, it is of more interest to address sensor detection performance rather than sensor type, especially if detection performance within sensor types can vary (Schlageter-Tello et al., 2014; Alsaaod et al.,
Our different sensor performance scenarios can represent different sensor types if necessary. The scenarios included in our research contribute to the literature concerning the economic value of automatic SOM detection sensors by combining various sensor-based SOM management that had not previously been combined (Van De Gucht et al., 2018; Kaniyamattam et al., 2020). We designed management scenarios that went beyond current SOM management, trying to bring out the full potential of sensor-based SOM management. The most favorable scenario, scenario 5 for a sensor with a sensitivity of 88% and specificity of 91% and a 7-day alert notification interval, obtained a mean net economic sensor effect of €6,360. The least favorable scenario, scenario 4 for a sensor with a sensitivity of 75% and specificity of 79% and a daily alert notification interval, obtained a mean net economic sensor effect of €−10,995.

Automatic SOM detection sensor systems will not add economic value to the farming operation when they are implemented in addition to current SOM management. Due to the perception of SOM by farmers under current management strategies (Leach et al., 2010; Alawneh et al., 2012; Bruijnis et al., 2013), alerts may be checked but treatment is ignored until routine hoof trimming as these alerts are perceived as false. Our study shows that checking alerts perceived as false is time-consuming and costly. However, these costs may be an overestimation because farmers are expected not to react to every alert they perceive as false (Eckelkamp and Bewley, 2020). In addition, over time some farmers may completely ignore alerts as they become familiar.
with the sensor system (Eckelkamp and Bewley, 2020). This entails that current management would remain with the additional sensor related costs (i.e., depreciation).

A change in SOM management with the implementation of automatic SOM detection sensor systems is required to obtain their economic value. This change requires farmers to react more proactively to alerts, which farmers do not often do with existing, non-SOM related, sensors (Steeneveld and Hogeveen, 2015). Pro-active alert reaction requires increased farmer awareness of SOM so that mild SOM associated alerts are verified and lead to subsequent treatment. Although alert verification of mild SOM in practice may remain subjective, our results show that the economic potential of sensor-based SOM management needs to be coupled with a change in SOM management that includes increased farmer awareness toward SOM so that cows detected with mobility scores 2 and 3 are treated sooner. In our study, increased farmer awareness toward SOM is proxied by an increase in treatment intensity with regard to mobility scores 2 and 3.

Increasing the treatment intensity with prompt treatment of mild SOM by the farmer following a daily notification interval for mild SOM, production loss costs such as culling and milk production losses can be reduced by approximately 80 and 100%, respectively. This is because the costs concerning mild SOM, which contribute to a large share of the overall SOM costs (Edwardes et al., 2022), as well as the subsequent severe SOM costs, are ultimately avoided. Furthermore, the costs associated with severe SOM are also avoided due to the treatment of mild SOM. However, increasing treatment intensity increased treatment and labor costs considerably when mild SOM treatments were performed by the farmer. Our results suggest that by increasing the frequency of hoof trimmer visits to treat specific cows detected with mild SOM by the sensor, opposed to twice-yearly routine hoof trimming as per scenario 0 and 1, more precise resource allocation is achieved and greater economic value in the sensors can be obtained. This is in contrast to Van De Gucht et al. (2018) who showed that the economic value for automatic SOM detection sensors was greater when only...

**Figure 3.** Sensitivity in mean net economic sensor effect due to changes in default values (DV) for labor and hoof trimmer price per hour. DV were €30.70 and €47.95 for labor and hoof trimmer price per hour, respectively. Hoof trimmer prices were not adjusted in scenarios 1, 2, and 4 because changes in hoof trimming frequency did not occur in scenario 1 and hoof trimming did not occur in scenarios 2 and 4. Values are rounded to 2 decimal places. Se = sensitivity; Sp = specificity; ntf. int. = notification interval.
The farmer performs treatments. This is because results from our study show that farmer-related treatment and labor costs are more expensive than the hoof trimmer costs. The labor price per hour associated with SOM management may vary based on the idea of the endowment effect (Kahneman et al., 1991). Results from the sensitivity analysis with regard to the 12 selected subscenarios showed that the mean net economic sensor effect was more sensitive to changes in the labor price when more labor was required (scenario 1, 2, and 4). These results imply that the additional economic value in automatic SOM detection sensors used for sensor-based SOM management will vary between farmers based on the endowment effect with regard to SOM management. This has been observed in mastitis management, for example (Huijps et al., 2010).

