Enhancing

Farm-Level Economics & Animal Welfare

through

Sensor-Based Animal Health Management

Francis Edwardes

Propositions

1. Sub-optimal mobility is not a binary problem.
   (this thesis)

2. High false alert frequencies are costly but promote animal welfare.
   (this thesis)

3. Chasing model performance metrics solely, reduces the research to a modelling exercise.

4. Increased education on sensitivity analyses is imperative for simulation modelers.

5. Market based animal welfare certification prevents widespread animal welfare improvements.

6. Connectedness with nature is lacking in digitally advanced societies.

Propositions belonging to the thesis, entitled

Enhancing farm-level economics and animal welfare through sensor-based animal health management

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Enhancing farm-level economics and animal welfare through sensor-based animal health management

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Enhancing farm-level economics and animal welfare through sensor-based animal health management

Francis Edwardes

Thesis

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Insecurity is like a wild stallion

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Chapter 1
General introduction

Animal farmers are faced with a myriad of challenges while operating their farms. One of these challenges is the optimisation of animal health within their animal husbandry system. This is because poor animal health affects production in a variety of ways. Some examples include reduced milk production in dairy cattle (Bonestroo et al., 2022; Dolecheck & Bewley, 2018), sheep (Alba et al., 2019) and goats (Rinaldi et al., 2007), lowered carcass weights in cattle (Gifford et al., 2012), chickens (Landman & van Eck, 2015), and pigs (Cornelison et al., 2018) and decreased egg production in layer chickens (Landman & van Eck, 2015). Reductions in production outputs will consequentially manifest into economic costs because the value of the associated production outputs cannot be realised. These costs have been widely documented (e.g., Dolecheck & Bewley, 2018; Halasa et al., 2007; Nathues et al., 2017; Skinner et al., 2010). For a farm afflicted with poor animal health to obtain the same level of production as a healthy farm additional resources could be required (Hogeveen & van der Voort, 2017). Therefore, depending on the dynamics of the health disorder at play, poor animal health reduces the efficient allocation of resources and ultimately has a negative effect on farm profitability.

Aside from the economic implications of poor animal health, animal welfare implications also exist. The most obvious implication is the presence of health disorders, which are commonly used as indicators of reduced animal welfare in assessments (Mellor, 2017; Welfare Quality®, 2009a, 2009b). Furthermore, the effect of animal health disorders on animal welfare manifests through a variety of factors. Some of these factors include an increased risk of death, either due to health disorder induced mortality (e.g., Chanchaidechachai et al., 2022) or health disorder reasoned culling (Lacasta et al., 2019; Rilanto et al., 2020; te Beest et al., 2011). Additionally, animal health disorders can limit the animals' ability to interact with their environments (Galindo & Broom, 2002), restrict their mobility (Meluzzi & Sirri, 2009; Whay & Shearer, 2017), and inflict pain (Dolan et al., 2000; Gentle, 2011; Passos et al., 2017). However, while it is common knowledge – at least in animal health research – that health disorders have a negative impact on animal welfare, studies quantifying these impacts are scarce.

These economic and animal welfare implications highlight the importance of addressing and mitigating animal health disorders to ensure the negative economic effects on farm profitability are limited and the overall well-being of animals are enhanced. For animal welfare this is paramount given the societal concern for the well-being of animals (e.g., EU Monitor, 2022; Eurobarometer, 2016) and the strict animal welfare legislations (Simonin & Gavinelli, 2019). To effectively address and mitigate animal health disorders and their negative implications, proactive animal health management becomes essential.

1.1 Animal health management

From an economic viewpoint, animal health is optimally managed when a combination of costs associated with the health disorder are minimised. These costs are often defined in unit terms that refer to market prices. To study this optimal combination of costs McInerney et al. (1992) proposed the expenditure-loss frontier, which has been the theoretical foundation of studies on the economics of animal health management (e.g., Hogeveen et al., 2011; Yalcin et al., 1999). More recently the expenditure-loss frontier was adapted by van Soest et al. (2016) and Hogeveen and van der Voort (2017) whereby *ex ante* health disorder costs constitute preventative expenditures and *ex post* health disorder costs constitute production losses, treatment expenditures and additional resources such as additional labour. According to van Soest et al. (2016) and Hogeveen and van der Voort (2017) *ex post* health disorder costs are collectively termed failure costs. A theoretical illustration of the expenditure-loss frontier depicts a trade-off between preventive and failure costs as a downward sloping convex curve. When preventive costs are higher, failure costs are lower, and vice versa. If no preventive measures are implemented, the failure costs reach their maximum. Conversely, with maximum prevention, the failure costs due to production diseases are minimised. The non-linear relationship between preventive and failure costs entails that an optimal level of animal health management exists. On the expenditure-loss frontier this optimal level occurs at the point where an increase in prevention costs is equivalent to the reduction in failure costs. Locating the global economically optimal point of management in practice is challenging because endless management scenarios exist. However, by referring to the theory laid out by McInerney et al. (1992) and promoted by Hogeveen and van der Voort (2017), the local economically optimal management scenario available can be determined by focussing on the minimum combination of preventive and failure costs of the observable animal health management strategies. Furthermore, the additional economic value of one management scenario compared to another can also be determined by examining the difference in the combination of preventive and failure costs between the management scenarios.

From an animal welfare viewpoint, animal health management is challenging. This is because defining an animal welfare unit representing the effect of a health disorder is a subjective process for different animals since it is their own individual well-being at stake. Moreover, the communication barrier between animals and humans adds to the challenge in determining the animal welfare outcome of animal health management. Therefore, an animal welfare unit representing the effect of a health disorder is required to facilitate animal health management in the context of animal welfare. Assuming such a unit exists, it can be said that animal health is optimally managed when the physical and mental well-being of the animals are prioritised (Fraser, 2013) by minimising the sum of the units in an attempt to reduce the occurrence and duration of health disorders. This can be achieved through animal health management factors such as: provision of appropriate nutrition and housing, preventive measures, regular monitoring and assessment of animal health status, prompt and accurate diagnosis of poor health followed by appropriate treatments of health disorders, implementation of effective biosecurity protocols, and promotion of a stress-free and enriched environment that meets their species-specific needs (e.g., Animal Welfare Council, 2009; Mellor, 2017). By studying how these factors minimise the animal welfare units representing the effect of health disorders on animal welfare, optimal animal health management can be determined. Furthermore, the additional animal welfare value of one management scenario compared to another can also be determined by examining the difference in aggregated animal welfare units representing the effect of health disorders on animal welfare.

By framing the factors that promote optimal animal welfare mentioned above into an economic animal health management context clearly demonstrates that animal welfare can be influenced by economic factors (Balzani & Hanlon, 2020). Despite the importance that health disorders have on animal welfare, the management of animal health is still mostly studied from an economic perspective. This is partially due to the relative ease in quantifying the economic management of health disorders in terms of units that refer to market prices opposed to quantifying the animal welfare management of health disorders in terms of non-monetary units (McInerney, 2004). As a result, this makes it incredibly challenging to support optimal decisions in animal health management that aim to avoid the negative effect of poor animal health on both farm economics and animal welfare. By adopting a more holistic approach that considers both economic and animal welfare perspectives, the complex interplay between farm-economics and animal welfare with respect to animal health can be better addressed.

1.2 Digitally supported animal health management

Digital agriculture is a concept that refers to the application and integration of advanced information and communication technologies, and digital systems with tools such as sensors to enhance the productivity, efficiency, and sustainability of various agricultural aspects (De Clercq et al., 2018; Morrone et al., 2022; Neethirajan & Kemp, 2021a; Rose et al., 2021). Precision livestock farming (PLF), a key component of digital agriculture, enables farmers to effectively manage their livestock through objective, continuous, and/or autonomous monitoring. By employing advanced technologies – such as sensors and statistical models – PLF technology collects and processes data from individual animals to generate animal specific information, enabling farmers the potential to monitor animal health more efficiently and effectively (Berckmans, 2017; Norton et al., 2019). This is achieved by generating early warning signals (i.e., alerts) for the onset of health disorders (Li et al., 2020; Vranken & Berckmans, 2017; Wathes, 2009) that would be challenging to achieve through traditional labour-intensive visual inspection methods.

Numerous PLF technologies have been, and continue to be, developed to digitally support animal health management (e.g., Alsaaod et al., 2019; Bausewein et al., 2022; Gómez et al., 2021; Morrone et al., 2022; Rutten et al., 2013). With their autonomous, individual animal-based early warning capabilities for poor animal health, it is expected that a PLF-based animal health management approach will add economic and animal welfare value to the farm (Banhazi et al., 2012; Berckmans, 2014, 2015; Wathes, 2009). This is because health disorders can be detected and treated sooner, resulting in an avoidance of consequential production losses in comparison to traditional visual labour-based animal health management approaches. Moreover, the sooner health disorders are treated the sooner their negative impact on animal welfare can be mitigated, ultimately improving the well-being of animals.

Considering the potential for additional economic and animal welfare value obtainable from a PLF-based animal health management approach, a new expenditure-loss frontier that accounts for animal welfare may exist. However, research quantifying the added economic and animal welfare value, along with corresponding optimal levels of animal health management, is scarce. This inhibits the potential farm-level integration of a PLF-based animal health management approach because farmers justify their investment decisions concerning PLF technology based on their added value (e.g., Steeneveld & Hogeveen, 2015).

1.3 Problem statement

Poor animal health in animal husbandry systems has wide-ranging implications. Animals suffering from health disorders experience decreased growth rates, diminished reproductive performance, and higher mortality rates. From an economic perspective it leads to inefficient resource utilisation, reduced productivity, and increased costs for farmers. Moreover, the negative impact of poor animal health extends to animal welfare, affecting both the well-being of the animals and the stakeholders involved. Animals experiencing health disorders may endure pain, distress, and a diminished quality of life, which raises ethical concerns. Consequentially, farmers face increasing animal health related costs and potential reductions in the value of their products as a result of demands for stricter animal welfare regulations and standards. These challenges call for *i*) innovative methods and *ii*) solutions to address the detrimental economic and animal welfare impacts of poor animal health.

First and foremost, tackling these challenges requires the impact of animal health disorders on animal welfare to be studied and factored into the animal health decision making framework. This is rarely done in animal health research due to a lack of available methods. Therefore, it is crucial that appropriate methods are developed to study the negative effect of animal health disorders on animal welfare. By integrating animal welfare into the animal health decision making framework, the possibility of making well-informed decisions that holistically account for both economic and animal welfare aspects can be enabled.

Secondly, digital technologies, particularly sensors found in PLF, offer promising solutions that address the detrimental economic and animal welfare impacts of poor animal health. However, there is a need for a comprehensive understanding of how these technologies can be leveraged at the farm-level to improve animal health, economic outcomes, and animal welfare. A thorough assessment is required to explore and determine the effective implementation of these digital technologies whereby economic and animal welfare value adding animal health strategies are identified.

1.4 The case of sub-optimal mobility in dairy cows

To study economic and animal welfare outcomes in the context of digitally supported animal health management, sub-optimal mobility (SOM) in dairy cows is used as an animal health disorder case. This is because it is a common dairy production health issue with significant economic and animal welfare importance.

As the name suggests, SOM is a health disorder whereby the mobility of a cow is affected, often resulting from the occurrence of hoof disorders (Alvergnas et al., 2019; Tadich et al., 2010). A recent review on SOM prevalence estimates – mostly in Europe and North America – reports a mean herd-level SOM prevalence of ~23 percent with a between study (53 studies reviewed) range from ~5 to ~45 percent, and a between herd range from 0 to ~88 percent (Thomsen et al., 2023).

SOM is identified by examining cow-level variables – such as gait symmetry, stride length, back posture, head bobbing etc. – whereby the severity of SOM is described by mobility scores congruent to the assessment of the observed cow-level variables. Various mobility scoring methods exist, but a review by Schlageter-Tello et al. (2014) showed that the five-point ordinal mobility scoring method developed by Sprecher et al. (1997) is most popular. SOM is often referred to as lameness, but the definition of lameness in conjunction with mobility scores has shown to vary between studies. For example, some studies define a cow as lame with mobility scores ≥2 (Olechnowicz & Jaśkowski, 2015), ≥3 (Amory et al., 2006; Randall et al., 2018; Somers et al., 2019), or ≥4 (Kovács et al., 2015). By avoiding the term lameness, we can specifically focus on varying levels of SOM as defined by the mobility scores themselves. More recently, other studies have avoided the term lameness and focused on specific mobility scores to describe SOM (O'Connor et al., 2019, 2020b).

SOM has detrimental effects on production. These effects include reduced milk production (Bicalho et al., 2008; O'Connor et al., 2020a; Reader et al., 2011), negative impacts on reproductive traits (Morris et al., 2011; Walker et al., 2010, 2008) that potentially contribute to reduced reproductive performance (Charfeddine & Pérez-Cabal, 2017; O'Connor et al., 2020a), and can increase the risk of culling (Booth et al., 2004; O'Connor et al., 2020a). Ultimately, these negative production effects manifest into negative economic effects, which have been widely studied (Ettema & Østergaard, 2006; Ettema et al., 2010; Kossaibati & Esslemont, 1997; Liang et al., 2017; Robcis et al., 2023). Most often the largest negative economic effects are due to milk production losses and culling (Dolecheck & Bewley, 2018). Mitigating the costly production losses in turn results in preventive and treatment expenditures (Dolecheck & Bewley, 2018).

SOM also negatively affects animal welfare (Broom & Corke, 2002; Nielsen et al., 2023; Whay & Shearer, 2017). It is associated with pain (O'Callaghan et al., 2003; Shearer et al., 2013) and reduced body condition (O'Connor et al., 2019), increases the risk of a reduced lifespan (Booth et al., 2004; O'Connor et al., 2020a), impairs feed intake (Galindo & Broom, 2002; Norring et al., 2014) and can influence social behaviour (Galindo & Broom, 2002; Walker et al., 2008). Moreover, SOM is an important animal welfare indicator in the animal welfare quality assessment protocol for cattle (Welfare Quality®, 2009a). Notably, a significant proportion of the scientific literature on SOM, approximately 30 percent of 830 articles published between 2010 and 2022, highlight the issue of SOM as an animal welfare concern[1]. Only two scientific studies have quantified the animal welfare impact of hoof disorders. Although the results of these studies can be easily associated to SOM, there are no studies that quantify the animal welfare impact of SOM.

Current SOM management practices constitute various components. They can include on farm labour-based detection and treatment. However, farmers generally underestimate the prevalence of SOM (Bran et al., 2018; Cutler et al., 2017; Richert et al., 2013), which can contribute to a prolonged detection and treatment (Alawneh et al., 2012a). It also includes routine hoof trimming at different intervals by external personnel as a preventive and curative measure (Frankena et al., 2009; Sadiq et al., 2019; Stoddard & Cramer, 2017; Van Hertem et al., 2014a). Despite the existing management approaches, the average SOM prevalence across dairy farms has not changed much in the last two decades (Thomsen et al., 2023).

PLF offers a promising solution to enhance the management of SOM while addressing the negative economic and animal welfare consequences associated with it. This is primarily due to the autonomous and continuous monitoring capabilities of PLF, which can provide real-time information on cows with SOM, enabling timely interventions and treatment as needed. While significant efforts have been invested by the PLF research community in the development of technology supporting SOM

[1] Unpublished data from a Web of Science literature review. Manuscript in compilation by: Steeneveld, W., van den Borne, B.H.P., Kok, A., Rodenburg, B., Hogeveen, H..

management (Alsaaod et al., 2019; Schlageter-Tello et al., 2014), there remains a need for research to quantify the effectiveness of these technologies to improve SOM management and to assess whether implementing them with their current capabilities contributes positively to both economic and animal welfare aspects of SOM management. It could also be worth investigating whether alternative PLF technological capabilities can add economic and animal welfare value to the farming operation.

In light of the economic and animal welfare significance of SOM and recent PLF developments, SOM is an interesting health disorder to investigate. It provides the opportunity to develop and explore methods and solutions to support decision making related to both economic and animal welfare factors in the context of digitally supported (PLF) animal health management. Consequently, utilising SOM as a case study in this thesis aligns well with the research objectives of this thesis.

1.5 Objectives and research questions

The general objective of this thesis is to provide economic and animal welfare decision support in the utilisation of digital technologies found in PLF, to enhance animal health management by adding economic and animal welfare value to the farming operation. The research is centred around SOM and focuses on sensor-based SOM management in Dutch dairy farms. This context serves as an example of digitally supported animal health management. This example provides valuable insights into the practical development and implementation of sensor technologies to support and enhance economic and animal welfare decisions and outcomes.

To achieve the general objective, the research aims to address two sub-objectives: *i*) to comprehensively identify the economic and animal welfare impacts of SOM by focusing on different constitutions of SOM, and *ii*) to identify how sensor-based management, taking into account the current capabilities of sensors and its potential future advancements, can further enhance economic and animal welfare outcomes. This investigation will explore the potential benefits and limitations of utilising sensors in managing SOM and propose approaches for enhancing the economic and animal welfare outcomes of sensor-based SOM management. To achieve the general objective, the following four research questions are addressed.

1. *What do the different dynamics of SOM contribute to the total economic cost of SOM?*

Research question one aims to investigate the contribution of different constitutions of SOM, characterised by mobility scores and prevalence rates, to the total economic cost of SOM under the current management strategy, i.e., management without sensors. To answer this question a dynamic, time-discrete, and stochastic bio-economic simulation model simulating the dynamics of SOM is developed to provide consequent economic impact insights at cow- and herd-level. Answering this question will provide comprehensive insights on how to effectively manage SOM with sensors from an economic perspective.

2. *What do the different dynamics of SOM contribute to the total animal welfare impact of SOM?*

In a similar line to research question one, research question two aims to investigate the contribution of different constitutions of SOM, characterised by mobility scores and respective dynamics, to the total animal welfare impact of SOM in a SOM management strategy without sensors. To answer this question, first, animal welfare impediment weights are derived from experts using adaptive conjoint analysis to elicit the conjoint trade-offs in animal welfare impairments associated to welfare indicators affected by SOM. Second, these animal welfare impairment weights associated to mobility scores are used as input to quantify the welfare impact of SOM using the bio-economic simulation model developed in research question one. Answering this question will provide comprehensive insights on how to effectively manage SOM with sensors from an animal welfare perspective.

3. *What changes in SOM management are required to obtain additional economic value from a sensor-based SOM management approach?*

The third research question aims to investigate the potential additional economic value that can be obtained through various sensor-based SOM management approaches. Simulation scenarios are designed to explore the full potential of different sensor-based management approaches, encompassing a range of changes in SOM management compared to a typical Dutch SOM management strategy without sensors. The scenarios will focus on aspects such as sensor performance, alert prioritisation, generation of immediate versus prolonged information for different SOM constitutions, and treatment providers. This simulation-based exploratory research aims to provide insights on the above-mentioned aspects that can support the development and implementation of economically effective sensor-based SOM management scenarios. The findings will address key aspects relevant to sensor developers, farmers, and external animal health service providers.

4. *How do changes in the underlying settings of sensors influence the economic and animal welfare outcomes apropos sensor-based SOM management?*

The fourth research question focuses on examining the effects of different settings governing sensor performance on the economic and animal welfare outcomes of sensor-based SOM management. Specifically, these settings pertain to the probability of correctly classifying cows into their respective SOM classes. This question builds upon the methods developed and employed in the preceding three research questions. By answering this question, valuable insights will be gained for sensor developers on how to customize sensors to align with the economic and animal welfare requirements of farmers.

In this thesis the four research questions, in the same order they were asked, are addressed in Chapters 2 – 5. The thesis is concluded with Chapter 6 whereby a general discussion of the research is presented.

Chapter 2
Simulating the mechanics behind sub-optimal mobility and the associated economic losses in dairy production

This chapter is based on: Edwardes, F., van der Voort, M., Halasa, T., Holzhauer, M. and Hogeveen, H. (2022). Simulating the mechanics behind sub-optimal mobility and the associated economic losses in dairy production. *Preventive Veterinary Medicine*, 199, p.105551. DOI: https://doi.org/10.1016/j.prevetmed.2021.105551

Abstract

Hoof disorders and sub-optimal mobility (SOM) are economically important health issues in dairy farming. Although the dynamics of hoof disorders have an important effect on cow mobility, they have not been considered in previous simulation models that estimate the economic loss of SOM. Furthermore, these models do not consider the varying severities of SOM. The objective of this study was to develop a novel bio-economic simulation model to simulate the dynamics of 8 hoof disorders: digital dermatitis (DD), interdigital hyperplasia (HYP), interdigital dermatitis/heel-horn erosion (IDHE), interdigital phlegmon (IP), overgrown hoof (OH), sole haemorrhage (SH), sole ulcer (SU) and white-line disease (WLD), their role in SOM, and estimate the economic loss of SOM in a herd of 125 dairy cows. A Reed-Frost model was used for DD and a Greenwood model for the other 7 hoof disorders. Economic analysis was conducted per mobility score according to a 5-point mobility scoring method (1 = perfect mobility; 5 = severely impaired mobility) by comparing a scenario with SOM and one without SOM. Parameters used in the model were based on literature and expert opinion and deemed credible during model validation rounds. Results showed that the mean cumulative incidence for maximum mobility scores 2–5 SOM cases were respectively 34, 16, 7 and <1 cases per 100 cows per pasture period and 39, 19, 8, <1 cases per 100 cows per housing period. The mean total annual economic loss due to SOM resulting from the hoof disorders under study was €15,342: €122 per cow per year. The economic analysis uncovered direct economic losses that could be directly linked to SOM cases and indirect economic losses that could not be directly linked to SOM cases but arose due to the presence of SOM. The mean total annual direct economic loss for maximum mobility score 2 – 5 SOM cases was €1129, €3098, €4354, and €480, respectively. The mean total annual indirect economic loss varied considerably between the 5th and 95th percentiles: €−6,174 and €19,499, with a mean of €6,281. This loss was composed of additional indirect culling due to SOM (~65 percent) and changes in the overall herd milk production (~35 percent) because of additional younger replacement heifers entering the herd due to increased culling rates. The bio-economic model presented novel results with respect to indirect economic losses arising due to SOM. The results can be used to stimulate farmer awareness and promote better SOM management.

2.1 Introduction

Hoof disorders are a costly health issue in dairy production (Dolecheck & Bewley, 2018). These costs vary within and between hoof disorders depending on their respective severity, duration, and recurrence. For example, the cost of a digital dermatitis case varied between €45 and €342 and for a sole ulcer case between €152 and €817 (Cha et al., 2010; Charfeddine & Pérez-Cabal, 2017; Dolecheck et al., 2019; Willshire & Bell, 2009). These costs can result in high economic losses for dairy producers, especially when the overall prevalence of hoof disorders can be as high as 81 percent (Somers et al., 2003). For example, Bruijnis et al. (2010) found that hoof disorders are responsible for an annual economic loss of €76 per average cow for a dairy farm with a hoof disorder prevalence similar to Somers et al. (2003). Many of these costs arise potentially unbeknownst to the farmer because farmers tend to underestimate the prevalence of hoof disorders (Bruijnis et al., 2013).

Farmers may underestimate the prevalence of hoof disorders because they primarily detect hoof disorders first by adverse changes in the mobility of a cow (Bruijnis et al., 2013). Moreover, hoof disorders are largely associated with mild sub-optimal mobility (SOM; O'Connor et al., 2019; Tadich et al., 2010), which farmers are less sensitive in detecting (Alawneh et al., 2012a).

Due to the association between SOM and hoof disorders, it is expected that SOM, as an effect of underlying hoof disorders, will result in economic losses. This is confirmed with cases of SOM reported to cost between €159 and €457 (Ettema & Østergaard, 2006; Guard, 2008; Liang et al., 2017). However, these studies focus on severe forms of SOM, omitting the potential economic losses associated with milder forms of SOM.

Mild SOM has not often been included in studies estimating the economic losses associated with SOM. Studies that include mild forms of SOM do so by usually employing a mobility scoring method. A mobility scoring method helps define a cow with SOM according to varying levels in severity of SOM based on the number of scores in the method (Schlageter-Tello et al., 2014). However, in doing so, the definition of a cow with SOM is generalised whereby a cow with a mobility score above a predefined mobility score threshold is defined as SOM. This generalisation reduces the ability of the method to help better identify which forms of SOM are of greater economic importance. For instance, Ettema et al. (2010) show the economic impact for SOM as defined by cows with mobility score ≥3 according to a 5-point mobility scoring method, but the economic impact for SOM respective of mobility scores $3-5$ are not reported. In addition, omitting lower mobility scores (i.e., 2) from the definition of SOM may also lead to an underestimation of costs.

There are several studies concerning the economic losses associated with hoof disorders and SOM (Dolecheck & Bewley, 2018). Most of the studies reporting the economic loss of hoof disorders and SOM are conducted by simulation modelling. However, studies simulating the economic loss of hoof disorders do not simulate the effect of hoof disorders on cow mobility (Bruijnis et al., 2010; Dolecheck et al., 2019). Conversely, studies simulating the economic impact of SOM do not simulate hoof disorders as responsible mechanisms for SOM and the definitions of SOM relate to severe forms (Ettema & Østergaard, 2006; Liang et al., 2017). An exception to the aforementioned studies simulating the economic loss of SOM is the study of Ettema et al. (2010) whereby hoof disorders are simulated as responsible mechanisms of SOM and milder forms of SOM are considered. However, Ettema et al. (2010) specify SOM in more general terms. More information is needed on the dynamics of SOM with hoof disorders acting as the responsible and the underlying mechanisms of SOM. Moreover, more precise information is needed on the economic losses due to different severities of SOM, including mild SOM.

We developed a novel stochastic bio-economic simulation model that creates a stronger link between SOM and hoof disorders whereby the hoof disorders act as the responsible mechanisms behind the dynamics of SOM. Adding to the literature concerning the economic losses due to SOM, we present the direct economic losses due to SOM, for mild and severe forms, as well as the indirect economic losses due to SOM.

2.2 Methodology

2.2.1 Model overview

A dynamic, stochastic, and mechanistic discrete time-step bio-economic model was developed in R version 3.6.1 – "Action of the toes" (R Core Team, 2019) to simulate the spread and occurrence of hoof disorders as responsible mechanisms of SOM in dairy cows as well as the management of SOM. A typical Dutch dairy production system of 125 milking cows was simulated. It was assumed that cows were housed in cubicles with slatted concrete floors during the Autumn and Winter months (housing period) and had access to pastures for >6 h a day in the Spring and Summer months (pasture period). The model simulated events in daily time-steps either at the hoof- or cow-level. Simulations at the hoof-level include hoof specific events (i.e., infection and treatment) whereas (re)production events (i.e., milking, calving, and culling) and mobility scoring are at the cow-level. A 5-point ordinal scale mobility scoring method was used to describe cow mobility (Sprecher et al., 1997). Per cow, per time-step and per mobility score the economic in-and outflows associated with SOM were computed. Based on these in-and outflows, the net partial economic results per year of the simulated farm were calculated. By comparing the net partial economic results of farms with and without hoof disorders, the total (direct and indirect) annual economic effect of SOM due to the hoof disorders under study could be estimated. The costs directly associated with SOM were also calculated per SOM per year.

2.2.2 Production dynamics

Cows were either lactating or dried-off and spent a number of days in either period. The dry period length (DPL) was a fixed length, and the lactation length depends on a fixed minimum voluntary waiting period (VWP) before first service, stochastic estimates of oestrus detection and conception, and possible removal by culling decisions. A cow was prescribed a maximum number of days to conceive. If the cow did not conceive by this day, she was culled for fertility reasons once her actual daily milk yield dropped below a fixed daily yield threshold. The decision to cull for fertility reasons was based on a cow's production level relative to the herd. The decision to cull for general reasons depended on the removal of cows due to health disorders other than SOM[2] and mortality and was calibrated so that the overall culling rate coincided with the ~30 percent for Dutch dairy farms (Nor et al., 2014). It was assumed that culling took place on the premise that a replacement heifer entered the milking herd on the following day a cow was culled. If a cow died, a replacement heifer entered the milking herd on a random day within a month after the cow died because those replacement events cannot be planned.

Expected daily milk yield for lactating cows depend on cow specific parameters and was modelled by fitting a lactation curve to each cow with the following equation;

$$M_{i,p,t}^{(emy)} = a_{i,p} + b_{i,p} \times M_{i,t}^{(dim)} + c \times \exp\left(-k \times M_{i,t}^{(dim)}\right) + M_i^{(rpl)} \times M_{i,p,t}^{(ady)} \tag{2.1}$$

Where $M_{i,p,t}^{(emy)}$ is the expected daily milk yield for cow i in parity p in time time-step t, $M_{i,t}^{(dim)}$ is the day in milk, $M_{i,p,t}^{(ady)}$ is the average daily yield, and $a_{i,p}$, $b_{i,p}$, c, and k are factors responsible for the shape of the curve (Wilmink, 1987). Variation in cow

[2] Comorbidity was not directly included in the simulation model. However, it was indirectly accounted for in the general culling decisions so that an overall culling rate was attainable.

lactations was achieved by assigning a cow specific production level relative to the mean herd production to each cow. This relative production level (RPL) is denoted by $M_i^{(rpl)}$ and was drawn from a normal distribution with a mean of 0 and a standard deviation of 0.1 (Kok et al., 2017).

Feed requirements, expressed in VEM (where 1 VEM = 1.65 kcal of NE_L), for each cow was modelled as a function of daily FPCM milk produced (kg) for lactating cows (Van Es, 1978). Parity 1, 2 and ≥3 cows respectively have a fat content (percent) of 4.48, 4.5 and 4.51, and a protein content (percent) of 3.55, 3.59 and 3.51 (Kok et al., 2017). Higher feed requirements for parity 1 and 2 cows, and four pregnancy stages were included to account for different feed requirements during pregnancy (Remmelink et al., 2015).

Body weights were assigned to parity 1 cows on their first milking day by a normal distribution with a mean of 540 kg and a standard deviation of 6 kg. Thereafter, cows gained 0.13 kg per day until the end of their second lactation (based on Kok et al., 2017).

2.2.3 Hoof disorders

Eight hoof disorders were modelled: five non-infectious and three infectious. The non-infectious hoof disorders include interdigital hyperplasia (HYP), overgrown hoof (OH), sole haemorrhage (SH), sole ulcer (SU) and white line disease (WLD). The infectious disorders include digital dermatitis (DD), interdigital dermatitis and heel horn erosion (IDHE), and interdigital phlegmon (IP). Infections and the dynamics of these disorders were modelled at hoof-level. However, cow-level infection risk factors were accounted for allowing individual variation in susceptibility. Non-infectious hoof disorders were modelled as environmental infections with the Greenwood model (Becker, 1989). Infectious hoof disorders, IDHE and IP, were also modelled as environmental infections, because, to our knowledge, there is no information on the transmission dynamics of IDHE and IP. Only DD was modelled as a contagious hoof disorder with the Reed-Frost model (Becker, 1989).

It was assumed that a hoof can hold only one disorder at a time since the dynamics between multiple disorders on the same hoof is not clearly understood. Therefore, a cow could have a maximum of four hoof disorders (one for each hoof) at a time. Once a cow received a hoof disorder, a mobility score was assigned at hoof-level. A hoof will remain with a disorder until it has fully cured, either spontaneously or following a successful treatment.

In our model, the hooves of cow i were defined by a set of properties and are represented by the hoof matrix Ω with $j \times k$ elements,

$$\Omega_i = \begin{pmatrix} j=1,k=1 & j=1,k=2 & j=1,k=3 & j=1,k=4 \\ j=2,k=1 & j=2,k=2 & j=2,k=3 & j=2,k=4 \\ j=3,k=1 & j=3,k=2 & j=3,k=3 & j=3,k=4 \\ j=4,k=1 & j=4,k=2 & j=4,k=3 & j=4,k=4 \\ j=5,k=1 & j=5,k=2 & j=5,k=3 & j=5,k=4 \\ j=6,k=1 & j=6,k=2 & j=6,k=3 & j=6,k=4 \\ j=7,k=1 & j=7,k=2 & j=7,k=3 & j=7,k=4 \\ j=8,k=1 & j=8,k=2 & j=8,k=3 & j=8,k=4 \end{pmatrix} \qquad (2.2)$$

where j is the property of hoof k for cow i. Front and hind hooves are $k = (1, 2)$ and $k = (3, 4)$, respectively. Property $j = 1$ represents the state of the hoof (susceptible $= 0$, infected $= 1$); property $j = 2$ represents the hoof disorder (DD, HYP, IDHE, IP, OH, SH, SU and WLD); $j = 3$ represents the mobility score (score 1, 2, 3, 4, and 5); $j = 4$ is the day of mobility score progression (respective of hoof disorder; uniform distribution); $j = 5$ is the treatment day (uniform distribution) after successful detection, and $j = 6$ is the day of mobility score regression after successful treatment (respective of hoof disorder; uniform distribution). The remaining two properties are DD specific. Property $j = 7$ represents the DD infectious lesion class (0, 1, 2, 3, 4) and $j = 8$ is the sojourn time of the DD lesion (uniform distribution).

Infection dynamics

Environmental infections. Infections of all hoof disorders, except for DD, were modelled as environmental infections with the Greenwood model. This model is suitable for the infection processes of hoof disorders when little is known about their spread dynamics and occurrence. It assumes that the probability of a susceptible hoof becoming infected with a disorder is independent of the number of already infected hooves with the same disorder once the infectious agent is present in a population, due to its sufficient abundance in the environment. In the Greenwood model, the prevalence or the incidence rate represent the probability of a cow receiving a hoof disorder per time unit (Becker, 1989). Parameters estimated and used in the Greenwood model are denoted by the subscript ε.

The infection process began with first identifying the total number of susceptible cows in the previous time step t. Susceptible cows ($S_{\varepsilon,t-1}$) were defined as the number of cows with at least one susceptible hoof: $\sum_{i=1}^{\Theta} [\![\sum_{k=1}^{4} \Omega_{i,j=1,k,t-1} < 4]\!]$ in a herd of Θ

cows. Second, the probability ($P_{\varepsilon,t}^{(total)}$) of susceptible cows becoming infected was estimated: $\sum_{d=1}^{7} \gamma_{d,l,t}$ where a daily infection risk $\gamma_{d,l,t}$ for each hoof disorder d occurring in period l = (1 = pasturing, 2 = housing) was stochastically drawn from a PERT distribution. With parameters $S_{\varepsilon,t-1}$ and $P_{\varepsilon,t}^{(total)}$ the number of cows that will become infected ($I_{\varepsilon,t}$) was estimated by the binomial process

$$I_{\varepsilon,t} \;=\; B\big(S_{\varepsilon,t-1}\,, P_{\varepsilon,t}^{(total)}\big). \tag{2.3}$$

Next, a bootstrap sample of length $I_{\varepsilon,t}$ was drawn from the vector of hoof disorders D = (HYP, IDHE, IP, OH, SH, SU, WLD) according to their relative risks of $\gamma_{d,l,t}$. We denote the bootstrap sample of disorders as $\overline{D_t}$ such that $\overline{d_t} \in \overline{D_t}$. With $\overline{D_t}$ disorders that infect $I_{\varepsilon,t}$ cows, the susceptibility of each cow is adjusted by the product of cow-level risk factors (i.e., parity, lactation stage, RPL and the number of susceptible hooves) corresponding to each $\overline{d_t}$. To calculate the cow-level risk factors, first parity cows in the first 30 days of lactation with a RPL between 41 and 60 percent were taken as the reference risk category. We included four parity risk factor classes (1, 2, 3, ≥4), four lactation stage, expressed as days in milk, risk factors classes (≤30, 31 – 60, ≥61 and dry) and five RPL classes (≤20 percent, 21 – 40 percent, 41 – 60 percent, 61 – 80 percent and >80 percent). A risk factor regarding the number of susceptible hooves was included to ensure that cows with one susceptible hind hoof were at less risk than cows with two susceptible hind hooves so that the proportional ratio of front to hind hooves infected with a disorder would approximately be 10:90 percent, respectively (Alvergnas et al., 2019). The risk factor concerning the number of susceptible hooves for cow i was derived by summing the risk factors associated with each susceptible hoof k. The probability of a susceptible cow becoming infected with each $\overline{d_t}$ is then

$$P_{\varepsilon,\bar{d},i,l,t}^{(infect)} = \gamma_{d,l,t} \times \prod_{r=1}^{4} \lambda_{d,i,r} \tag{2.4}$$

where $P_{\varepsilon,\bar{d},i,l,t}^{(infect)}$ is the probability of susceptible cow i becoming infected with disorder $\bar{d}$ in time-step t of period l, $\gamma_{d,l,t}$ is the daily risk of infection for disorder d corresponding to $\bar{d}$, λ is the risk factor associated with susceptible cow i and disorder d corresponding to $\bar{d}$ and r is one of the four risk factors. Finally, a cow was then randomly selected according to the probability of infection in Eq. 2.4 by a sample distribution to be infected with $\overline{d_t} \in \overline{D_t}$. Once cow-level processes are completed and a susceptible cow for $\overline{d_t} \in \overline{D_t}$ was selected, a susceptible hoof k for each selected cow i was drawn from a sample of susceptible hooves according to their relative risks and the corresponding first three properties in Ω are updated such that the state of hoof k was infected with disorder $\bar{d}$:

$$\Omega_{i,j=1,k} = 1 \tag{2.5}$$

$$\Omega_{i,j=2,k} = \bar{d}. \tag{2.6}$$

Contagious infections. Hooves that escaped an environmental infection in the current time-step were then subjected to the probability of becoming infected with DD. The Reed-Frost model was used to simulate this process where the probability of a susceptible hoof becoming infected with DD was dependent on the number of already infected hooves in the herd and the spread dynamics of the disease is explained by β (Becker, 1989). Throughout this subsection the parameters estimated and used in the Reed-Frost model are denoted by the subscript φ.

Unlike in the Greenwood model, the infection process of hooves occurred directly at the hoof-level since only one disorder was of concern. Consequently, more than one susceptible hoof per cow had the probability of becoming infected with DD in time-step t. The probability of a hoof becoming infected with DD was then calculated as follows

$$P_{\varphi,i,k,t}^{(infect)} = 1 - \exp\left(\frac{-\left(\sum_{m=1}^{4} \beta_m \times \eta \times I_{\varphi,m,t-1}\right) \times \prod_{r=1}^{4} \lambda_{i,r}}{N_{\varphi,t-1}}\right) \tag{2.7}$$

where $P_{\varphi,i,k,t}^{(infect)}$ is the probability of infection for cow i with susceptible hoof k in time step t. Hooves infected with DD can go through multiple infectious lesion classes resulting in more than one β denoted by m = (1, 2, 3, 4) (Biemans et al., 2018). The parameter $I_{\varphi,m,t-1}$ is the number of infected hooves with infectious lesion class m from the previous time-step: $\sum_{i=1}^{\Theta} \sum_{k=1}^{4} [\![\Omega_{i,j=7,k,t-1} = m]\!]$. Variation in the susceptibility for each susceptible hoof k of cow i was adjusted by the product of risk factors λ as described in the infection process of the Greenwood model except that the risk factors associated with front and hind hooves are no longer summed. By including risk factors, variation in the susceptibility of individual cows was accounted for but scaled the β's to the extent that the probability of infection and resulting trends of DD became unrealistic. Therefore, we included a calibration factor η that allowed the scaling of each β maintaining the relative ratio between the respective β's such that realistic infection rates and disorder trends would hold while still allowing for the effect of varied susceptibility between individuals. Lastly, the denominator $N_{\varphi,t-1}$ is the total number of hooves in the previous time-step. With

$P_{\varphi,i,k,t}^{(infect)}$ each susceptible hoof was then subject to this probability of becoming infected by a binomial process

$$\Omega_{i,j=1,k,t} = B\left(1, P_{\varphi,i,k,t}^{(infect)}\right). \quad (2.8)$$

For each hoof that succumbed to a DD infection, the following properties j = (2, 7) of infected hoof k were updated accordingly

$$\Omega_{i,j=2,k} = \text{DD} \quad (2.9)$$

$$\Omega_{i,j=7,k} = 1. \quad (2.10)$$

2.2.4 Mobility scores

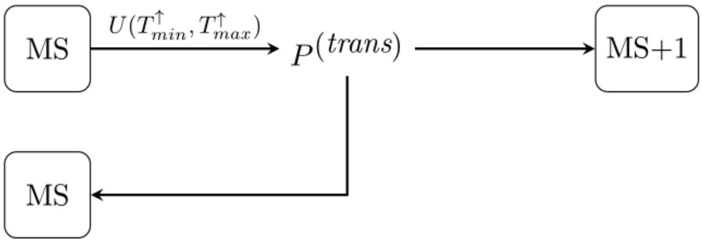
The effect of hoof disorders on cow mobility were described by mobility scores. We used the 5-point ordinal scale mobility scoring method developed by Sprecher et al. (1997) where cows were scored 1 (optimal mobility) to 5 (severe SOM). A cow with a mobility score ≥2 is defined as sub-optimally mobile: a cow with SOM. Ultimately, mobility scores were expressed at the cow level, albeit certain processes were first modelled at hoof-level allowing the dynamics of hoof disorders and the consequential effects on cow mobility to be established. Each hoof of a cow will have its own mobility score where the maximum score between each of a cow's four hooves defines the cow-level mobility score. Modelling the dynamics of mobility scores is described in the following subsections.

Mobility score progression

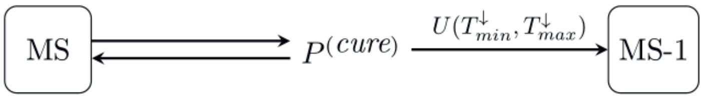
Following an infection with any of the eight hoof disorders, a hoof was immediately assigned a mobility score 2 (Eq. 2.11). The hoof will hold a mobility score 2 until a random day scheduled by a stochastic draw from a uniform distribution (Eq. 2.12)

$$\Omega_{i,j=3,k} = 2 \quad (2.11)$$

$$\Omega_{i,j=4,k} = U\left(T_{min,s,d}^{\uparrow}, T_{max,s,d}^{\uparrow}\right) + t \quad (2.12)$$



(a) Mobility score progression dynamics after infection.



(b) Mobility score regression dynamics after infection.

Figure 2.1 Diagram of the mobility score (MS) dynamics. In (a), the duration of each mobility score and the probability of transitioning to a succeeding score will continue until a mobility score 5 is reached unless a mobility score transition does not occur to which the hoof will no longer be subject to mobility score progression processes. In (b), mobility scores will regress until a mobility score 1 is reached after successful intervention. If intervention is unsuccessful the mobility score will remain.

where $T^{\uparrow}_{min,s,d}$ and $T^{\uparrow}_{max,s,d}$ are the minimum and maximum transition intervals of T days from time-step t for mobility score s and disorder d, and the superscript $\uparrow$ denotes mobility score progression. For DD, $\Omega_{i,j=8,k} = \Omega_{i,j=4,k}$ will hold.

We assume that after infection the progression of mobility scores occurred in an ordered manner as illustrated by Figure 2.1(a). A hoof will hold a mobility score for a minimum number of days until $t = \Omega_{i,j=4,k}$, thereafter the probability of transitioning to a succeeding score was estimated with following equation

$$P^{(trans)}_{i,k,t} = \Lambda^{(ms)}_{i,k,s,t-1} \times \prod_{r=5}^{7} \lambda_{i,k,r} \tag{2.13}$$

where $P^{(trans)}_{i,k,t}$ is the probability of hoof k for cow i to transition into a succeeding mobility score in time-step t, $\Lambda^{(ms)}_{i,k,s,t-1}$ is the base risk of transitioning to a succeeding mobility score for cow i with hoof k and mobility score s in the previous time-step t, $\lambda_{i,k,r}$ is a risk factor and r one of the risk factors. With $P^{(trans)}_{i,k,t}$ the probability of

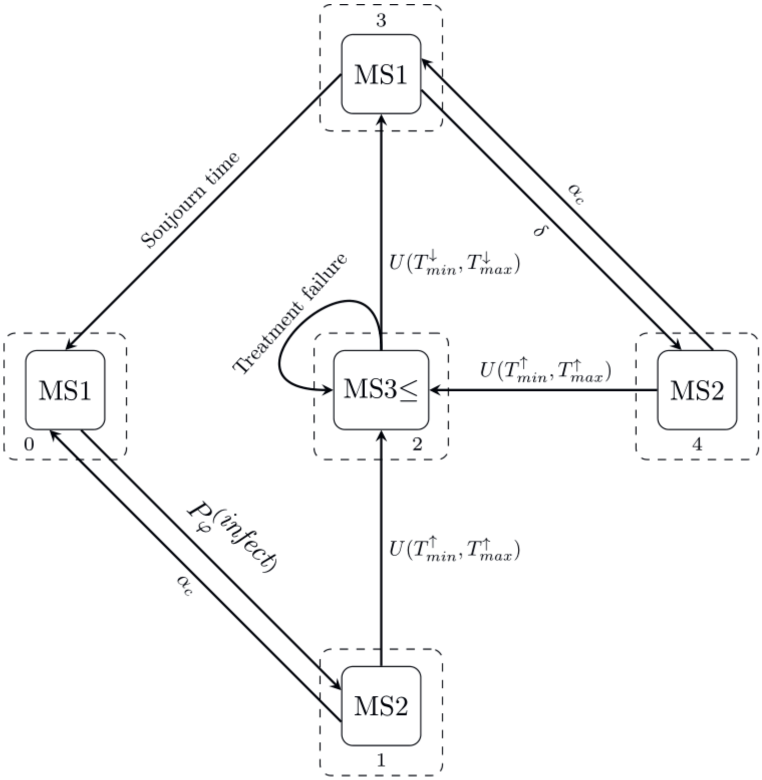


Figure 2.2 Diagram of the mobility score (MS; solid lined nodes) dynamics with respect to the modelled digital dermatitis infectious lesion classes (m; dashed lined nodes).

a hoof transitioning into a succeeding mobility score was then predicted by a binomial process

$$\Omega_{i,j=3,k,t} = B\left(1, P_{i,k,t}^{(trans)}\right) + \Omega_{i,j=3,k,t-1}\,. \tag{2.14}$$

If hoof k progressed to a succeeding mobility score, Eq. 2.12 was re-run.

Figure 2.2 illustrates the dynamics associated with an infectious lesion class for a hoof infected with DD. As the mobility score of a hoof was updated (solid lined nodes in Figure 2.2) the corresponding infectious lesion class (dashed lined nodes in Figure 2.2; property $j = 7$) was updated accordingly. The process of mobility score progression continued until the maximum mobility score for hoof disorder d was reached. The hoof would then remain with this score until treated or cured spontaneously.

Intervention

Intervention of SOM occurred either by routine hoof trimming or by additional treatments. Routine hoof trimming was performed by a professional hoof trimmer who visited the farm at the start of each pasture and housing period. Hind hooves of every cow were trimmed by the hoof trimmer and exceptions were made for front hooves with a mobility score ≥3. Additional treatments occurred beyond hoof trimmer visits and followed SOM detection by the farmer during daily farm activities. Farmers are generally better at detecting cows with severe SOM compared to cows with mild SOM (Alawneh et al., 2012a); thus, the probability of SOM detection was modelled as an exponential function to mimic an increased probability of detection with each day a cow was SOM as

$$P_{i,s,t}^{(detect)} = \phi_s \times \exp\left(\phi_s \times t_{i,t}^{(som)}\right) \tag{2.15}$$

where $P_{i,s,t}^{(detect)}$ is the probability of SOM detection for cow i with mobility score s as a function of the constant daily detection rate ϕ_s respective of mobility score s and $t_{i,t}^{(som)}$ is the duration in days that cow i is SOM from the onset of a mobility score 3. Modelling the probability of detection as an exponential function for each cow with SOM also ensures that it would not surpass a threshold duration of an undetected SOM period. The detection probability for a cow with SOM and a mobility score ≥3 was updated in each time-step t. A cow with SOM was then subject to the detection probability by a binomial process

$$\pi_{i,s,t} = B\left(1, P_{i,s,t}^{(detect)}\right) \tag{2.16}$$

where $\pi_{i,s,t}$ is the success outcome of detection for cow i experiencing SOM with mobility score s in time-step t.

Cows that were successfully detected by the farmer were then scheduled an intervention day respective of the mobility score they were detected with. An intervention day was stochastically drawn from a uniform distribution

$$\Gamma_{i,s} = U\left(\tau_{min,s}, \tau_{max,s}\right) + t \tag{2.17}$$

where $\Gamma_{i,s}$ is the intervention day for cow i with mobility score s, and $\tau_{min,s}$ and $\tau_{max,s}$ is the range of days it takes for intervention to occur after a cow with SOM and a mobility score s was detected. Since farmers are more likely to treat sooner if a cow is detected with a greater mobility score (Alawneh et al., 2012a), scheduled intervention days were updated accordingly if a cow progressed in a mobility score before the original intervention day had occurred. Once $\Gamma_{i,s}$ was determined, every hoof k of cow i with a hoof-level mobility score ≥3 was assigned an intervention day

$$\Omega_{i,j=5,k,t} = \Gamma_{i,s}. \tag{2.18}$$

A farmer may detect a cow with SOM and a mobility score 3, but treatment for these cows occurred only at the routine hoof-trimming. Cows with SOM and mobility score 4 that were detected by the farmer are assumed to be subsequently treated by the farmer. If the farmer detected cows with SOM and mobility score 5, the veterinarian was called to treat these cows. It was assumed that the veterinarian will also treat all cows with SOM and detected with a mobility score ≥4. On the treatment day where $\Omega_{i,j=5,k} = t$, hoof k was treated with a treatment type specific to the hoof disorder $\Omega_{i,j=2,k}$. The outcome of treatment then determined the mobility score regression dynamics.

Mobility score regression

The regression of mobility scores correspond to recovery and will succeed successful intervention($P^{(cure)}$ in Figure 2.1(b)), or spontaneous cure (DD only; α_c in Figure 2.2). After successful intervention, a mobility score regression day (property j = 6) was scheduled for the successfully treated hoof by a stochastic draw from a uniform distribution respective of disorder the hoof was infected with

$$\Omega_{i,j=6,k} = U\left(T^{\downarrow}_{min,s,d}, T^{\downarrow}_{max,s,d}\right) + t \tag{2.19}$$

where $T^{\downarrow}_{min,s,d}$ and $T^{\downarrow}_{max,s,d}$ are the minimum transition intervals of T days from time-step t for mobility score s and disorder d, and the superscript ↓ denotes mobility score regression. Once a mobility score regression day was scheduled, $\Omega_{i,j=3,k,t} = \Omega_{i,j=3,k,t-1} - 1$ will occur when $t = \Omega_{i,j=6,k}$, and consequentially a new mobility score regression day was set. This process occurred until the mobility score for hoof k was 1. Thereafter, the hoof fully recovered and was in a susceptible state and all properties excluding j = 3 were reset to zero. In the case that successful intervention did not occur, the hoof remained with a mobility score until successful intervention did occur (Figure 2.1(b)).

2.2.5 Production effects

Milk yield. The expected daily milk yield for cows was adjusted by a mean percentage reduction of their expected daily milk yield per mobility score. This realised an actual daily milk yield for each cow respective of mobility score. The actual daily milk yield was calculated with the following equation

$$M_{i,s,t}^{(amy)} = M_{i,s,t}^{(emy)} \times \left(1 - M_s^{(myr)}\right) \tag{2.20}$$

where $M_{i,s,t}^{(amy)}$ is the actual milk yield produced by cow i with mobility score s in time-step t, and $M_{i,s,t}^{(emy)}$ is the daily percentage milk yield reduction for mobility score s.

Discarded milk. Cows that were treated with antibiotics respective of disorder d had their actual daily milk yield discarded for 5 days: $M_{i,d,s,t}^{(discard)} = M_{i,d,s,t}^{(amy)}$.

Feed. As previously described in the Production dynamics section, feed requirements are modelled as VEM and expressed as a function of daily FPCM yield. The impact of mobility scores on VEM was calculated by taking the difference between expected VEM, as a function of expected daily FPCM yield, and actual VEM, as a function of actual daily FPCM yield.

Reproduction. Mobility scores affected the reproductive performance of cows in two ways. The first effect was associated with oestrus detection by the farmer. Walker et al. (2008) reported that cows with higher mobility scores dedicated less time to oestrus behaviour when compared to cows with lower mobility scores. Thus, decreasing the probability of oestrus detection by the farmer. A reduced probability in oestrus detection was accounted for by including a relative risk of oestrus detection for each mobility score where a cow with a mobility score 1 was taken as the reference category. The outcome of oestrus detection $\left(\Psi_{i,s,t}^{(oest)}\right)$ for cow i with mobility score s in time-step t was estimated by a binomial process

$$\Psi_{i,s,t}^{(oest)} = B\left(1, \Lambda^{(oest)} \times \lambda_s^{(oest)}\right) \tag{2.21}$$

where $\Lambda^{(oest)}$ is the base risk of oestrus detection and $\lambda_s^{(oest)}$ is the relative risk of oestrus detection with respect to mobility score s.

The second effect of mobility scores on reproduction dealt with conception. Insemination took place after oestrus was successfully detected by the farmer. The probability of conception depended on the number of previous inseminations and mobility score. Alawneh et al. (2011) found that cows with mobility scores ≥3 were less likely to conceive compared to cows with mobility scores ≤2. Since it is unclear how the specific mobility scores ≥3 effect conception, conception was scaled by relative risks associated with mobility scores ≥3 that were drawn from a PERT distribution. The probability of conception was calculated with

$$P_{i,s,t}^{(conc)} = \Lambda_{i,n,t}^{(conc)} \times \mathrm{PERT}\left(\lambda_{min,s}^{(conc)}, \lambda_{med,s}^{(conc)}, \lambda_{max,s}^{(conc)}\right) \tag{2.22}$$

where $P_{i,s,t}^{(conc)}$ is the probability of conception for cow i with mobility score s in time step t, $\Lambda_{i,n,t}^{(conc)}$ is the base risk of conception respective of the n^{th} insemination, and $\lambda_{min,s}^{(conc)}$, $\lambda_{med,s}^{(conc)}$, and $\lambda_{max,s}^{(conc)}$ are the minimum, median and maximum relative risks used in the PERT distribution. Finally, the outcome of a successful conception is then determined by a binomial process

$$\Psi_{i,s,t}^{(conc)} = B\left(1, P_{i,s,t}^{(conc)}\right) \tag{2.23}$$

where $\Psi_{i,s,t}^{(conc)}$ is the conception outcome.

Culling. The effect of mobility scores on culling occurred indirectly or directly. Indirect culling due to mobility scores occurred in the form of fertility related culling due to the impact of mobility scores on a cow's reproductive performance. In the case that a mobility score impacted the reproductive performance of a cow, the cow's conception period was lengthened. A longer conception period resulted in an increased risk of culling. Direct culling due to mobility scores occurred when a cow was ultimately culled for SOM, respective of SOM severity. The culling of a cow with SOM is based on a daily probability where the general culling rate was taken as the base risk and scaled by mobility score, parity, and relative production level risk factors. Cows that were subject to culling were immediately removed on the day of culling. Furthermore, a culling rule based on a maximum number of additional treatments per lactation was assumed. A cow needing an additional treatment that would result in this maximum additional lactational treatment threshold being surpassed would be culled. We assumed a maximum of 3 additional lactational treatments.

2.2.6 Economic calculations

In order to calculate the net partial economic result for a farm, the economic in- and outflows were first calculated for each cow i with mobility score s in time-step t. The economic inflow is actual milk returns and the economic outflows are the costs concerning milk yield losses, discarded milk, feed, insemination, culling, hoof trimming, veterinary services, labour, and additional treatments. The descriptions for each economic flow are described in the subsequent subsections.

Milk returns. Actual milk returns are based on the actual milk yield and was calculated with the following equation

$$R_{i,s,t}^{(milk)} = M_{i,s,t}^{(amy)} \times M^{(price)} \tag{2.24}$$

where $R_{i,s,t}^{(milk)}$ is the actual milk returns for cow i with mobility score s in time-step t and $M^{(price)}$ is the milk price per kilogram of milk.

Milk yield loss. The cost of milk yield losses is based on the loss in expected milk yield due to a mobility score and is calculated with the following equation

$$C_{i,s,t}^{(milk)} = \left(M_{i,s,t}^{(emy)} - M_{i,s,t}^{(amy)}\right) \times M^{(price)} \tag{2.25}$$

where $C_{i,s,t}^{(milk)}$ is the cost of milk yield losses for cow i with mobility score s in time-step t.

Discarded milk. The cost of discarded milk was calculated with the following equation

$$C_{i,s,t}^{(discard)} = M_{i,s,t}^{(discard)} \times M^{(price)} \tag{2.26}$$

where $C_{i,s,t}^{(discard)}$ is the cost of discarded milk for cow i with mobility score s in time-step t.

Feed. Feed costs $\left(C^{(feed)}\right)$ for each cow is based on the cost of VEM and a cows required VEM. Since VEM is dependent on $M^{(amy)}$ feed costs are adjusted when the effect of mobility scores on milk production occurs.

Reproduction. Reproduction costs considered only the cost to inseminate a cow. The costs of insemination $\left(C^{(ins)}\right)$ were accounted for on a per cow per insemination basis.

Culling. We calculated the cost of culling with a depreciation method (Steeneveld et al., 2019). Using a depreciation method allows for a more accurate assessment of the net worth of a farming operation and accrual adjusted income. Dairy cows are treated as capital that diminish in value over time. In other words, cows are culled at the end of their production life because they are no longer fit to produce. We used expected number of lactations instead of years of production life. For this depreciation method to work, the rearing costs, or purchase price of a replacement heifer, less the cull value of the cow is depreciated over its expected number of lactations. A cow needs to accumulate this depreciation at the end of its expected number of lactations so that the cull value is fully realised. If a cow is culled before completing the expected number of lactations, the cull value of the cow will not be realised and a capital loss is incurred, which is treated as a culling cost.

Replacement heifer rearing costs were sampled from a PERT distribution and averaged by the number of required replacement heifers. The revenue received for a culled cow was calculated by multiplying the slaughter weight of the cow with the slaughter price per kilogram. The slaughter weight was based on an average 60 percent carcass dressing of a cow's body weight (Rutten et al., 2014). The body weight of the cows that were culled for SOM reasons had their body weight decreased by an adjustment factor drawn from a PERT distribution (Alawneh et al., 2012b). The slaughter price per kilogram of slaughter weight was estimated by taking the mean of first to third grade slaughter cow prices (Wageningen Economic Research, 2020) sampled on the day of culling with a sample size equal to the number of culled cows. The cost of culling was calculated with the following equation

$$C_{i,s,t}^{(cull)} = \frac{C_t^{(rear)} - R_{i,s,t}^{(cull)}}{L} \times \left(L - \left[\left(Par_{i,t} - 1\right) + \frac{M_{i,s,t}^{(dim)}}{M_{i,s,t}^{(end)}}\right]\right) \tag{2.27}$$

where $C_{i,s,t}^{(cull)}$ is the cost of culling cow i with mobility score s in time step t, $C_t^{(rear)}$ is the average of the rearing costs for the replacement heifers, $R_{i,s,t}^{(cull)}$ is the revenue received for the culled cow i with mobility score s in time step t, L is the expected number of lactations, $Par_{i,t}$ is the parity of cull cow i in time step t, $M_{i,s,t}^{(dim)}$ is the day in milk for cull cow i in time step t and $M_{i,s,t}^{(end)}$ is the end day of milking for cull cow i in time step t of the current lactation. In summary, annual cow depreciation is reflected in the fraction on the left of the multiplication sign and the number of incomplete lactations is reflected within the round parentheses on the right of the multiplication sign. Mortality related culling costs were accounted for with a revenue of €0 and disposed of with a €39/cow cost.

Hoof trimmer. The hoof trimmer trimmed hooves twice a year. All hind hooves were trimmed and only front hooves with a mobility score ≥3. Hoof trimming costs $C^{(ht)}$were estimated per trimmed hoof. These costs include treatments costs if hooves had a disorder.

Veterinary services. Costs for veterinary services $\left(C^{(vet)}\right)$ are estimated per cow considering the costs for the call out fee $\left(C^{(cof)}\right)$, the number of cows requiring veterinary assistance, hourly rate of the veterinarian $\left(C^{(vrate)}\right)$, the time spent ushering a cow into the trimming chute $\left(V^{(usher)}\right)$ and treatment time. $\left(V^{(treat)}\right)$. Treatments per disorder and the associated costs are recorded as veterinary related treatment costs.

Labour. Labour costs $\left(C^{(labour)}\right)$ due to treating cows with SOM were only accounted for when the farmer was required to treat them. These costs were estimated on a per cow basis considering the time it would take to usher a cow with SOM into the trimming chute $\left(F^{(usher)}\right)$, the time to treat a hoof $\left(F^{(treat)}\right)$ and the hourly wage rate of the farmer $\left(C^{(treat)}\right)$. Treatments per disorder and the associated costs were recorded as farmer related treatment costs.

Additional treatments. The cost of additional treatments $\left(C^{(treat)}\right)$ concern all treatments applied by either the veterinarian or the farmer respective of hoof disorder. An exception for an additional treatment of HYP was made where only the veterinarian treated this hoof disorder since a claw-amputation was required. As a result, more time than $V^{(treat)}$ was needed to treat this disorder and the associated cost of HYP treatment by the veterinarian was adjusted by a time factor.

2.2.7 Model parameterisation

Input parameters are tabulated in Tables 2.1 – 2.4 (and Tables A 2.1 – A 2.10 in the Appendix) and were derived from the most recent and available literature. Input parameters were chosen in such a way to represent the Dutch situation as much as possible. This was done by choosing, where possible, input parameters with respect to Dutch research first. The next best alternatives of input parameters considered research conducted in countries with similar dairy production systems such as the UK and Germany. Lastly, input parameters that were needed but were not associated with the aforementioned countries were finally accepted. Expert opinion was relied upon for input parameters that were not at all available in the literature. Inputs regarding risk factors reported in the literature as odds ratios were converted to relative risks depending on the information and methods used to derive the odds ratios as described in the respective studies. Inputs associated with mobility scores described by scoring methods that were not the method of Sprecher et al. (1997) were adapted according to the definition of scores best fitting that of the mobility scoring method of Sprecher et al. (1997).

Table 2.1 Parameters and values used for the infection dynamics of hoof disorders. All parameter values are implemented in daily time-steps.

Parameter	Description	Hoof disorder (d)[a]	Value	Lower bound	Upper bound	Source
γ	Risk of hoof disorder in period l[b,c]	HYP	4.63e–4; 4.12e–4	3.16e–4; 2.88e–4	5.85e–4; 5.56e–4	Somers et al. (2003), van der Spek et al. (2013), DigiKlauw (2020)
		IDHE	1.72e–5; 7.18e–4	1.44e–5; 7.18e–5	3.59e–4; 1.22e–3	
		IP	3.84e–4; 3.84e–4	1.28e–12; 1.29e–12	1.66e–3; 1.66e–3	
		OH	5.48e–5; 5.48e–5	5.48e–13; 5.48e–13	5.48e–5; 5.50e–5	
		SH	3.97e–3; 3.42e–4	1.78e–4; 1.10e–4	1.16e–3; 1.16e–3	
		SU	4.79e–4; 3.64e–4	3.16e–4; 3.07e–4	9.59e–4; 9.59e–4	
		WLD	6.58e–4; 1.13e–3	3.78e–4; 1.32e–4	1.32e–3; 1.64e–3	
β	Transmission rate[d]	DD	1.14e–3; 2.77e–3; 2.91e–3; 2.29e–2			Biemans et al. (2018)
δ	Probability of reinfection[e]	DD	0.0167			Döpfer et al. (2012)
α_c	Probability of spontaneous cure	DD[f]	1.04e–2; 3.71e–3			Biemans et al. (2018)
η	Calibration factor	DD	1.4			Calibrated input

[a] HYP = interdigital hyperplasia; IDHE = interdigital dermatitis/heel horn erosion; IP = interdigital phlegmon; OH = overgrown hoof; SH = sole haemorrhage; SU = sole ulcer; WLD = white line disease; DD = digital dermatitis.
[b] Ordered as pasturing (l = 1), housing (l = 2).
[c] Risk of receiving disorder is estimated by a PERT distribution, i.e., PERT (a = lower bound, b = mean, c = upper bound).
[d] Ordered as infectious class 1; 2; 3; 4.
[e] From DD lesion class 4 to 2.
[f] From DD lesion class 1 to 0; 4 to 3.

Table 2.1 details the hoof disorder infection inputs. Inputs with respect to the modelled non-infectious hoof disorders (i.e., γ) were based on the prevalence

Table 2.2 Risk factors associated with mobility score transitions.

Risk factor (λ)	Mobility score	Class	Base risk	Relative risk	Source
$\Lambda^{(ms)}$[a]	2		0.15		Based on Frankena et al. (2009)
	3		0.083		
	4		0.03		
Parity		1		1	Reader et al. (2011)
r =5		2		1.61	
		3		1.91	
		>3		2.03	
DIM[b]		<60		1.05	O'Connor et al. (2020b)
r = 6		60 – 120		1.9	
		>120		1	
		Dry		1	
RPL		<33.3%		1	O'Connor et al. (2020b)
r = 7		33.3% – 66.6%		1.22	
		>66.6%		1.4	

[a] Risk of transition from mobility score.
[b] Days in milk.

estimates from the relevant literature and unpublished data from DigiKlauw (2020). With respect to DD, Biemans et al. (2018) described five infectious lesion classes (M1, M2, M3, M4, M4.1). We collapsed M3 and M4 into one class since they are considered as latent infections that are assumed to have a similar effect on mobility and because their transmission rates differed by 1.4×10^{-4}. This resulted in four infectious lesion classes (m; Biemans et al., 2018).

To the best of our knowledge, little information exists on the dynamics of mobility scores. Therefore, the risk in transitioning from one mobility score to a succeeding score $\left(\Lambda^{(ms)}\right)$ was based on the prevalence and incidence of mobility scores reported by Frankena et al. (2009) and Tadich et al. (2010) (Table 2.2). O'Connor et al. (2020b) reported associations between lactation stage and mobility scores; to account for the progression of mobility scores given the lactation stage we shifted these relative risks back by one class (Table 2.2). The interval between mobility score transitions respective of hoof disorder were derived through expert knowledge elicitation (Table A 2.7).

The constant daily detection rate (ϕ) was estimated by ensuring that a 100 percent probability of detection would occur after a reasonable number of days of transitioning into a respective score and were based on Alawneh et al. (2012a) and

Table 2.3 Farmer detection and intervention parameters with respect to mobility scores.

Parameter	Description	Mobility score				Source
		2	3	4	5	
ϕ	Constant daily detection rate	0	0.014	0.1	0.5	Based on Alawneh et al. (2012a)
τ_{min}	Minimum days to intervene	—[a]	—	1	1	Authors' expertise
τ_{max}	Maximum days to intervene	—	—	21	3	

[a] — implies that a farmer will not intervene nor call a veterinarian for cow with these scores and rather wait until the routine hoof trimming carried out by the hoof trimmer.

the authors' expertise (Table 2.3). The number of days to treat a cow following detection were based on authors' expertise.

Cure rates reported in the literature are sparse with regards to specific hoof disorders. We adapted cure probabilities reported in the literature (i.e., Bruijnis et al., 2010; Holzhauer et al., 2008a), in combination with authors' expertise, to base cure risks (Table A 2.8). The base cure risks were scaled by relative risks corresponding to cow characteristics and hoof disorder duration (Reader et al., 2011) (Table A 2.9).

The effect of mobility scores on production are detailed in Table A 2.10. Production losses per mobility score were derived by taking the quotient of an average 305-day yield production loss per mobility score reported by O'Connor et al. (2020a) and the fraction of a median duration of a SOM case of a maximum mobility score output by the model. O'Connor et al. (2020a) reported that no production losses were associated with a mobility score 1 of the Agriculture and Horticulture Development Board (2020) scoring method; congruent to a mobility score 2 of Sprecher et al. (1997). To estimate the effect of mobility scores on milk production corrected for 305-day lactation we excluded the duration of mobility score 2. The effect of mobility scores on fertility was estimated by including relative risks of oestrus detection and conception, respective of mobility score. Walker et al. (2008) reported that cows with SOM dedicated 64 percent less of their time to oestrus behaviour compared with cows that were not SOM. Therefore, the relative risk of oestrus detection was incremented by −0.09 from 1 to 0.64 for cows with a mobility score 1 to 5 since it was assumed that cows with mobility score 1 are more easily detectable when in oestrus compared to cows with SOM and a mobility score 5. The relative risk of conception after successful oestrus detection, followed by insemination, is based on Alawneh et al. (2012a). The probability of culling due to mobility scores is the product of the general culling rate per parity and the relative risk of culling per mobility score where the general culling rate is taken as the base risk (Table A 2.3 and Table A 2.10).

The economic parameters are found in Table 2.4. Where monthly price data was available the average of the monthly price was taken as the default input.

Table 2.4 Economic inputs and parameters used for economic variable calculations.

Parameter	Default value(s)	Description	Source
$M^{(price)}$	0.3502	Average monthly milk price (€/kg) for the years 2016–2020	Wageningen Economic Research (2020)
$C^{(kVEM)}$	0.1766	Average monthly cost of supplements (€/kVEM) for the years 2019–2020	Wageningen Livestock Research (2020)
$C^{(HT)}$	3.5	Cost of hoof trimmer adapted to a per hoof basis (€/hoof)	Blanken et al. (2017)
$C^{(ins)}$	12.85	Cost per insemination (€/insemination)	Blanken et al. (2017)
Culling			
L	6	Expected minimum number of lactations	Authors' expertise
$C^{(rear)}$	PERT(919; 1790; 3307)	Rearing costs per replacement heifer (€/heifer)	Nor et al. (2015)
$P^{(dress)}$	0.6	Carcass dressing; factor of live body weight	Rutten et al. (2014)
$R^{(kg)}$	sample(2.77, 2.44, 2.06)	Sample price received (€/kg) for first to third grade slaughter cows; average monthly prices for the years 2016–2020	Wageningen Economic Research (2020)
$P^{(bw.adj)}$	PERT(0.81; 0.83; 0.88)	Adjustment factor for the live body weight of cows culled for SOM	Based on Alawneh et al. (2012b)
Labour			
$C^{(frate)}$	30.7	Farmer hourly wage rate (€/h)	Blanken et al. (2017)
$F^{(usher)}$	10	Time for farmer to usher cow into hoof trimming chute (min/cow)	Authors' expertise
$F^{(treat)}$	10	Time for farmer to treat hoof (min/hoof)	Authors' expertise
Veterinarian			
$C^{(cof)}$	31.35	Call out fee (€/visit)	Expertise
$C^{(vrate)}$	139.2	Veterinarian hourly rate (€/h)	Expertise
$V^{(usher)}$	10	Time for veterinarian to usher cow into hoof trimming chute (min/cow)	Authors' expertise
$V^{(treat)}$	10	Time for veterinarian to treat hoof (min/hoof)	Authors' expertise
Treatments		Additional treatment costs (€) per disorder per hoof applied by either veterinarian or farmer	Expertise
$C^{(SH)}$; $C^{(SU)}$; $C^{(WLD)}$	8.1		
$C^{(IP)}$; $C^{(IDHE)}$	0.6		
$C^{(DD)}$	2.61		
$C^{(OH)}$	0		

$C^{(HYP)}$[a]	182.02[b]; 0[c]

[a] Only differences between costs for veterinarian and farmer deal with interdigital hyperplasia (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.
[b] Veterinarian treatment costs.
[c] Farmer treatment costs.

2.2.8 Model calibration and validation

Model calibration was a necessary step in model development since inputs were drawn from various literature sources and expert opinion. Calibrated inputs were validated in five rounds of rational validation by the authors. This included outcome testing of various scenarios to test output credibility (i.e., setting certain parameters to 0 or 1); individual cows were tracked and traced in the output data; logical testing of processes through debugging modes allowing for the inspection of computations during a live simulation; and face validity were performed internally. External validation was performed through discussions with experts and by comparing certain model outputs with results reported in the literature and unpublished data.

2.2.9 Model outputs and simulation

Epidemiological outputs include prevalence and cumulative incidence of hoof disorders and mobility scores as well as the cumulative incidence of hoof disorders per mobility score at the cow-level for either daily, periodical, or yearly time horizons. Daily prevalence of mobility scores at the cow-level further allows for outputs concerning the duration of SOM cases. A SOM case is defined as the period a cow is scored a mobility score ≥2 and the mobility score associated with this case is the maximum mobility score of the case. Four maximum mobility score SOM case categories were defined as MMSC2, MMSC3, MMSC4 and MMSC5 accounting for maximum mobility scores 2 - 5, respectively. Mild forms of SOM are represented by MMSC2, MMSC3 and severe forms by MMSC4, MMSC4.

Economic outputs include the economic in- and outflows per cow i per mobility score s in each time-step t. In turn, the difference between the sum of the economic inflows and the sum of the economic outflows represents the net partial economic results for a farm with a distribution of mobility scores and in turn a combined SOM prevalence. The net partial economic results reflect both the direct and indirect economic effects due to SOM for a farm. The economic effects due to SOM were evaluated during the economic analysis.

2.2.10 Economic analysis

In order to assess the mean total annual economic effect (Δ) due to SOM in a one-year time horizon, the net partial economic results of two scenarios, each of 500 simulations, were compared. The first scenario ($z = 0$) was one where hoof disorders were absent and consequently SOM was also absent: a "without" scenario. The second scenario ($z = 1$) was one where hoof disorders were present and consequently SOM was also present: a "with" scenario. By this approach, the direct as well as the indirect economic effects due to SOM could be evaluated (Rushton, 2009).

Before obtaining Δ, three preceding procedures were conducted. First, for each of the 500 simulations ($y = 1, ..., 500$) in both scenarios, the economic in- and outflows for all cows during the one-year time horizon were summed to obtain the annual total of each economic flow, respectively in Equations 2.28 and 2.29. With respect to the total annual economic outflows calculated with Equation 2.29 we denote $X = \{$*milk, discard, feed, ins, cull, ht, vet, labour, treat*$\}$ where $x \in X$ for notational convenience.

$$TR_{y,z}^{(milk)} = \sum_{i=1}^{\Theta} \sum_{t=1}^{365} R_{i,t,y,z}^{(milk)} \tag{2.28}$$

$$TC_{y,z}^{(x)} = \sum_{i=1}^{\Theta} \sum_{t=1}^{365} C_{i,t,y,z}^{(x)} \tag{2.29}$$

where $TR_{y,z}^{(milk)}$ is the total annual actual milk returns and $TC_{y,z}^{(x)}$ is the total annual economic outflow x in simulation y of scenario z.

Secondly, the net partial economic result was calculated with

$$\Upsilon_{y,z} = TR_{y,z}^{(milk)} - \sum_{x\,=\,discard}^{x} TC_{y,z}^{(x)} \tag{2.30}$$

where $\Upsilon_{y,z}$ is the net partial economic result for simulation y of scenario z. To avoid double counting of the total costs in milk losses $TC_{y,z}^{(milk)}$ was excluded from the summation of the total annual economic outflows because it had already been accounted for in $TR_{y,z}^{(milk)}$ since $TR_{y,z}^{(milk)}$ is based on actual milk returns.

Thirdly, the net partial economic results of the 500 simulations for both scenarios were then bootstrapped 1500 times, rendering y = 1, ..., 750,000 (i.e., 500 × 1,500), before comparing the net partial economic results of both scenarios. Bootstrapping the net partial economic results ensured that an adequate comparison of all simulations would be achieved.

Lastly, a comparison of the net partial economic results for both scenarios was performed and Δ due to SOM was obtained with the following equation

$$\Delta = \frac{\sum_{y=1}^{750000} \Upsilon_{y,0} - \Upsilon_{y,1}}{750000} \tag{2.31}$$

where $\Delta > 0$ entails an economic loss and $\Delta < 0$ entails an economic gain. Δ is the total annual economic effect due to SOM, which includes both the direct and indirect economic effects due to SOM. We evaluated Δ further to gain insight on the distribution of the direct and indirect economic effects due to SOM.

The direct economic effects include economic outflows that are attributable to a SOM case MMSC2 – MMSC5. These are: the cost of direct milk yield losses ($C^{(milk)}$), the cost of discarded milk ($C^{(discard)}$), the cost of feed ($C^{(feed)}$), the cost of culling for SOM reasons ($C^{(cull)}$), the cost of hoof trimming ($C^{(ht)}$), the cost of veterinary services ($C^{(vet)}$), the cost of labour ($C^{(labour)}$), and the cost of additional treatments ($C^{(treat)}$). For convenience we introduce $\overline{X} = X \setminus \{ins\}$ where $\bar{x} \in \bar{X}$ to represent the direct economic outflows due to SOM. These direct economic outflows occurred only in the scenario when SOM was present (i.e., z = 1: the "with" scenario). This meant that a summation of these direct economic outflows during the year per SOM case MMSC2 – MMSC5 obtained the total annual direct economic effect due to SOM per direct economic outflow. We denote $DTC_{e,y,1}^{(\bar{x})}$ as the total annual direct economic outflow $\bar{x}$ per SOM case e = (MMSC2, MMSC3, MMSC4, MMSC5) for simulation y in scenario z = 1.

The indirect economic effects include herd-level changes in the expected milk returns, changes in culling costs for non-SOM reasons and changes in insemination costs between scenarios z = 0 and z = 1. Because these economic flows occurred in both scenarios the annual totals of these economic flows per simulation were compared and are respectively described by Equations 2.32 – 2.34

$$ITR_y^{(milk)} = -\left[\left(TR_{y,1}^{(milk)} + TC_{y,1}^{(milk)}\right) - TR_{y,0}^{(milk)}\right] \quad (2.32)$$

$$ITC_y^{(cull)} = \left(TC_{y,1}^{(cull)} - \sum_{e=\mathrm{MMSC2}}^{\mathrm{MMSC5}} DC_{e,y,1}^{(cull)}\right) - TC_{y,0}^{(cull)} \quad (2.33)$$

$$ITC_y^{(ins)} = TC_{y,1}^{(ins)} - TC_{y,0}^{(ins)} \quad (2.34)$$

where $ITR_y^{(milk)}$is the total indirect economic effect on total expected milk returns, $ITC_y^{(cull)}$is the total indirect economic effect on culling costs for non-SOM reasons and $ITC_y^{(ins)}$is the total indirect economic effect on insemination costs, for simulation y due to SOM.

2.2.11 Sensitivity analysis

A local sensitivity analysis was performed to assess the effect of parameter adjustments on the mean total annual economic loss due to SOM for the default scenario. This was performed by 206 parameter adjustments of the default parameter inputs (Tables 2.1 – 2.4 and A 2.6 – A 2.10). Parameters used for the infection dynamics of HYP, IDHE, IP, OH, SH, SU and WLD were independently increased and decreased by 25 percent in both periods. The DD transmission rate, probability of reinfection, and spontaneous cure were increased and decreased by 10 and 20 percent, and the calibration factor was adjusted by 5 percent. The transitional risk of mobility scores 2, 3, 4 and 5 were independently increased and decreased by 20 percent. Mobility score progression intervals respective of hoof disorder were doubled and halved. Cure rates of hoof disorders respective of mobility score were increased and decreased by 20 percent for farmer, hoof trimmer and veterinarian treatments. Relative risks were all increased and decreased by 20 percent. In addition, the relative risks with respect to the effect of mobility scores on oestrus detection together with conception were set to 1 so that they would not have an effect on reproductive performance. The detection constant for all scores was increased and decreased by 20 percent. The maximum number of days for the farmer to treat a cow with a mobility score 4 after successful detection was decreased to 11 and 7 days. Maximum additional lactational treatments was increased to 4, 5, and 7. The daily milk yield percentage loss for mobility scores 2, 3, 4, and 5 were each increased and decreased

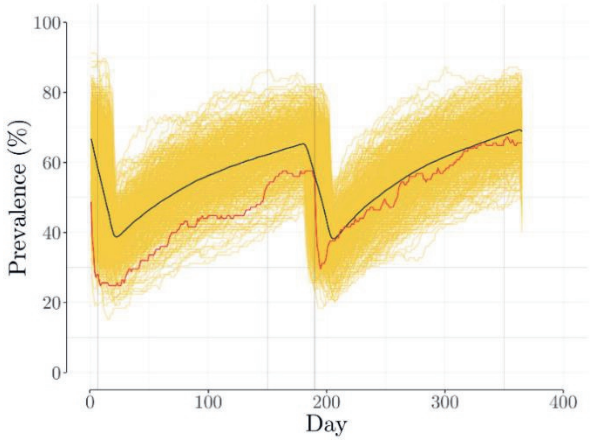


Figure 2.3 Daily cow-level mobility score ≥2 prevalence. The figure depicts the mean daily prevalence (dark line) of the 500 iterations (yellow lines) and one random iteration (red line). The black vertical lines represent the median day of hoof trimmer visits in the pasturing and housing period at day 7 and 190, respectively.

by 20 percent. For the milk and slaughter price per kg, minimum and maximum prices were approximately 20 percent of the respective means (Wageningen Economic Research, 2020). Therefore, the milk and slaughter price per kg were increased and decreased by 20 percent. For the rearing costs, minimum and maximum prices were already included in the PERT distribution for the default situation. Therefore, the entire distribution was shifted in either direction by 20 percent.

2.3 Results

Convergence was tested by running 1000 simulations for 10 years. Visual inspection of variance in total milk produced, totals of all hoof disorder incidence, total mobility score 3, 4 and 5 incidence and total number of cows culled showed that results stabilised at 500 simulations. Visual inspection of all daily hoof disorder and mobility score prevalence showed consistent trends from the beginning of the sixth year. Herd demographics with respect to parity distributions matching the initial inputs from the beginning of the sixth year implied that culling rates had also stabilised by this time. Hence, a 5-year burn-in period was warranted. After model convergence and the burn-in period was identified the following results were derived from a stable year simulation.