Changes in the hoof trimmers’ price per hour may occur as their services become required more frequently with a change in SOM management. The sensitivity analysis showed that the mean net economic sensor effect remained positive for all changes in the hoof trimmer price per hour. This suggests that sensor-based SOM management, such as in the top 5% subscenarios, will remain economically positive due to changes in the hoof trimmer price per hour. Farm personal may also be required more often during hoof trimming visits to assist the hoof trimmer, which would incur additional labor-related costs. Our scenarios did not include additional farm labor assistance. Inferring additional labor-related assistance costs through increasing labor prices per hour coupled with hoof trimming, as in the sensitivity analysis, showed that increased labor prices did not affect the net economic sensor effect as much as increasing hoof trimmer prices. Including additional management scenarios in future research alongside the novel sensor-based SOM management scenarios described within this study can improve the advice farmers require to make economically optimal choices with regard to sensor-based SOM management.

It is crucial to maintain farmer confidence in sensors by conveying the correct information and avoid an altogether disregard of alerts over time (Eckelkamp and Bewley, 2020) that may contribute to prolonged SOM cases resulting in production losses. The quality of sensor-generated information is indicated by sensor performance metrics (i.e., sensitivity and specificity). These metrics must be interpreted with caution as they can be inflated through the transformation of non-binary prediction outcomes (i.e., mobility scores).

### Table 5. Number of alerts during the year for the 12 selected subscenarios; subscenarios are ordered by net economic results in descending order, and rows with center 5% scenarios are indicated with an asterisk

| Simulated scenario details | Mean total yearly alerts\(^1\) (5th and 95th percentiles) | Mean alert rate per alert notification\(^2\) (5th and 95th percentiles) |
|---------------------------|---------------------------------------------------------------|---------------------------------------------------------------|
|                           | True | False |                           | True | False |
| Scenario                  |      |       |                      |      |       |
| 5                         |     |       |                      |      |       |
| Sensitivity; specificity   |      |       |                      |      |       |
| 5                         | 88%; 91% | 7 | 316 | 184 | 6.1 | 3.5 |
|                           | (188; 464) | (126; 252) | (3.6; 8.9) | (2.4; 4.8) |
|                           |      |       |                      |      |       |
| 3                         | 88%; 91% | 7 | 115 | 194 | 2.2 | 3.7 |
|                           | (77; 160) | (162; 225) | (1.5; 3.1) | (3.1; 4.3) |
|                           |      |       |                      |      |       |
| 5                         | 88%; 91% | 14 | 335 | 61 | 12.9 | 2.3 |
|                           | (187; 481) | (41; 82) | (7.2; 18.5) | (1.6; 3.2) |
|                           |      |       |                      |      |       |
| 3                         | 82%; 81% | 7 | 115 | 649 | 2.2 | 12.5 |
|                           | (78; 156) | (563; 730) | (1.5; 3) | (10.8; 14) |
|                           | 2\* 88%; 91% | 1 | 119 | 4,370 | 0.3 | 12 |
|                           | (75; 170) | (3,890; 4,814) | (0.2; 0.5) | (10.7; 13.2) |
|                           | 2\* 75%; 79% | 30 | 83 | 334 | 6.9 | 27.8 |
|                           | (58; 113) | (290; 378) | (4.8; 9.4) | (24.2; 31.5) |
|                           | 2\* 82%; 81% | 30 | 92 | 301 | 7.7 | 25 |
|                           | (62; 124) | (258; 342) | (5.2; 10.3) | (21.5; 28.5) |
|                           | 2\* 68%; 88% | 1 | 117 | 5,732 | 0.3 | 15.7 |
|                           | (73; 171) | (5,160; 6,229) | (0.2; 0.5) | (14.1; 17.1) |
|                           | 1 82%; 81% | 1 | 29 | 10,778 | 0.1 | 29.5 |
|                           | (14; 44) | (8,033; 13,340) | (0; 0.1) | (22; 36.5) |
|                           | 4 68%; 88% | 1 | 234 | 20,719 | 0.6 | 56.8 |
|                           | (169; 317) | (20,496; 20,933) | (0.5; 0.9) | (56.2; 57.4) |
|                           | 4 82%; 81% | 1 | 226 | 22,406 | 0.6 | 61.4 |
|                           | (172; 326) | (22,191; 22,604) | (0.5; 0.9) | (60.8; 61.9) |
|                           | 4 75%; 79% | 1 | 235 | 24,630 | 0.6 | 67.5 |
|                           | (171; 327) | (24,398; 24,855) | (0.5; 0.9) | (66.8; 68.1) |

\(^1\)Values are rounded to the nearest whole number.

\(^2\)Mean alert rate is the average number of alerts (either true or false) expected every time an alert is generated.
obtain predictive performance of binary outcomes [e.g., SOM vs. non-SOM, (Van Hertem et al., 2016)]. Due to limited information on sensor performance at a non-binary level, we included hypothetical non-binary sensor performance inputs. Our results show that although the specificity of a sensor is high at the binary level, the underlying performance of the sensor at a non-binary level generates an undesirable number of false alerts. Ultimately this can contribute to an increase in alert confirmation costs large enough to outweigh the reduction in production losses. This especially occurred when the prevalence of mobility scores skewed toward a distribution of mobility scores considered as non-SOM. Ideally, a high sensitivity and also a high specificity should be present across all non-binary levels to ensure a consistent performance with changing mobility score prevalences. Future research with regard to sensor development should also report the predictive performance of non-binary outcomes.

Including a time dimension can help improve the information quality of sensors by alert prioritization because SOM is continuous and progressive in severity, making sensitivity and specificity alone not complete (Friggens et al., 2007). In their review, Dominiak and Kristensen (2017) found a limited number of published research concerning alert prioritization sensors. In our study, we included a simple and novel alert prioritization method by incorporating a time dimension (i.e., Eq. 2) in the form of notification intervals respective of SOM severity. Notification intervals of 7, 14, or 30 days are illustrated in Figure 4.
d for cases of mild SOM reduced the total number of false alerts generated throughout the year in contrast to a daily notification interval, but additional production losses and associated costs were incurred. However, these scenarios with intervals of >1 d obtained greater economic benefits compared with daily notification intervals because tradeoffs in intervention related costs were greater than the additional production losses, considering potential mobility score transitions, during the notification intervals (i.e., Figure 2). Within sensor performance scenarios, optimal economic results were most often obtained with a notification interval of 7 d. For example, the mean net economic sensor effect was €1,212 for a 7-d notification interval compared with −€372 for a daily notification interval for a sensor with 68% sensitivity and 88% specificity in scenario 2. A notification interval of 7 d meant that fewer false alerts were generated, and consequently checked, reducing the associated intervention costs more than the additional production losses incurred during the 7-d interval. Despite a 7-d increase in production losses, large production losses were still avoided in a timely manner as prompt treatment after the onset of SOM was still achieved in comparison to scenario 0. Additional benefits of an alert notification interval can arise in the form of a setting that farmers can specify to meet their individual preferences (Van De Gucht et al., 2017).

Automatic SOM detection sensors generally do not consider mobility score 2 as SOM (Alsaaod et al., 2019). We explored the economic value of sensors detecting this score as mild SOM. When only the farmer treated mild SOM cows, our results show that it was never economically viable because farm labor and treatment costs outweighed the reductions in production losses. However, when the hoof trimmer treated cows with mild SOM, the mean net economic sensor effect was positive for all scenarios with an alert notification interval of 7, 14, or 30 d. Although more alerts were generated, the additional associated costs were outweighed by a reduction in culling costs because the risk of cows indirectly culled due to SOM was reduced. This shows that mobility score 2 should be considered as the threshold value for SOM during sensor development due to the overall indirect costs associated with this mobility score (Edwardes et al., 2022). Treating cows with this score shows economic benefits as additional costs associated with transitions from mobility score 2 to mobility score ≥3 where ultimately avoided.