Figure 2.3 depicts the daily prevalence of cows with SOM showing that the prevalence of these cows decreased twice during the year, which happened after routine hoof trimming. The mean daily prevalence of cows with SOM increased during the housing period from 38 percent at the start of the housing period (after hoof trimming) to 69 percent at the end of the housing period (before hoof trimming). Overall, the mean yearly prevalence of cows with SOM and a mobility score ≥2 was 57 percent (45 percent; 68 percent)[3]. Table 2.5 shows the mean prevalence of mobility scores and the cumulative incidence of SOM cases per 100 cows per period. Both metrics showed that there were more cows with SOM during the housing period compared with the pasture period. Most of these cows had mobility scores 2 and 3, and MMSC2 and MMSC3 in both the pasture and housing periods. In contrast, there were fewer cows with severe SOM in both periods: mobility scores 4 and 5, and MMSC4 and MMSC5. Despite the low prevalence of mobility score 5 and MMSC5 cumulative incidence per period in both periods, they increased the most when moving from pasture to housing compared with the relative increase in mobility scores 2 – 4 prevalence and MMSC2 – MMSC4 cumulative incidence.

The median duration of SOM cases in general was 80 (4; 365) days. MMSC3 had the longest median duration of 134 (7; 365) days spending a median of 10 (1; 218) days with a mobility score 2 during the SOM case. The median duration of MMSC2, MMSC4 and MMSC5 were shorter with 60 (4; 322), 53 (10; 365) and 44 (6; 365) days, respectively. The median duration of mobility score 4 of MMSC4 lasted a median of 17 (2; 46) days and mobility scores 4 and 5 of MMSC5 respectively lasted a median duration of 5 (1; 15) and 5 (2; 13) days.

[3] 5th and 95th percentiles of the 500 simulations are shown in parentheses.

Table 2.5 Summary of mobility score mean prevalence (%) and SOM case mean cumulative incidence per 100 cows per period rounded to 2 decimal points (5th and 95th percentiles shown in parentheses).

	Pasture period	**Housing period**
Mobility score	Prevalence	
1	45.37 (35.03; 57.33)	43.36 (32.94; 55.02)
2	33.43 (26.24; 40.52)	34.85 (28.14; 41.41)
3	20.33 (13.12; 27.44)	20.85 (13.91; 27.97)
4	0.85 (0.36; 1.45)	0.91 (0.39; 1.54)
5	0.02 (0.00; 0.08)	0.03 (0.00; 0.08)
SOM case	Cumulative incidence	
MMSC2	33.66 (23.20; 46.00)	38.59 (28.80; 50.00)
MMSC3	16.38 (10.40; 23.00)	19.15 (12.00; 26.00)
MMSC4	7.07 (3.20; 11.00)	7.72 (4.00; 12.00)
MMSC5	0.65 (0.00; 2.00)	0.81 (0.00; 2.00)

The cumulative incidence per 100 cows per period for infectious hoof disorders increased during the housing period while it decreased for non-infectious hoof disorders, except for WLD (Table 2.6). Small differences were seen in the cumulative incidence per 100 cows per period between the pasture and housing period for most hoof disorders. The hoof disorders that showed the largest difference in cumulative incidence per 100 cows per period between the pasture and housing period were IDHE and WLD. Most hoof disorders had a cumulative incidence per 100 cows per period below 10 in both periods while WLD and DD were the only two hoof disorders with a cumulative incidence per 100 cows per period above 10. The DD cumulative incidence per 100 cows per period during both the pasture and housing periods was highest of all hoof disorders. Table 2.7 shows that the high DD cumulative incidence per 100 cows per period accounted for approximately a third of MMSC2 (30 percent), MMSC3 (33 percent) and MMSC4 (29 percent) SOM cases. Although the IP cumulative incidence per 100 cows per period in both periods were lower compared with DD (Table 2.6), IP accounted for most of the MMSC5 SOM cases (38 percent). Wide variations between 0 and 100 percent were seen in the DD, IP and WLD prevalence of MMSC5 cumulative incidence per 100 cows per period due to the low cumulative incidence per 100 cows per period of MMSC5.

Table 2.6 Summary of mean hoof disorder cumulative incidence per 100 cows per period rounded to 2 decimal points (5th and 95th percentiles shown in parentheses).

Hoof disorder[a]	Pasture period	Housing period
DD	28.99 (7.20; 49.60)	29.42 (8.00; 51.20)
HYP	8.21 (4.76; 12.00)	7.34 (3.20; 12)
IDHE	3.19 (0.80; 5.60)	12.42 (7.96; 17.60)
IP	9.41 (4.80; 13.60)	9.50 (5.60; 13.60)
OH	1.31 (0.80; 2.40)	1.31 (0.80; 2.44)
SH	8.90 (4.76; 13.60)	8.00 (4.00; 12.80)
SU	9.30 (5.56; 13.60)	8.16 (4.80; 12.00)
WLD	12.70 (8.00; 17.60)	17.75 (12.00; 24.00)

[a] DD = digital dermatitis; HYP = interdigital hyperplasia; IDHE = interdigital dermatitis/ heel horn erosion; IP = interdigital phlegmon; OH = overgrown hoof; SH = sole haemorrhage; SU = sole ulcer; WLD = white line disease

Table 2.7 Mean hoof disorder prevalence per annual SOM case cumulative incidence per 100 cows per year (5th and 95th percentiles shown in parentheses).

Hoof disorder[a]	SOM case			
	MMSC2	MMSC3	MMSC4	MMSC5
DD	30.68 (7.47; 46.83)	33.91 (9.07; 54.49)	29.56 (0.00; 52.66)	24.98 (0.00; 100.00)
HYP	9.12 (5.49; 13.67)	8.74 (3.84; 14.48)	7.27 (0.00; 19.05)	-
IDHE	10.57 (6.73; 15.67)	10.06 (4.57; 16.67)	6.90 (0.00; 17.42)	5.51 (0.00; 50.00)
IP	9.57 (5.56; 14.03)	5.08 (1.23; 9.79)	22.43 (6.21; 40.00)	35.80 (0.00; 100.00)
OH	1.22 (0.00; 2.66)	-	-	-
SH	11.64 (7.26; 17.16)	10.91 (5.22; 18.45)	7.88 (0.00; 20.00)	4.89 (0.00; 50.00)
SU	9.59 (6.21; 14.20)	10.67 (4.80; 17.58)	9.09 (0.00; 20.00)	7.79 (0.00; 50.00)
WLD	17.62 (11.81; 24.81)	20.63 (12.67; 30.80)	16.87 (4.17; 32.13)	21.03 (0.00; 100.00)

[a] DD = digital dermatitis; HYP = interdigital hyperplasia; IDHE = interdigital dermatitis/ heel horn erosion; IP = interdigital phlegmon; OH = overgrown hoof; SH = sole haemorrhage; SU = sole ulcer; WLD = white line disease

Cows that had SOM during their conception period had on average 6 (−23; 57) additional days to their first service compared with cows that were not SOM during their conception period. The number of additional days to the first service for cows with a maximum mobility score 2 during their conception period was 7 (−23; 57) days compared with cows that had a maximum mobility score 1 during their conception period. The number of additional days to the first service increased linearly with each increase in maximum mobility score during the conception period to 25 (−7; 76) days for cows with a maximum mobility score 5 during the conception period. Only 2 (0; 5) cows with a mobility score 1 during the conception period were culled due to fertility reasons. In contrast, 19 (12; 26) cows with a maximum mobility ≥2 were culled for fertility reasons: most with mobility scores 2 (42 percent) and 3 (47 percent). The mean number of cows culled for SOM reasons was 6 (2; 11). The total number of cows culled per mobility score for SOM reasons was on average 2 (0; 4), 1 (0; 3); 3 (0; 6) and 0 (0; 1) for mobility score 2 – 5, respectively. Milk yield losses of 270 (0; 704) and 181 (0; 437) kg for MMSC4 and MMSC5 were greatest, respectively. Cows experiencing MMSC3 had an average milk yield loss of 86 (0; 270) kg and no milk yield losses occurred for cows experiencing MMSC2.

The mean total annual economic effect (Δ) due to SOM resulted in an annual economic loss of €15,342 (€2,562; €28,904): an annual loss of €122 per average cow. Total annual production losses[4], expenditures[5] and labour contributed 96 percent, 2 percent, and 2 percent to the total annual economic loss, respectively.

As shown in Table 2.8, the mean direct annual economic loss amounted to 59 percent of the mean total annual economic loss and was mostly composed of direct milk yield losses (52 percent) and culling (31 percent). A significant amount of the direct milk yield losses was due to MMSC3 (54 percent) and MMSC4 (43 percent), and for culling mostly due to MMSC4 (56 percent). MMSC3 and MMSC4 SOM cases during the year respectively contributed 34 percent and 48 percent to the mean direct annual economic loss.

[4] Milk production losses, culling, discarded milk.
[5] Veterinary services, treatments, hoof trimming, inseminations, and feed.

Table 2.8 Mean total annual direct economic losses (€) due to SOM cases (5th and 95th percentiles shown in parentheses).

Cost variable	SOM case				Total
	MMSC2	MMSC3	MMSC4	MMSC5	
Milk losses	0 (0; 0)	2,580 (1,714; 3,399)	2,055 (1,159; 3,161)	136 (0; 357)	4,771 (3,320; 6,223)
Culling	700 (0; 2,186)	454 (0; 1618)	1579 (0; 3703)	79 (0; 643)	2,812 (626; 5,482)
Discarded milk	429 (166; 707)	240 (70; 464)	200 (39; 387)	28 (0; 95)	898 (483; 1,331)
Veterinary services	0 (0; 0)	0 (0; 0)	223 (0; 667)	222 (0; 594)	445 (0; 1,217)
Labour	0 (0; 0)	0 (0; 0)	276 (148; 440)	5 (0; 20)	281 (154; 445)
Treatments	0 (0; 0)	0 (0; 0)	174 (59; 469)	19 (0; 49)	193 (68; 480)
Hoof trimmer	0 (0; 0)	18 (3; 41)	2 (0; 7)	0 (0; 0)	20 (3; 45)
Feed	0 (0; 0)	−194 (−255; −129)	−155 (−239; −87)	−10 (−27; 0)	−360 (−468; −251)
Total	1,129 (265; 2,644)	3098 (1,978; 4,498)	4354 (0; 1,368)	480 (0; 1,459)	**9,061 (5,932; 12,983)**

The mean indirect annual economic loss was €6,281 (€−6,174; €19,499). The largest contributor to the mean indirect annual economic loss was due to changes in culling costs for cows not directly culled as a result of SOM. This loss amounted to €4,053 (€−2,883; €11,373). The second largest indirect annual economic loss arose due to herd-level changes in the expected milk returns and amounted to €2,185 (€−8,242; €13,143). The third and last indirect annual economic loss was due to changes in insemination costs amounting to €43 (€−270; €360).

The sensitivity analysis showed that economic parameters concerning the cost of culling are important for the total annual economic loss due to SOM (Figure 2.4). Increasing replacement heifer rearing costs by 20 percent resulted in an increase of the total annual economic loss to €22,354 while reducing these costs resulted in €8,379. A 20 percent increase and decrease for the price received per kg of slaughter weight for a culled cow respectively resulted in a decrease of the total annual economic loss to €12,097 and increase to €18,640. In addition, the economic importance of culling due to SOM was shown by the sensitivity analysis in two ways. Firstly, allowing the maximum number of additional treatments in one lactation to

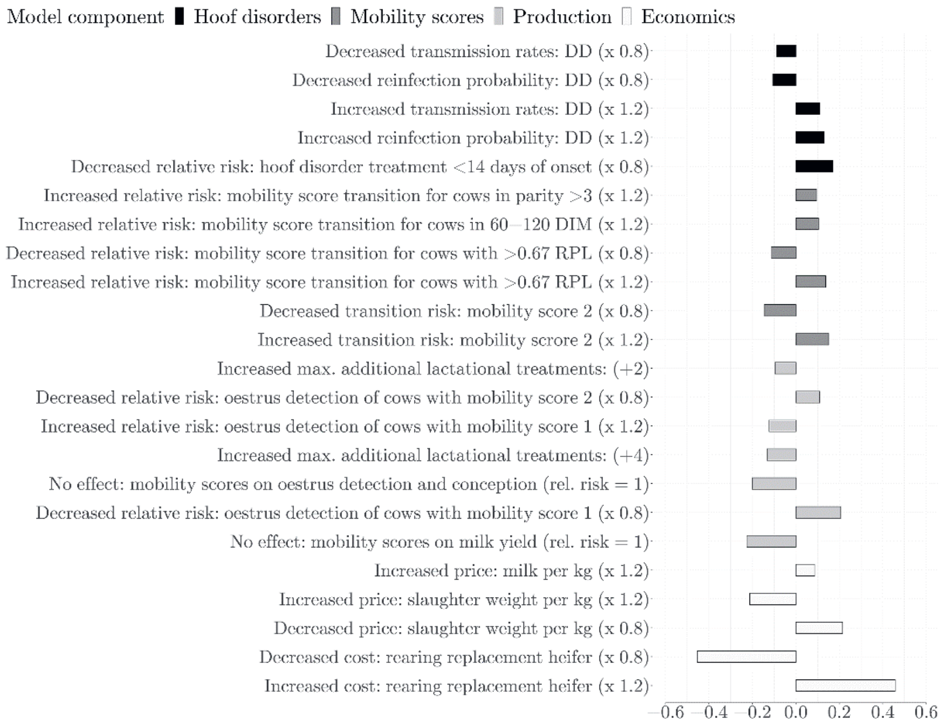


Figure 2.4 Top 10 percent most important results from the sensitivity analysis, showing the positive or negative effect of parameter adjustments on the total annual economic loss due to SOM ordered by magnitude of effect per model component. The y-axis shows the important parameters with their respective adjustments in parentheses. The x-axis shows the relative effect of parameter adjustments on the total annual economic loss due to SOM.

be increased by 2 and then 4 treatments reduced the total annual economic loss to €13,862 and €13,305, respectively. Secondly, when mobility scores had no effect on oestrus detection and conception, by setting the respective relative risks to 1, less cows were culled for fertility reasons resulting in a reduced total annual economic loss of €12,257. Increasing and decreasing the transitional risk from a mobility score 2 respectively increased and decreased €17,662 and €13,110. Adjustments in the parameters concerned with only DD infection dynamics showed to have an important effect on the total annual economic loss due to SOM.

2.4 Discussion

The bio-economic simulation model we developed is the first to simulate the economic effect of all SOM case severities in association with the incidence and dynamics of hoof disorders at hoof level, providing insight on the direct and indirect economic effect due to SOM. It includes two epidemiological modules, the Greenwood and the Reed-Frost model. This makes our model the first bio-economic model with respect to hoof disorders and SOM to simulate the incidence of infectious DD infections with a contagious disease spread module. Although our model includes other infectious hoof disorders (i.e., IDHE and IP), their incidence was modelled as environmental infections due to a lack in information pertaining to their transmission dynamics. As this information for these infectious hoof disorders become more available, they can be included in the contagious disease spread module.

The simulated mean annual prevalence of hoof disorders in our study was 58 percent, which is lower than the 80 percent prevalence previously reported by Somers et al.(2003). However, unpublished data from DigiKlauw (2020) showed that the prevalence of hoof disorders in the Netherlands has been decreasing since 2007 reaching a 55 percent prevalence in 2020. Despite this, the prevalence of hoof disorders in our study are longitudinal estimates that consider changes in hoof disorder prevalence after hoof trimming occurred. Whereas in practice, prevalence estimates are cross-sectional at the time of hoof trimming (DigiKlauw, 2020).

The routine hoof trimming showed visible positive effects as the prevalence of HYP, IDHE, IP, OH, SH, SU, and WLD decreased after hoof trimmer visits. The positive effect, however, were only short lasting since the prevalence increased quickly after hoof trimming. Consequently, the prevalence of mobility scores ≥2 increased, which has also been observed by Frankena et al. (2009). On the other hand, a positive effect of hoof trimming on the prevalence of DD was not as clear. Small increases in DD prevalence occurred for approximately 3 months after hoof trimming in both periods before an observable decrease in DD prevalence occurred. This corresponds to the positive associations of DD prevalence and short hoof trimming intervals (<6 months) compared with longer hoof trimming intervals (≥12 months) that have previously been observed (Holzhauer et al., 2006).

Parameterisation of the transitional risks between mobility score progression per hoof disorder was challenging due to a lack of relevant information. Therefore, a general transitional risk per mobility score was assumed irrespective of hoof disorder, while studies have shown that some hoof disorders are more prevalent in mild forms of SOM than in severe forms and vice versa (Blackie et al., 2013; Tadich et al., 2010). Despite this, the simulated results from our study showed that DD, IP, and WLD were the three most common hoof disorders that occurred with the severe MMSC4 and MMSC5 forms of SOM. These disorders also have previously been reported as the more common hoof disorders associated with severe SOM (Charfeddine & Pérez-Cabal, 2017; Dolecheck et al., 2019; Tadich et al., 2010). On the other hand, SU is often associated with higher mobility scores due to its large impact on a cow's gait (Blackie et al., 2013; Tadich et al., 2010) and this is not shown in our results. The general transitional risk between mobility scores and assuming that a hoof could not have more than one hoof disorder at a time could restrict the potential losses in production if the hoof disorder with highest prevalence had the lowest effect on mobility, thus the lowest impact on production, or vice versa. This demonstrates a limitation in the model. More information on the transitional risks between mobility scores respective of hoof disorders as well as hoof level comorbidities are needed to simulate these specific dynamics more accurately.

The annual distribution of mobility scores in our model corresponds with what has been previously reported (Frankena et al., 2009; O'Connor et al., 2019; Tadich et al., 2010). The annual prevalence of cows with SOM and a mobility score ≥2 from our model was 56 percent. This is higher than the 17 percent found in The Netherlands (Amory et al., 2006), 20 percent found in Ireland (Somers et al., 2019) and 21 percent found in the UK (Randall et al., 2018). Our annual prevalence of cows with SOM is higher because we included mobility score 2 in our definition of SOM, whereas the aforementioned studies omit this mobility score in their definitions. When we omitted mobility score 2 from the annual prevalence of cows with SOM in our study the annual prevalence was 21 percent; corresponding to the aforementioned studies.

Other studies investigating the economic losses associated with hoof disorders exist (Bruijnis et al., 2010; Charfeddine & Pérez-Cabal, 2017; Guard, 2008; Willshire & Bell, 2009), but do not include the effect of hoof disorders on cow mobility. Therefore, comparing the economic losses of SOM cases from our study with the economic losses of mild or severe hoof disorder cases reported in the aforementioned studies is difficult. However, results from our model show that culling and milk yield losses contribute the most to the total direct economic loss due to SOM. These results are in general agreement with other studies investigating the economic losses due to hoof disorders (Bruijnis et al., 2010; Cha et al., 2010; Charfeddine & Pérez-Cabal, 2017; Guard, 2008; Willshire & Bell, 2009).

Simulation studies that estimated the direct economic loss due to SOM have only considered severe SOM. The mean economic loss in our study for severe SOM cases MMSC4 and MMSC5 were respectively €226 and €259 (a combined mean of €229). These results are higher than the estimated mean economic loss of €192 per SOM case reported by Ettema et al. (2006) but within the range of €185 – €333 reported by Liang et al. (2017). New results from our model show that the costs associated with mild forms of SOM per MMSC2 and MMSC3 were respectively €13 and €49:

significantly lower than the losses of MMSC4 and MMSC5. However, these mild forms of SOM contribute 47 percent to the total direct economic loss due to SOM because of the high MMSC2 and MMSC3 incidence suggesting that previous studies underestimate the total direct economic losses due to SOM. In addition, these new calculations imply that the herd-level economic losses due to mild forms of SOM are no less important than those due to severe forms of SOM. This observation is supported by the results from the sensitivity analysis whereby adjustments made to the transitional risk from a mobility score 2 to a mobility score 3 increased the total annual economic loss by 15 percent. Cows with mild forms of SOM are treated during the routine hoof trimming that happens twice a year. Treating these cows on a more regular basis may help reduce the economic losses associated with mild SOM, reduce the number of cows transitioning to a mobility score 4 and increase cow welfare.

An interesting result of our study is the distribution of total annual economic losses of SOM. We discovered that the indirect economic losses due to SOM contributed 41 percent to the total annual economic loss, which is a substantial proportion. The economic analysis showed that changes in culling costs for non-SOM reasons and herd-level changes in expected milk returns were the most significant.

An increase in indirect culling costs due to culling for non-SOM reasons arose because of the effect that SOM had on reproductive performance (i.e., oestrus detection and conception). This meant that more cows on average were culled for fertility reasons before completing their expected number of lactations. This was confirmed in the validation rounds showing that there was no mean effect on the number of cows culled for fertility reasons in a scenario where SOM had no effect on reproductive performance compared with the "without" SOM scenario. Poor reproductive performance is often the primary cause of culling (Nor et al., 2014). However, culling is multi-factorial in practice and fertility related culling may be due to a culmination of health problems that lead to poor reproductive performance. Results from the "with" SOM scenario showed that most of the cows culled for fertility reasons had a maximum mobility score 2 or 3 during the conception period. These results further suggest that better detection leading to earlier intervention of the mild mobility scores may benefit reproductive performance, in turn reducing the risk of fertility related culling costs indirectly due to SOM.

The second indirect economic losses in expected milk returns reflect production losses that arose with more young replacement heifers entering the herd due to an increased culling rate because of SOM. Young replacement heifers produce less milk than older cows. Therefore, the total milk yield of a younger herd in the "with" SOM scenario is lower when compared with an older herd in the "without" SOM scenario. This was confirmed in the validation rounds when the mean total annual milk yield in a scenario where SOM had no effect on culling was the same as that of the "without"

SOM scenario. The wide variation between the 5^{th} and 95^{th} percentiles for the losses in expect milk yield in the "with" SOM scenario is due to the stochastic determination of each cow's RPL that was either culled or entered the herd.

Our simulation study has helped provide insight on the direct and indirect losses due to SOM for all level of severity resulting from hoof disorders. At herd-level, the results show that mild SOM contributes significantly, both directly and indirectly, to the total annual economic loss due to SOM. Farm personnel are less sensitive in detecting mild forms of SOM, and if detected treatment is often prolonged (Alawneh et al., 2012a). This may be due to farmers perceptions and attitudes towards SOM (Bruijnis et al., 2013) or work plan. It is also possible that mild SOM is not detected by farmers at all because farmers perceive SOM prevalence to be lower than the actual SOM prevalence (Bruijnis et al., 2013). This entails that mild SOM is often only treated twice a year during routine hoof trimming. Emphasis must be placed on the economic importance of mild forms of SOM that occur more frequently than severe forms. The use of sensors to continuously monitor the mobility of cows may help identify cows with mild SOM faster and more frequently, promote cow specific intervention in a timelier manner and in turn reduce the economic losses due to SOM and improve cow welfare. In addition, sensor generated data could help better parameterise uncertain input variables used in our model and other bio-economic simulation models.

The developed bio-economic model is flexible and can be applied for a wide range of options for various situations with necessary parameter adjustments. With the model's ability to simulate the dynamics of SOM per mobility score, it can be further applied to evaluate cost-effectiveness of different management strategies tailored to the dynamics of specific mobility scores found in other dairy systems. In addition, the model also provides a foundation for research on the impact of mobility scores on cow welfare.

2.5 Conclusion

The dynamic, stochastic, and mechanistic bio-economic simulation model described in this study is a novel simulation model that provides an estimation on the economic losses due to SOM in relation to the hoof disorders described within this study. The total annual economic loss due to SOM for a typical Dutch dairy farm of 125 cows was €15,342. This loss was composed of direct and indirect economic losses. The total direct economic loss was €9,061, of which 47 percent was due to cows with mild forms of SOM. The model generated novel insights on the indirect economic losses due to SOM: making up 41 percent of the total annual economic loss due to SOM.

These indirect economic losses were mostly due to decreases in the expected milk returns and increases in culling costs for non-SOM reasons. These results, along with the direct economic losses, imply that the economic losses due to SOM are more substantial than farmers might think. The results from this study can help stimulate dairy farmer awareness with respect to the economic importance of SOM, especially in the mild forms. Timely intervention of cows with SOM could reduce the economic losses and lead to improved cow health and welfare provided suitable intervention methods can be established.

2.6 Appendix

Table A 2.1 Distribution of cow parity.

Parity	Default value	Distribution	Description	Source
1	0.31	Sample	Proportion of cows in parity 1 - ≥5	CRV (2019)
2	0.26			
3	0.20			
4	0.12			
≥5	0.11			

Table A 2.2 Reproduction related parameters and values.

Parameter	Default values(s)	Distribution	Description	Source
First oestrus		Sample	Days to first oestrus post-calving	Authors' expertise
Parity 1	14 – 27			
Parity ≥2	18 – 21			
Following oestrus	21	Fixed	Days to subsequent oestrus	Authors' expertise
$\Lambda^{(oest)}$	0.55	$B(n, P)$	Base risk of oestrus detection	Based on Rutten et al. (2014)
$\Lambda^{(conc)}$		$B(n, P)$	Base risk of successful conception following n^{th} insemination (Ins.)	Based on Inchaisri et al. (2011)
Ins. 1	0.69			
Ins. 2	0.58			
Ins. 3	0.54			
Ins. 4	0.50			
Ins. 5	0.42			
Ins. ≥6	0.16			
Gestation (days)	$\mu = 281$; $\sigma = 3$	$\mathcal{N}(\mu, \sigma)$	Gestation period length	Based on Inchaisri et al. (2010)
VWP (days)	84	Fixed	Voluntary waiting period	Inchaisri et al. (2010)
DPL (days)	56	Fixed	Dry period length	Inchaisri et al. (2010)

Table A 2.3 Culling and replacement parameters and values.

Parameter	Default values(s)	Distribution	Description	Source
General culling		$B(n,P)$	Daily probability for general culling reasons for cows in parity $1-\geq 5$	Calibrated input
Parity 1	6.58e − 5			
Parity 2	1.53e − 4			
Parity 3	1.53e − 4			
Parity 4	2.19e − 4			
Parity ≥5	4.38e − 4			
Yield threshold	15	Fixed	Daily milk yield (kg) threshold for cows culled due to infertility	Authors' expertise
Mortality	0.02	$B(n,P)$	Probability of general cull cow succumbing to death	Authors' expertise
Replacement	0.3	Geometric	Probability of heifer replacing a dead cow on a given day within a month	Calibrated input

Table A 2.4 Lactation curve parameters and values.

Parameter	Default values(s)	Distribution	Description	Source
$M^{(ady)}$		Fixed	Average daily yield (kg) for cows in parity 1 – ≥3	Kok et al. (2017)
Parity 1	23.9			
Parity 2	28.9			
Parity ≥3	30.5			
a		Fixed	Factors modelling shape of lactation curve	Kok et al. (2017)
Parity 1	31.6			
Parity 2	40.6			
Parity ≥3	44.1			
b		Fixed		
Parity 1	−0.0447			
Parity 2	−0.0708			
Parity ≥3	−0.0835			
c	−16.1	Fixed		
k	0.06	Fixed		

Table A 2.5 Cow energy requirement (VEM) parameters and values.

Parameter	Default values(s)	Distribution	Description	Source
Growth		Fixed	Daily growth energy requirements for cows in parity ≤2	van Es (1978)
Parity 1	660			
Parity 2	330			
Pregnancy stage		Fixed	Daily energy requirements for pregnant cows from 4 months to last month before calving	Remmelink et al. (2015)
4 months pre-calving	450			
3 months pre-calving	850			
2 months pre-calving	1500			
1 month pre-calving	2700			

Table A 2.6 Risk factors associated with hoof disorder *d*.

Risk factor (λ)	Class	Hoof disorder (d) relative risks								Source
		HYP	IDHE[a]	IDP	OH	SH	SU	WLD	DD[a,b]	
Parity	1	1	1; 1	1	1	1	1	1	1; 1.05	Somers et al. (2005a, 2005b);
$r = 1$	2	1	1.25; 1.55	1	1	1	1	1.51	0.97; 1.01	Holzhauer et al. (2008b);
	3	1	1.92; 1.89	1	1	1	1.31	1.9	0.91; 0.95	Barker et al. (2009)
	≥4	1	1.97; 2.04	1	1	1	1.92	2.92	0.62; 0.66	
Lactation stage	≤30	1	1	1	1	1	1	1	1	Somers et al. (2005a
$r = 2$	31 – 60	1	1.51	1	1	1	1.32	1	1.2	Holzhauer et al.
	>60	1	1.78	1	1	1	1.63	1	1.2	(2008b);
	Dry	1	0.72	1	1	1	1.16	1	1	Holzhauer et al. (2006)
RPL[c]	<20%	1	1	1	1	1	1	1	1	
$r = 3$	21 – 40%	1	1	1	1	1	1	1	1	
	41 – 60%	1	1	1	1	1	1	1	1	
	61 – 80%	1	1	1	1	1	1	1	1	
	>80%	1	1	1	1	1	1	1	1	
Hoof	Front	0.05	0.02	0.02	0.05	0.05	0.05	0.05	0.05	Based on
$r = 4$	Hind	1	1	1	1	1	1	1	1	Alvergnas et al. (2019)

[a] Parity risk factors are provided for both periods (pasturing; housing).
[b] Effect of housing on parity risk factor is adjusted by approximate estimation.
[c] RPL = relative production level.

Table A 2.7 Time spent with each mobility score before probable transition to the succeeding mobility score for hoof disorder *d*.

Parameter[a]	**Mobility score**	**Days**[b]							
		HYP	IDHE	IDP	OH	SH	SU	WLD	DD
$T^{\uparrow}_{min}$	2	7	9	0	0	7	3	1	14
	3	7	14	0	0	13	3	2	4
	4	14	7	0	0	4	3	2	4
$T^{\uparrow}_{max}$	2	7	17	1	0	17	4	2	17
	3	7	22	1	0	28	4	2	7
	4	14	14	1	0	14	4	3	7
$T^{\downarrow}_{min}$	2	2	2	0	0	5	2	2	2
	3	2	2	0	0	0	2	2	2
	4	1	1	1	0	0	2	2	1
	5	1	1	1	0	0	1	1	1
$T^{\downarrow}_{max}$	2	3	3	1	1	10	3	3	3
	3	3	3	1	0	0	2	2	3
	4	2	2	1	0	0	2	2	3
	5	2	2	1	0	0	1	1	1

[a] Intervals between score transitions; superscripts ↑ and ↓ denote mobility score progression and recovery, respectively.

[b] Mean values of expert opinion except for DD mobility score 2 where $T^{\uparrow}_{min}$ = 14 and $T^{\uparrow}_{max}$ = 17 were derived by the sojourn time a DD lesion would spend in lesion class M1 as per Biemans et al. (2018).

Table A 2.8 Hoof disorder cure base risk after treatment by farmer, hoof trimmer or veterinarian.

Hoof disorder[a]	Mobility score cure base risks				Source
	2	3	4	5	
Treated by farmer					
DD	0.79	0.79	0.79	0.79	Holzhauer et al. (2008a)
HYP[b]	0	0	0	0	Authors' expertise
IDHE	0.65	0.65	0.6	0.5	Authors' expertise
IDP	1	0.98	0.98	0.98	Bruijnis et al. (2010)
OH	1	1	1	1	Authors' expertise
SH	0.7	0.6	0.55	0.45	Authors' expertise
SU	0.79	0.68	0.63	0.53	Authors' expertise
WLD	0.79	0.68	0.63	0.53	Authors' expertise
Treated by hoof trimmer or veterinarian					
DD	0.79	0.79	0.79	0.79	Holzhauer et al. (2008a)
HYP	1	0.8	0.8	0.8	Authors' expertise
IDHE	0.8	0.7	0.65	0.6	Authors' expertise
IDP	1	1	0.98	0.98	Bruijnis et al. (2010)
OH	1	1	1	1	Authors' expertise
SH	0.75	0.65	0.6	0.5	Authors' expertise
SU	1	0.8	0.75	0.75	Authors' expertise
WLD	1	0.8	0.8	0.8	Authors' expertise

[a] Base cure risks had to be estimated due to the little information available. Where information was available it was used.

[b] Farmers will not treat a case of interdigital hyperplasia (HYP) since a veterinarian is required to perform a claw-amputation.

Table A 2.9 Risk factors associated with cure of hoof disorder.

Risk factor (λ)	**Class**	**Relative risk**	**Source**
Parity	1	1	Reader et al. (2011)
$r = 8$	2	1.05	
	3	0.91	
	≥4	0.8	
Lactation stage	<90	1	Reader et al. (2011)
$r = 9$	90 – 180	0.92	
	>180	0.8	
	Dry	1	
Duration of disorder (days)	<14	1	Reader et al. (2011)
$r = 10$	15 – 28	0.7	
	29 – 126	0.54	
	>126	0.28	

Table A 2.10 Mobility score effects on production parameters.

Parameter	Class					Source
	Mobility score					
	1	2	3	4	5	
$M^{(myr)}$[a]	0	0	0.05	0.48	0.53	Based on O'Connor et al. (2020a)
$\lambda^{(oest)}$[b]	1	0.91	0.82	0.73	0.64	Walker et al. (2008)
$\lambda^{(conc)}$[c,d]	1	1	PERT(0.41, 0.78, 0.88)			
Culling[e]	1	1.07	1.18	1.48	1.48	Walker et al. (2008)
	Parity					
	1	2	3	4	≥5	
Culling[e]	1	1.1	1.2	1.3	1.5	O'Connor et al. (2020a)
	Relative production level					
	≤20%	21 – 40%	41 – 60%	61 – 80%	≥80%	
Culling[e]	1	0.34	0.24	0.16	0.06	Booth et al. (2004)

[a] Daily percentage milk yield reduction per mobility score.

[b] Relative risk of oestrus detection where the default input in Table A 2.2 is taken as the base risk.

[c] Relative risk of conceiving after successful oestrus detection and artificial insemination (AI) where the default probability of conception after insemination inputs in Table A 2.2 are taken as the base risks.

[d] PERT(min, med, max) distribution is distributed over mobility scores ≥3.

[e] Relative risk of a cow being culled with mobility score 1 – 5 in parity 1 – ≥5 and in one of five relative production level classes where general culling rate in Table A 2.3 is taken as the base risk.

Chapter 3
A new approach and insights on modelling the impact of production diseases on animal welfare

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Abstract

Animal welfare is becoming an important consideration in animal health related decision making. Incorporating animal welfare in the animal health decision making requires the impact of health disorders to be known. Yet little research quantifies the impact, making it difficult to include animal welfare in the animal health decision making process. Quantifying the impact of health disorders on animal welfare is incredibly challenging due to empirical animal-based data collection constraints. An approach to circumvent these constraints is to rely on expert knowledge whereby welfare impairment weights are indicative of the negative welfare effect. In this research, we propose an expertise-based method to quantify the impact of sub-optimal mobility (SOM) on welfare of dairy cows, because of its welfare importance. We first quantified welfare impairment weights of SOM by eliciting expert knowledge using adaptive conjoint analysis (ACA). Second, using the welfare impairment weights we derived the welfare disutility (i.e., negative welfare effect) of mobility scores $1 - 5$ ($1 =$ optimally mobility, $5 =$ severely impaired mobility). Third, using the welfare disutility per mobility score we quantified the welfare impact at case- and herd-level of SOM for different SOM severity. Results showed that the welfare disutility increased with each increase in mobility score. However, the welfare impact of SOM cases with lower mobility scores were higher compared to SOM cases with higher mobility scores. This was because of the longer lasting duration of the SOM cases with lower mobility scores. Moreover, the herd-level welfare impact was largely due to SOM cases with lower mobility scores because of the longer duration and more frequent incidence compared to the SOM cases with higher mobility scores. These results entail that better welfare of dairy cows with respect to SOM can be achieved if lower mobility scores are detected and treated sooner. Our research demonstrates a novel approach that quantifies the impact of health disorders on animal welfare.

3.1 Introduction

Farm animal welfare is an ever-pressing societal concern, especially in European countries (Eurobarometer, 2016). For farmers this means that animal welfare should be an aspect considered in the decision-making process. Among other welfare risks, health disorders are important factors leading to impaired animal welfare (Broom & Corke, 2002). While there is a growing need to include farm animal welfare in the animal health decision-making process, decision-making in animal health is largely considered from an economic perspective (Hennessy & Marsh, 2021; McInerney et al., 1992; Rushton, 2009). Incorporating animal welfare into the decision-making process requires the impact of health disorders on animal welfare to be known. However, quantifying welfare impacts is challenging, demonstrated by the relatively few studies reporting the welfare impacts of health disorders (Bruijnis et al., 2012; Nielsen et al., 2021).

Animal welfare is complex and best understood as a combination of scores in different domains. This is for instance illustrated by the Five Domains model, whereby animals should have good feeding, good housing, good health, the ability to show natural behaviour and the possibility to experience positive emotions, where each domain lists several welfare indicators (Mellor et al., 2020). Understanding the impact of health disorders on these welfare domains through the welfare indicators can help identify their impact on overall animal welfare (EFSA, 2012). Previous studies have used a weighting approach combined with expert knowledge elicitation to quantify the impact of health disorders on various welfare indicators whereby a "welfare impact score" is obtained by summing the weights associated to the welfare indicators respective of health disorders (Bruijnis et al., 2012; Nielsen et al., 2021; Teng et al., 2018). Similarly, this weight-based approach has also been used to assess the welfare impact of different housing and management systems in swine and dairy farming (Bracke et al., 2002; Ursinus et al., 2009). Obtaining these weights by expert knowledge elicitation is deemed appropriate when a lack of empirical evidence exists (EFSA, 2014).

The Delphi method is a commonly used expert knowledge elicitation method in animal welfare related studies (Bertocchi et al., 2018; Lorenzi et al., 2022; Rioja-Lang et al., 2020). Bruijnis et al. (2012) and Nielsen et al. (2021) used derivations of the Delphi method in their health disorder welfare impact assessments for swine and dairy cows. However, using this method may lead to obscured weights because the welfare indicators are addressed individually, ignoring the health disorder's relative effect on other welfare indicators, while a health disorder may affect several welfare indicators simultaneously with varied effects per welfare indicator. Assessing welfare indicators simultaneously via comparison-based elicitation techniques may help obtain more accurate weights since the relative effect of a health disorder on welfare indicators are considered in the expert knowledge elicitation process. To date only Teng et al. (2018) used a paired comparison-based elicitation method to assess the welfare impact of disease. However, their study concerned companion animals and not farm animals. For now, assessing the welfare impact of health disorders in farm animals is mostly Delphi based, which lacks depth in the weighing process.

The objective of this study was to propose a new method apropos quantifying the impact of health disorders on animal welfare and to apply this method to an estimation of the welfare effect of suboptimal mobility in dairy cattle. Our method incorporates a comparison-based elicitation technique, known as Adaptive Conjoint Analysis (ACA), to obtain the necessary weights required to quantify the impact of a health disorder on animal welfare. ACA is a fitting methodology because it allows for multiple welfare indicators to be assessed simultaneously, which is an advantage over the more commonly used Delphi method. We then demonstrate how the elicited weights can be used to quantify the impact of a health disorder on animal welfare via simulation modelling. We position this research in the context of dairy cow sub-optimal mobility (SOM), because this is a common health disorder in dairy farming with high animal welfare importance (Broom & Corke, 2002; Welfare Quality®, 2009a; Whay & Shearer, 2017). SOM is characterised by different severities that are often described by mobility scores, such as the 5-point ordinal mobility scoring scale (1 = optimal mobility, 5 = severe SOM; Sprecher et al., 1997). Using SOM as a case study demonstrates how our proposed method can identify the welfare impact of different health disorder severities.

3.2 Methodology

The approach used in this research was multi-faceted. First, we identified animal-based welfare indicators affected by SOM with reference to the 5-Domains model of Animal Welfare by Mellor et al. (2020). Second, welfare impairment weights were elicited for various levels of the animal-based welfare indicators using ACA (Orme, 2006; Sawtooth Software, 2007). Third, the relative importance of welfare indicators was estimated. Lastly, the welfare impairment weights were then used in a simulation model (Edwardes et al., 2022a) to quantify the welfare impact of SOM. The approach is described in greater detail in the following sub-sections.

3.2.1 Animal-based welfare indicators

Animal-based welfare indicators are important in the assessment of animal welfare (EFSA, 2012). These welfare indicators offer more accurate insight on the response of, and the effects of, the individual animal when afflicted with a welfare debilitating factor such as a health disorder. The 5-Domains model of Animal Welfare is a framework (Mellor et al., 2020) that includes several animal-based welfare indicators in the nutrition, health, and behaviour domains. These animal-based welfare indicators can then be linked to the fifth affective experience domain (i.e., mental state) meaning that every animal-based welfare indicator that is affected may be followed by an emotional or subjective response that may also affect the mental state. For example, a reduction in food intake (i.e., welfare indicator) affects the nutrition domain and may lead to the experience of hunger, affecting the mental state domain.