Beyond the economic value of automatic SOM detection sensors, a largely discussed topic with regard to sensors is the increased level of animal welfare that can be achieved through their use (Berckmans, 2014; Buller et al., 2020; van Erp-van der Kooij, 2020; Hogeveen and van der Voort, 2021; Manning et al., 2021). SOM prevalence is often used as a welfare indicator in welfare assessments (Welfare Quality, 2009). Using similar indicators from our simulation scenario results, we observed reductions in SOM prevalence in all the scenarios that included a management shift (Figure 4). This demonstrates that improvements of animal welfare with sensors are possible while increasing the net economic returns of production when SOM management changes. However, in some scenarios the highest level of welfare, in terms of SOM prevalence, resulted in the lowest net economic results (scenario 4). If this optimal level of welfare is at the forefront of dairy farming, then future research is required to quantify the added economic value of sensors concerning optimal gains in animal welfare to compensate for the losses in net economic returns due to increased intervention costs as found in our sensor-based SOM management scenarios.

**CONCLUSIONS**

We extended a recently developed bioeconomic simulation model that can evaluate the economic effects of sensor-based SOM management. The model allowed us to estimate a wide range of hypothetical sensor performance levels in combination with management scenarios. Results from the simulated scenarios showed that the maximum gain in terms of the mean net economic sensor effect was €6,360 per year (€51 per cow per year). To obtain the economic value of automatic SOM detection sensor systems, SOM management should be adapted to the use of sensors by stimulating farmer awareness with regard to mild SOM because a large part of the economic gain is in early treatment of mobility scores 2 and 3. Results from our simulations suggest that whole herd hoof trimming twice a year should be replaced with more frequent intervals of cow specific treatment by the hoof trimmer following SOM detection by the sensor. Seven-day intervals within sensor performance scenarios obtained economic optimal results. Furthermore, the development of proper detection algorithms before commercial rollout is important because the results were very sensitive to the sensitivity and specificity of the sensors, especially with regard to mobility score specific sensitivities and specificities and changing mobility score distributions.

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ORCIDS

Francis Edwardes © https://orcid.org/0000-0002-7908-7596

Mariska van der Voort © https://orcid.org/0000-0003-0503-259X

Henk Hogeveen © https://orcid.org/0000-0002-9443-1412
### APPENDIX

| Parameter | Description | Value | Source |
|-----------|-------------|-------|--------|
| **Lactation** | | | |
| \(a\) | Factors responsible for shape of lactation curve | 31.6 | Kok et al. (2017) |
| Parity 1 | | 60.6 |
| Parity \(\geq 3\) | | 44.1 |
| \(b\) | | |
| Parity 1 | | -0.0447 |
| Parity 2 | | -0.0708 |
| Parity \(\geq 3\) | | -0.0835 |
| \(c\) | | |
| | | -16.1 |
| \(k\) | | |
| | | 0.06 |
| **M**<sub>loss</sub> | Proportional daily milk loss per mobility score \(s\) | Based on O'Connor et al. (2020) |
| Mobility score 1 | | 0 |
| Mobility score 2 | | 0 |
| Mobility score 3 | | 0.05 |
| Mobility score 4 | | 0.48 |
| Mobility score 5 | | 0.53 |
| **Fertility and reproduction** | | | |
| Gestation | Length of gestation period (days) | \(N(281, 3)\) | Inchaisri et al. (2010) |
| Voluntary waiting period | Voluntary waiting period before first insemination postpartum (days) | 84 | Inchaisri et al. (2010) |
| Dry period | Dry period length prepartum (days) | 56 | Inchaisri et al. (2010) |
| First estrus | Days to first calving postpartum | | Authors’ expertise |
| Primiparous | | 14–27 |
| Multiparous | | 18–21 |
| Following estrus | Days to following estrus | 21 | Authors’ expertise |
| Estrus detection | Base risk of estrus detection | 0.55 | Based on Rutten et al. (2014) |
| Adjusted estrus detection | Relative risk of estrus detection per mobility score | | Walker et al. (2008) |
| Mobility score 1 | | 1 |
| Mobility score 2 | | 0.91 |
| Mobility score 3 | | 0.82 |
| Mobility score 4 | | 0.73 |
| Mobility score 5 | | 0.64 |
| Conception | Base risk of successful conception after insemination (ins.) number 1 to \(\geq 6\) | | Inchaisri et al. (2011) |
| Ins. 1 | | 0.45 |
| Ins. 2 | | 0.42 |
| Ins. 3 | | 0.41 |
| Ins. 4 | | 0.38 |
| Ins. 5 | | 0.33 |
| Ins. \(\geq 6\) | | 0.27 |
| Adjusted conception | Relative risk of successful conception per mobility score | | Alawneh et al. (2011) |
| Mobility score 1 | | 1 |
| Mobility score 2 | | 1 |
| Mobility score 3 | | PERT (0.41, 0.78, 0.88) |
| Mobility score 4 | | |
| Mobility score 5 | | |
| **Energy requirements (VEM)** | Daily growth energy requirements for parity \(\leq 2\) cows | 660 | Van Es (1978) |
| Growth | | 330 |
| Parity 1 | | |
| Parity 2 | | |
| Months prepartum | Daily energy requirements for pregnant cows from 4 to last month before calving | | Remmelink et al. (2015) |
| 4 | | 450 |
| 3 | | 850 |
| 2 | | 1,500 |
| 1 | | 2,700 |
| **Culling** | Daily general culling probability for parity 1 to \(\geq 5\) cows | 2.74e-5 | Calibrated input |
| General culling | | 6.85e-5 |
| Parity 1 | | 6.85e-5 |
| Parity 2 | | 2.74e-4 |
| Parity 3 | | 5.48e-4 |
| Parity \(\geq 5\) | | |
| Yield threshold | Daily milk yield threshold (kg) for cows culled due to infertility | 15 | Authors expertise |

*Continued*
Table A1 (Continued). Production and production loss parameters

| Parameter                        | Description                                                                 | Value  | Source                        |
|----------------------------------|-----------------------------------------------------------------------------|--------|-------------------------------|
| Adjusted culling (mobility scores) | Relative risk of culling per mobility score for cows with mobility score >1² |        | O’Connor et al. (2020)       |
| Mobility score 2                 |                                                                             | 1.07   |                               |
| Mobility score 3                 |                                                                             | 1.18   |                               |
| Mobility score 4                 |                                                                             | 1.48   |                               |
| Mobility score 5                 |                                                                             | 1.48   |                               |
| Adjusted culling (parity)        | Relative risk of culling per parity for cows with mobility score >1²       |        | Walker et al. (2008)          |
| Parity 1                         |                                                                             | 1      |                               |
| Parity 2                         |                                                                             | 1.1    |                               |
| Parity 3                         |                                                                             | 1.2    |                               |
| Parity 4                         |                                                                             | 1.3    |                               |
| Parity ≥5                        |                                                                             | 1.5    |                               |
| Adjusted culling (RPL)           | Relative risk of culling per relative production level (RPL) category for cows with mobility score >1² |        | Booth et al. (2004)          |
| ≤20%                             |                                                                             | 1      |                               |
| 21–40%                           |                                                                             | 0.34   |                               |
| 41–60%                           |                                                                             | 0.24   |                               |
| 61–80%                           |                                                                             | 0.16   |                               |
| >80%                             |                                                                             | 0.06   |                               |

¹Daily lactation was modeled using the Wilmink lactation curve with general form \( y = a + b \times \text{DIM} + c \times \exp(-k \times \text{DIM}) \), where \( \text{DIM} \) is days in milk (Wilmink, 1987). Individual cow variation in daily milk production was accounted for with \( y = \bar{y} \times \text{RPL} \), where \( \bar{y} \) is the average 305-d lactation and \( \text{RPL} \) is an individual cow’s relative production level modeled as \( N(0, 0.1) \) (Kok et al., 2017; Edwardes et al., 2022). \( \text{VEM} = \text{feed unit lactation} \); \( \text{PERT} = \text{program evaluation and review technique} \) (minimum, mean, maximum).