We identified animal-based welfare indicators physically affected by the occurrence of SOM in dairy cows with reference to the nutritional, health, and behavioural domains of the 5-Domains model of Animal Welfare (Mellor et al., 2020) in combination with scientific literature and expert discussions (expert group 1; EG1) apropos dairy cow SOM and hoof health. The degree to which the welfare indicators are physically affected by SOM were defined by intervals in terms of *welfare indicator levels.* The defined welfare indicators and respective welfare indicator levels are presented in Table 3.1. For the feed and water intake welfare indicator, cows with SOM may have a reduced feed and water intake of 0 percent, 10 percent and 20 percent compared to a cow without SOM (Norring et al., 2014). The functional impairment welfare indicator refers to difficulties in performing everyday activities, and in this case, it is the functional use of a cow's hoof. It is assumed a hoof is functionally impaired due to the presence of a hoof disorder. Functional impairment is reflected by 5 mobility scores where 1 = no functional impairment and 5 = severe functional impairment (Sprecher et al., 1997). The body condition score (BCS) welfare indicator is a visual and an indirect estimate of energy balance and is associated with SOM (O'Connor et al., 2019). A cow experiencing sub-optimal mobility may decrease in BCS by 0, 0.5 or 1 (O'Connor et al., 2019). The behavioural change welfare indicator was based on a cow's activity budget. Within this budget cows behave in certain ways based on activities. Due to SOM the behaviour in relation to an activity may change, ultimately affecting at least one other behaviour since the activity budget is limited. For example, when afflicted with SOM a cow can experience increased lying resulting in decreased standing (Walker et al., 2008). The behavioural change indicator was kept broad due to the inherent interaction of behaviours and to capture all changes in behaviour. Hence, three levels of behavioural change percentages were defined of 0 percent, 10 percent, or 20 percent. With respect to the cow-human interaction welfare indicator, signs of avoidance in distance, stepping back and/or turning head, is a measure of cow-human interaction (Welfare

Quality®, 2009a). For example, a cow with SOM may feel more vulnerable and perceive a human approaching as a threat and show signs of avoidance (Sharma & Phillips, 2019). Three levels of cow-human interaction indicators were defined as signs of withdrawal at an additional distance of 0cm, 1cm – 50cm, 51cm – 100cm, >100cm (Welfare Quality®, 2009a).

The welfare indicator levels are the physical and measurable effects of SOM on the respective welfare indicator. After identifying the welfare indicators and respective levels, we then estimated their effect on the mental state. The effects of welfare indicator levels on the mental state were represented by welfare impairment weights, which were obtained through expert elicitation.

Table 3.1 Welfare indicators and respective welfare indicator levels.

Welfare indicator (*j*)	**Indicator abbreviation**	**Welfare indicator level (*k*)**	**Source**
Feed and water intake (% reduction)	fwi	0 10 20	Norring et al. (2014)
Functional impairment (mobility score)	fim	1 (no functional impairment) 2 (mild functional impairment) 3 (moderate functional impairment) 4 (marked functional impairment) 5 (severe functional impairment)	Sprecher et al. (1997)
Body condition score (point decrease)	bcs	0 0.5 1	O'Connor et al. (2019)
Behavioural change (% change)	bch	0 10 20	Expert discussions
Cow-human interaction (withdrawal at an additional distance)	chi	0cm 1cm - 50cm 51cm - 100cm >100cm	Welfare Quality® (2009a)

3.2.2 Eliciting welfare impairment weights

We used ACA to elicit welfare impairment weights. Traditionally used in economic and marketing research, ACA is centred on Lancaster's (1966) theory postulating that consumers make consumption decisions based on a combination of product aspects rather than the overall product itself. For example, consider a 1 litre milk carton: this product can be decomposed into multiple attributes J where $j \in J$ (e.g., welfare label, origin, price, fat content) that vary by K^j attribute levels where $k \in K^j$ (e.g., high, medium, or low welfare for the welfare label attribute). ACA is designed as an experiment used to elicit consumer preferences for existing or hypothetical products with varying attribute levels. A consumer's preference for a product is based on a combination of attribute levels, one for each attribute, and reflected in the utility U for a specific product. The utility U is expressed as $\sum_{j \in J} \beta_{j,k}$ where $\beta_{j,k}$ is the part-worth utility (the utility associated with a particular aspect level in a multi-aspect conjoint analysis model) for attribute j with attribute level k over J different product attributes. So, $\beta_{j,k}$ represents a "preference weight" that a consumer places on an attribute level of a product. For additional information on ACA see Orme (2006) and Sawtooth Software (2007).

To elicit welfare impairment weights apropos SOM we adapted the ACA terminology to suit the objectives of this study. Welfare indicators J represented the *attributes* with $j \in J$ and welfare indicator levels K^j represented the *attribute levels* per welfare indicator j with $k \in K^j$. The welfare impairment weight $\beta_{j,k}$ represented the *part-worth utility* for welfare indicator j with welfare indicator level k. Therefore, the combination of welfare indicator levels, one for each welfare indicator, represents the *product* and reflects the welfare disutility D, representing *utility*, given the combination of welfare indicator levels and their associated welfare impairment weights: $D = \sum_{j \in J} \beta_{j,k}$. In other words, D represents the negative effect of the combined welfare indicator levels on the mental state.

The ACA took form of a survey and was distributed online to dairy cow welfare experts (expert group 2; EG2) that were participating in the 54th Congress of the International Society of Applied Ethology (2nd – 6th August 2021: ISAE 2021), which took place online due to the covid-19 pandemic). Prior to survey distribution it was unknown how many dairy cow welfare experts would attend ISAE 2021. By the end of ISAE 2021, 33 experts took part in the survey. From the pool of 33 experts, a total of 10 were removed from the original dataset for either not having completed the survey (n = 7) or showing a low degree of involvement (n = 3).

Survey design

The welfare indicators and respective welfare indicator levels were treated as inputs in the design of the ACA survey (Table 3.1). The survey took form in an electronic 3-step procedure and was designed in Lighthouse Studio (Sawtooth Software, 2021). In the design of the survey, prior information was specified for the welfare indicator levels for each welfare indicator assuming that welfare was impaired more for each increase in welfare indicator level. For example, a 10 percent reduction of feed and water intake will impair welfare more than a 0 percent reduction, and a 20 percent reduction of feed and water intake will impair welfare more than a 10 percent reduction.

The first step of the survey dealt with collecting prior information from the experts whereby they specified the relative importance for each welfare indicator. This was done by identifying the magnitude in differences among the considered welfare indicator levels. Magnitudes in differences between welfare indicator levels within a welfare indicator is more informative than importance specifications per welfare indicator level. Hence, experts were asked to specify the importance of a change from the lowest to the highest welfare indicator level for each welfare indicator in terms of welfare impairment. Seven possible answers ranged between "not important" to "extremely important". This prior information was used in the second step.

In the second step, experts were shown a series of customised paired-comparison trade-off questions. These paired-comparison questions were defined in combination with the prior information from the first step. In each paired-comparison trade-off question, experts were shown two cards representing virtual cows with SOM where the effect of SOM on welfare indicators varied according to the respective welfare indicator levels. Each time the two virtual cow cards were nearly equal in welfare disutility, which is reflected in the sum of the welfare impairment weights (i.e., $\sum_{j \in J} \beta_{j,k}$). After each paired-comparison question per expert, the welfare impairment weights were updated with ordinary least squares regression (Sawtooth Software, 2007). The updated welfare impairment weights were then used to select a combination of welfare indicator levels for the next paired-comparison question that would generate two virtual cow cards being nearly equal in welfare disutility. This process ultimately forced the experts to consider the importance of the welfare indicator levels for each welfare indicator, which is a strength of ACA that helps identify the most important welfare indicator levels per welfare indicator per expert.

In the third step, the experts' degree of involvement during the survey was investigated. A series of questions were asked about a single virtual cow's welfare described by varying combinations of welfare indicator levels. Experts were asked to specify a "likely welfare impairment score" between 0 and 100 (0 = cow's welfare is not at all impaired; 100 = cow's welfare is most impaired). The degree of involvement was used to determine an intercept and regression coefficient for the welfare impairment weights to best predict logits of likelihood responses (Sawtooth Software, 2007). The experts' degree of involvement was identified by correlating the experts' logit of likelihood responses and welfare impairment weights (estimated in the preceding step).

Data processing and analysis

The final set of welfare impairment weights for each expert was extracted from Lighthouse Studio (Sawtooth Software, 2021) then processed and analysed with R in RStudio (R Core Team, 2022). Experts that showed a low degree of involvement ($R^2 < 0.5$, estimated in step 3) were removed from the final data set because their degree of involvement was not correlated with their welfare impairment weights (estimated in step 2). With the remaining expert responses (n = 23), the mean and standard deviation of welfare impairment weights for each welfare indicator level were calculated. In addition, the relative importance of each welfare indicator was calculated per expert by finding the range between welfare impairment weights per welfare indicator divided by the sum of all welfare indicator impairment weight ranges. Hence, the relative importance $\rho_{i,j}$ of welfare indicator j in J welfare indicators for expert i is expressed as

$$\rho_{i,j} = \frac{\max\limits_{k\in K^j}(\beta_{i,j,k}) - \min\limits_{k\in K^j}(\beta_{i,j,k})}{\sum_{j\in J}\left[\max\limits_{k\in K^j}(\beta_{i,j,k}) - \min\limits_{k\in K^j}(\beta_{i,j,k})\right]} \tag{3.1}$$

where $\beta_{i,j,k}$ is the welfare impairment weight for expert i with respect to welfare indicator level k in K^j welfare indicator levels for welfare indicator j across J welfare indicators. With $\rho_{i,j}$, the mean of the experts' relative importance, and standard deviation between experts per welfare indicator was also calculated.

3.2.3 Disutility of SOM on animal welfare

After estimating the welfare impairment weights for all welfare indicator levels, we then identified the welfare disutility for different severity of SOM. Identifying the welfare disutility per mobility score was a necessary step to quantify the welfare impact of SOM since the welfare disutility reflects the total effect on the mental state. In Edwardes et al. (2022a), SOM severity is described by a 5-point ordinal mobility scoring scale (1 = optimal mobility, 5 = severe SOM) as per Sprecher et al. (1997). To identify the welfare disutility per mobility score we asked the SOM and hoof health experts in EG1 to participate in a questionnaire. Per welfare indicator, they were asked to specify the welfare indicator level that best fitted each mobility score 1 – 5. Experts in EG1 were blind to the elicited welfare impairment weights obtained from the experts in EG2. After experts in EG1 completed the questionnaire the median welfare indicator level per welfare indicator per mobility score was calculated. Thereafter, the corresponding welfare impairment weights per median welfare indicator level per welfare indicator per mobility score were identified and used as input for the simulation model. Furthermore, the welfare disutility D_l for mobility score l was estimated: $D_l = \sum_{j \in J} \beta_{j,k,l}$. In other words, D_l represents the negative effect of the mobility score on the mental state.

3.2.4 Modelling SOM welfare impacts

In brief, the model described in Edwardes et al. (2022a) simulates a typical Dutch dairy herd in daily time-steps where cows are housed in cubicles with concrete slatted floors in Autumn and Winter, have pasture access for >6 hours a day in Spring and Summer, and have their hooves routinely trimmed at the start of Spring and Autumn. SOM is modelled at cow-level using a 5-point ordinal mobility scoring scale (1 = optimal mobility, 5 = severe SOM; Sprecher et al., 1997) and could occur due to the incidence of eight different hoof disorders (digital dermatitis, interdigital hyperplasia, interdigital dermatitis/heel-horn erosion, interdigital phlegmon, overgrown hoof, sole haemorrhage, sole ulcer, and white-line disease). Hoof disorders and SOM were first modelled at the hoof-level (detailed explanation in Edwardes et al., 2022a), this means that a cow could have 4 possible mobility scores (i.e., one for each hoof; detailed explanation in Edwardes et al., 2022a). If no hoof disorder or a latent digital dermatitis lesion was present, the hoof was assigned a mobility score 1. If a hoof became infected with any of the eight hoof disorders, a mobility score 2 was first assigned to the hoof. Thereafter, mobility score transitions were probabilistically determined after a minimum mobility score duration occurred respective of hoof disorder. Minimum mobility score durations were determined by sampling from uniform distributions respective of mobility score and hoof disorder. After these hoof-level processes were simulated, the cow-level mobility score dynamics were determined in each time step as the maximum mobility score between the 4 possible hoof-level mobility scores resulting from the underlying hoof disorders.

The incidence and duration of SOM cases (mobility score ≥2) were then quantified for a one-year period. SOM cases were allocated to a Maximum Mobility Score SOM

Case (MMSC) category because a SOM case can be composed of more than one mobility score. Hence, four MMSC were defined as MMSC2, MMSC3, MMSC4, and MMSC5 for maximum mobility scores 2 – 5, respectively. For each of these MMSC categories, the duration of mobility scores within a SOM case was also quantified. MMSC incidence and duration were used as input to quantify the welfare impact of SOM at MMSC- and herd-level (Table A 3.1).

Simulating the welfare impact

The corresponding welfare impairment weights per mobility score (identified in Section 3.2.3) were used as inputs to quantify the welfare impact, expressed as "welfare impact scores", per SOM MMSC (i.e., MMSC2, MMSC3, MMSC4, MMSC5) incident that occurred in a one-year period. The duration of mobility scores within an MMSC per incident per cow were respectively weighed by the welfare impairment weights with the following equation:

$$WI_{h,i} = \sum_{j=1}^{4} \sum_{l \in L^h} \beta_{j,k,l} \times \alpha_{h,i,l} + \sum_{l \in L^h} \beta_{j=5,k,l} \times \gamma_{h,i,l} \qquad (3.2)$$

where $WI_{h,i}$ is the total welfare impact score of SOM case h for cow i, $\beta_{j,k,l}$ is the welfare impairment weight for welfare indicator j with welfare indicator level k in association with mobility score l in the L^h set of mobility scores that occurred during SOM case h, $\alpha_{h,i,l}$ is the duration (days) of mobility score l during SOM case h for cow i, and $\gamma_{h,i,l}$ is the number of cow-human interactions directly related to SOM (i.e., treatments) for mobility score l during SOM case h for cow i. Cow-human interactions were separated from the summation of the 4 other welfare indicators to limit the indirect effects of SOM on cow-human interactions that may occur during daily farming activities.

The welfare impact scores were analysed at MMSC-level and normalised to the maximum welfare impact score to obtain welfare impact scores between 0 and 100. The mean (5th and 95th percentiles) of MMSC-level welfare impact scores produced by the 500 simulations were then calculated. The normalised MMSC-level welfare impact scores per MMSC were aggregated to obtain herd-level welfare impact scores per MMSC category.

Sensitivity analysis

A global sensitivity analysis was run to assess the variation in total MMSC welfare impact scores at herd-level (i.e., output) attributable to the variation in welfare impairment weights per welfare indicator per mobility score (i.e., input parameter $\beta_{j,k,l}$). Variation attributable to welfare impairment weights were represented by first- and total-order sensitivities and were quantified with a variance decomposition method (Saltelli et al., 2008). First-order sensitivity indices indicate the contribution of variation in output caused by the variation in $\beta_{j,k,l}$ without interactions with other input parameters. Total-order sensitivity indices indicate the contribution of variation in output caused by the variation in $\beta_{j,k,l}$ including all variation caused by its interactions, of any order, with any other input parameter. In summary, first- and total-order sensitivity indices indicate the relative importance of $\beta_{j,k,l}$ with higher values indicative of larger effects on the output variance. First- and total-order sensitivity indices were computed after Azzini et al. (2020) in R (R Core Team, 2022) using the **sensobol** package (Puy et al., 2022b) and sensitivity indices of >0.05 were reported. Gamma distributions of 5000 draws for each $\beta_{j,k,l}$ were drawn with a Latin hyper cube sample design to efficiently cover the parameter space of each $\beta_{j,k,l}$. To gain better insight on the variation in herd-level welfare impact scores attributable to the variation in welfare impairment weights we fixed the duration (i.e., α) and number of cow-human interactions (i.e., γ) per mobility scores per MMSC to their means.

3.3 Results

3.3.1 Relative importance of welfare indicators and welfare indicator level impairment weights

Results from the 23 experts were included in the final data set and are presented in Table 3.2. From the 5 welfare indicators included in the ACA experiment, the mean relative importance of functional impairment and reduced feed and water intake were respectively the most (38.1 percent) and second most (20.8 percent) important welfare indicators identified by the experts. For all welfare indicators, the welfare impairment weights indicate that experts collectively agreed that each increase in welfare indicator level increases welfare impairment. A note of caution is that individual welfare impairment weights between different welfare indicators cannot be compared, but changes in welfare impairment weights within a welfare indicator can be compared between welfare indicators. For example, a change from no functional

Table 3.2 Mean (standard deviation between experts) relative importance of welfare indicators and welfare impairment weights per welfare indicator level.

Welfare indicator and levels	% Relative importance (sd)	Welfare impairment weight (sd)
Feed and water intake (% reduction)	20.8 (7.26)	
0		0.00 (0.18)
10		0.57 (0.16)
20		1.14 (0.28)
Functional impairment (mobility score)	38.1 (9.58)	
1 (no functional impairment)		0.00 (0.22)
2 (mild functional impairment)		0.42 (0.30)
3 (moderate functional impairment)		1.01 (0.24)
4 (marked functional impairment)		1.46 (0.20)
5 (severe functional impairment)		2.06 (0.37)
Body condition score (point decrease)	14.2 (5.95)	
0		0.00 (0.26)
0.5		0.39 (0.18)
1		0.67 (0.24)
Behavioural change (% change)	14.4 (5.78)	
0		0.00 (0.21)
10		0.42 (0.18)
20		0.75 (0.19)
Cow-human interaction (withdrawal at an additional distance)	12.5 (4.90)	
0cm		0.00 (0.23)
1cm - 50cm		0.20 (0.18)
51cm - 100cm		0.40 (0.19)
>100cm		0.62 (0.22)

impairment to mild functional impairment can be compared with a change in behaviour from 0 and 10 percent, and, in this example, these changes are equal in terms of welfare impairment.

3.3.2 Mobility score welfare disutility

The welfare disutility, reflecting the total effect on the mental state, of mobility scores on animal welfare were identified by fitting welfare impairment weights per welfare indicator to mobility scores (Table 3.3). Mobility score 1 was considered not to impair animal welfare since the welfare impairment weights were 0 across all

Table 3.3 Welfare impairment weight $\boldsymbol{\beta_{j,l}}$ for welfare indicator $\boldsymbol{j}$ and mobility score $\boldsymbol{l}$.

Mobility score ($\boldsymbol{l}$)	**Welfare indicator ($\boldsymbol{j}$)[a]**					**Welfare disutility ($\sum_{j\in J}\boldsymbol{\beta_{j,k,l}}$)**
	fwi	fim	bcs	bch	chi	
1	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.42	0.00	0.00	0.00	0.42
3	0.57	1.01	0.39	0.42	0.20	2.59
4	1.14	1.46	0.67	0.75	0.20	4.22
5	1.14	2.06	0.67	0.75	0.20	4.82

[a] Welfare indicator j abbreviations: fwi = feed and water intake; fim = functional impairment; bcs = body condition score; bch = behavioural change; chi = cow-human interaction.

welfare indicators. Mobility score 2 was considered to impair animal welfare only through the mild functional impairment welfare indicator level belonging to the functional impairment welfare indicator. Mobility scores ≥3 impaired animal welfare across all welfare indicators. Mobility score 3 was considered to impair animal welfare less than mobility scores 4 and 5, across all welfare indicators except the cow-human interaction welfare indicator.

3.3.3 Welfare impact of Maximum Mobility Score sub-optimal mobility Case (MMSC)

The simulation model produced welfare impact scores between 0 – 100 per MMSC. Aggregating these welfare impact scores produced the total welfare impact at herd-level. The relative shares of MMSC to the total herd-level welfare impact are found in Table 3.4. The less severe MMSC2 and MMSC3 contribute the most (~87 percent) to the total herd-level welfare impact with MMSC3 being the dominant contributor. This is due to the more frequent cumulative incidence and longer duration of MMSC2 and MMSC3 despite the lower welfare disutility associated with mobility scores 2 and 3. MMSC4 and MMSC5 contribute less (~13 percent) to the total welfare impact at herd-level because of the lower incidences although welfare disutility associated with mobility scores 4 and 5 are highest.

Table 3.4 Maximum Mobility Score sub-optimal mobility Cases (MMSC) relative share of total herd-level welfare impact.

MMSC	Mean (5th; 95th percentiles)
2	16.43 (12.06; 22.18)
3	70.49 (62.36; 77.31)
4	12.06 (6.41; 18.72)
5	1.17 (0.12; 3.38)

The average welfare impact score due to SOM was 14 (0; 60) considering all MMSC welfare impact scores together. For specific MMSC, MMSC2 had the lowest average welfare impact score of 4 (0; 14) and MMSC3 had the highest average welfare impact score of 30 (1; 91). Average welfare impact scores for a MMSC4 and MMSC5 were 20 (3; 64) and 17 (2; 66), respectively. Welfare impact scores were not indicative of specific MMSC due to variations in duration within and between MMSC (Figure 3.1). For all MMSC the welfare impact scores increased as the MMSC duration increased. For MMSC2, the welfare impact score is the result of the presence of mobility score 2 only. Because of this no variation in welfare impact scores for specific durations were observed. The variation in welfare impact scores for MMSC3, MMSC4 and MMSC5 increased with increasing MMSC duration. This was due to the composition of mobility score duration within the MMSC. For example, keeping MMSC3 duration constant (i.e., at the mean MMSC3 duration) the welfare impact score was higher when the proportion of mobility score 3 duration was more than half the total MMSC3 duration (brown points) in comparison to the lower welfare impact scores when the proportion of the mobility score 3 duration was less than half the total MMSC3 duration (green points). Due to the composition of mobility score durations within a MMSC, MMSC4 and MMSC5 with higher welfare impact scores and longer durations mostly occurred because of preceding mobility scores with a longer duration.

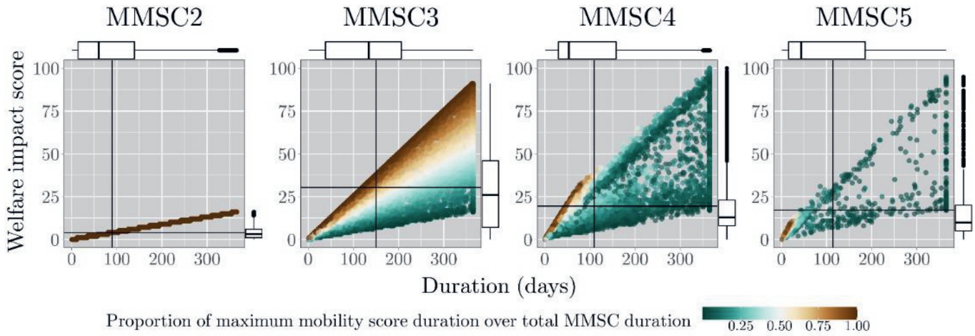


Figure 3.1 Relationship between welfare impact score and duration of Maximum Mobility Score sub-optimal mobility Case (MMSC). Each point represents a sub-optimal mobility case per MMSC category that occurred in the 500 simulations for 1 year. Point colours represent the proportion of the maximum mobility score duration over the total MMSC duration. Black horizontal and vertical lines respectively indicate the mean MMSC welfare impact score and MMSC duration. Boxplots indicate the interquartile range for MMSC welfare impact scores and MMSC duration.

3.3.4 Sensitivity analysis

The global sensitivity analysis showed that herd-level welfare impact scores per MMSC are most sensitive to variations in welfare impairment weights apropos functional impairment as it was the prominent occurring welfare indicator across herd-level welfare impact scores per MMSC (Figure 3.2). For MMSC2 and MMSC3 welfare impairment weights respective of the maximum mobility score of the MMSC contributed most to the variation in welfare impact scores per MMSC. For MMSC4 and MMSC5 welfare impairment weights respective of mobility scores preceding the maximum mobility score of the MMSC contributed the most to the variation in welfare impact scores per MMSC. Complete first and total order sensitivity indices for herd-level welfare impact scores per MMSC are found in Table A 3.2 and Table A 3.3 of the Appendix.

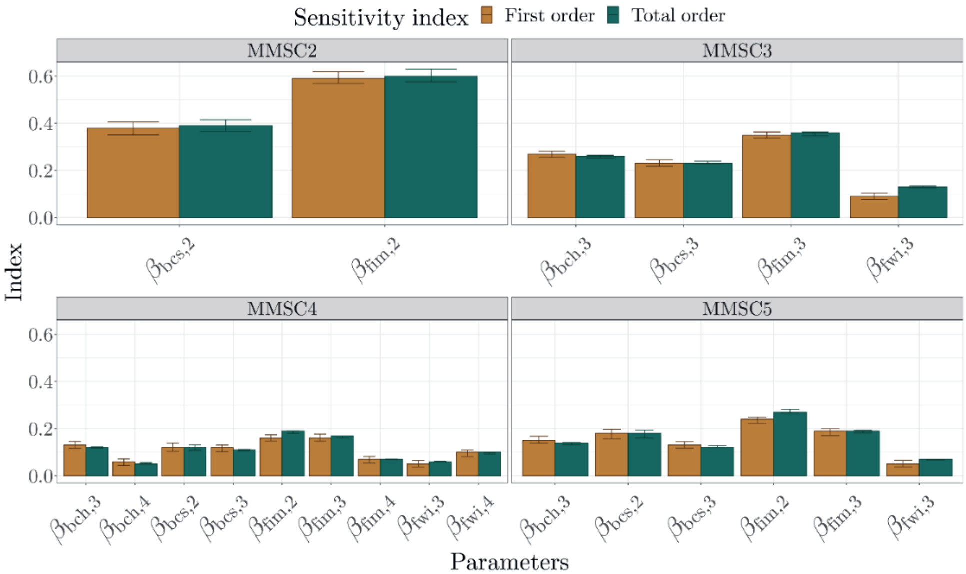


Figure 3.2 First and total-order sensitivity indices >0.05 apropos welfare impairment weight parameters $\boldsymbol{\beta_{j,l}}$ for welfare indicator $\boldsymbol{j}$ and mobility score $\boldsymbol{l}$ per Maximum Mobility Score sub-optimal mobility Case (MMSC). Welfare indicator $\boldsymbol{j}$ abbreviations: bch = behavioural change; bcs = body condition score; fim = functional impairment; fwi = feed and water intake.

3.4 Discussion

We proposed a multi-faceted approach, that can contribute to future research apropos the impact of health disorders on animal welfare. Our research is positioned in the context of SOM due its welfare importance (Broom & Corke, 2002; Welfare Quality®, 2009a; Whay & Shearer, 2017). The first step was to identify animal welfare indicators whereby the effect of SOM on these welfare indicators can be physically measured. The second step in this research was to estimate the welfare impairment weights per welfare indicator level that were indicative the welfare effects per welfare indicator level, and the relative importance of welfare indicators. With the first and second step complete, the third step could be achieved, and this was to quantify the welfare impact of SOM.

We chose to identify animal-based welfare indicators with reference to the 5-Domains model of Animal Welfare (Mellor et al., 2020) because it discriminates between 4 physical domains and 1 affective experience domain. The nutrition, health and behaviour domains list several animal-based welfare indicators whereby the effect of a health disorder on these welfare indicators can be physically measured. These physical effects were defined as welfare indicator levels in our study. Although these effects possess information on the degree to which the welfare indicators are affected, they remain physical effects and do not provide information on the degree of animal welfare impairment they cause. A more informative metric apropos the welfare impairment caused by these welfare indicator levels are in the form of welfare impairment weights that indicate the effects on the mental state. We identified 5 welfare indicators where the effects of SOM on these animal-based welfare indicators have been measured. With sufficient resources it is possible to physically measure the effects of SOM on more animal-based welfare indicators as well. However, linking the physical effects of SOM on the animal-based welfare indicators in the physical domains to the affective experience domain (i.e., mental state) is much more difficult and seems impossible in animals. In other words, we can measure how SOM can affect BCS or food intake, but it is incredibly challenging to measure how the mental state of the animals is affected by these conditions. Therefore, we estimated these physical effects on animal welfare in the form of welfare impairment weights that were obtained with expert elicitation.

Welfare impairment weights were estimated through an expert knowledge elicitation exercise. Using elicited expert knowledge is a suitable alternative when empirical evidence is limited (EFSA, 2014). We used ACA as an elicitation method instead of the Delphi method proposed by the European Food Safety Authorisation (2014) that is often used in animal welfare related research (Bertocchi et al., 2018; Bruijnis et al., 2012; Lorenzi et al., 2022; Nielsen et al., 2021; Rioja-Lang et al., 2020) because ACA is advantageous over the Delphi method. ACA is a paired-comparison elicitation method that allows for the degree of SOM welfare impairment on multiple welfare indicators to be assessed relative to each other instead of independently like in the Delphi method. This feature of ACA allows for a more realistic assessment of SOM welfare impairment on welfare indicators because SOM can affect these indicators simultaneously. Moreover, the selection of welfare indicator levels are chosen with mathematical reasoning per expert respondent ensuring that the welfare indicator levels with similar welfare impairment weights are properly compared relative to other welfare indicator levels. A relative assessment of SOM welfare impairment on welfare indicator levels contributes to a better understanding of the relative importance of welfare indicators, which in turn provide more informed welfare impairment weights.

Functional impairment was the welfare indicator with highest average relative importance in terms of welfare impairment. Using mobility scores to describe the functional impairment welfare indicator may have subconsciously influenced respondents to select the cow card with the highest mobility score always. Ultimately resulting in an overestimated relative importance and welfare impairment weights. This is because SOM overall is an indicator of poorer welfare (Welfare Quality®, 2009a; Whay & Shearer, 2017) and is described by mobility scores. In other words, the welfare impact in a functional impairment level may have been perceived to be greater than the level itself, leading to an overestimated functional impairment relative importance and welfare impairment weights per functional impairment level. However, if the cow card with the highest mobility score was always chosen, we could expect a 100 percent relative importance for the functional impairment indicator. Our results show the relative importance for functional impairment per respondent ranged between 22 – 56 percent, meaning that other indicator levels were considered to impact animal welfare more than the highest level of functional impairment shown. Respondents may have selected the cow card with the higher functional impairment level more frequently because higher mobility scores are associated with increasing levels of pain (Dyer et al., 2007). These results imply that the subjective experience of pain, a welfare indicator in the mental state domain (Mellor et al., 2020), is an important contributor to impaired animal welfare.

Defining the behavioural change welfare indicator and respective welfare indicator levels apropos SOM for the purpose of the ACA was challenging and may impose a limitation to the ACA. We defined it as a broad welfare indicator to capture all behavioural changes for a cow afflicted with SOM. Behaviour can be expressed as activities performed during an activity-budget and SOM is known to effect behavioural activities in various ways (Navarro et al., 2013; Walker et al., 2010, 2008). Therefore, we considered that a change of x percent in the duration of one activity would lead to a cumulative change of x percent in the duration of all other activities within the activity budget. This description may have influenced the respondents' degree of attention toward the welfare indicator and respective welfare indicator levels ultimately affecting the welfare impairment weights resulting in the lower relative importance of behavioural change. On the other hand, a behavioural change for a cow afflicted with SOM may also benefit animal welfare because the negative effects are compensated for to cope with SOM. Respondents may have considered this lending explanation to the lower relative importance of the welfare indicator because a change in behaviour may not always impair welfare when afflicted with a health disorder.

The distribution of welfare impairment weights per welfare indicator were expected: the weights increased with each increase in welfare indicator level. Using ACA permitted us to link welfare indicator levels to mobility scores per welfare indicator to obtain a welfare disutility per mobility score. This process emulates what is typically done with ACA in economic and marketing research to obtain the utility (respectively: welfare disutility) of a product (mobility score) given a combination of product attribute levels (welfare indicator levels). Resultingly, we found that the welfare disutility was non-linear in increasing mobility scores. By using the welfare impairment weights linked to specific mobility scores as inputs for the simulation model we were able to assess the welfare impact of SOM. A better understanding of the welfare impacts of SOM at MMSC-level over time was realised.

Interestingly MMSC5 on average had the second lowest welfare impact score despite mobility score 5 having the highest welfare disutility (i.e., strongest negative welfare effect). This is because the duration of mobility score 5 during the cases was short on average. Conversely, the longer MMSC3 had the highest welfare impact score despite mobility score 3 having an intermediate welfare disutility. These results imply that disease severity at individual animal-level should be assessed over the duration of the case to assess the welfare impacts because a cross-sectional assessment does not capture the entirety of the welfare impact. Moreover, the total welfare impact at herd-level were largest for MMSC3 SOM cases due to the high frequency in MMSC3 cumulative incidence. In practice, better animal welfare apropos SOM can be achieved at cow- and herd-level if cows with lower mobility scores are detected and treated sooner since they contribute significantly to impaired animal welfare.

The global sensitivity analysis showed interesting results regarding the effects in welfare impairment weights associated with mobility scores 2 and 3 on the total MMSC4 and MMSC5 welfare impact scores at herd-level. The results showed that the uncertainty in welfare impairment weights for mobility scores 2 and 3 outweigh the uncertainty in welfare impairment weights for mobility scores 4 and 5. This means that efforts in understanding the welfare impairment of longer lasting mobility scores 2 and 3 should be prioritised because of the cumulative effect they have on cow welfare under current SOM management.

The welfare impact of SOM per MMSC were calculated based on cow-level mobility scores. However, it could be that a cow has more than one mobility score (i.e., each hoof can be scored individually). Future research should consider the effect of multiple less severe mobility scores at hoof-level compared to a single mobility score at cow-level. Future research should also focus on coping mechanisms associated with mobility scores that reduce the negative welfare impact of a mobility score over time. These coping mechanisms could be represented by dynamic marginal changes in welfare impairment weights. Our simulation model does not include dynamic marginal changes in welfare impairment weights. Including dynamic marginal changes could help attain welfare estimates more representative of "actual welfare" as aggravating or coping mechanisms are captured for each additional day spent with a mobility score. This could be achieved by including a time variable in the adaptive conjoint analysis to obtain a time-adjusted welfare impairment weight.

We focussed on the welfare impact of SOM, without considering the effect on mortality and early culling, therefore forgetting the length of life. Welfare Adjusted Life Years (WALY; Teng et al., 2018) is a metric that takes both into account, where the effect of a health disorder on life years is corrected for. It may be of interest for future studies to combine our approach with the WALY approach to provide additional insight on the life year corrected welfare impact of health disorders.

Our approach can be expanded to quantify the welfare impact of multiple health disorders at the same time. This can be achieved by identifying multiple welfare indicator levels across multiple health disorders. Using ACA welfare impairment weights can be estimated per welfare indicator level irrespective of health disorder. Then the welfare disutility per health disorders per severity can be obtained by linking health disorder severities to corresponding welfare indicator levels, as we did for mobility scores (Table 3.3). Using this elicitation approach to quantify the welfare impact across multiple health disorders, with simulation modelling for example, ensures that the quantified welfare impacts across health disorders and severities are comparable because the underlying welfare impairment weights are elicited relative to each other. Additionally, the comparison of welfare impacts across health disorders and respective severities with simulation modelling makes it possible to evaluate the effects of disease prevention and/or management that can support disease management decisions apropos animal welfare.

3.5 Conclusion

In this research we demonstrate a multi-faceted approach to estimate the welfare effect of a health disorder. The approach consisted of an estimation of the effect of a disorder on welfare indicators in combination with a weighing of these indicators regarding the total welfare. This approach allowed us to quantify the welfare impact of the health disorder on animal welfare given the derived animal welfare weights. Our research shows that ACA is a suitable methodology to elicit expert knowledge to simultaneously evaluate the effect of a health disorder, SOM in this case, on various animal welfare indicators and to obtain the relative importance of welfare indicators and welfare impairment weights per welfare indicator level. This is an advantage of this method because welfare impairment weights per health disorder severity class, mobility scores in this case, can be derived. Our results showed that welfare impairment weights were non-linearly increasing in mobility score severity. Albeit cases of SOM with lower mobility scores had the largest impact on herd-level welfare. This demonstrates the importance of early detection and treatment of lower mobility scores to improve animal welfare and that welfare impacts of different health disorder severities should be assessed over the duration of a case and not only at a cross-sectional level.

3.6 Appendix

Table A 3.1 Mean (5th; 95th percentiles) cumulative incidence, cases/125 cows per year, duration (days), and direct cow-human interactions due to sub-optimal mobility (SOM) per maximum mobility score SOM case (MMSC). Mean results for preceding mobility score.

SOM case	Preceding mobility score(s) in SOM case	Cumulative incidence 125 cows/year [a]	Duration (days)	Cow-human interactions
MMSC2	2	131.60 (107; 153)	90.08 (75; 108)	0.64 (0.30; 1.01)
MMSC3	3	74.77 (54; 97)	115.85 (93; 145)	0.81 (0.41; 1.27)
	2	65.70 (47; 86)	39.34 (24; 57)	0.13 (0.04; 0.23)
MMSC4	4	19.88 (12; 29)	19.79 (15; 25)	1.49 (1.14; 1.85)
	3	17.89 (10; 27)	39.03 (12; 73)	0.21 (0.00; 0.47)
	2	18.33 (11; 27)	58.62 (21; 100)	0.25 (0.05; 0.53)
MMSC5	5	2.21 (1; 5)	5.71 (3; 11)	1.41 (1.00; 2.57)
	4	2.01 (1; 4)	6.19 (1; 15)	0.16 (0.00; 1.00)
	3	2.16 (1; 4)	39.25 (1; 174)	0.23 (0.00; 1.00)
	2	2.11 (1; 5)	70.66 (1; 237)	0.32 (0.00; 1.00)

[a] Cumulative incidence of preceding mobility scores may not match the cumulative incidence of maximum mobility score of the MMSC because some cases may have occurred at the start of the year with the maximum mobility score.

Table A 3.2 First and total order sensitivity indices for herd-level welfare impact scores per Maximum Mobility Score sub-optimal mobility Case (MMSC) apropos MMSC2 and MMSC3.

Parameter[a]	MMSC2		MMSC3	
	First Order	**Total order**	**First Order**	**Total order**
$\beta_{fwi,2}$	0	0	-0.02	0
	(-0.02; 0.03)	(0; 0)	(-0.05; 0.01)	(0; 0)
$\beta_{fwi,3}$	0	0	0.09	0.13
	(-0.02; 0.03)	(0; 0)	(0.06; 0.12)	(0.12; 0.14)
$\beta_{fwi,4}$	0	0	-0.02	0
	(-0.02; 0.03)	(0; 0)	(-0.05; 0.01)	(0; 0)
$\beta_{fwi,5}$	0	0	-0.02	0
	(-0.02; 0.03)	(0; 0)	(-0.05; 0.01)	(0; 0)
$\beta_{fim,2}$	0.59	0.6	-0.02	0.01
	(0.54; 0.64)	(0.55; 0.65)	(-0.04; 0.01)	(0.01; 0.02)
$\beta_{fim,3}$	0	0	0.35	0.36
	(-0.02; 0.03)	(0; 0)	(0.33; 0.38)	(0.34; 0.37)
$\beta_{fim,4}$	0	0	-0.02	0
	(-0.02; 0.03)	(0; 0)	(-0.05; 0.01)	(0; 0)
$\beta_{fim,5}$	0	0	-0.02	0
	(-0.02; 0.03)	(0; 0)	(-0.05; 0.01)	(0; 0)
$\beta_{bcs,2}$	0.38	0.39	-0.01	0.01
	(0.33; 0.44)	(0.34; 0.44)	(-0.04; 0.02)	(0.01; 0.01)
$\beta_{bcs,3}$	0	0	0.23	0.23
	(-0.02; 0.03)	(0; 0)	(0.21; 0.26)	(0.22; 0.25)
$\beta_{bcs,4}$	0	0	-0.02	0
	(-0.02; 0.03)	(0; 0)	(-0.05; 0.01)	(0; 0)
$\beta_{bcs,5}$	0	0	-0.02	0
	(-0.02; 0.03)	(0; 0)	(-0.05; 0.01)	(0; 0)
$\beta_{bch,2}$	0.02	0.01	-0.02	0
	(-0.01; 0.05)	(0.01; 0.02)	(-0.05; 0.01)	(0; 0)
$\beta_{bch,3}$	0	0	0.27	0.26
	(-0.02; 0.03)	(0; 0)	(0.24; 0.29)	(0.25; 0.27)
$\beta_{bch,4}$	0	0	-0.02	0
	(-0.02; 0.03)	(0; 0)	(-0.05; 0.01)	(0; 0)
$\beta_{bch,5}$	0	0	-0.02	0
	(-0.02; 0.03)	(0; 0)	(-0.05; 0.01)	(0; 0)
$\beta_{chi,2}$	0	0	-0.02	0
	(-0.02; 0.03)	(0; 0)	(-0.05; 0.01)	(0; 0)
$\beta_{chi,3}$	0	0	-0.02	0
	(-0.02; 0.03)	(0; 0)	(-0.05; 0.01)	(0; 0)
$\beta_{chi,4}$	0	0	-0.02	0
	(-0.02; 0.03)	(0; 0)	(-0.05; 0.01)	(0; 0)
$\beta_{chi,5}$	0	0	-0.02	0
	(-0.02; 0.03)	(0; 0)	(-0.05; 0.01)	(0; 0)

[a] Welfare impairment parameter $\beta_{j,l}$ for welfare indicator j and mobility score l. Welfare indicator j abbreviations: fwi = feed and water intake; fim = functional impairment; bcs = body condition score; bch = behavioural change; chi = cow human interactions.

Table A 3.3 First and total order sensitivity indices for herd-level welfare impact scores per Maximum Mobility Score sub-optimal mobility Case (MMSC) apropos MMSC4 and MMSC5.

Parameter[a]	MMSC4		MMSC5	
	First Order	**Total order**	**First Order**	**Total order**
$\beta_{fwi,2}$	0	0	0	0
	(-0.02; 0.03)	(0; 0)	(-0.02; 0.03)	(0; 0)
$\beta_{fwi,3}$	0.05	0.06	0.05	0.07
	(0.02; 0.08)	(0.06; 0.06)	(0.03; 0.08)	(0.06; 0.07)
$\beta_{fwi,4}$	0.1	0.1	0.01	0.01
	(0.07; 0.12)	(0.09; 0.1)	(-0.02; 0.04)	(0.01; 0.01)
$\beta_{fwi,5}$	0	0	0.01	0.01
	(-0.02; 0.03)	(0; 0)	(-0.01; 0.04)	(0.01; 0.01)
$\beta_{fim,2}$	0.16	0.19	0.24	0.27
	(0.13; 0.19)	(0.17; 0.2)	(0.21; 0.26)	(0.26; 0.29)
$\beta_{fim,3}$	0.16	0.17	0.19	0.19
	(0.13; 0.19)	(0.16; 0.17)	(0.16; 0.21)	(0.18; 0.2)
$\beta_{fim,4}$	0.07	0.07	0.01	0.01
	(0.04; 0.1)	(0.07; 0.07)	(-0.02; 0.03)	(0.01; 0.01)
$\beta_{fim,5}$	0	0	0.01	0.01
	(-0.02; 0.03)	(0; 0)	(-0.01; 0.04)	(0.01; 0.01)
$\beta_{bcs,2}$	0.12	0.12	0.18	0.18
	(0.09; 0.16)	(0.1; 0.14)	(0.14; 0.22)	(0.15; 0.21)
$\beta_{bcs,3}$	0.12	0.11	0.13	0.12
	(0.09; 0.14)	(0.1; 0.12)	(0.11; 0.16)	(0.12; 0.13)
$\beta_{bcs,4}$	0.04	0.04	0	0
	(0.01; 0.07)	(0.04; 0.05)	(-0.02; 0.03)	(0; 0)
$\beta_{bcs,5}$	0	0	0	0
	(-0.02; 0.03)	(0; 0)	(-0.02; 0.03)	(0; 0)
$\beta_{bch,2}$	0.01	0	0.01	0.01
	(-0.02; 0.04)	(0; 0.01)	(-0.02; 0.04)	(0; 0.01)
$\beta_{bch,3}$	0.13	0.12	0.15	0.14
	(0.11; 0.16)	(0.11; 0.13)	(0.13; 0.18)	(0.13; 0.14)
$\beta_{bch,4}$	0.06	0.05	0.01	0
	(0.03; 0.08)	(0.05; 0.06)	(-0.02; 0.03)	(0; 0)
$\beta_{bch,5}$	0	0	0.01	0
	(-0.02; 0.03)	(0; 0)	(-0.02; 0.03)	(0; 0)
$\beta_{chi,2}$	0	0	0	0
	(-0.02; 0.03)	(0; 0)	(-0.02; 0.03)	(0; 0)
$\beta_{chi,3}$	0	0	0	0
	(-0.02; 0.03)	(0; 0)	(-0.02; 0.03)	(0; 0)
$\beta_{chi,4}$	0	0	0	0
	(-0.02; 0.03)	(0; 0)	(-0.02; 0.03)	(0; 0)
$\beta_{chi,5}$	0	0	0	0
	(-0.02; 0.03)	(0; 0)	(-0.02; 0.03)	(0; 0)

[a] Welfare impairment parameter $\beta_{j,l}$ for welfare indicator j and mobility score l. Welfare indicator j abbreviations: fwi = feed and water intake; fim = functional impairment; bcs = body condition score; bch = behavioural change; chi = cow human interactions.

Chapter 4
The economics of sensor-based management of dairy cow sub-optimal mobility

This chapter is based on: Edwardes, F., van der Voort, M. and Hogeveen, H. (2022). The economics of sensor-based management of dairy cow suboptimal mobility. *Journal of Dairy Science*, 105(12), pp.9682-9701. DOI: https://doi.org/10.3168/jds.2021-21726

Abstract

Sub-optimal 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, while the detection and subsequent treatment of cows with mild SOM is delayed or non-existent resulting in prolonged cases of mild SOM being treated at twice-yearly 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 when 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 bio-economic 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 trade-offs in production losses and additional labour 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. 39 of the 80 simulated scenarios obtained a positive mean net economic sensor effect: the highest was €6,360 per year (€51 per cow per year). Based on evidence from our scenarios we suggest that twice-yearly routine hoof trimming with the addition of automatic SOM detection sensors 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.

4.1 Introduction

Sub-optimal mobility (SOM) 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 & Bewley, 2018). Farmers generally underestimate the economic impact and prevalence of SOM (Bruijnis et al., 2013; Leach et al., 2010) meaning that cows with severe SOM are mostly detected visually and treated shortly afterwards while the detection and subsequent treatment of cows with mild SOM is often delayed (Alawneh et al., 2012a). The associated mild SOM production losses contribute significantly to the total direct cost of SOM (Edwardes et al., 2022a). 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., 2022a).

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 it's 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 (Alsaaod et al., 2019; Schlageter-Tello et al., 2014). Despite the growing body of literature on automatic SOM detection, their detection performance varies, due to difference in algorithms applied for example (Alsaaod et al., 2019; Schlageter-Tello et al., 2014), and only a few of these sensor systems are available in practice. The farmers' willingness to implement these sensors in practice depends, amongst others, on whether their added economic value is clear (Steeneveld & 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. (2017a) 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. (2017a) considered changes in SOM management but not sensor system costs, while 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. It is expected that farmers will need to react to sensor generated alerts more frequently as Steeneveld and Hogeveen (2015) found that many farmers hardly use the output of sensors (i.e., alerts). More frequent reaction to alerts will increase the associated labour costs of SOM management, especially if the performance of an automatic SOM detection sensor is poor. Including the additional opportunity costs of labour to check alerts will provide a better estimate of the economic value apropos automatic SOM detection sensors systems. These labour costs were not considered by Van De Gucht et al. (2017a) 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 apropos automatic SOM detection sensors (Dominiak & 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 labour 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 value 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 bio-economic simulation modelling. A variety of sensor-based SOM management scenarios were simulated. Based on these results, the considerations for future research are discussed.

4.2 Methodology

To quantify the economic value of automatic SOM detection sensors we used a recently developed bio-economic simulation model (Edwardes et al., 2022a). 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 sub-scenarios 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 lastly Sensor classification parametrization.

4.2.1 Simulation model in brief

The developed stochastic, mechanistic, and time-discrete bio-economic simulation model simulates a typical Dutch dairy herd of 125 cows (extensively described in Edwardes et al., 2022a). The model was parameterized for a system where cows have access to pasture for >6 hours 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 [6] at the hoof-level as the underlying mechanisms responsible for the dynamics of SOM expressed at cow-level. Cow mobility is modelled 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 & 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 (O'Connor et al., 2020a) Furthermore, mild forms of SOM are

[6] Eight hoof disorders were included in the model described in Edwardes et al. (2022a). The hoof disorders are: digital dermatitis, interdigital hyperplasia, interdigital dermatitis/heel-horn erosion, interdigital phlegmon, overgrown hoof, sole haemorrhage, sole ulcer, and white-line disease.

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 while cows detected with mobility score 5 are treated by a veterinarian, uniformly distributed 1 – 21 (Alawneh et al., 2012a) and 1 – 3 days after detection, respectively. Treatment efficacy depended on the underlying hoof disorder and agent performing the treatment. All hoof disorders were treated regardless of clinical sign. It was assumed that farmer related treatment was 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 days in total. Cows with SOM are subject to a SOM culling probability per mobility score. Additionally, cows with severe SOM were culled if they required a fourth treatment.

(Re)Production events were: milking, feeding, culling, oestrus detection, insemination, and calving, all simulated in daily time-steps. These (re)production events are affected per mobility score 1 – 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 Tables A 4.1 – A 4.4 of the Appendix.

4.2.2 Model extensions

For brevity of this manuscript, we omit the description of simulation processes already described in Edwardes et al. (2022a). The following sections describe only the model extensions apropos 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 five 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

$$\phi_{i,s,t} = B(1, P_s) \tag{4.1}$$

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.

After the mobility score classification process has run, alerts are generated for the cows classified with SOM as per on the mobility score threshold value for SOM. To limit the number of false alerts that may potentially arise given the performance of the sensor, we imposed a simple alert condition. The condition considers the ratio of total classifications per mobility score per cow to an alert notification interval (1, ..., n days) and a threshold value for the ratio. Between notification intervals mobility scores for each cow are continuously classified and the alert notification interval can be specified for each mobility score. Hence, at each alert notification, interval alerts are generated if

$$\frac{\sum_{a=1}^{n} \alpha_{a,i,s}}{n_s} \geq x_s \tag{4.2}$$

where α is a vector of logical classification outcomes for mobility score s of cow i during an interval of n_s days and x_s is a predefined classification threshold.

If an alert is generated, intervention is prompted. Intervention is described in more detail in Section 4.2.4. Briefly, it is a two-step procedure where an alert is first confirmed by the farmer by setting aside time and visually inspecting the mobility of the identified cows. Second, if the cow is perceived as SOM by the farmer, treatment is performed by either the farmer, hoof trimer or veterinarian.

Economic calculations

We briefly summarize the important economic calculations described in Edwardes et al. (2022a). The respective parameter inputs are found in Table A 4.5 of the Appendix. Refer to Edwardes et al. (2022a) 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 – 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 305d yield production loss per mobility score reported in O'Connor et al. (2020a) and the median duration of a SOM case 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. (2020a) 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 modelled as a function of daily kg FPCM production and expressed as VEM (1 VEM = 1.65 kcal of NE_L; van Es, 1978). Additional VEM were included for cows in parity ≤ 2 and pregnancy stage (Remmelink et al., 2015; Van Es, 1978). The daily cost of VEM per cow was calculated as the product of VEM and price per kVEM.

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 realised 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. (2022a) 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

$$C_i^{(confirm)} = \frac{N(\mu_{confirm}, \sigma_{confirm})}{60} \times C^{(labour)} \tag{4.3}$$

where $C_i^{(confirm)}$ is the alarm confirmation cost for cow i, $\mu_{confirm}$ is the mean alert confirmation duration in minutes, $\sigma_{confirm}$ is the standard deviation of an alarm confirmation duration in minutes and $C^{(labour)}$ is the farmer labor price per hour. We assumed 1 minute for $\mu_{confirm}$, 0.2 minutes for $\sigma_{confirm}$ 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 cow basis using an hourly rate of €47.95 assuming a hoof trimmer can attend to 7 cows per hour (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 (Nedap, 2021; Sleurink, 2018) because few automatic SOM detection sensors are commercially available and Van De Gucht et al. (2017b) 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 €1553.75. This annual sensor cost is composed of an initial investment cost of €110 per unit per cow (Nedap, 2021; Sleurink, 2018), an annual depreciation of the sensor system initial investment cost depreciated over a 10-year useful life, annual maintenance costs at 0.5 percent of the initial investment cost, and sensor replacement costs at a rate of one unit per year.

4.2.3 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-year time horizon were computed. This was obtained with

$$NER_{y,z} = \sum_{i=1}^{125}\sum_{t=1}^{365} R_{i,t,y,z}^{(milk)} - \sum_{i=1}^{125}\sum_{t=1}^{365}\sum_{k\in K} C_{i,t,y,z}^{(k)} - C_{y,z}^{(sensor)} \tag{4.4}$$

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, labour, 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 oestrus, *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, *labour* 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. Lastly, $C_{y,z}^{(sensor)}$ 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):

$$NESE_z = \frac{1}{R}\left(\sum_{r=1}^{R} NER_{r,z} - \sum_{r=1}^{R} NER_{r,0}\right) \tag{4.5}$$

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 top, centre, and bottom 5 percent of the mean net economic result distribution for the 80 sensor scenarios.

4.2.4 Simulation scenarios

Several simulation scenarios were defined (Table 4.1). 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 (Alsaaod 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 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). The farmer perceived alerts generated for cows with mobility score 3 as false because farmers tend to underestimate the prevalence of SOM (Bruijnis et al., 2013; Leach et al., 2010), consequentially leading to cows with mobility scores 4 and 5 being treated. Hence, only severe cases of SOM were treated by the farmer (mobility score 4) or veterinarian (mobility score 5) after detection (Bruijnis et al., 2013; Leach et al., 2010). Different SOM management were introduced in Scenarios 2 – 5. Firstly, 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. This includes treatment of mild SOM, which is prevention of severe SOM, and treatment of severe SOM. Thus, the intensity of treatments was increased where all cows detected with SOM as per the threshold value for SOM classification by the sensor (Scenario 2 – 3: mobility score ≥3; Scenario 4 – 5: mobility score ≥2) were treated. 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. (2022a), was removed.

In addition, sub-scenarios for each Scenario 1 – 5 were simulated. The sub-scenarios included changes in the performance of the sensor in terms of sensitivity and specificity and the ability of the sensor system to distinguish between mild and severe SOM by means of the alert notification interval. For example, a daily notification interval entails that the sensor system cannot 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 between mild and severe SOM. Changes in sensor performance and mild SOM notification intervals respectively occurred at 4 levels. Including mild SOM notification intervals help address trade-offs between alert confirmation costs and additional production losses incurred, considering potential mobility score transitions, during the interval.

A full factorial of 16 sub-scenarios 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.

Table 4.1 Description of simulated scenarios and sub-scenarios.

Aspect	Scenario					
	0[a]	1	2	3	4	5
Sensors on farm	No	Yes	Yes	Yes	Yes	Yes
Mobility score threshold value for SOM	NA	Mobility score ≥3	Mobility score ≥3	Mobility score ≥3	Mobility score ≥2	Mobility score ≥2
Routine hoof trimming at start of pasture and housing period	Yes	Yes	No	No	No	No
SOM cow treated by:						
- Mild SOM[b]	NA	NA	Farmer	Hoof trimmer	Farmer	Hoof trimmer
- Severe SOM[c]	Farmer/ vet.	Farmer/ vet.	Farmer/ vet.	Farmer/ vet.	Farmer/ vet.	Farmer/ vet.
		Sub-scenarios				
Overall sensor performance[d]	NA	a) Sensitivity = 68%; Specificity = 88% b) Sensitivity = 75%; Specificity = 79% c) Sensitivity = 82%; Specificity = 81% d) Sensitivity = 88%; Specificity = 91%				
Notification interval (n) for mild SOM alerts[b]	NA	a) 1 day b) 7 days c) 14 days d) 30 days				

Predefined alert threshold for mobility score (x_s)[e]		$x_3 = 0.5$	$x_{2:3} = 0.5$

[a] Baseline simulation scenario: visual detection as per Edwardes et al. (2022a).
[b] In Scenarios 2 and 3 mild SOM is defined by mobility score 3 and in Scenarios 4 and 5 mild SOM is defined by mobility scores 2 – 3.
[c] Severe cases of SOM with mobility score 5 are treated by the veterinarian.
[d] Mobility score specific classification probabilities are found in Table 4.2.
[e] See Equation 4.2.

4.2.5 Sensitivity analysis

A sensitivity analysis allowed us to assess the sensitivity in mean net economic sensor effect due to changes in the farmer labour and hoof trimmer price per hour. We performed a sensitivity analysis apropos these two parameters because of their economic uncertainty regarding changes in SOM management as per the simulated scenarios previously described.

Farm labour 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 behavioural, 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 & Kahneman, 1992). This idea is encapsulated in the endowment effect (Kahneman et al., 1991). Thus, the labour price to perform SOM related management activities may vary based on the farmers perception towards SOM management, and respective changes in SOM management. Hoof trimmer fee structures may also change due to changes in the frequency of hoof trimmer visits. To account for these uncertainties and the resulting sensitivity in mean net economic sensor effects, the default farm labour 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, centre, and bottom 5 percent selected sub-scenarios.

4.2.6 Sensor classification parameterisation

For sub-scenario (a) apropos the sensor performance, P_s (Eq. 4.1) was directly based on the mobility score classification sensitivity reported in Van Hertem et al. (2016) in their 4-tier mobility confusion matrix as shown in Table 4.2. The weights used in the weighted random sample to simulate incorrect mobility score classifications (i.e., when $\phi_{i,s,t} = 0$) was obtained by setting the diagonals of 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 4.3). 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 – 5 (Table 4.1).

Table 4.2 Sensor mobility score classification probabilities.

Sensor performance sub-scenario	Probability (P_s) of correct mobility score classification				Source
	1	2	3	≥4	
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	

Other than the study by Van Hertem et al. (2016), current literature at the time of publication apropos specific mobility score classification sensitivity does not exist. Thus, we hypothetically set the sensor performance P_s for each mobility score for sub-scenarios (b), (c) and (d) (Table 4.2). In sub-scenarios (b) and (c), P_s were hypothetically set to achieve overall gains in sensitivity and losses in specificity compared with sub-scenario (a); a trade-off apparent in literature (Dominiak & Kristensen, 2017). In sub-scenario (d), P_s was hypothetically set to emulate a sensor with the highest performance in both sensitivity and specificity in comparison to sub-scenarios (a), (b) and (c); in practice high performance in terms of sensitivity and specificity is a desirable sensor feature (Dominiak & Kristensen, 2017; Van De Gucht et al., 2017b). Weights for the weighted random sample of incorrect mobility scores in sub-scenarios (b), (c) and (d) remained as per Table 4.3. Using the hypotheticals set for P_s found in Table 4.2, the number of correct mobility score classifications were calculated in accordance with the row total per observed mobility score in the 4-tier

Table 4.3 Incorrect mobility score classification weights for sub scenarios a, b, c, and d.

Simulated (correct) mobility score	Incorrect classification weights				Source
	1	2	3	≥4	
1	NA	0.95	0.05	0.00	Van Hertem et al. (2016)
2	0.33	NA	0.65	0.02	
3	0.03	0.83	NA	0.15	
≥4	0.01	0.17	0.83	NA	

confusion matrix. The remaining observations not correctly classified were then distributed along the incorrect mobility scores per the weights in Table 4.3. The overall sensor performance was then estimated through a binary scale transformation as described for sub-scenario (a).

4.3 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 sub-scenarios (Figure 4.1). Overall, the mean net economic results for 39 of the 80 simulated sub-scenarios were greater than the mean net economic results for the baseline Scenario 0. Of these 39 simulated sub-scenarios, most were either part of Scenario 3 (16 sub-scenarios), had an alert notification interval of 7 or 14 days for mild SOM (12 sub-scenarios, respectively) or concerned a sensor system with an 88 percent sensitivity and 91 percent specificity (12 sub-scenarios). On the other hand, the 41 sub-scenarios with a mean net economic result lower than the baseline Scenario 0, most were either part of Scenario 1 or Scenario 4 (16 sub-scenarios, respectively), had an alert notification interval of 1 day for mild SOM (14 sub-scenarios) or concerned a sensor system with a 68 percent sensitivity and 88 percent specificity, or a 75 percent sensitivity and 79 percent specificity, or an 82 percent sensitivity and 81 percent specificity (11 sub-scenarios, 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

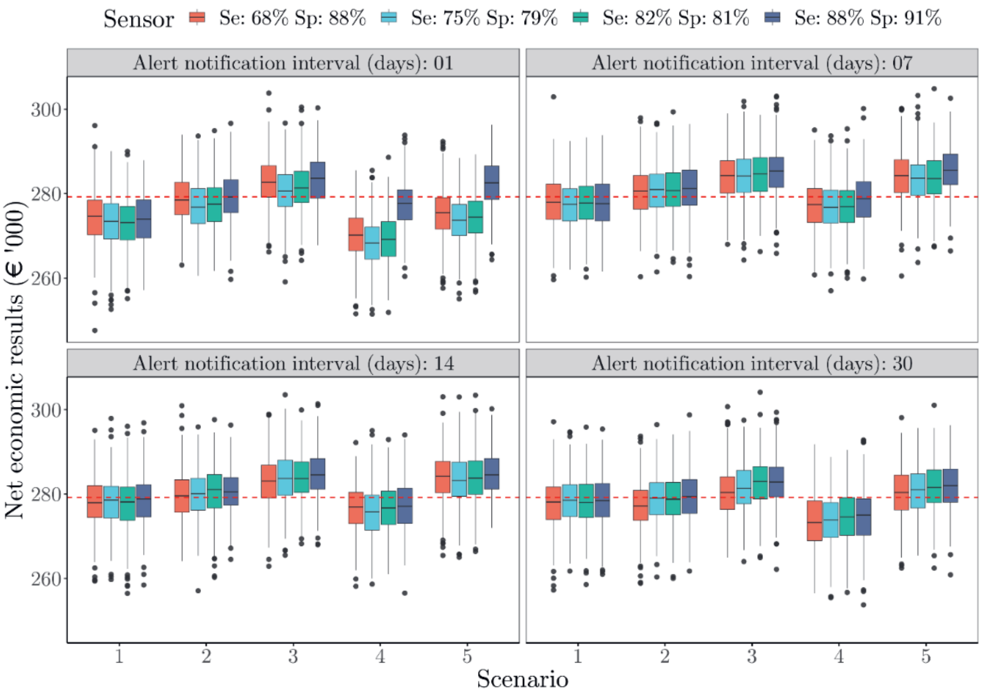


Figure 4.1 Distributions of net economic results for the 80 sensor scenarios (boxplots) separated by alert notification intervals (panels) and coloured by sensor performance. The horizontal red dashed line represents the mean net economic results for the baseline without sensor scenario. Scenarios on the x-axis refer to SOM management alterations (see Table 4.1 for details on Scenarios).

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 day to 7 days showed an increase in mean net economic results for all Scenarios 1 – 5 respective of the sensor performance. A notification interval of 7 days for mild SOM resulted in the highest mean net economic result for most Scenarios 1 – 5 respective of sensor performance. Compared to the sensor with a 68 percent sensitivity and 88 percent 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 percent sensitivity and 79 percent specificity or 82 percent sensitivity and 81 percent 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 days for mild SOM.

The composition of mean net economic results for the 12 selected sub-scenarios – including the baseline Scenario 0 – are shown in Table 4.4 (top 5 percent), Table 4.5 (centre 5 percent), and Table 4.6 (bottom 5 percent). Sub-scenarios in the top 5 percent 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 threshold value for SOM classification by the sensor, after an alert for cows requiring treatment for mild SOM was generated every 7 or 14 days. On the other hand, sub-scenarios in the bottom 5 percent 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 percent and Sp: 91 percent) were included in 3 of the 4 top 5 percent selected sub-scenarios. No other observable commonality with respect to sensor performance was clear in the 12 selected sub-scenarios. To illustrate the differences between the economic factors in the 12 selected sensor sub-scenarios in contrast to the without sensor scenario a graphical representation of the mean absolute changes in the economic factors are shown in Figure 4.2 with the mean net economic sensor effect in the top-right corner of each sub-scenario panel. The mean net economic sensor effect was positive for all top 5 percent selected scenario. In the centre 5 percent selected scenarios, 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 percent selected sub-scenarios. Similar reductions in the milk production loss and culling costs were observed in the centre 5 percent selected sub-scenarios. But these reductions were offset by the increase in labour costs due to increased labour time required to treat cows with SOM and/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 percent of selected sensor sub-scenarios. This was largely due to the high costs incurred for confirming alerts daily. This especially held for scenarios when the 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 percent sub-scenarios being similar to those observed in the top 5 percent performing sub-scenarios.

Table 4.4 Composition of net economic results in €'000 for top 5 percent selected scenarios (5th and 95th percentiles shown in parenthesis).

Scenario	0	5	3	5	3
Sensor performance[a]					
Sensitivity	-	88%	88%	88%	82%
Specificity		91%	91%	91%	81%
Alert (days)[a]	-	7	7	14	7
Returns					
Gross milk returns	388.9 (381.29; 396.37)	389.57 (382.08; 396.71)	389.67 (382.09; 397.65)	389.46 (382.22; 396.44)	389.59 (383; 397.04)
Costs					
Milk production loss	4.3 (2.94; 5.79)	0.3 (0.17; 0.44)	0.55 (0.32; 0.84)	0.65 (0.41; 0.91)	0.58 (0.35; 0.85)
Discarded milk	0.91 (0.55; 1.32)	1.08 (0.67; 1.48)	0.57 (0.31; 0.88)	1.05 (0.68; 1.53)	0.58 (0.27; 0.9)
Inseminations	2.67 (2.43; 2.9)	2.65 (2.4; 2.9)	2.58 (2.35; 2.83)	2.65 (2.4; 2.89)	2.61 (2.36; 2.85)
Feed	78.06 (77.54; 78.62)	78.6 (78.08; 79.11)	78.48 (77.95; 79.04)	78.55 (78.04; 79.1)	78.48 (77.99; 79.03)
Culling	21.41 (15.44; 27.52)	16.21 (10.71; 22.02)	18.38 (13.15; 24.5)	16.75 (11.97; 21.93)	18.61 (12.79; 24.36)
Treatment labour	0.24 (0.12; 0.37)	0.19 (0.08; 0.33)	0.28 (0.13; 0.47)	0.26 (0.12; 0.43)	0.27 (0.13; 0.46)
Alert confirmation labour	0 (0; 0)	0.26 (0.17; 0.37)	0.17 (0.13; 0.2)	0.23 (0.13; 0.32)	0.41 (0.35; 0.46)
Hoof trimmer	1.7 (0.88; 2.65)	2.94 (2.04; 3.96)	1.37 (1.03; 1.73)	2.57 (1.59; 3.54)	1.37 (1.06; 1.7)
Veterinarian	0.24 (0; 0.69)	0.1 (0; 0.36)	0.2 (0; 0.51)	0.15 (0; 0.47)	0.2 (0; 0.55)
Treatments	0.16 (0.05; 0.35)	0.12 (0.03; 0.29)	0.39 (0.08; 0.89)	0.31 (0.06; 0.91)	0.39 (0.09; 0.89)
Sensor (fixed cost)	0 (0; 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)
Total costs	109.7 (103.19; 115.93)	104 (98.35; 109.74)	104.53 (98.99; 110.88)	104.72 (99.35; 110.03)	105.05 (99.3; 110.82)
Net economic result	279.21 (270.13; 289.58)	285.57 (276.45; 293.64)	285.14 (276.07; 294.28)	284.74 (276.4; 293.28)	284.54 (275.12; 294.03)

[a] Alert notification interval (days)

Table 4.5 Composition of net economic results in €'000 for centre 5 percent selected scenarios (5th and 95th percentiles shown in parenthesis).

Scenario	0	2	2	2	2
Sensor performance					
Sensitivity	-	88%	75%	82%	68%
Specificity		91%	79%	81%	88%
Alert (days)[a]	-	1	30	30	1
Returns					
Gross milk returns	388.9 (381.29; 396.37)	389.32 (381.95; 396.81)	389 (381.19; 396.76)	388.94 (381.72; 396.49)	389.37 (382.23; 397.29)
Costs					
Milk production loss	4.3 (2.94; 5.79)	0.15 (0.08; 0.25)	2.23 (1.55; 3)	1.79 (1.23; 2.39)	0.19 (0.1; 0.3)
Discarded milk	0.91 (0.55; 1.32)	0.57 (0.31; 0.89)	0.53 (0.29; 0.82)	0.54 (0.27; 0.85)	0.55 (0.27; 0.85)
Inseminations	2.67 (2.43; 2.9)	2.59 (2.34; 2.83)	2.61 (2.36; 2.84)	2.6 (2.36; 2.84)	2.58 (2.35; 2.83)
Feed	78.06 (77.54; 78.62)	78.5 (77.95; 79.05)	78.26 (77.71; 78.8)	78.31 (77.78; 78.86)	78.49 (77.97; 79.07)
Culling	21.41 (15.44; 27.52)	18.38 (12.92; 24.17)	19.44 (13.95; 25.73)	19.57 (13.93; 25.29)	18.3 (12.61; 24.06)
Treatment labour	0.24 (0.12; 0.37)	1.36 (0.83; 1.98)	1 (0.66; 1.37)	1.09 (0.72; 1.51)	1.34 (0.83; 1.99)
Alert confirmation labour	0 (0; 0)	2.3 (2.04; 2.53)	0.39 (0.33; 0.47)	0.3 (0.25; 0.36)	2.99 (2.7; 3.25)
Hoof trimmer	1.7 (0.88; 2.65)	0 (0; 0)	0 (0; 0)	0 (0; 0)	0 (0; 0)
Veterinarian	0.24 (0; 0.69)	1.21 (0.56; 1.91)	1.14 (0.57; 1.75)	1.19 (0.68; 1.82)	1.21 (0.61; 1.93)
Treatments	0.16 (0.05; 0.35)	3.32 (1.87; 4.97)	2.97 (1.69; 4.34)	3.17 (1.94; 4.68)	3.32 (1.93; 5)
Sensor (fixed cost)	0 (0; 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)
Total costs	109.7 (103.19; 115.93)	109.93 (104.28; 116.01)	110.13 (104.12; 116.28)	110.11 (104.56; 115.89)	110.54 (104.88; 117.04)
Net economic result	279.21 (270.13; 289.58)	279.4 (270.26; 289.26)	278.86 (269.06; 287.93)	278.84 (269.48; 288.76)	278.83 (270.35; 287.69)

[a] Alert notification interval (days)

Table 4.6 Composition of net economic results in €'000 for bottom 5 percent selected scenarios (5th and 95th percentiles shown in parenthesis).

Scenario	0	1	4	4	4
Sensor performance					
Sensitivity	-	82%	68%	82%	75%
Specificity		81%	88%	81%	79%
Alert (days)[a]	-	1	1	1	1
Returns					
Gross milk returns	388.9 (381.29; 396.37)	388.24 (380.06; 395.36)	389.56 (381.75; 397.02)	389.42 (382.53; 397)	389.61 (381.32; 397.41)
Costs					
Milk production loss	4.3 (2.94; 5.79)	2.83 (1.82; 3.82)	0.02 (0; 0.05)	0.02 (0; 0.05)	0.02 (0; 0.05)
Discarded milk	0.91 (0.55; 1.32)	0.95 (0.59; 1.37)	1.03 (0.68; 1.41)	1.05 (0.71; 1.45)	1.02 (0.64; 1.44)
Inseminations	2.67 (2.43; 2.9)	2.66 (2.4; 2.89)	2.66 (2.42; 2.92)	2.67 (2.44; 2.9)	2.66 (2.4; 2.89)
Feed	78.06 (77.54; 78.62)	78.19 (77.58; 78.73)	78.61 (78.06; 79.19)	78.6 (78.06; 79.15)	78.62 (78.07; 79.17)
Culling	21.41 (15.44; 27.52)	20.72 (14.69; 27.12)	16.26 (11.43; 21.48)	16.23 (10.99; 22.43)	16.18 (11.27; 21.71)
Treatment labour	0.24 (0.12; 0.37)	0.29 (0.15; 0.44)	2.31 (1.67; 3.16)	2.34 (1.69; 3.24)	2.32 (1.68; 3.22)
Alert confirmation labour	0 (0; 0)	5.53 (4.11; 6.83)	10.72 (10.62; 10.81)	11.59 (11.49; 11.68)	12.72 (12.62; 12.82)
Hoof trimmer	1.7 (0.88; 2.65)	1.74 (0.88; 2.65)	0 (0; 0)	0 (0; 0)	0 (0; 0)
Veterinarian	0.24 (0; 0.69)	0.24 (0; 0.62)	1.5 (0.93; 2.05)	1.46 (0.98; 1.94)	1.52 (1.01; 2.11)
Treatments	0.16 (0.05; 0.35)	0.53 (0.1; 1.25)	4.73 (3.27; 6.21)	4.65 (3.37; 5.94)	4.78 (3.45; 6.25)
Sensor (fixed cost)	0 (0; 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)
Total costs	109.7 (103.19; 115.93)	115.24 (108.46; 122.2)	119.38 (113.65; 125.52)	120.17 (114.41; 126.51)	121.4 (116; 127.29)
Net economic result	279.21 (270.13; 289.58)	272.98 (262.75; 282.26)	270.18 (260.49; 279.21)	269.26 (259.51; 278.8)	268.21 (257.96; 277.77)

[a] Alert notification interval (days)

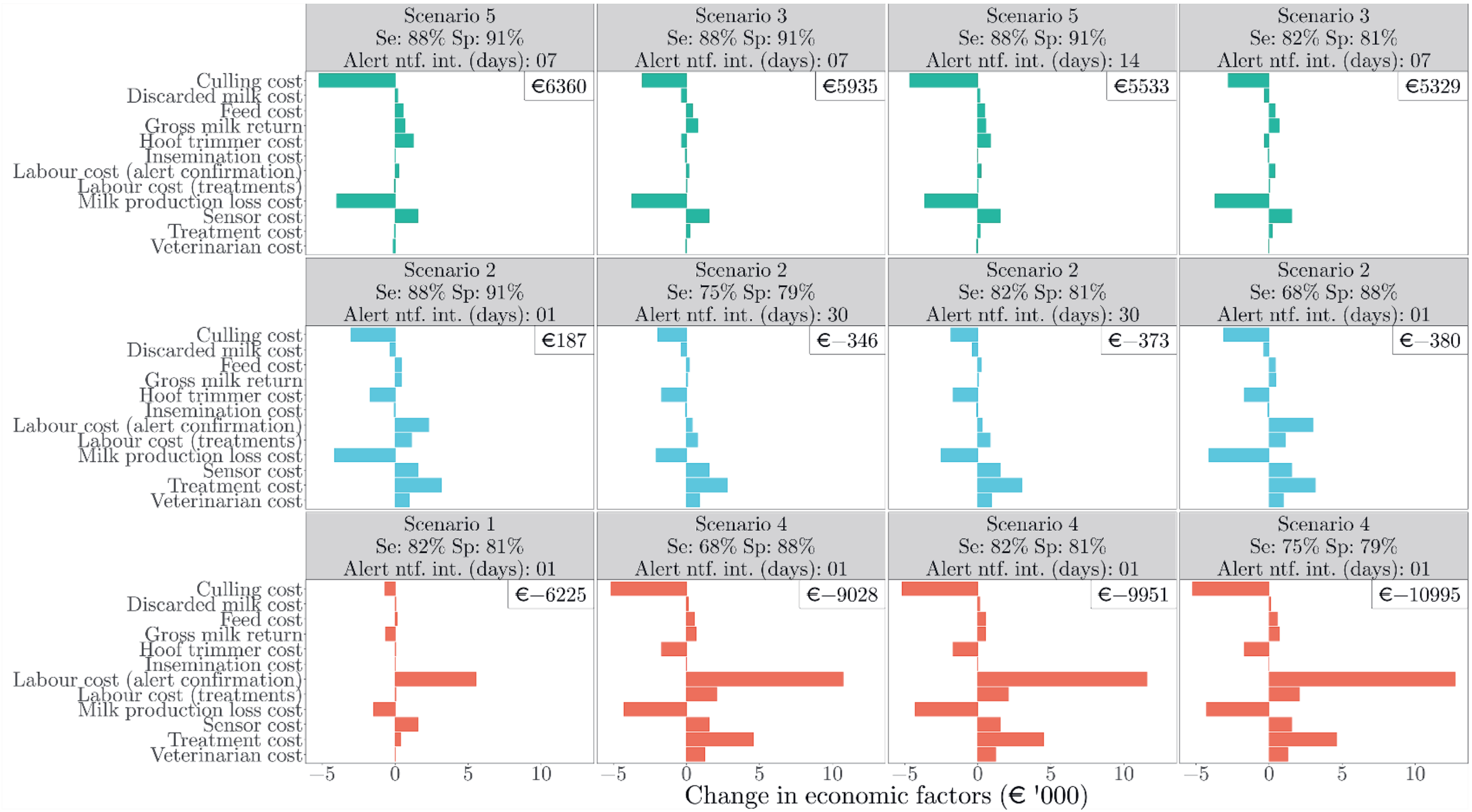


Figure 4.2 Absolute change in mean economic factors. The top (green), centre (blue) and bottom (red) row of panels respectively correspond to the scenarios selected in the top, centre, and bottom 5 percent of the mean net economic results. Economic factors are plotted on the y-axis and the mean absolute change in the economic factors are plotted on the x-axis. The mean net economic sensor effect is labelled in the top right-hand corner of each plot.

Results from the sensitivity analysis showed that the mean net economic sensor effect remained positive due to changes in the farm labour and hoof trimmer price per hour in the top 5 percent sub-scenarios (Figure 4.3). The mean net economic sensor effects were more sensitive to changes in the hoof trimmer price per hour compared to changes in the farm labour price per hour, especially for sub-scenarios in Scenario 5. The mean net economic sensor effect for sub-scenarios in the centre 5 percent were positive with a €10 reduction in the labour price. The mean net economic sensor effect for sub-scenario in the bottom 5 percent remained negative across all changes in the farm labour price.

The mean total number of alerts generated during the year varied considerably between the 12 selected sub-scenarios (Table 4.7). The highest number of alerts were generated in sub-scenarios from the bottom 5 percent where on average >98 percent of the alerts generated were false. Sub-scenarios from the bottom 5 percent all had a daily alert notification interval for cows with mild SOM and 3 of the 4 sub-scenarios included mobility score 2 as a threshold value for SOM (Scenario 4). Increasing the notification interval from 1 to either 7, 14 or 30 days for mild SOM reduced the mean total number of generated alerts considerably. The fewest number of mean alerts was generated in the sub-scenario for a sensor with a 30-day alert notification interval and, 82 percent sensitivity and 81 percent specificity. Increasing the alert notification alert intervals from 1 day also reduced the false alert rate. False alert rates were on average >40 percent 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 percent sensitivity and 91 percent specificity.

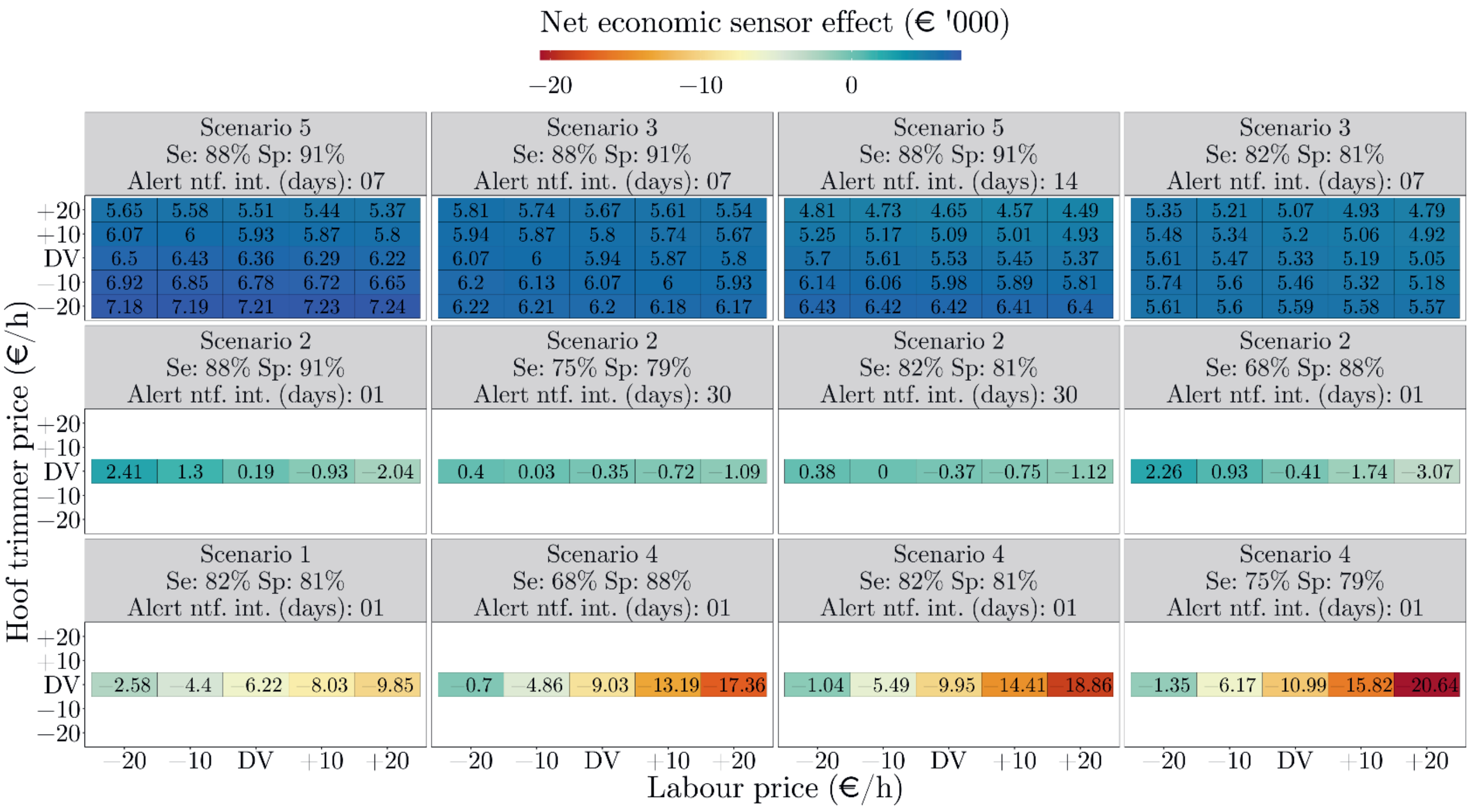


Figure 4.3 Sensitivity in mean net economic sensor effect due to changes in default values (DV) for labour and hoof trimmer price per hour. DV were €30.70 and €47.95 for labour and hoof trimmer price per hour, respectively. Hoof trimmer prices were not adjusted in Scenarios 1, 2, ad 4 because changes in hoof trimming frequency did not occur in Scenario 1 and hoof trimming did not occur in Scenarios 2 and 4. Values rounded to 2 decimal places.