²General culling probability per parity was taken as base risk.

Table A2. Economic parameters

| Parameter                  | Description                                                                 | Value          | Source                                                                 |
|----------------------------|-----------------------------------------------------------------------------|----------------|------------------------------------------------------------------------|
| Milk price                 | Average monthly milk price (€/kg) for the period 01/2016–02/2022             | 0.3559         | Wageningen Economic Research (2022)                                    |
| kVEM price                 | Average monthly price of supplement feed (€/kg) for the period 09/2019–06/2020 | 0.1766         | Wageningen Livestock Research (2020)                                   |
| Farmer hourly rate         | Price per hour of farm labor (€/h)                                         | 30.70          | Blanken et al. (2017)                                                  |
| Hoof trimmer hourly rate²  | Price per hour of hoof trimming (€/h)                                       | 47.95          | Blanken et al. (2017)                                                  |
| Hoof trimmer call out fee  | Price per hoof trimmer visit (€/visit)                                      | 17.50          | Blanken et al. (2017)                                                  |
| Veterinarian hourly rate    | Price per hour of veterinarian treatment (€/h)                              | 139.20         | Expertise                                                              |
| Veterinarian call out fee   | Price per veterinarian visit (€/visit)                                      | 31.35          | Expertise                                                              |
| Farmer treatment time      | Farmer treatment time per cow (min/cow)                                    | 20             | Authors’ expertise                                                    |
| Hoof trimmer treatment time| Hoof trimmer treatment time per cow (min/cow)                              | 8.6            | Blanken et al. (2017)                                                  |
| Veterinarian treatment time| Veterinarian treatment time per cow (min/cow)                              | 20             | Authors’ expertise                                                    |
| Treatments per hoof disorder¹ | Additional treatment costs (€) per disorder per hoof applied by either veterinarian or farmer | 8.1 | Expertise |
| SH; SU; WLD                |                                                                             | 0.6            |                                                                         |
| IP; IDHE                   |                                                                             | 2.61           |                                                                         |
| DD                         |                                                                             | 0              |                                                                         |
| OH                         |                                                                             | 0              |                                                                         |
| HYP⁴                       |                                                                             | 0              |                                                                         |
| Rearing costs              | Rearing costs per replacement heifer (€/heifer)                             | 182.02⁵        | Mohd Nor et al. (2015)                                                 |
| Carcass dressing           | Carcass dressing as factor of live BW for culled cow                         | 0.6            | Rutten et al. (2014)                                                   |
| Meat price                 | Average monthly meat price (€/kg) discreetly sampled for first- to third-grade slaughter cows for the period 01/2016–02/2022 | 2.86; 2.54; 2.17 | Wageningen Economic Research (2022)                                    |
| Expected lactations        | Expected minimum number of lactations                                       | 6              | Authors’ expertise                                                    |

¹kVEM = ×1,000 VEM (feed unit lactation); \( \text{PERT} = \text{program evaluation and review technique} \) (minimum, mean, maximum).

²The hoof trimmer hourly rate includes hoof disorder treatment costs as in Edwardes et al. (2022).

³DD = digital dermatitis; HYP = interdigital hyperplasia; IDHE = interdigital dermatitis/heel-horn erosion; IP = interdigital phlegmon; OH = overgrown hoof; SH = sole hemorrhage; SU = sole ulcer; and WLD = white-line disease.

⁴Only differences between costs for veterinarian and farmer deal with HYP since only a veterinarian will perform a claw amputation; high costs account for the time involved for this procedure, and zero additional treatment costs are incurred by the farmer.

⁵Veterinarian treatment costs.