Table 4.7 Number of alerts during the year for the 12 selected sub-scenarios. Sub-scenarios are ordered by net economic results in descending order. Centre 5 percent scenarios are shown in shaded rows.

Simulated scenario details			Mean total yearly alerts[a] (5th and 95th percentiles)		Mean alert rate per alert notification[a,b] (5th and 95th percentiles)	
Scenario	Sensitivity; Specificity	Alert (days)	TRUE	FALSE	TRUE	FALSE
5	88%; 91%	7	316 (188; 464)	184 (126; 252)	6.1 (3.6; 8.9)	3.5 (2.4; 4.8)
3	88%; 91%	7	115 (77; 160)	194 (162; 225)	2.2 (1.5; 3.1)	3.7 (3.1; 4.3)
5	88%; 91%	14	335 (187; 481)	61 (41; 82)	12.9 (7.2; 18.5)	2.3 (1.6; 3.2)
3	82%; 81%	7	115 (78; 156)	649 (563; 730)	2.2 (1.5; 3)	12.5 (10.8; 14)
2	88%; 91%	1	119 (75; 170)	4370 (3890; 4814)	0.3 (0.2; 0.5)	12 (10.7; 13.2)
2	75%; 79%	30	83 (58; 113)	334 (290; 378)	6.9 (4.8; 9.4)	27.8 (24.2; 31.5)
2	82%; 81%	30	92 (62; 124)	301 (258; 342)	7.7 (5.2; 10.3)	25 (21.5; 28.5)
2	68%; 88%	1	117 (73; 171)	5732 (5160; 6229)	0.3 (0.2; 0.5)	15.7 (14.1; 17.1)
1	82%; 81%	1	29 (14; 44)	10778 (8033; 13340)	0.1 (0; 0.1)	29.5 (22; 36.5)
4	68%; 88%	1	234 (169; 317)	20719 (20496; 20933)	0.6 (0.5; 0.9)	56.8 (56.2; 57.4)
4	82%; 81%	1	236 (172; 326)	22406 (22191; 22604)	0.6 (0.5; 0.9)	61.4 (60.8; 61.9)
4	75%; 79%	1	235 (171; 327)	24630 (24398; 24855)	0.6 (0.5; 0.9)	67.5 (66.8; 68.1)

[a] Values rounded to the nearest whole number.
[b] Mean alert rate is the average number of alerts (either true or false) expected at every time an alert is generated.

We report 1 sub-scenario from each Scenario 1– 5 to demonstrate the effect that changes in SOM management, in terms of increasing treatment intensity, apropos the use of sensors have on yearly mobility score prevalence trends in contrast to SOM management without sensors (Figure 4.4). Scenario 0 illustrates the trend apropos

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 like the prevalence trend for the same mobility scores compared to 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 days for these cow (Scenario 3) compared with when the farmer treated cows with a mobility score 3 after an alert was generated every 30 day 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 threshold value for SOM classification by the sensor (mobility score 3). Including mobility score 2 in the 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 percent 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 days) 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 day) in Scenario 4.

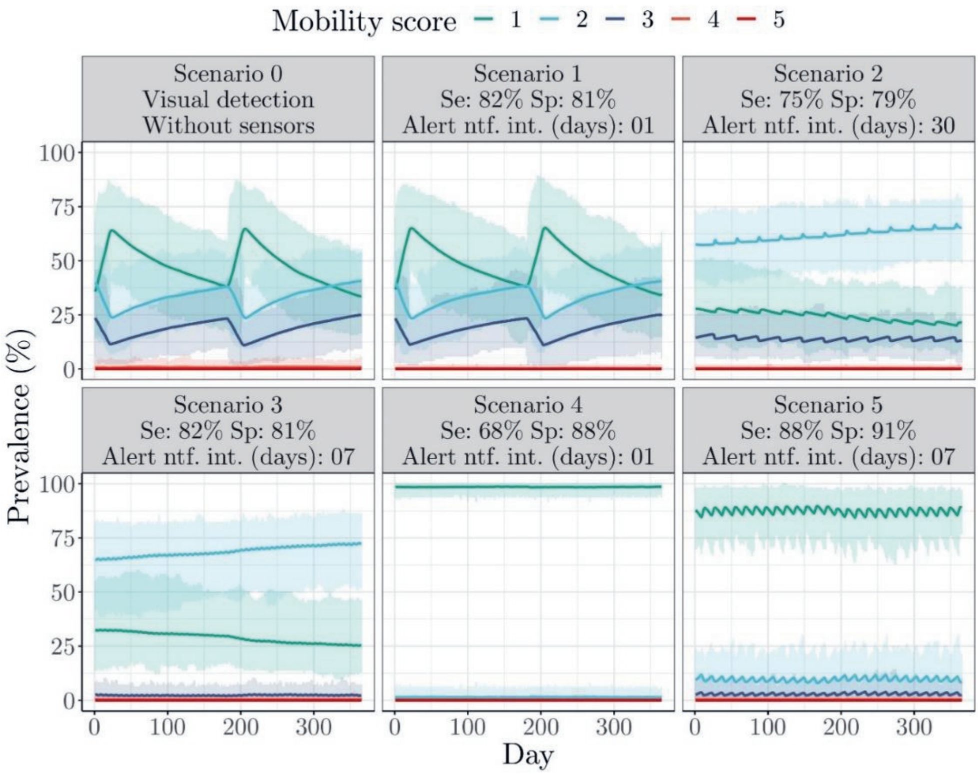


Figure 4.4 Daily mobility score prevalence. Mean daily prevalence is illustrated by the solid-coloured lines. Variation in mobility score prevalence between the 500 replications is illustrated by the shaded areas. Panels are ordered from top left to bottom right by increasing Scenario as per an increase in treatment intensity.

4.4 Discussion

In light of the automatic SOM detection sensor systems that are documented in the literature (Alsaaod et al., 2019; Schlageter-Tello et al., 2014), 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 since differences within other important economic factors such as SOM prevalence, automatic SOM detection sensor cost and type were excluded (Kaniyamattam et al., 2020; Van De Gucht et al., 2017a). Including different sensor types may have been of interest since farmers have shown preferences for different sensor types (Van De Gucht et al., 2017b). We opted for a sensor type that farmers show greatest preference for (Van De Gucht et al., 2017b). However, the scenarios apropos different sensor performance can represent different sensor types (Alsaaod et al., 2019; Schlageter-Tello et al., 2014).

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 (Kaniyamattam et al., 2020; Van De Gucht et al., 2017a). We designed management scenarios that went beyond current SOM management, trying to bring out the full potential of sensor-based SOM management. The most favourable scenario, Scenario 5 for a sensor with a sensitivity of 88 percent and specificity of 91 percent and a 7-day alert notification interval, obtained a mean net economic sensor effect of €6,360. The least favourable scenario, Scenario 4 for a sensor with a sensitivity of 75 percent and specificity of 79 percent and a daily alert notification interval, obtained a mean net economic sensor effect of €-10,995.

Implementing automatic SOM detection sensor systems to be used in addition to current SOM management, i.e., twice-yearly routine hoof trimming, did not obtain any additional economic value. A change in SOM management is required to obtain their economic value. By 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 percent and 100 percent, respectively. This is because the costs concerning mild SOM, which contribute to a large share of the overall SOM costs (Edwardes et al., 2022a), 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 labour 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, allows for a more precise resource allocation and as such greater economic value in the sensors can be obtained. This is in contrast to Van De Gucht et al. (2017a) who showed that the economic value for automatic SOM detection sensors was greater when only the farmer performs treatments. This is because results from our study show that farmer related treatment and labour costs are more expensive than the hoof trimmer costs.

The labour 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 apropos the 12 selected sub-scenarios showed that the mean net economic sensor effects were more sensitive to changes in the labour price when more labour 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 apropos 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 like in the top 5 percent sub-scenarios will remain economically positive due to changes in the hoof trimmer price per hour. Farm personal may also be required more often during hoof trimmer visits to assist the hoof trimmer, which would incur additional labour related costs. Our scenarios did not include additional farm labour assistance. Inferring additional labour related assistance costs through increasing labour prices per hour coupled with hoof trimming, as in the sensitivity analysis, showed that increased labour 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 apropos sensor-based SOM management. It would also be interesting to compare sensor-based SOM management scenarios with scenarios that address farmer training apropos SOM awareness and intervention in the absence of automatic SOM detection sensors.

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 (Alawneh et al., 2012a; Bruijnis et al., 2013; Leach et al., 2010), alerts may be checked but treatment is ignored 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 is false (Eckelkamp & Bewley, 2020). Besides, over time some farmers may completely ignore alerts as they become familiar with the sensor system (Eckelkamp & Bewley, 2020).

It is crucial to maintain farmer confidence in sensors by conveying the correct information and avoid an altogether disregard of alerts over time (Eckelkamp & 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) to obtain predictive performance of binary outcomes (i.e., 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 towards 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 prevalence. Future research apropos 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. 4.2) in the form of notification intervals respective of SOM severity. Notification intervals of 7, 14 or 30 days for cases of mild SOM reduced the total number of false alerts generated through-out 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 day obtained greater economic benefits compared to daily notification intervals because trade-offs in intervention related costs were greater than the additional production losses, considering potential mobility score transitions, during the notification intervals (i.e., Figure 4.2). Within sensor performance scenarios, optimal economic results were most often obtained with a notification interval of 7 days. For example, the mean net economic sensor effect was €1,212 for a 7-day notification interval compared to €−372 for a daily notification interval for a sensor with 68 percent sensitivity and 88 percent specificity in Scenario 2. A notification interval of 7 days 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-day interval. Despite a 7-day 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., 2017b).

Automatic SOM detection sensors generally do not consider mobility score 2 as a 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 since farm labour 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. Although more alerts were generated, the additional associated costs were outweighed by a reduction in culling costs since 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., 2022a). 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 apropos sensors is the increased level of animal welfare that can be achieved through their use (Buller et al., 2020; Hogeveen & van der Voort, 2021; Manning et al., 2021; Schlageter-Tello et al., 2014; van Erp-van der & Rutter, 2020). SOM prevalence is often used as a welfare indicator in welfare assessments (Welfare Quality® (2009a)). Using similar indicators from our simulation scenario results, we observed reductions in SOM prevalence in all the scenarios that included a management shift (Figure 4.4). This demonstrates that improvement of animal welfare with sensors is 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.

4.5 Conclusion

We extended a recently developed bio-economic 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 since 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 roll-out is important because the results were very sensitive to the sensitivity and specificity of the sensors, especially apropos mobility score specific sensitivities and specificities and changing mobility score distributions.

4.6 Appendix

Table A 4.1 Lactation parameters.

Parameter	Description	Value	Source
a	Factors responsible for shape of lactation curve		Kok et al. (2017)
Parity 1		31.6	
Parity 2		40.6	
Parity ≥3		44.1	
b			
Parity 1		−0.0447	
Parity 2		−0.0708	
Parity ≥3		−0.0835	
c		−16.1	
k		0.06	
$M_s^{(loss)}$	Proportional daily milk loss per mobility score s		Based on O'Connor et al. (2020a)
Mobility score 1		0	
Mobility score 2		0	
Mobility score 3		0.05	
Mobility score 4		0.48	
Mobility score 5		0.53	

Note: Daily lactation was modelled using the Wilmink lactation curve with general form $y = a + b \times DIM + c \times \exp(-k \times DIM)$ where DIM is day in milk (Wilmink, 1987). Individual cow variation in daily milk production was accounted for with $y + \bar{y} \times RPL$ where $\bar{y}$ is the average 305d daily lactation and RPL is an individual cow's relative production level modelled as $N(0, 0.1)$ (Edwardes et al., 2022a; Kok et al., 2017).

Table A 4.2 Fertility and reproduction parameters.

Parameter	Description	Value	Source
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 oestrus	Days to first calving postpartum		Authors' expertise
Primiparous		14 – 27	
Multiparous		18 – 21	
Following oestrus	Days to following oestrus	21	Authors' expertise
Oestrus detection	Base risk of oestrus detection	0.55	Based on Rutten et al. (2014)
Adjusted oestrus detection	Relative risk of oestrus 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 – ≥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. ≥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 scores 3 – 5	PERT(0.41, 0.78, 0.88)

Table A 4.3 Energy requirements (VEM) parameters.

Parameter	Description	Value	Source
Growth	Daily growth energy requirements for parity ≤2 cows		van Es (1978)
Parity 1		660	
Parity 2		330	
Months pre-partum	Daily energy requirements for pregnant cows from 4 to last month before calving		Remmelink et al. (2015)
4		450	
3		850	
2		1500	
1		2700	

Table A 4.4 Culling parameters.

Parameter	Description	Value	Source
General culling	Daily general culling probability for		Calibrated input
Parity 1	parity 1 - ≥5 cows	2.74e-5	
Parity 2		6.85e-5	
Parity 3		6.85e-5	
Parity 4		2.74e-4	
Parity ≥5		5.48e-4	
Yield threshold	Daily milk yield threshold (kg) for cows culled due to infertility	15	Authors expertise
Adjusted culling (mobility scores)	Relative risk of culling per mobility score for cows with mobility score		O'Connor et al. (2020a)
Mobility score 2	>1[b]	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 >1[a]		Walker et al. (2008a)
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		Booth et al. (2004)
≤20%	cows with mobility score >1[b]	1	
21 – 40%		0.34	
41 – 60%		0.24	
61 – 80%		0.16	
>80%		0.06	

[a] General culling probability per parity was taken as base risk.

Table A 4.5 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 labour (€/h)	30.70	Blanken et al. (2017)
Hoof trimmer hourly rate[a]	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 disorder[b] SH; SU; WLD IP; IDHE DD OH HYP[c]	Additional treatment costs (€) per disorder per hoof applied by either veterinarian or farmer	 8.1 0.6 2.61 0 182.02[d]; 0[e]	Expertise
Rearing costs	Rearing costs per replacement heifer (€/heifer)	PERT(919, 1790, 3307)	Mohd Nor et al. (2015)
Carcass dressing	Carcass dressing as factor of live body weight for culled cow	0.6	Rutten et al. (2014)

Meat price	Average monthly meat price (€/kg) discretely 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	Author's expertise

[a] The hoof trimer hourly rate includes hoof disorder treatment costs as in Edwardes et al. (2022a).

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

[c] Only 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.

[d] Veterinarian treatment costs.

[e] Farmer treatment costs.

Chapter 5
Quantifying the economic and animal welfare trade-offs of classification models in precision livestock farming for sub-optimal mobility management

This chapter is based on: Edwardes, F., van der Voort, M. and Hogeveen, H. (2023). Quantifying the economic and animal welfare trade-offs of classification models in precision livestock farming for sub-optimal mobility management. *Computers and Electronics in Agriculture* (revised and resubmitted).

Abstract

Animal health disorders, such as sub-optimal mobility (SOM; mobility score 1 = perfect mobility and mobility score 5 = severely impaired mobility) in dairy farming, have significant economic and welfare consequences in animal husbandry. Precision livestock farming (PLF) offers a technology-based management approach with the potential gains such as efficient and cost-effective monitoring of animal health thereby also enhancing animal welfare. The quality of these technologies lies in the performance of the underlying diagnostic test that produces diagnostic marker values used to classify cows into SOM classes. To classify cows to one SOM class, cut-off threshold values are used, which results in probabilities for correct and incorrect SOM classification (i.e., classification outcomes). However, changing these cut-off threshold value may influence the economic and welfare outcomes depending on the diagnostic test built into sensor. In addition, SOM is often classified as a binary health disorder while SOM is not binary. Using PLF technology that classifies SOM into more than two classes may be more economically and welfare beneficial. However, additional classification classes increase the complexity in deciding on appropriate cut-off threshold values for the various SOM classes as the classification outcomes are highly interactive. In this study we assess whether economic and welfare gains can be achieved with 3-class SOM classifiers. Moreover, we quantify the trade-offs in classification outcomes as cut-off threshold values are varied and how these trade-offs affect the economic and welfare gains. Eight classifiers each with 600 different classification outcomes were defined for SOM classification and management. Mobility scores were grouped into various SOM classes depending on the classifier. A bio-economic simulation model was used to simulate the economic and welfare effects of the various classifiers and respective classification outcomes. The simulated output data was first analysed using an exploratory approach to explore the general effects of classifiers and classification outcomes on economic and welfare. Second, a novel method accounting for the highly interactive classification outcomes was developed to quantify the trade-offs in classification outcomes and how these trade-offs affected the economic and welfare gains. All tested classifiers showed economic and welfare gains on average. Classifiers with larger separation between non-SOM and SOM classes showed the highest economic gains. Including mobility score 2 into a SOM class showed meaningful welfare gains on average as opposed to when mobility score 2 was included in a non-SOM class. Larger increases in economic gains were often achieved at the cost of smaller reductions in welfare gains with trade-offs in classification outcomes. This study provides valuable insights on designing appropriate 3-class SOM classifiers that could also be beneficial when designing classifiers for health disorders other than SOM. This study also demonstrates the value in using simulation models to test classifiers by highlighting interesting classification outcomes that can be further validated in practice.

5.1 Introduction

Animal health disorders pose significant economic and welfare consequences in animal husbandry (Hennessy & Marsh, 2021; Rushton, 2009). To overcome these consequences, it is crucial to improve the detection and management of health disorders. However, traditional labour-based approaches for detecting animal health disorders are often time-consuming that may result in high opportunity costs as other important farming activities, such as oestrus detection and subsequent artificial inseminations, could be potentially ignored as a result.

Precision livestock farming (PLF) offers a promising solution to this problem. PLF is a technology-based approach that involves continuous and autonomous monitoring of animals, generating specific information per animal that farmers can use for animal health decision-making (Berckmans, 2017). By using advanced technologies such as sensors and statistical models, PLF technology collects and processes data from individual animals to generate animal specific information, enabling farmers the potential to monitor animal health more efficiently and cost-effectively (Banhazi et al., 2012; Wathes, 2009).

In terms of animal health, PLF technology serves as a diagnostic test that classifies animals into various health classes based on the collected and processed data. The added value of the PLF technology is influenced by the quality of generated classification information (Rojo-Gimeno et al., 2019). The quality of classification is often assessed in terms of sensitivity and specificity (Dominiak & Kristensen, 2017). Sensitivity refers to the probability of correctly classifying animals to the class of interest (i.e., sick), and specificity refers to the probability of correctly classifying animals to the alternative class (i.e., healthy) when compared to a golden standard of health classes. High sensitivity and specificity are essential for reducing misclassifications. This is important to farmers (Van De Gucht et al., 2017b), because the misclassifications may incur unnecessary costs. For example, a sick animal that is misclassified as healthy may incur prolonged production losses whereas a healthy animal misclassified as sick may incur unnecessary intervention costs.

However, achieving high sensitivity may come at the cost of lowering specificity because a cut-off threshold is required to separate the distributions of diagnostic marker values generated by the diagnostic test into the healthy and sick classes (Flach, 2016). Furthermore, sensitivity and specificity are applicable to binary classification problems whereas health disorders in animals are often not binary, such as sub-optimal mobility (SOM) in dairy cows, which can be described by multiple classes (Sprecher et al., 1997).

SOM is a common health disorder in dairy cows that has negative economic (Dolecheck & Bewley, 2018; Edwardes et al., 2022a) and welfare (Whay & Shearer, 2017) consequences. Significant efforts have been invested into developing PLF technology to monitor SOM, but many of the underlying diagnostic tests classify SOM into only two health classes, non-SOM and SOM (Alsaaod et al., 2019; Schlageter-Tello et al., 2014). With this approach certain mobility scores are grouped together into either the non-SOM or SOM class, meaning that farmers' reaction to the generated information apropos SOM classification is the same for all cows classified to the SOM class. However, it might be economically beneficial to generate information for some cows while prolonging information generation for other cows. Edwardes et al. (2022b) classified SOM into three classes and showed that economic outcomes could be improved through this approach because classification information apropos one SOM class could be prolonged and allowed opportunities to improve the information quality that ultimately contributed towards more precise intervention decisions. However, Edwardes et al. (2022b) showed that SOM prevalence, an important welfare indicator (Welfare Quality®, 2009a), was lower in SOM management situations where the underlying diagnostic tests classified SOM into two classes. Albeit SOM prevalence was still noticeably reduced when it was classified into three SOM classes. These results suggest that a trade-off between economic and welfare value exists when using PLF technologies for SOM management.

Understanding the potential economic and welfare value, as well as the trade-offs between them, is important for prospective SOM related PLF technology developers to ensure that farmers' technology use preferences are satisfied. This is especially true when developing the underlying diagnostic tests to classify SOM into three classes. However, this is challenging for the PLF technology developers because the underlying diagnostic tests can produce an array of classification outcomes with various classification outcome trade-offs (Nakas & Yiannoutsos, 2004), ultimately affecting the quality of classification information generated. Although potential diagnostic tests that classify SOM into three, or more, classes exist, only one classification outcome is reported (Thorup et al., 2015; Van Hertem et al., 2016). Therefore, understanding how trade-offs in classification outcomes for three SOM classes affect the potential economic and welfare value is of interest.

The objective of this study is to quantify the effect of trade-offs in classification outcomes on economic and welfare value for various diagnostic tests that classify SOM into three SOM classes. With this study we provide insight on the direction prospective SOM related PLF technology developers should strive for when developing the underlying diagnostic tests that classify SOM into three classes. The insights from this study will also have implications for other PLF technology interested in health disorders other than SOM. Additionally, this research can also benefit farmers by providing decision support apropos how they can achieve their desired economic and welfare outcomes from a PLF-based SOM management approach.

5.2 Methodology

In this section we describe the steps taken to achieve our objectives. First, we present a conceptual framework that allowed us to understand the trade-offs in classification outcomes for diagnostic tests. Second, using the conceptual framework we apply it to SOM to define hypothetical diagnostic tests that generate different SOM classification outcomes based on the quality of the respective diagnostic tests. Third, we briefly describe a simulation model that was used to gain insight on the effects of sampled classification outcomes per diagnostic test. Lastly, methods to analyse the simulated results are described.

5.2.1 Conceptual framework

Receiver operator characteristic (ROC) analysis is a powerful evaluation technique used to determine the quality of diagnostic tests that classify subjects belonging to classes, as per a golden standard, into the respective classes (Flach, 2016; Nakas, 2014; Nakas and Alonzo, 2007; Sahiner et al., 2008a). For brevity we further refer to diagnostic tests as "classifiers". Classifier types can vary between those that use a single variable to those that use multiple variables, such as statistical models, to classify subjects into classes. The classification of subjects is dependent on the subjects' diagnostic marker value generated by the classifier, and some cut-off threshold c that determines the boundary between the distribution of diagnostic marker values for each class. The diagnostic marker values for subjects in each class can be real valued numbers, and c can be any value within the domain of diagnostic marker values. For all values of c, a square matrix (P) of classification outcomes exists, where P_{ij} denotes the classification probability of subjects belonging to class i being classified to class j.

For a binary classification problem, let $K = \{1, 2\}$ be the set of classes where $i, j \in K$, mv_i be the distribution of diagnostic marker values for class i, as per the golden standard, where diagnostic marker value $x_i \in mv_i$, and $c \in \{mv_1, mv_2\}$. Four classification probabilities P_{ij} exist (i.e., $|K|^2$) whereby the probability of classifying subjects from class i to class j is as follows: $P_{i1} = P(x_i \leq c)$ and $P_{i2} = P(x_i > c)$ where $\sum_{j \in K} P_{ij} = 1$ for any subject belonging to class i with diagnostic marker value x_i. Therefore, as c increases trade-offs in correct classification probabilities P_{11} and

P_{22} and incorrect classification probabilities P_{12} and P_{21} occur given some overlap between mv_1 and mv_2 exists. The quality of a binary class classifier is therefore dependent on the overlap between the two distributions and their densities.

For a 3-class classification problem, now let $K = \{1, 2, 3\}$, maintaining $i, j \in K$, meaning that three distributions of diagnostic marker values exist: mv_1, mv_2, mv_3, where diagnostic marker value $x_i \in mv_i$. Two cut-off thresholds c_1 and c_2 are required to discriminate between the three classes, where $c_1, c_2 \in \{mv_1, mv_2, mv_3\}$ subject to $c_1 \leq c_2$. Hence, nine classification probabilities P_{ij} will exist whereby the probability of classifying subjects from class i to class j is as follows: $P_{i1} = P(x_i \leq c)$, $P_{i2} = P(c_1 \leq x_i < c_2)$ and $P_{i3} = P(x_i > c_2)$ maintaining $\sum_{j \in K} P_{ij} = 1$ for any subject belonging to class i with diagnostic marker value x_i. Trade-offs between correct classification probabilities P_{11}, P_{22} and P_{33} will exist depending on whether one or both cut-off thresholds vary. The relationship between incorrect classification probabilities is more complex because of the increased dimensionality of the probability space whereby trade-offs and synergies between the different incorrect classification probabilities exist.

5.2.2 Application to SOM classification

SOM was defined by five ordinal mobility scores as per Sprecher et al. (1997), where mobility score 1 represents optimal mobility and mobility score 5 represents severely impaired mobility. Three classes of SOM, $K = \{1, 2, 3\}$ where $i, j \in K$, were defined for eight different classifiers for two management scenarios. For classifiers 1 – 4 (management scenario 1), mobility scores 1 and 2, mobility score 3, and mobility scores 4 and 5 were respectively grouped into SOM classes $K_1, K_2,$ and K_3. For classifiers 5 – 8 (management scenario 2), mobility score 1, mobility scores 2 and 3, and mobility scores 4 and 5 were respectively grouped into SOM classes $K_1, K_2,$ and K_3.

The distribution of diagnostic marker values mv_i used in our study were arbitrary[7] but necessary values to calculate classification probabilities P_{ij} with respect to the overlap in diagnostic marker values and cut-off thresholds values of c_1 and c_2. The distribution of diagnostic marker values mv_i for SOM class K_i are found in Table 5.1.

[7] Diagnostic marker values in general can be any real number. Diagnostic marker values in the context of SOM can be derived from one variable, such as back posture (Piette et al., 2020), or multiple variables (Van Hertem et al., 2016). Therefore, the values are dependent on how the variables are measured and integrated.

The mean and standard deviation for the distributions of mv_i were chosen to reflect classifiers that had noticeable differences in their ability to discriminate between different SOM classes, which reflected the quality of the classifiers in SOM class classification. The ability in SOM class discrimination is determined by the overlap in mv_i where complete overlap entails a useless classifier and complete separation entails a perfect classifier (Nakas & Yiannoutsos, 2004). A constant standard deviation of 0.885 was used for all mv_i per classifier 1 – 8. Three mean values of -1, 0, 1 were used as reference points that were either shifted ($\pm$) by half a standard deviation (0.4425) or two standard deviations (1.77).

The resulting theoretical distributions of mv_i of SOM class K_i for the eight classifiers are shown in Figure 5.1 to illustrate their ability in SOM class discrimination. Classifiers 1 and 5 show a weak ability in SOM class discrimination due to the considerable overlap between the diagnostic marker values for SOM classes K_i. Classifiers 2 and 6 show less overlap between the diagnostic marker values for SOM classes K_i. Classifier 3 and 7 shows considerably less overlap between diagnostic marker values for SOM classes K_1 and K_2, while considerable overlap between diagnostic marker values for SOM classes K_2 and K_3 exists. Classifier 4 and 8 shows considerable overlap between diagnostic marker values for SOM classes K_1 and K_2, while considerably less overlap between diagnostic marker values for SOM classes K_2 and K_3 exists. In summary, the smaller the overlap between the diagnostic marker values for SOM classes K_i, the better the classifier is at discriminating between SOM classes K_i.

Classification probabilities P_{ij} for the eight classifiers were determined as per the conceptual framework with the distributions of diagnostic marker values mv_i found in Table 5.1. The number of draws per mv_i were based on scientific literature describing classifiers for three, or more, SOM classes ensuring the relative share of mv_i between SOM classes was maintained (Bicalho et al., 2007; Ghotoorlar et al., 2012; Thorup et al., 2015; Van Hertem et al., 2016, 2014b). For classifiers 1 – 4, the number of draws for mv_1, mv_2, and mv_3 were 288, 122, and 89, respectively. For classifiers 5 – 8, the number of draws for mv_1, mv_2, and mv_3 were 121, 289, and 89, respectively. Hence, a total of 499 diagnostic marker values were used for all classifiers. This generated 125,250 different classification outcome matrices for each classifier 1 – 8.

Table 5.1 Distribution of diagnostic marker values for classifiers 1 - 8.

Classifier	Mobility score[a] SOM class	Distribution[b] of diagnostic marker values ($\boldsymbol{mv_i}$) for class $\boldsymbol{K_i}$
1	K_1 = ms1, ms2	$mv_1 \sim \mathcal{N}(\mu = -1, \sigma = 0.885)$
	K_2 = ms3	$mv_2 \sim \mathcal{N}(\mu = 0, \sigma = 0.885)$
	K_3 = ms4, ms5	$mv_3 \sim \mathcal{N}(\mu = 1, \sigma = 0.885)$
2	K_1 = ms1, ms2	$mv_1 \sim \mathcal{N}(\mu = -1.4425, \sigma = 0.885)$
	K_2 = ms3	$mv_2 \sim \mathcal{N}(\mu = 0, \sigma = 0.885)$
	K_3 = ms4, ms5	$mv_3 \sim \mathcal{N}(\mu = 1.4425, \sigma = 0.885)$
3	K_1 = ms1, ms2	$mv_1 \sim \mathcal{N}(\mu = -2.77, \sigma = 0.885)$
	K_2 = ms3	$mv_2 \sim \mathcal{N}(\mu = 0, \sigma = 0.885)$
	K_3 = ms4, ms5	$mv_3 \sim \mathcal{N}(\mu = 1, \sigma = 0.885)$
4	K_1 = ms1, ms2	$mv_1 \sim \mathcal{N}(\mu = -1, \sigma = 0.885)$
	K_2 = ms3	$mv_2 \sim \mathcal{N}(\mu = 0, \sigma = 0.885)$
	K_3 = ms4, ms5	$mv_3 \sim \mathcal{N}(\mu = 2.77, \sigma = 0.885)$
5	K_1 = ms1	$mv_1 \sim \mathcal{N}(\mu = -1, \sigma = 0.885)$
	K_2 = ms2, ms3	$mv_2 \sim \mathcal{N}(\mu = 0, \sigma = 0.885)$
	K_3 = ms4, ms5	$mv_3 \sim \mathcal{N}(\mu = 1, \sigma = 0.885)$
6	K_1 = ms1	$mv_1 \sim \mathcal{N}(\mu = -1.4425, \sigma = 0.885)$
	K_2 = ms2, ms3	$mv_2 \sim \mathcal{N}(\mu = 0, \sigma = 0.885)$
	K_3 = ms4, ms5	$mv_3 \sim \mathcal{N}(\mu = 1.4425, \sigma = 0.885)$
7	K_1 = ms1	$mv_1 \sim \mathcal{N}(\mu = -2.77, \sigma = 0.885)$
	K_2 = ms2, ms3	$mv_2 \sim \mathcal{N}(\mu = 0, \sigma = 0.885)$
	K_3 = ms4, ms5	$mv_3 \sim \mathcal{N}(\mu = 1, \sigma = 0.885)$
8	K_1 = ms1	$mv_1 \sim \mathcal{N}(\mu = -1, \sigma = 0.885)$
	K_2 = ms2, ms3	$mv_2 \sim \mathcal{N}(\mu = 0, \sigma = 0.885)$
	K_3 = ms4, ms5	$mv_3 \sim \mathcal{N}(\mu = 2.77, \sigma = 0.885)$

[a.] ms1 = mobility score 1; ms2 = mobility score 2; ms3 = mobility score 3; ms4 = mobility score 4; ms5 = mobility score 5.

[b] Normal distribution $\mathcal{N}(\cdot)$ with parameters: μ = mean; σ = standard deviation.

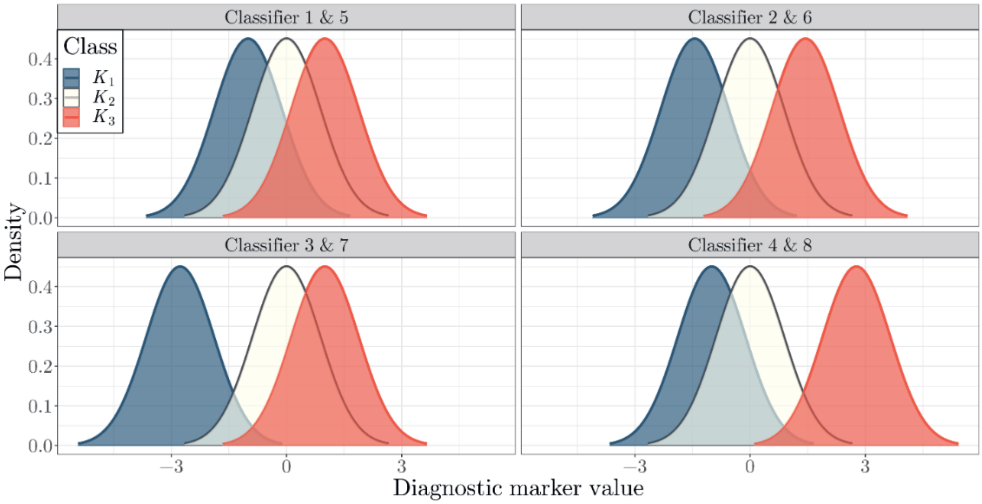


Figure 5.1 Theoretical distributions of diagnostic marker values for the eight classifiers.

5.2.3 Quantifying the economic and welfare effects of classification outcomes

For this study we used an existing stochastic cow-level dynamic bio-economic simulation model that incorporated PLF technology (i.e., a classifier) in the management of SOM (Edwardes et al., 2022b). For both management scenario 1 and 2, cows that were classified to class K_1 were not treated for SOM (because no alerts for these cows were generated). The model includes an alert prioritisation criterion whereby alerts for cows classified to class K_2 are generated every 7 days on condition that K_2 classifications per cow occurred at least 50 percent of the time during a 7-day hoof-trimming interval. Following an alert on the 7th day, they were treated if necessary (mobility score 3 [management scenario 1]; mobility score 2 and 3 [management scenario 2]) by a professional hoof-trimmer. Alerts were generated immediately for cows classified to class K_3 and were treated immediately if necessary by the farmer (mobility score 4) or veterinarian (mobility score 5).

The model calculates the annual net economic results as a function of the daily milk revenue per cow less the daily SOM and SOM management associated costs per cow. The costs include: milk losses, discarded milk due to SOM related antibiotic use, feed, insemination, culling, hoof-trimming, veterinary, labour, and the annual depreciation of the PLF technology. For complete information please refer to Edwardes et al. (2022a, 2022b).

The model was extended for this study with a SOM welfare impact component as described in Edwardes et al. (2023) to assess the effect of PLF technology in the management of SOM on the SOM welfare impact. In brief, the annual SOM welfare impact is calculated as the aggregated product of mobility score duration per SOM case and a mobility score welfare impairment weight for all SOM cases that occurred during the year.

To study the SOM economic and welfare effects of classification outcomes, 600 of the 125,250 classification outcome matrices per classifier 1 − 8 were randomly selected[8] and used as input for the updated simulation model used in this study. Due to model stochasticity, 500 replications per classification outcome per classifier 1 − 8 were run. The mean net economic results and welfare impact per classification outcome per classifier 1 − 8 were then computed and compared to a baseline situation that represented current SOM management without PLF technology to obtain the relative differences in economic and welfare SOM impact. Relative difference values were expressed as a gain (y) where $y > 0$ represent the relative reduction in economic and welfare SOM impact (i.e., positive gain) compared to the baseline situation whereas values of $y < 0$ represent the relative increase in economic and welfare SOM impact (i.e., negative gain) compared to the baseline situation.

5.2.4 Exploratory overview of results

First, we explored the general economic and welfare effects simulated output per classifier 1 − 8. Of the eight classifiers, two were then selected for further detailed analysis. The two classifiers were selected for either having the lowest or highest mean aggregated economic and welfare effect (assuming equal weighting for both economic and welfare effects).

Secondly, for the two selected classifiers we explored the economic and welfare effects of classification probabilities P_{11}, P_{22}, and P_{33} through a visual analysis of plots. P_{11}, P_{22}, and P_{33} values were plotted against the range of economic and welfare gains that were divided into 15 intervals. This visual analysis allowed us to study the general

[8] A random selection of 600 classification outcomes per classifier was done due to the computational expense required from this study; an estimated 12,000 simulation hours was required from 8×600 classification outcomes.

requirements of P_{11}, P_{22}, and P_{33}, without considering other P_{ij} interactions, to achieve higher economic and welfare gains.

5.2.5 Synthesis model

The simulation model produced output that made it difficult present the economic and welfare effects succinctly with respect to each P_{ij}. Therefore, to estimate the economic and welfare effects of P_{ij} we first developed a method that accounted for the complex behaviour of classifiers apropos trade-offs and synergies between P_{ij} when the cut-off threshold values of c_1 and c_2 varied (described in Appendix 1 with accompanying Table A 5.1). This method contributed to the development of a synthesis model that permitted us to ultimately estimate the economic and welfare effects P_{ij}. The general form of the synthesis model is

$$y = \sum x_{ij} P_{ij}; \qquad \forall\, i, j \tag{5.1}$$

where y is the economic or welfare gain and x_{ij} is the effect of P_{ij} on y. Parameter values of x_{ij} were calibrated on the simulated outputs with maximum likelihood estimation using the **bbmle** package (Bolker & R Development Core Team, 2022) for R (R Core Team, 2022). The synthesised results apropos economic and welfare gains were expressed in terms of P_{11} and P_{22} (Appendix 1).

5.3 Results

5.3.1 Overview of results

Figure 5.2 shows the distribution of economic and welfare gains for the 600 different classification outcomes for classifiers 1 – 8, respective of management scenario (summary statistics are found in Table A 5.2) relative to a baseline situation that represented current SOM management without PLF technology (i.e., no-classifier situation). For all classifiers, most of the simulated classification outcomes resulted in positive economic and welfare gains (i.e., reductions in SOM economic and welfare impact). In management scenario 1, the highest economic and welfare gains were observed in classifier 3, whereby the economic and welfare impact of SOM was respectfully reduced by ~20 and ~40 percent on average.

In management scenario 2, the highest economic gains were observed in classifier 7 (second highest average welfare gains) with an average ~33 percent reduction in SOM economic impact, and the highest welfare gains were observed in classifier 8 (lowest average economic gains) with an average ~87 percent reduction in SOM welfare impact. When mobility score 2 was grouped in class K_2 (management scenario 2) as opposed to class K_1 (management scenario 1) higher economic and

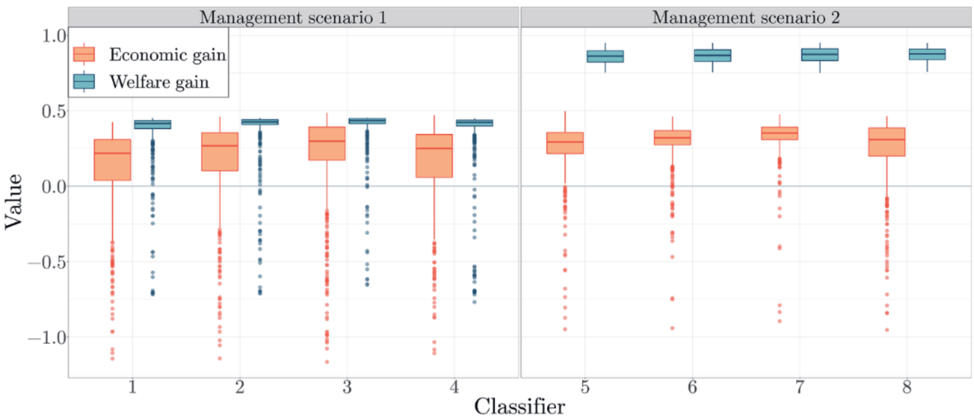


Figure 5.2 Distributions of the economic and welfare effects for the 600 different classification outcomes per classifier 1 – 8. The Value on the y-axis is interpreted as the relative difference in economic and welfare SOM impact compared to a no-classifier situation. Positive values indicate a reduction in SOM economic or welfare impact (i.e., positive gain), while negative values indicate an increase in SOM economic or welfare impact (i.e., negative gain).

welfare gains were observed on average as well as a reduction in variance for both economic and welfare gains.

Of the 8 classifiers, classifier 1 (weak ability in SOM class discrimination for all SOM classes) and classifier 7 (strong ability in K_1 and K_2 SOM class discrimination; weak ability in K_2 and K_3 SOM class discrimination) respectively produced the lowest and highest mean aggregated economic and welfare gain. Figure 5.3 (classifier 1) and Figure 5.4 (classifier 7) illustrate the general trends in classification probabilities P_{11}, P_{22}, and P_{33} as the economic and welfare gains increase from minimum to maximum. Both for classifier 1 and classifier 7, P_{11} showed increasing trends for increases in economic gains while P_{11} showed decreasing trends for increases in welfare gains, indicating economic and welfare trade-offs for changes in P_{11}. P_{22} showed increasing trends for both increases in economic and welfare gains, indicating economic and welfare synergies for changes in P_{22}. P_{33} showed decreasing trends for increases in economic gains while P_{33} showed increasing trends for increases in welfare gains, indicating economic and welfare trade-offs for changes in P_{33}. Wider ranges of P_{ij} values within quantile ranges were due to a higher number of classification outcomes that produced economic and welfare gains within the specified interval. Similar trends as described were observed for the other six classifiers (Figures A 5.1 – A 5.6 of Appendix 2).

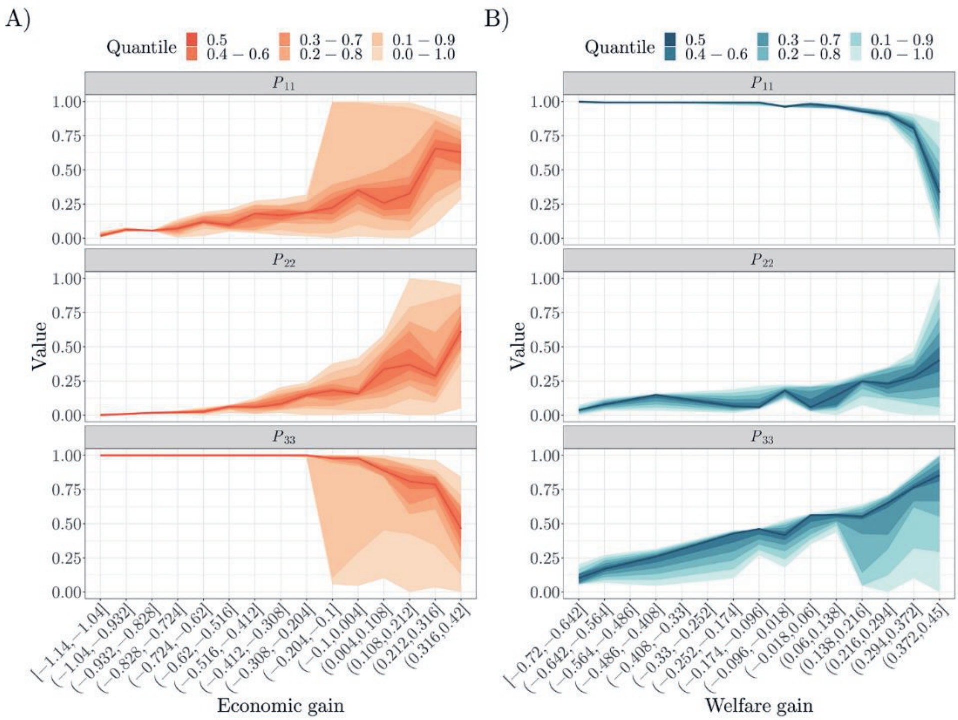


Figure 5.3 Trends in classification probabilities P_{11}, P_{22}, and P_{33} for classifier 1 with respect to economic gains (A) and welfare gains (B). The Value on the y-axis is interpreted as the P_{ij} value.

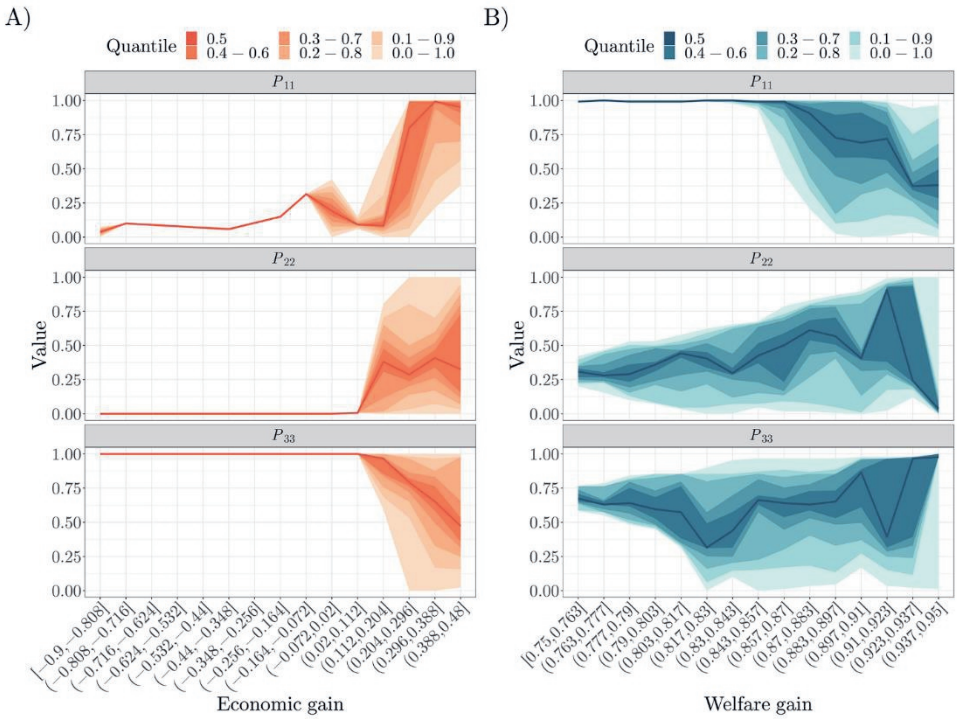


Figure 5.4 Trends in classification probabilities P_{11}, P_{22}, and P_{33} for classifier 7 with respect to economic gains (A) and welfare gains (B). The Value on the y-axis is interpreted as the P_{ij} value.

5.3.2 Synthesis model output: estimated economic and welfare effects of P_{ij}

Figure 5.5 illustrates the economic and welfare effect of P_{11} and five levels of P_{22}, while considering the underlying trade-offs and synergies between different P_{ij}, of classifier 1 and classifier 7[9]. Classifier 1 had the lowest economic gains and the highest welfare gains when P_{11} and P_{22} were both set to 0. Increasing levels of P_{22} generally led to increased economic gains (illustrated by the upward shift in P_{22} lines) but decreased welfare gains (illustrated by the downward shift in P_{22} lines). However, the reductions in welfare gains were smaller than the increases in economic gains for increases in P_{22}. Lines respective of different P_{22} levels generally showed trade-offs in economic and welfare gains as P_{11} increased. Synergies in economic and welfare gains were observed at higher values of P_{11} where the gradients of the economic and welfare gain lines were both negative. Increasing P_{11} had a larger positive effect on economic gains than negative effects on welfare gains, as indicated by the steeper positive gradient of lines representing economic gains compared to the flatter negative gradient of lines representing welfare gains. For example, the economic and welfare gain lines representing P_{22} when set to 0 showed that as P_{11} increased from 0 to 0.82, the additional economic gains were larger as illustrated by steeper positive gradient compared to the reductions in welfare gains as illustrated by flatter negative gradient. However, as P_{11} increased beyond 0.82 to 1, the additional economic gain diminished until increases in P_{11} had a negative effect on economic gains and reductions in welfare gains became larger.

For classifier 7, the effect of increasing P_{22} from 0 to 0.25 was largest on the economic gain. Thereafter, increasing levels of P_{22} had smaller effects on economic and welfare gains. For all levels of P_{22}, increases in P_{11} generally lead to larger increases in economic gains compared to smaller reductions in welfare gains. However, when P_{11} increased beyond ~0.9, economic gains began to diminish and then reduce and reductions in welfare gains became larger. Following decreases in economic and welfare gains for P_{11} values near the extremity of 1, acute increases in economic and welfare gains occurred. This was due to the limited number of observations from our simulations with P_{11} values near 1, ultimately influencing the maximum likelihood estimation of x_{ij}. Albeit increases in economic and welfare gains were observed in the simulated data as P_{11} approached 1, but not as extreme as shown in Figure 5.5.

[9] Figure A 5.7 illustrates the economic and welfare effects of P_{11} and five levels of P_{22} for the remaining classifiers 2 – 6, and 8.

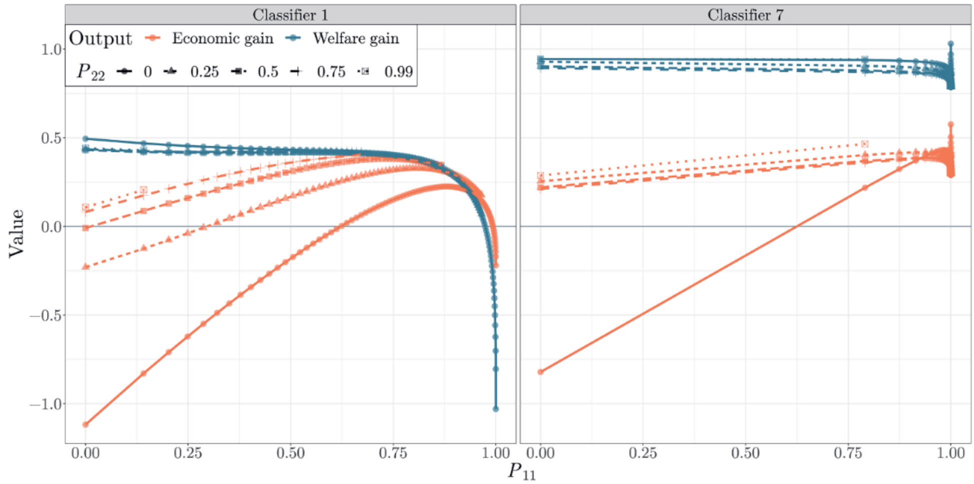


Figure 5.5 Effects of P_{11} and P_{22} on the economic and welfare gains for classifier 1 and classifier 7. The Value on the y-axis is interpreted as the relative difference in economic and welfare SOM impact compared to a no-classifier situation. Positive values indicate a reduction in SOM economic or welfare impact (i.e., positive gain), while negative values indicate an increase in SOM economic or welfare impact (i.e., negative gain).

5.4 Discussion

In this research, we studied the economic and welfare effects of different classification outcomes for underlying classifiers in the context of a PLF based approach to SOM management. Our focus was on 3-class classifiers, which were designed as hypothetical scenarios due to limited information on 3-class SOM classifiers for SOM management. The scenarios were created in a way that would allow for noticeable separation or overlap between the distribution of diagnostic marker values among classes, thereby enhancing our understanding of their effects on economic and welfare outcomes. We chose to study hypothetical 3-class classifiers rather than the more common 2-class classifiers described in scientific literature (Alsaaod et al., 2019; Schlageter-Tello et al., 2014) because they offer the potential to improve the quality of information generated by the classifier and facilitate more precise intervention decisions, such as prolonged or immediate intervention procedures (Edwardes et al., 2022b). The results of our study indicate that implementing a 3-class classification PLF based SOM management approach can yield additional economic and welfare value.

Among the eight classifiers tested, classifier 7 (management scenario 2) produced the highest average economic gain. This result was due to the considerably large separation between diagnostic marker values mv_1 and mv_2, as well as between mv_1 and mv_3. This separation allowed for many different classification outcomes whereby cows belonging to class K_1, which are not SOM and do not incur production losses, were correctly classified thus unnecessary intervention costs were avoided. At the same time, high correct classification probabilities were maintained for cows in classes K_2 and K_3, enabling timely intervention to avoid prolonged production losses. In addition, classifier 3, which had the same theoretical distribution of diagnostic marker values as classifier 7, produced the highest economic gains on average compared to classifiers in management scenario 1 for the same reasons described apropos classifier 7. Conversely, classifiers 1 and 4 (management scenario 1) and classifiers 5 and 8 (management scenario 2) had the smallest separation between diagnostic marker values mv_1 and mv_2 and resulted in the two lowest economic gains on average within management scenario.

These findings highlight the need for the PLF research community to primarily develop SOM classifiers that can sufficiently discriminate between the non-SOM class and different SOM classes based on their underlying diagnostic marker values. This may also be beneficial for other health disorders. A PLF-based health management approach can enable earlier and more effective intervention for unhealthy animals, resulting in a large proportion of the animal population returning to the healthy class once treated and recovered. Consequently, even a small misclassification probability for healthy cows can lead to high economic costs due to the additional and unnecessary opportunity cost of labour to check false alerts or costs for unnecessary interventions.

Welfare gains were achieved overall for all the eight classifiers. Including mobility score 2 to class K_2 in classifiers $5-8$ (management scenario 2) drastically improved the additional welfare gains compared to classifiers $1-4$ (management scenario 1). This was because of two reasons. First, the welfare of cows with mobility score 2 is already negatively affected (Edwardes et al., 2023), and in management scenario 2 these cows were being treated. Second, by including cows with mobility score 2 to class K_1, as in management scenario 1, the proportion of cows with mobility score 2 would steadily increase over time because they would not be treated. This trend occurred in Edwardes et al. (2022b) for a PLF based SOM management scenario as management scenario 1 in this study. Similar trends were also observed in practice when treatment frequency increased (Groenevelt et al., 2014). Including mobility score 2 into a class that requires intervention will have positive welfare effects because it enables the earliest possible intervention of SOM, which is beneficial as cows can quickly become SOM again following treatment (Frankena et al., 2009). In addition, economic gains also improved slightly when mobility score 2 was included in class K_2 because indirect economic effects were avoided.

Although additional economic and welfare values were generally attainable with all the classifiers under study, improving economic outcomes through changes in classification outcomes often came at the cost of reductions in welfare gains. In general, larger increases of economic gains were achieved through smaller reductions in welfare gains, but when the increases in additional economic gains began to diminish the reductions in additional welfare gains became larger (see Figure 5.5 and Figure A 5.7). This phenomenon can be explained with reference to classification probabilities P_{ij}. For example, when P_{11} and P_{22} were set to 0, the lowest economic gains were achieved, but the highest welfare gains were also achieved. This is because setting P_{11} and P_{22} to 0 requires the cut-off threshold values of c_1 and c_2 to be equal and set at the minimum diagnostic marker values possible. Ultimately all cows were classified to class K_3 because P_{13}, P_{23} and P_{33} all equal 1. Hence, alerts were generated daily for all cows that were consequently checked and treated if necessary (mobility score ≥3 in management scenario 1; mobility score ≥2 in management scenario 2), which resulted in maximum additional welfare gains. But because of recovery following treatment, the proportion of cows in class K_1 increased and alerts were still generated for these cows. This incurred unnecessary opportunity costs of labour to check these alerts, which contributed to the negative economic gains. Although checking multiple alerts for cows that were recently treated may not be representative of what happens in practice (Eckelkamp & Bewley, 2020), the assumptions made in this example provide insight on the economic and welfare phenomena for changes in P_{ij}. As P_{11} increased the economic gains increased but welfare gains decreased. This was because more cows in class K_1 were classified to class K_1, reducing the opportunity costs of checking unnecessary alerts. As P_{11} increased, P_{21} and P_{31} increased and P_{33} decreased, leading to cows in class K_2 and K_3 being classified to class K_1 that did not have alerts generated for. This incurred additional welfare impacts and reduced the welfare gains. The economic welfare gains began to reduce drastically when increasing P_{11} by an additional percentage unit would decrease P_{33} by more than one percentage unit. This was because more cows in class K_2 and K_3 were classified to class K_1 and did not have alerts generated for, meaning that greater production losses occurred while larger reductions in welfare gains continued.

Although setting P_{22} to 0 suggests that there may be economic value in a 2-class classifier with a management strategy as in this study, it contradicts the purpose of a 3-class classifier. This is because cows in class K_2 were never classified to class K_2, thereby making the classifier unable to generate improved information quality with an alert prioritisation criterion to facilitate more precise intervention decisions, such as prolonged or immediate intervention procedures. Our results demonstrate that additional economic value can be achieved with a 3-class classification approach because increases in P_{22}, which ensured that cows could be classified into one of three classes, constantly produced higher economic gains as a result of decisions taken with improved information (Rojo-Gimeno et al., 2019).

In addition to the research described in this chapter, during the study we also assessed a 4-class classification of SOM classes and defined classification outcomes based on the logic described in the conceptual framework. Mobility scores 1 – 3 represented independent classes and only mobility scores 4 and 5 were grouped into one class. Comparing the highest average economic and welfare gains for 4-class classifiers with the highest average economic and welfare gains for 3-class classifiers from management scenario 1 and 2 showed little absolute difference. These results further suggest that classifying mobility scores into three classes will suffice in providing additional economic and welfare value. It may be that additional values exists in a 4-class classifier if each class had very different intervention procedures, which we did not test.

Although methods apropos assessing the performance of 3-class classifiers are well documented in the scientific literature (i.e., Sahiner et al., 2008; Xin He & Frey, 2009), the scope of this study dealt with the economic and welfare effects of varying classifier performance. This meant that the highly interactive behaviour of P_{ij} trade-offs and synergies had to be accounted for first. To the best of our knowledge, methods to study this behaviour do not exist, making our approach, the synthesis model, described in Appendix A1 the first. After developing the synthesis model, we could effectively estimate the economic and welfare effects of P_{ij} with maximum likelihood estimation to gain more insights that the exploratory overview of the results could not provide.

The maximum likelihood estimates of x_{ij} were potentially influenced by the sample size of classification outcomes (Psutka & Psutka, 2019), which would ultimately affect the output of our synthesis model (Equation 1). Increasing the sample size of classification outcomes could potentially improve the maximum likelihood estimates of x_{ij} (Psutka & Psutka, 2019), consequentially improving the output of the synthesis model. However, while synthesis model output apropos classifiers 5 – 8 showed exaggerated outcomes apropos increases in economic gains and welfare gains >1 when P_{11} approached 1, similar but less exaggerated trends were observed in the simulation model output. Moreover, we validated the synthesis model with the estimated x_{ij} parameter values by correlating its output with the simulation model outputs (Bolker, 2008). The correlation between the synthesis model and simulation model outputs achieved R^2 values between 0.92 – 0.99 and 0.86 – 0.97 respectively for economic and welfare outcomes. This instilled confidence that our synthesis model with the estimated x_{ij} parameter values as inputs was still a good fit to explain the economic and welfare effects of P_{ij} trade-offs and synergies.

From this study it is difficult to specify which classification outcomes are optimal because this depends on farmer preferences towards economic and welfare gains (e.g., Läpple & Osawe, 2022). However, the methods we proposed to study the effects of varying P_{ij} on classification outcomes (Appendix A1) and the economic and welfare effects of such variations (see Equation 1) provide a research foundation for future classification model development that is able to match farmer preferences of classification outcomes (Van De Gucht et al., 2017b) with their economic and animal welfare preferences (e.g., Hansson & Lagerkvist, 2014, 2015).

This study demonstrates the value of using simulation models to assess the economic and welfare effects in response to the quality and performance of SOM classifiers in combination with novel designs in PLF based SOM management strategies. A wide range of classification outcomes were tested that would be almost impossible to implement in practice and provide insight by narrowing down on interesting classification outcomes that can be further validated in practice. This approach may be very useful for other health disorders as well.

5.5 Conclusion

This research focussed on the economic and welfare effects of different SOM classification outcomes for 3-class classifiers in the context of a PLF-based SOM management approach, extending beyond the typical binary SOM classifiers currently developed. Results from the study demonstrated that economic and welfare gains are achievable on average with a 3-class SOM classification approach under the simulated management strategies. Moreover, our findings suggest that prolonged and immediate intervention procedures for cows classified into different SOM classes can be improved by harnessing the opportunities only offered by 3-class classification approach.

Assuming that economic and welfare gains are valued equally, classifiers 3 and 7 in management scenario 1 and 2 produced the highest economic and welfare gains on average within management scenarios. Overall, classifier 7 in management scenario 2 produced the highest average economic gain due to significant separation between diagnostic marker values, allowing for accurate classification and avoidance of unnecessary intervention costs. These results suggest that future developments in SOM classification models should focus on achieving better K_1 class discrimination from K_2 and K_3 classes.

In some cases, highest welfare gains were achieved while economic gains were negative. Larger increases in economic gains came at the cost of smaller reductions of welfare gains as classification outcomes varied. Hence, this study emphasises the value of simulation models in assessing economic and welfare implications across a wide range of different classifiers and classification outcome scenarios, allowing a thorough testing before they are implemented in practice. Ultimately, this the study, and the results within, can further support farmer decision making apropos the economic and welfare implications of different classification outcomes that best fit their PLF-based SOM management preferences. This research also serves the potential to further study the economic and welfare implications for 3-class classification PLF-based management for other health disorders and support farmer decision making apropos the economic and welfare implications of other health disorders.

5.6 Appendix 1

5.6.1 Describing the trade-offs and synergies of P_{ij}

Describing the trade-offs and synergies between different P_{ij} of a 3-class classifier is complex due to the locations, and distance between, the cut-off threshold values c_1 and c_2 along the range of diagnostic marker value distributions (i.e., mv_1, mv_2, mv_3). To estimate the values of P_{ij} we require two P_{ij} to be known. We begin with P_{22} and P_{21}, under the following constraints

Describing the trade-offs and synergies between different P_{ij} of a 3-class classifier is complex due to the locations, and distance between, the cut-off threshold values c_1 and c_2 along the range of diagnostic marker value distributions (i.e., mv_1, mv_2, mv_3). To estimate the values of P_{ij} we require two P_{ij} to be known. We begin with P_{22} and P_{21}, under the following constraints

$$P_{22} = [0; 1] \tag{A 5.1}$$

$$P_{21} = [0; 1 - P_{22}]. \tag{A 5.2}$$

The value of P_{22} is determined by the distance between c_1 and c_2 and the density of mv_2 between c_1 and c_2. For example, when $P_{22} = 0$, then $c_1 = c_2$. With P_{22} and P_{21} defined, the remaining seven P_{ij} are estimated as follows

$$P_{23} = 1 - P_{22} - P_{21} \tag{A 5.3}$$

$$P_{11} = 1 - \left(1 - P_{21}^{\alpha_1}\right)^{1/\beta_1} \tag{A 5.4}$$

$$P_{31} = (1 - [1 - P_{21}]^{\alpha_2})^{1/\beta_2} \tag{A 5.5}$$

$$P_{13} = (1 - [1 - P_{23}]^{\alpha_3})^{1/\beta_3} \tag{A 5.6}$$

$$P_{33} = 1 - \left(1 - P_{23}^{\alpha_4}\right)^{1/\beta_4} \tag{A 5.7}$$

$$P_{12} = 1 - P_{11} - P_{13} \tag{A 5.8}$$

$$P_{32} = 1 - P_{31} - P_{33}. \quad \text{(A 5.9)}$$

The parameters α and β in equations A 5.4 – A 5.7 determine the shape of the functions and are bound between [0; 1]. To estimate their values, we set $c_1 = c_2$ meaning that $P_{12} = 0$, $P_{22} = 0$, and $P_{32} = 0$ because all values in mv_i would never lie between c_1 and c_2 as they vary together across the range of diagnostic marker values for all classes. Then empirical probability values for P_{11}, P_{13}, P_{21}, P_{23}, P_{31} and P_{33} were calculated for all $c_1, c_2 \in \{mv_1, mv_2, mv_3\}$ maintaining $c_1 = c_2$. Second, with the calculated probability values we estimated the parameter values for α and β, respective of functions A4 – A7, with maximum likelihood estimation using the **bbmle** package (Bolker & R Development Core Team, 2022) for R (R Core Team, 2022).

5.6.2 Expressing economic and welfare gains in terms of P_{11} and P_{22}

With two known P_{ij}, as per equations A 5.1 and A 5.2, the trade-offs and synergies between different P_{ij} are controlled for (equations A 5.3 – A 5.9). Then we can estimate the effect of P_{ij} on output y (i.e., economic or welfare gain) with the following function in general form

$$y = \sum x_{ij} P_{ij}; \qquad \forall\, i, j \quad \text{(A 5.10)}$$

where x_{ij} is the effect of P_{ij} on y. Parameter values of x_{ij} were estimated with maximum likelihood estimation using the **bbmle** package (Bolker & R Development Core Team, 2022) for R (R Core Team, 2022).

Expressing y in terms of P_{11} and P_{22} requires an additional term. We introduce w, where $w \in [0; 1-P_{22}]$ is a placeholder term for P_{21}. Referring to equation A4, we solve w for P_{11}, which yields

$$w = exp\left(\frac{ln(-exp(ln(-P_{11} + 1)\beta_1) + 1)}{\alpha_1}\right) \quad \text{(A 5.11)}$$

and assign w to P_{21}: $w \mapsto P_{21}$. Now, the trade-offs and synergies between different P_{ij} can be described by two known values of P_{11} and P_{22}. Through the manipulation of P_{21}, as described, y is now expressed in terms of P_{11} and P_{22} because equations A 5.3, A 5.5, A 5.6, A 5.7, and A 5.9 become direct functions of P_{11} and P_{22}. In addition, this further allows for the marginal effects of P_{11} on y to be estimated with respect to fixed values of P_{22}.

5.6.3 Parameter values for $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$

Table A 5.1 Estimated values for $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ parameters.

Classifier[a]	Parameter	Estimate	Std. Error	z value	Pr(z) [b]
1 & 5	α_1	0.5356	0.0319	16.8027	2.33E-63 ***
1 & 5	β_1	0.5799	0.0413	14.0540	7.28E-45 ***
1 & 5	α_2	0.5759	0.0337	17.0744	2.30E-65 ***
1 & 5	β_2	0.5280	0.0393	13.4432	3.37E-41 ***
1 & 5	α_3	0.5356	0.0319	16.8027	2.33E-63 ***
1 & 5	β_3	0.5799	0.0413	14.0540	7.28E-45 ***
1 & 5	α_4	0.5759	0.0337	17.0744	2.30E-65 ***
1 & 5	β_4	0.5280	0.0393	13.4432	3.37E-41 ***
2 & 6	α_1	0.4448	0.0271	16.3999	1.92E-60 ***
2 & 6	β_1	0.4374	0.0378	11.5676	6.02E-31 ***
2 & 6	α_2	0.4892	0.0299	16.3810	2.61E-60 ***
2 & 6	β_2	0.3910	0.0358	10.9130	9.99E-28 ***
2 & 6	α_3	0.4448	0.0271	16.3999	1.92E-60 ***
2 & 6	β_3	0.4374	0.0378	11.5676	6.02E-31 ***
2 & 6	α_4	0.4892	0.0299	16.3810	2.61E-60 ***
2 & 6	β_4	0.3910	0.0358	10.9130	9.99E-28 ***
3 & 7	α_1	0.3588	0.0257	13.9381	3.72E-44 ***
3 & 7	β_1	0.1246	0.0230	5.4125	6.21E-08 ***
3 & 7	α_2	0.5810	0.0363	16.0237	8.73E-58 ***
3 & 7	β_2	0.5213	0.0429	12.1390	6.56E-34 ***
3 & 7	α_3	0.3588	0.0257	13.9381	3.72E-44 ***
3 & 7	β_3	0.1246	0.0230	5.4125	6.21E-08 ***
3 & 7	α_4	0.5810	0.0363	16.0237	8.73E-58 ***
3 & 7	β_4	0.5213	0.0429	12.1390	6.56E-34 ***
4 & 8	α_1	0.5386	0.0343	15.7145	1.20E-55 ***
4 & 8	β_1	0.5754	0.0455	12.6586	1.00E-36 ***
4 & 8	α_2	0.3062	0.0271	11.2865	1.53E-29 ***
4 & 8	β_2	0.1853	0.0335	5.5332	3.14E-08 ***
4 & 8	α_3	0.5386	0.0343	15.7145	1.20E-55 ***
4 & 8	β_3	0.5754	0.0455	12.6586	1.00E-36 ***
4 & 8	α_4	0.3062	0.0271	11.2865	1.53E-29 ***
4 & 8	β_4	0.1853	0.0335	5.5332	3.14E-08 ***

[a] Classifiers were grouped together because the diagnostic marker values for each class in K follow the same theoretical normal distribution. Hence, parameter value estimates were the same.

[b] Significance codes: ° $p < 0.01$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5.7 Appendix 2

5.7.1 Descriptive summary results

Table A 5.2 Descriptive summary results on the economic and welfare effects for the 600 different classification outcomes per classifier 1 – 8.

Management scenario	Classifier	Output variable	Mean	Median	Sd[a]	Min.[b]	Percentiles 0.05	Percentiles 0.95	Max.[c]
1	1	Economic gain	0.126	0.218	0.275	-1.143	-0.499	0.391	0.424
		Welfare gain	0.367	0.416	0.166	-0.718	0.107	0.446	0.452
	2	Economic gain	0.179	0.267	0.270	-1.142	-0.418	0.420	0.461
		Welfare gain	0.376	0.426	0.180	-0.711	0.072	0.449	0.452
	3	Economic gain	0.197	0.298	0.301	-1.165	-0.521	0.430	0.485
		Welfare gain	0.398	0.435	0.144	-0.654	0.227	0.451	0.453
	4	Economic gain	0.159	0.250	0.272	-1.107	-0.409	0.420	0.470
		Welfare gain	0.360	0.423	0.223	-0.768	-0.065	0.448	0.450
2	5	Economic gain	0.253	0.293	0.173	-0.948	-0.037	0.414	0.497
		Welfare gain	0.859	0.862	0.049	0.753	0.776	0.936	0.948
	6	Economic gain	0.291	0.320	0.147	-0.941	0.037	0.421	0.461
		Welfare gain	0.864	0.867	0.050	0.754	0.773	0.940	0.948
	7	Economic gain	0.331	0.352	0.123	-0.895	0.190	0.435	0.475
		Welfare gain	0.868	0.873	0.053	0.750	0.771	0.947	0.949
	8	Economic gain	0.248	0.308	0.209	-0.953	-0.136	0.426	0.463
		Welfare gain	0.871	0.876	0.048	0.758	0.777	0.943	0.948

[a] Standard deviation
[b] Minimum
[c] Maximum

5.7.2 Exploratory results

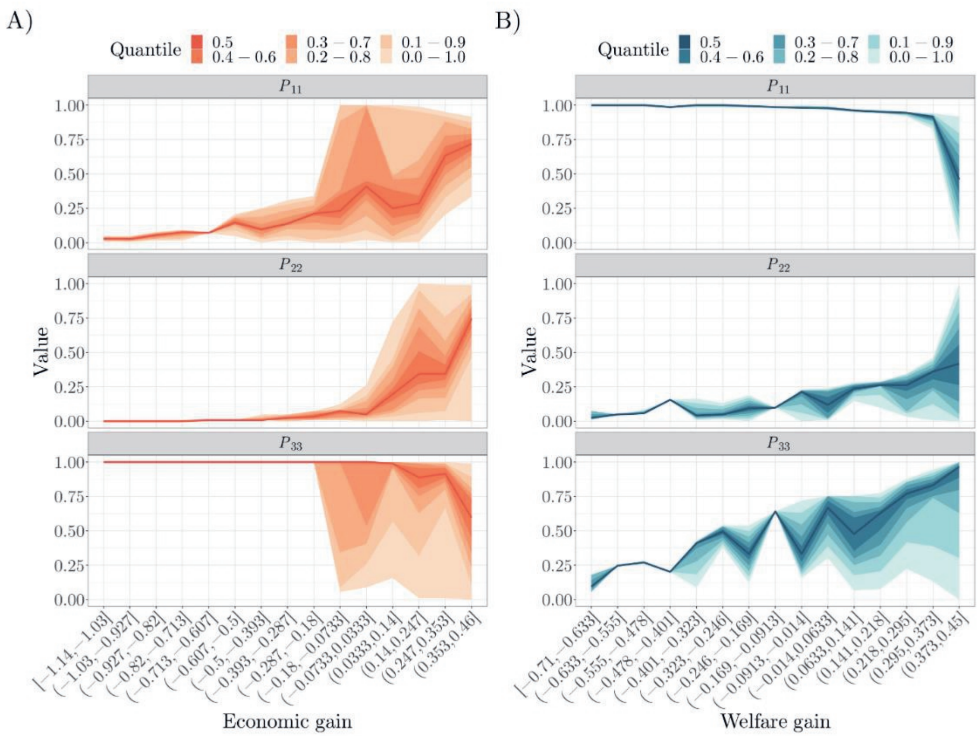


Figure A 5.1 Trends in classification probabilities P_{11}, P_{22}, and P_{33} for classifier 2 with respect to economic gains (A) and welfare gains (B). The Value on the y-axis is interpreted as the P_{ij} value.

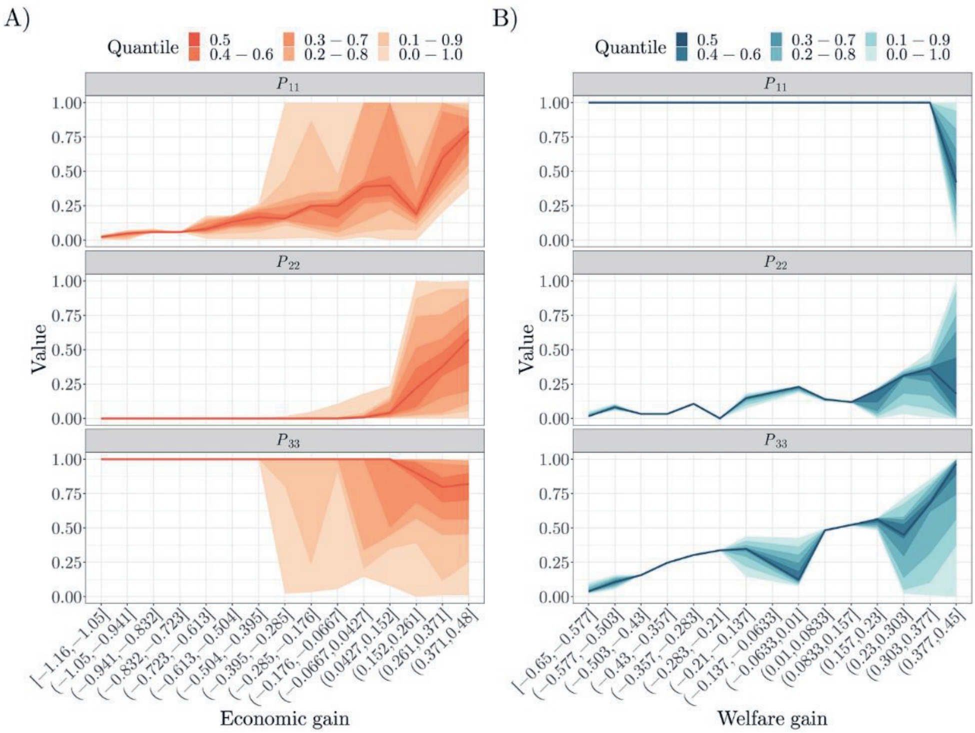


Figure A 5.2 Trends in classification probabilities P_{11}, P_{22}, and P_{33} for classifier 3 with respect to economic gains (A) and welfare gains (B). The Value on the y-axis is interpreted as the P_{ij} value.

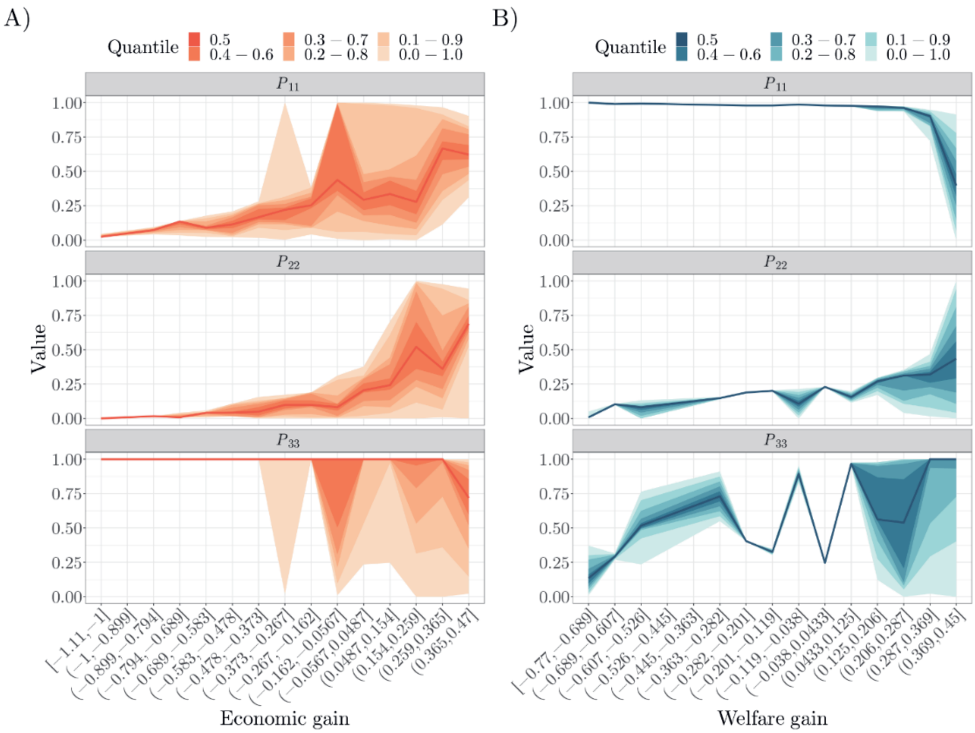


Figure A 5.3 Trends in classification probabilities P_{11}, P_{22}, and P_{33} for classifier 4 with respect to economic gains (A) and welfare gains (B). The Value on the y-axis is interpreted as the P_{ij} value.

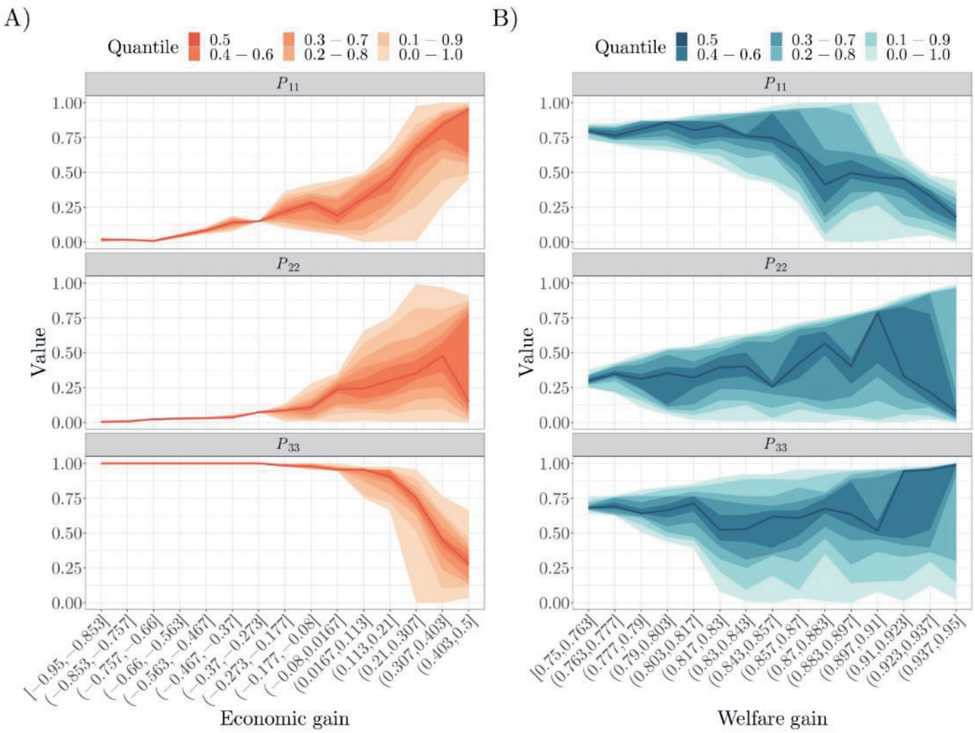


Figure A 5.4 Trends in classification probabilities P_{11}, P_{22}, and P_{33} for classifier 5 with respect to economic gains (A) and welfare gains (B). The Value on the y-axis is interpreted as the P_{ij} value.

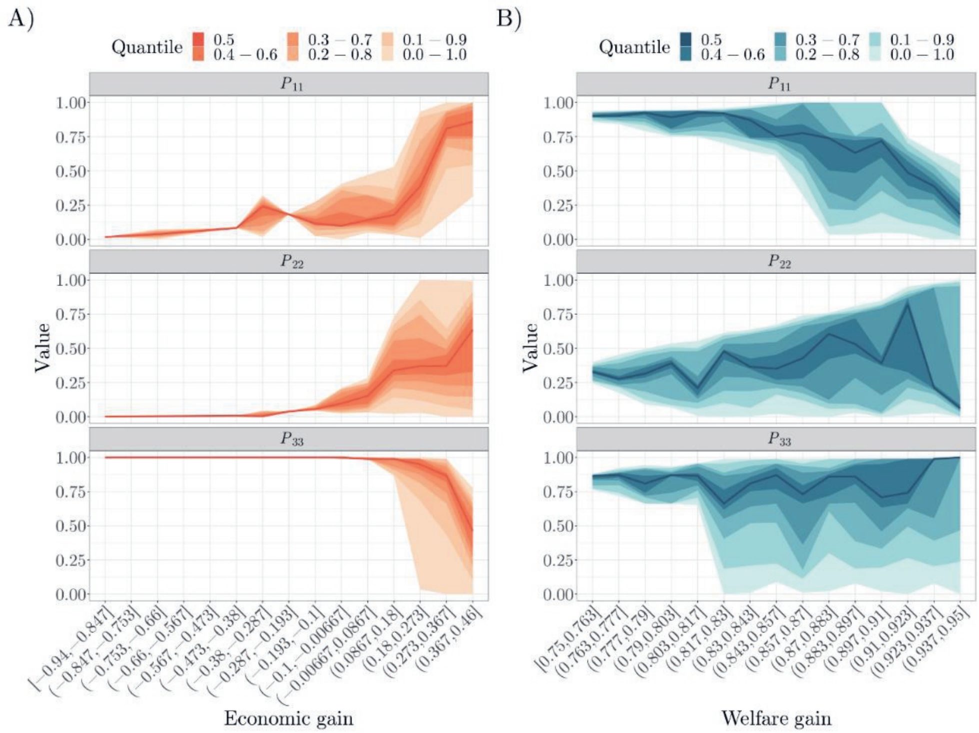


Figure A 5.5 Trends in classification probabilities P_{11}, P_{22}, and P_{33} for classifier 6 with respect to economic gains (A) and welfare gains (B). The Value on the y-axis is interpreted as the P_{ij} value.

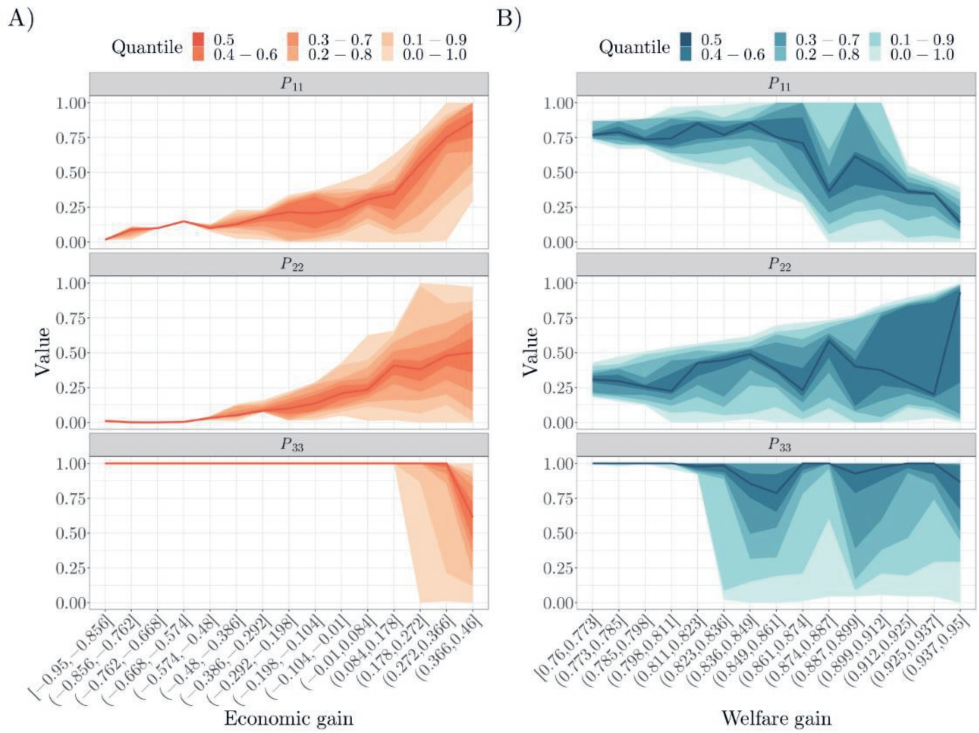


Figure A 5.6 Trends in classification probabilities P_{11}, P_{22}, and P_{33} for classifier 8 with respect to economic gains (A) and welfare gains (B). The Value on the y-axis is interpreted as the P_{ij} value.

5.7.3 Estimates of x_{ij}

Table A 5.3 Estimates of x_{ij} for economic outputs of management scenario 1 with classifiers 1 – 4.

Classifier	Parameter x_{ij}	Estimate	Std. Error	z value	Pr(z)
1	x_{11}	0.6662	1.0007	0.6657	0.5056
	x_{12}	-0.0269	0.8620	-0.0312	0.9751
	x_{13}	-1.4369	1.1684	-1.2299	0.2188
	x_{21}	-0.4986	1.2712	-0.3923	0.6949
	x_{22}	0.1442	0.6551	0.2201	0.8258
	x_{23}	0.3885	1.1099	0.3500	0.7263
	x_{31}	-0.3880	1.0716	-0.3621	0.7173
	x_{32}	-0.0035	0.4079	-0.0085	0.9932
	x_{33}	-0.0701	0.5409	-0.1296	0.8969
2	x_{11}	0.7129	0.2085	3.4200	0.0006 ***
	x_{12}	0.1585	0.1965	0.8066	0.4199
	x_{13}	-1.2549	0.3266	-3.8419	0.0001 ***
	x_{21}	-0.6239	0.2895	-2.1555	0.0311 *
	x_{22}	-0.0267	0.2745	-0.0974	0.9224
	x_{23}	0.2672	0.2851	0.9371	0.3487
	x_{31}	-0.3230	0.6938	-0.4655	0.6416
	x_{32}	0.0065	0.2965	0.0218	0.9826
	x_{33}	-0.0669	0.2759	-0.2426	0.8083
3	x_{11}	0.5414	0.1332	4.0634	0.0000 ***
	x_{12}	0.2052	0.1324	1.5493	0.1213
	x_{13}	-1.0621	0.1962	-5.4121	0.0000 ***
	x_{21}	-0.4108	0.3520	-1.1670	0.2432
	x_{22}	-0.0878	0.2824	-0.3110	0.7558
	x_{23}	0.1832	0.3016	0.6072	0.5437
	x_{31}	-0.3394	0.7253	-0.4680	0.6398
	x_{32}	0.1132	0.3443	0.3288	0.7423
	x_{33}	-0.0892	0.3316	-0.2690	0.7879
4	x_{11}	0.8868	0.2641	3.3583	0.0008 ***
	x_{12}	0.0296	0.2209	0.1342	0.8932
	x_{13}	-1.2719	0.3506	-3.6274	0.0003 ***
	x_{21}	-0.8915	0.3052	-2.9214	0.0035 **
	x_{22}	0.1788	0.2557	0.6992	0.4844
	x_{23}	0.3573	0.2806	1.2734	0.2029
	x_{31}	-0.1749	0.6754	-0.2590	0.7957
	x_{32}	-0.0804	0.2493	-0.3225	0.7471
	x_{33}	-0.1001	0.2384	-0.4200	0.6745

[a] Significance codes: ° $p < 0.01$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A 5.4 Estimates of x_{ij} for economic outputs of management scenario 2 with classifiers 5 – 8.

Classifier	Parameter x_{ij}	Estimate	Std. Error	z value	Pr(z)
5	x_{11}	0.8009	0.3946	2.0293	0.0424 *
	x_{12}	0.2779	0.3982	0.6980	0.4852
	x_{13}	-1.1110	0.7135	-1.5570	0.1195
	x_{21}	-0.5811	0.6043	-0.9615	0.3363
	x_{22}	0.0634	0.5341	0.1188	0.9054
	x_{23}	0.4854	0.5964	0.8140	0.4157
	x_{31}	0.4313	0.7437	0.5799	0.5620
	x_{32}	-0.1421	0.4043	-0.3515	0.7252
	x_{33}	-0.3214	0.3979	-0.8076	0.4193
6	x_{11}	0.6095	0.2524	2.4147	0.0157 *
	x_{12}	0.2873	0.2673	1.0748	0.2825
	x_{13}	-0.8957	0.5480	-1.6344	0.1022
	x_{21}	-0.2843	0.2964	-0.9592	0.3375
	x_{22}	0.0263	0.2871	0.0917	0.9269
	x_{23}	0.2592	0.3078	0.8418	0.3999
	x_{31}	0.2642	0.5082	0.5198	0.6032
	x_{32}	-0.0580	0.2494	-0.2324	0.8162
	x_{33}	-0.2051	0.2454	-0.8359	0.4032
7	x_{11}	0.5124	0.1654	3.0974	0.0020 **
	x_{12}	0.3194	0.1764	1.8112	0.0701 °
	x_{13}	-0.8091	0.4161	-1.9442	0.0519 °
	x_{21}	-0.2692	0.2647	-1.0170	0.3091
	x_{22}	0.0304	0.2361	0.1287	0.8976
	x_{23}	0.2616	0.2709	0.9655	0.3343
	x_{31}	0.3320	0.4648	0.7143	0.4750
	x_{32}	-0.0346	0.2651	-0.1306	0.8961
	x_{33}	-0.2746	0.2669	-1.0287	0.3036
8	x_{11}	0.5678	0.2777	2.0446	0.0409 *
	x_{12}	0.1953	0.2543	0.7680	0.4425
	x_{13}	-0.7761	0.4478	-1.7333	0.0830 °
	x_{21}	-0.1871	0.3134	-0.5969	0.5506
	x_{22}	0.0822	0.2501	0.3286	0.7424
	x_{23}	0.0918	0.2925	0.3138	0.7537
	x_{31}	0.0987	0.3971	0.2486	0.8037
	x_{32}	-0.0327	0.1814	-0.1802	0.8570
	x_{33}	-0.0791	0.1723	-0.4591	0.6462

[a] Significance codes: ° $p < 0.01$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A 5.5 Estimates of x_{ij} for welfare outputs of management scenario 1 with classifiers 1 – 4.

Classifier	Parameter x_{ij}	Estimate	Std. Error	z value	Pr(z)
1	x_{11}	-0.1015	1.0007	-0.1014	0.9192
	x_{12}	0.0029	0.8620	0.0033	0.9973
	x_{13}	0.1165	1.1684	0.0997	0.9206
	x_{21}	0.8544	1.2712	0.6721	0.5015
	x_{22}	0.4540	0.6550	0.6931	0.4882
	x_{23}	0.3818	1.1099	0.3440	0.7308
	x_{31}	-1.7832	1.0716	-1.6641	0.0961 °
	x_{32}	-0.0174	0.4079	-0.0427	0.9659
	x_{33}	-0.0043	0.5409	-0.0080	0.9936
2	x_{11}	-0.0429	0.2085	-0.2056	0.8371
	x_{12}	-0.1006	0.1965	-0.5120	0.6087
	x_{13}	-0.0255	0.3266	-0.0780	0.9379
	x_{21}	-0.1587	0.2895	-0.5483	0.5835
	x_{22}	0.0116	0.2745	0.0423	0.9662
	x_{23}	-0.0218	0.2851	-0.0765	0.9390
	x_{31}	-1.1845	0.6938	-1.7071	0.0878 °
	x_{32}	0.5002	0.2965	1.6871	0.0916 °
	x_{33}	0.5154	0.2759	1.8679	0.0618 °
3	x_{11}	-0.0236	0.1332	-0.1768	0.8596
	x_{12}	-0.0047	0.1324	-0.0355	0.9716
	x_{13}	-0.0051	0.1962	-0.0259	0.9794
	x_{21}	0.1538	0.3520	0.4370	0.6621
	x_{22}	-0.1213	0.2824	-0.4295	0.6675
	x_{23}	-0.0659	0.3016	-0.2185	0.8271
	x_{31}	-1.1274	0.7253	-1.5545	0.1201
	x_{32}	0.5688	0.3443	1.6518	0.0986 °
	x_{33}	0.5253	0.3316	1.5841	0.1132
4	x_{11}	0.2739	0.2641	1.0374	0.2996
	x_{12}	-0.3041	0.2209	-1.3763	0.1687
	x_{13}	-0.1542	0.3506	-0.4397	0.6602
	x_{21}	-0.8539	0.3052	-2.7981	0.0051 **
	x_{22}	0.3940	0.2557	1.5409	0.1233
	x_{23}	0.2756	0.2806	0.9823	0.3259
	x_{31}	-0.7427	0.6754	-1.0996	0.2715
	x_{32}	0.2658	0.2493	1.0663	0.2863
	x_{33}	0.2925	0.2384	1.2273	0.2197

[a] Significance codes: ° $p < 0.01$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A 5.6 Estimates of x_{ij} for welfare outputs of management scenario 2 with classifiers 5 – 8.

Classifier	Parameter x_{ij}	Estimate	Std. Error	z value	Pr(z)
5	x_{11}	0.2687	0.3946	0.6810	0.4959
	x_{12}	0.3254	0.3982	0.8171	0.4139
	x_{13}	0.4217	0.7135	0.5910	0.5545
	x_{21}	0.1626	0.6043	0.2691	0.7879
	x_{22}	0.3831	0.5341	0.7172	0.4732
	x_{23}	0.4701	0.5964	0.7883	0.4305
	x_{31}	0.6315	0.7437	0.8491	0.3958
	x_{32}	0.2627	0.4043	0.6498	0.5158
	x_{33}	0.1216	0.3979	0.3056	0.7599
6	x_{11}	0.2653	0.2524	1.0509	0.2933
	x_{12}	0.3396	0.2673	1.2704	0.2040
	x_{13}	0.3968	0.5480	0.7241	0.4690
	x_{21}	0.2468	0.2964	0.8324	0.4052
	x_{22}	0.3433	0.2871	1.1956	0.2318
	x_{23}	0.4116	0.3078	1.3370	0.1812
	x_{31}	0.5141	0.5082	1.0114	0.3118
	x_{32}	0.2948	0.2494	1.1818	0.2373
	x_{33}	0.1928	0.2454	0.7859	0.4319
7	x_{11}	0.3175	0.1654	1.9193	0.0549 °
	x_{12}	0.3422	0.1764	1.9407	0.0523 °
	x_{13}	0.3194	0.4161	0.7675	0.4428
	x_{21}	0.1073	0.2647	0.4054	0.6852
	x_{22}	0.3508	0.2361	1.4858	0.1373
	x_{23}	0.5211	0.2709	1.9232	0.0545 °
	x_{31}	0.6054	0.4648	1.3026	0.1927
	x_{32}	0.2703	0.2651	1.0197	0.3079
	x_{33}	0.1035	0.2669	0.3876	0.6983
8	x_{11}	0.1322	0.2777	0.4761	0.6340
	x_{12}	0.2951	0.2543	1.1605	0.2459
	x_{13}	0.5616	0.4478	1.2542	0.2098
	x_{21}	0.4248	0.3134	1.3556	0.1752
	x_{22}	0.3555	0.2501	1.4213	0.1552
	x_{23}	0.2086	0.2925	0.7131	0.4758
	x_{31}	0.3594	0.3971	0.9052	0.3654
	x_{32}	0.3251	0.1814	1.7919	0.0731 °
	x_{33}	0.3044	0.1723	1.7668	0.0773 °

[a] Significance codes: ° $p < 0.01$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5.7.4 Synthesis of other classifiers

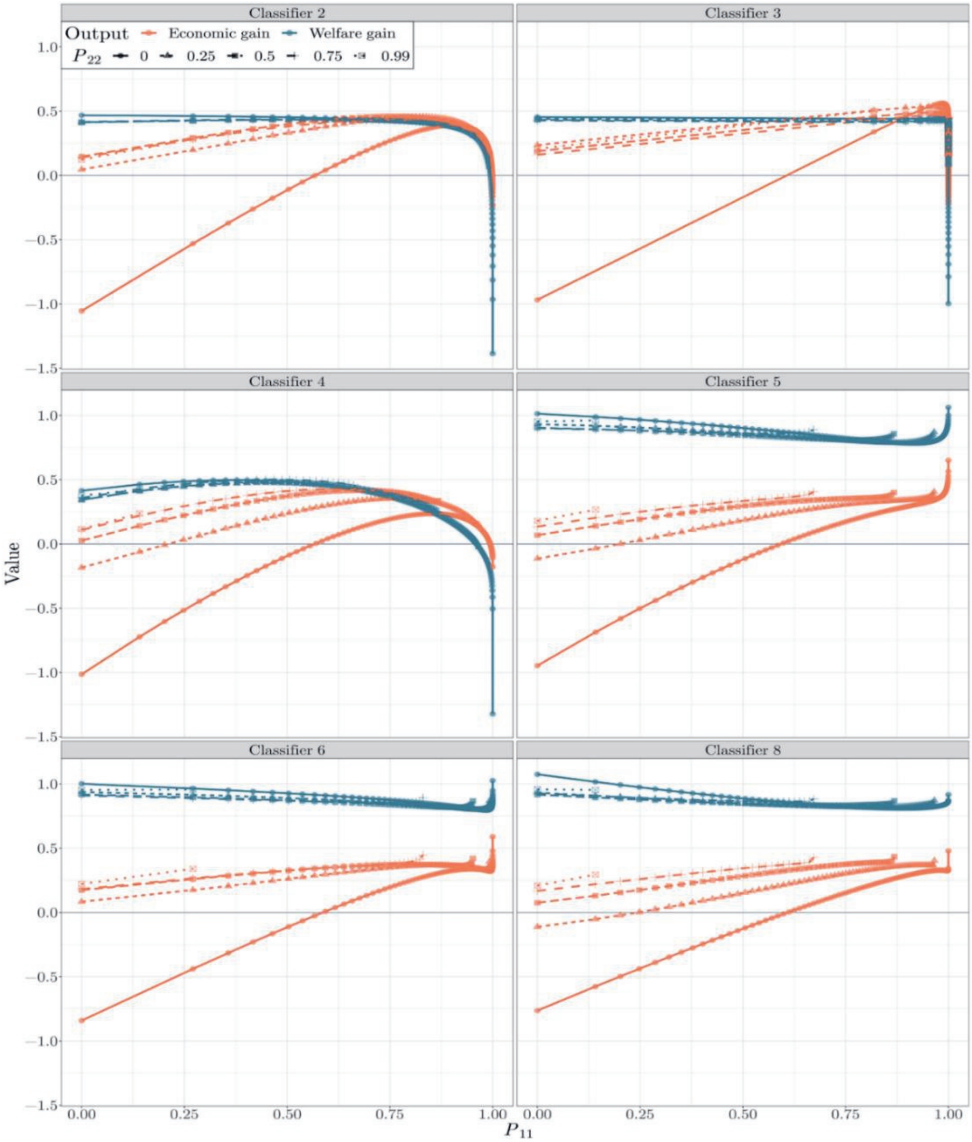


Figure A 5.7 Effects of P_{11} and P_{22} on the economic and welfare gains for classifiers 2 – 6 and 8. The Value on the y-axis is interpreted as the relative difference in economic and welfare SOM impact compared to a no-classifier situation. Positive values indicate a reduction in SOM economic or welfare impact (i.e., positive gain), while negative values indicate an increase in SOM economic or welfare impact (i.e., negative gain).

Chapter 6
General discussion

This thesis adopts an interdisciplinary approach by integrating three distinct elements, namely, *i*) economics, *ii*) animal welfare, and *iii*) data driven insights, under one *digitally supported animal health management* lens to gain insights on the value of precision livestock farming (PLF) at the farm-level. Specifically, the research within the thesis focuses on decision support apropos the economic and animal welfare implications of a prevalent dairy cow health disorder, sub-optimal mobility (SOM), which has been the subject of significant amounts of research in the field of PLF. By quantifying the economic and animal welfare value of a PLF based strategy in the management of SOM, this thesis contributes to the realm of digitally supported animal health management by providing insights that can support more effective economic and animal welfare decision making. In addition, the thesis also contributes towards future PLF technological developments by delivering evidence demonstrating how favourable economic and animal welfare outcomes can be achieved in digitally supported animal health management.

In this general discussion, research Chapters 2 – 5 are first summarised by highlighting the main results and methodological novelties (section 6.1). The summary of research chapters is then followed by sections whereby the results are synthesised by placing them in the broader context of digitally supported animal health management (section 6.2), methodological reflections are presented (section 6.3), future research avenues are put forward (section 6.4), and implications for animal welfare assessors and the environment are briefly discussed (section 6.5). Finally, the general discussion concludes with a list of main conclusions drawn from this thesis (section 6.6).

6.1 Summary of research chapters

A bio-economic simulation model was developed and used for all research chapters to address the research questions in Chapter 2 – 5. The biological component of the simulation model served as a basis to study how epidemiological events manifested into economic (Chapter 2 and Chapter 5) and animal welfare impacts (Chapter 3 and Chapter 5), and management events (Chapter 4 and Chapter 5). Below a summary of the research chapters are presented.

Chapter 2 describes the development of the dynamic cow-level stochastic bio-economic simulation model that was used to assess the annual economic impact of SOM for a typical SOM management strategy. The model is the first of its kind to simulate the incidence of hoof disorders at hoof-level, and as the responsible mechanisms for dairy cow SOM. To simulate the incidence of hoof disorders, two epidemiological sub-models are included (Greenwood and Reed-Frost models), making it the first bio-economic simulation model to simulate the infectious hoof disorder, digital dermatitis, with a contagious spread model. Given the underlying hoof-disorders responsible for SOM, SOM is ultimately described at cow-level by five mobility scores. Per day, for every cow spent with one of five mobility scores, production- and management-based economic calculations were computed. This allowed the opportunity to quantify the annual direct economic impact of SOM per maximum mobility score SOM case category accounting for mobility score transitions within each case. It also allowed the opportunity to quantify the annual indirect economic impact of SOM in general. Key results highlight the direct and indirect economic importance of mobility scores 2 and 3, especially concerning mobility score 2 because the associated economic impact has never been studied before. By promoting targeted intervention procedures aimed at reducing the incidence and prevalence of mobility scores 2 and 3, the economic impact associated with these mobility scores can be mitigated as well as the incidence of mobility scores 4 and 5, and their associated economic impact. The methodological contribution of this chapter is the simulation model itself. It also demonstrates how future economic impact assessments of animal health disorders can be modelled by considering all adverse health effects on production parameters that contribute to alterations in herd-level dynamics, capturing the indirect economic effects, rather than only the affected production performance of individual animals. That is by herd-level comparisons of *with* and *without* disease scenarios.

Chapter 3 builds on Chapter 2 whereby the impact of SOM on animal welfare was studied and simulated. To better understand the negative effects of SOM on animal welfare, additional parameters representing welfare impairment weights were incorporated into the model. These weights were based on welfare expert knowledge in combination with an understanding apropos the physical effects of SOM on welfare indicators. The welfare impairment weights were obtained using adaptive conjoint analysis (ACA), which is a well-established research tool in economics and marketing used to understand the relative importance of product attributes in consumption related decision making. By applying this approach to animal welfare indicators (i.e., attributes) that compose animal welfare, the negative effects of SOM – depending on the degree of physical effects and SOM severity – on individual welfare indicators were quantified, which collectively contribute to the negative welfare effects of SOM. Populating the simulation model with the derived welfare impairment weights showed that under a typical SOM management strategy the herd-level welfare impact was mostly due to maximum mobility score 3 SOM cases because of the cumulative effect of impaired welfare due to dynamics of mobility scores 2 and 3. Cow welfare could be enhanced by promoting targeted intervention procedures aimed at reducing the incidence and prevalence of mobility scores 2 and 3. In terms of methodological contributions, this chapter demonstrates exciting opportunities to *i*) quantify welfare impairment weights apropos physical effects of various health disorders on welfare indicators, *ii*) combine these welfare impairment weights respective of health disorder and health disorder severities and *iii*) simulate the animal welfare impact of different health disorders to gain insight on which health disorders farmers, researchers and policy makers should primarily focus on.

Chapter 4 describes a study whereby insights were derived on the economic value of sensor-based SOM management strategies. Multiple novel sensor-based SOM management strategies that included different *i*) farmer perceptions towards SOM constitution, *ii*) combinations of sensor detection quality, *iii*) SOM interventionists, and *iv*) intervention intervals respective of mobility scores were compared against a typical SOM management strategy without sensors. A simple and original alert prioritisation criterion was implemented in the simulated sensor-based SOM management scenarios, which allowed for more effectively timed intervention intervals of different mobility scores and provided additional insights on the trade-offs between production losses and labour costs. Results showed that fundamental changes in SOM management are required to obtain the economic benefits from a sensor-based SOM management strategy. These changes entailed changes in farmer perception towards SOM constitution whereby treating mobility scores 2 and 3 can be economically beneficial, and bi-annual whole herd routine hoof-trimming should be replaced with more frequent cow specific hoof trimming. Furthermore, the alert prioritisation criterion that allowed an intervention interval of seven days proved economically beneficial because costly false alerts could be avoided while maintaining earlier mitigations of production losses. The alert prioritisation criterion is a valuable contribution to the literature, offering the opportunities for future sensor developers to improve sensor generated information without major adjustments to existing sensors with the potential for higher levels of additional economic value.

Chapter 5 provides a comprehensive analysis on the trade-offs and synergies in economic and animal welfare value of different sensor-based SOM management strategies by integrating methodological approaches and result driven insights from Chapters 2, 3, and 4. Specifically, this chapter contributes to the PLF research community and relevant literature by exploring the potential application of 3-class, as opposed to binary, classification models in PLF for SOM management, with the aim of quantifying the trade-offs and synergies between economic and animal welfare value while considering the complex classification behaviour exhibited by such models. Results showed that 3-class classification models do have the potential for additional economic and animal welfare value when used for SOM management. The chapter contributes to the literature concerning multi-class receiver operating characteristics analysis by introducing a novel methodology that was developed to study the complex behaviour between classification probabilities. With this approach it was found that, although overall economic and welfare benefits were achieved, additional economic benefits were traded for reductions in animal welfare benefits. Chapter 5 provides a valuable contribution to the field of PLF and sheds light on the potential benefits, and consequential effects of increased benefits, in the utilisation of 3-class classification models for SOM management. Furthermore, it enables developers of classification models to gain valuable insights into the performance of their models and ensure that they align with the preferences of farmers.

In summary the research described in Chapters 2, 3, 4, and 5 contribute to the literature by providing insights on methodological approaches that *i*) capture indirect costs of health disorders *ii*) quantify expertise based welfare impacts of health disorders, *iii*) highlight the importance of less severe but prevalent levels of animal health disorders, *iv*) demonstrate significant opportunities for sensor supported animal health management that includes novel sensor-based management strategies, *v*) incorporates economics and animal welfare into the animal health decision making framework, and *vi*) propose a tractable approach to understand the complex and interdependent nature of 3-class classification models.

6.2 Synthesis of results

In this section the results found in Chapters 2 – 5 are synthesised in the broader context of digitally supported animal health management in relation to relevant research. The aim of this section is to provide a comprehensive understanding on how digital technologies found in PLF can be effectively implemented and used at the farm-level to mitigate the negative economic and animal welfare impacts of health disorders. To facilitate the discussion, three dominant themes were identified. The first theme presents a discussion on the necessity of comprehensive animal health impact assessments so that health disorder severities with critical economic and animal welfare impacts are appropriately identified. Building on the insights gained through the comprehensive impact assessment, the second theme presents a discussion on important animal health aspects, the design of management strategies, and technological developments to ensure economic and animal welfare benefits are obtained with digitally supported animal health management. Lastly, the third theme presents a discussion on the complex interplay of synergies and antagonisms between various economic and animal welfare aspects following the implementation of digitally supported animal health management.

6.2.1 The necessity of comprehensive animal health impact assessments

Comprehensive animal health impact assessments refer to thorough evaluations that examine the effects of health disorders from various perspectives, including a range of severities and their underlying dynamics (i.e., cumulative incidence and duration). By doing so, critical impacts congruent to health disorder severities can be appropriately identified. This provides direction on designing more effective health disorder management strategies that include different intervention approaches depending on the dynamics of the severity and associated impacts.

Typically, impact assessments concern the economic impact of health disorders (e.g., Bonestroo et al., 2023; Gussmann et al., 2018). However, animal welfare is affected by health disorders too (Broom & Corke, 2002; Galindo & Broom, 2002; Nielsen et al., 2021). Given the fact that animal welfare is becoming increasingly important for citizens, at least in Europe (EU Monitor, 2022; Eurobarometer, 2016), and is considered an integral part towards achieving sustainable livestock production systems (FAO, 2018), incorporating animal welfare into the animal health disorder impact assessment will provide a more holistic understanding towards the consequences of animal health disorders and provide better insights on how to effectively manage them from economic and animal welfare perspectives.

The research in Chapter 2 is a typical economic impact assessment that is linked to hoof disorders. Hence, this study can be filed in the same drawer with, for instance, the research of Kossaibati and Esslemont (1997), Bruijnis et al. (2010), Charfeddine and Pérez-Cabal (2017), and Dolecheck et al. (2019) who estimated the economic impact of different hoof disorders. Chapter 2 builds on this research by simulating the economic impacts caused by hoof disorders through their impact on cow mobility. Doing it this way allows the dynamics of hoof disorders to manifest into the dynamics of SOM. This approach is more informative and contributes to the literature from a managerial perspective because hoof disorders, which often induce SOM (Alvergnas et al., 2019), are typically addressed after their effects are detected in the form of SOM (Alawneh et al., 2012a). Thus, providing comprehensive information on the economic impact of SOM can support SOM management decisions.

Indeed, the economic impact of SOM[10] has been studied before. Besides the study of Ettema et al. (2010) and O'Connor et al. (2023), other SOM economic impact studies did not include the dynamics of hoof disorders (Ettema & Østergaard, 2006; Guard, 2008; Liang et al., 2017; Willshire & Bell, 2009). In addition, except for O'Connor et al. (2023), all other aforementioned authors studying the economic impact of SOM only addressed SOM in general by transforming SOM into a binary health state when it can be described by more than two severities in the form of mobility scores (e.g., Sprecher et al., 1997). This binary transformation of SOM ultimately reduces the level of comprehensiveness pertaining to the dynamics of SOM, such as the cumulative incidence and prevalence of mobility scores, and consequential cost contribution of mobility scores to the overall economic impact. Ultimately little insight is provided on how to effectively manage specific mobility scores.

In Chapter 2 SOM was not transformed to a binary health disorder. Rather, SOM was described by independent mobility scores allowing for the dynamics and consequential economic impacts to be comprehensively studied. More recently this approach was also adopted by O'Connor et al. (2023). However, O'Connor et al. (2023) studied the economic impact of mobility scores in an Irish seasonal calving dairy system using a 4-point mobility scoring system (see Agriculture and Horticulture Development Board, 2020). This is unlike the research in Chapter 2 where the economic impact of mobility scores were studied in a Dutch continuous calving dairy system using the 5-point mobility scoring system by Sprecher et al. (1997). The epidemiological results in Chapter 2 showed that mobility scores 2 and 3 were more prevalent and lasted longer than mobility scores 4 and 5. Consequentially, due to the underlying mobility score dynamics, the economic results showed that maximum mobility score 3 SOM cases contributed almost a third to the annual total direct economic impact. This is a considerable contribution to the annual total direct economic impact of SOM that cannot be identified when mobility scores ≥3 are grouped into a binary SOM state (Ettema & Østergaard, 2006; Guard, 2008; Liang et al., 2017; Willshire & Bell, 2009). The economic impact assessment in Chapter 2 extended to mobility score 2, which has not been done in the aforementioned studies since cows with this mobility score are typically considered to not have SOM. By doing so, the economic results also revealed that maximum

[10] Sub-optimal mobility is referred to as lameness by the mentioned authors.

mobility score 2 SOM cases contributes almost 13 percent to the annual total direct economic impact due to the dynamics of maximum mobility score 2 SOM cases. An interesting and novel result from Chapter 2 was that the indirect annual economic impact of SOM was found to be 41 percent of the total annual economic impact mostly due to the negative effects of mobility score 2 and 3 on reproductive performance (i.e., fertility related culling). These results suggest that previous studies underestimated the economic impact of SOM. More importantly these results contribute to our understanding on the economic importance of mobility scores 2 and 3 that previous studies could not provide as a result of grouping mobility scores ≥3 together and omitting mobility score 2. Consequentially, the results from Chapter 2 provide valuable managerial insights. Specifically, these insights suggest that mobility score 2 and 3 should be managed differently compared to mobility scores 4 and 5. The reason is that their different dynamics contribute substantially to the annual total cost of SOM. This highlights the significance of comprehensively studying the economic impact of health disorders across a range of severities and their underlying dynamics to provide more nuanced managerial insights that cannot be achieved if health disorders are reduced to a binary state.

The impact assessment of SOM in this thesis is not limited to the economic impact found in Chapter 2, but also the animal welfare impact of SOM described in Chapter 3. In general, quantifying the impact of health disorders on animal welfare is incredibly challenging due to the obvious fact that animals cannot directly communicate how they are feeling when afflicted with a health disorder. Overcoming this communication barrier by studying how animal-based welfare indicators are physically affected when an animal is afflicted with a health disorder can offer important insights on the consequential welfare effects of health disorders (EFSA, 2012; Nielsen et al., 2023). Considering this, the research in Chapter 3 describes an innovative approach towards quantifying the impact of SOM on animal welfare through the physically affected welfare indicators and is based on expert knowledge elicitation and simulation modelling. By focussing on the total contribution of different SOM cases to the total welfare impact the study produced novel insights demonstrating that maximum mobility score 2 and 3 SOM cases respectively contributed ~16 and ~71 percent to the total welfare impact compared to the ~12 and ~1 percent contribution of maximum mobility score 4 and 5 SOM cases, respectfully. Despite mobility scores 2 and 3 having lower welfare disutility scores than mobility scores 4 and 5, the higher welfare impact of maximum mobility score 2 and 3 SOM cases are due to cumulative effect of welfare disutility for mobility score 2 and 3 in conjunction with their dynamics. Comparing these results with other SOM welfare impact assessments is challenging because – to the best of my knowledge – no other published studies reporting the welfare impact of SOM are available. However, the results can be compared in the context of hoof disorders whereby increasing hoof disorder severities have been associated with increasing mobility scores (O'Connor et al., 2019). Bruijnis et al. (2012) estimated that subclinical hoof disorders contributed substantially to the total welfare impact of hoof disorders (~54 percent), corroborating the results in Chapter 3 apropos the substantial contribution of lower mobility scores to the total welfare impact. Hence, this comprehensive information apropos the contribution of different SOM cases to the total SOM welfare impact is crucial for the design of appropriate animal welfare centric management strategies that cannot be achieved if SOM continues to be reduced to a binary health disorder, as done in previous SOM economic impact assessment literature.

Therefore, by quantifying the economic and animal welfare impact in Chapter 2 and Chapter 3 of specific SOM cases (i.e., maximum mobility score SOM cases) in conjunction with their dynamics, a more comprehensive understanding of, and unique perspectives on, the economic and animal welfare impact of SOM was achieved. This is especially with regards to the lower mobility scores, which have not been independently studied before. With a better understanding on the SOM dynamics and consequential economic and animal welfare effects, more nuanced SOM management approaches tailored to different mobility scores can be designed that consider the different economic and animal welfare impacts as a result of different mobility score dynamics. These original insights contribute to the literature from a SOM managerial viewpoint whereby they can be utilised to promote the uptake of newly designed economic and animal welfare enhancing SOM management strategies. This can be achieved by demonstrating the economic and welfare importance of mobility scores 2 and 3, particularly in situations where farmers tend to underestimate SOM prevalence (Cutler et al., 2017; Leach et al., 2010) or where farmers perceive less severe forms of SOM as non-problematic on their farms (Bruijnis et al., 2013) in a time of ever increasing animal welfare importance (EU Monitor, 2022; Eurobarometer, 2016; FAO, 2018).

6.2.2 Digitally supported animal health management: successful integration and necessary developments

Digital agriculture is a concept that refers to the application and integration of advanced information and communication technologies, and digital systems with tools such as sensors to enhance the productivity, efficiency, and sustainability of various agricultural aspects (e.g., De Clercq et al., 2018; Morrone et al., 2022; Neethirajan & Kemp, 2021a; Perrett et al., 2017). PLF, a key component of digital agriculture, enables farmers to effectively manage their livestock through objective, continuous, and autonomous monitoring. PLF can provide real-time information at the individual animal level (Berckmans, 2017; Norton et al., 2019), offering the potential for early warnings of poor animal health for more effective animal health management (Li et al., 2020; Vranken & Berckmans, 2017; Wathes, 2009).

Discussions apropos the added value of PLF technologies in animal health management is widespread (e.g., Banhazi et al., 2012; Berckmans, 2014, 2015; Perrett et al., 2017; Wathes, 2009), but research quantifying the added value is sparse. Building on the insights gained from Chapter 2 and Chapter 3, innovative sensor-based animal health management strategies were designed in Chapter 4 to evaluate the value of PLF. These management scenarios contribute to the existing PLF literature as they are the first of their kind. Alongside the sensor-based management scenarios, the results from Chapter 4 and 5 provide clear normative evidence that enriches the academic discourse on the additional economic and animal welfare benefits that can be achieved by using PLF technologies for sensor-based animal health management. However, achieving these benefits of sensor-based animal health management, changes in the cognitive framework of farmers regarding animal health disorders are required. In this general discussion the cognitive framework refers to a structured system of mental processes and strategies used for organising, interpreting, and understanding information (Spink & Cole, 2006). It encompasses various cognitive functions such as perception, beliefs, and attitudes that ultimately influence decision-making and behaviour. Therefore, fostering changes in the cognitive framework in general towards animal health disorders allows for the design of unique PLF-based animal health interventions that go beyond simply replacing old interventions with technology. In addition, changes in the cognitive framework should also be coupled with additional technological developments. The notion on requirements for changes in the cognitive framework and technological developments are expanded in the discussion below in conjunction with the results from Chapter 4 and Chapter 5 to inform and guide future integration and advancements of PLF technologies for sensor-based animal health management.

Changes in the cognitive framework of farmer's apropos health disorders are first and foremost required. This is crucial for two reasons. Firstly, a farmer's cognitive framework influences animal health and subsequent management of animal health (Adler et al., 2019; Garforth et al., 2013; Jansen et al., 2009; Suit-B et al., 2020). For example, in the study by Jansen et al. (2009) the authors found associations between farmer attitudes apropos a normative reference frame apropos mastitis (i.e., what a normal mastitis situation is on the farm) and mastitis incidence; suggesting different beliefs apropos the constitution of a mastitis problem. In the case of SOM, farmers may perceive the constitution of SOM differently, considering cows with the higher mobility scores 4 and 5 as SOM, while disregarding the lower mobility scores 2 and 3 (Horseman et al., 2014) and potentially considering these cows as having normal mobility (i.e., cows that are not SOM). This lends further explanation to why farmers generally underestimate the prevalence of SOM compared with personnel trained in mobility scoring (Bran et al., 2018; Cutler et al., 2017; Richert et al., 2013). Hence, one aspect of the cognitive framework that needs to change is how farmers perceive the constitution of health disorders. For instance, farmers should acknowledge that mobility scores 2 and 3 do constitute SOM – because they have economic and animal welfare impacts lends more evidence to this (Chapter 2 and Chapter 3). The second reason is contingent upon the first reason. Judgements made by personnel trained in animal health concerning healthy and unhealthy states are often used to define the golden standard for the PLF technology to distinguish between healthy and unhealthy states. If a farmer's cognitive framework has not been aligned with the golden standard, appropriate decisions made with the technology generated animal health information may not occur, thereby reducing the potential to obtain the additional economic and animal welfare value (Rojo-Gimeno et al., 2019).

Results from management scenario 1 in Chapter 4 demonstrated that while a farmer's cognitive framework with respect to SOM remained unchanged (i.e., the farmer did not consider mobility scores 2 and 3 to constitute SOM; Horseman et al., 2014) and, resultingly, SOM management did not change, no additional economic benefits nor meaningful reductions in SOM prevalence were obtained. Changing the cognitive framework of farmers towards animal health is complex. However, to align it with the golden standard of automatic SOM[11] detection sensors, some rudimentary changes were made. These changes proxied an improvement of the farmer's understanding and perception towards the constitution of SOM. Moreover, it fostered the uniquely designed sensor-based management approaches. As a result, economic benefits in management scenarios 2, 3 and 5 and reductions of SOM prevalence in management scenarios 2 – 5 were achieved (Chapter 4). The reductions in SOM prevalence ultimately resulted in animal welfare benefits in Chapter 5. These results highlight the importance in addressing the cognitive framework of farmers apropos health disorders as an initial step towards achieving the successful integration of PLF technologies in animal health management. However, this necessitates external assistance from animal health experts to offer guidance and advice on suitable health management (e.g., Main et al., 2012), and – in the context of SOM – can be supported by the research presented in this thesis.

Future implementation of PLF-based animal health management strategies will also require technological developments apropos technology driven classification. Currently, PLF technologies developed to support mastitis and SOM management primarily focus on binary health disorder classifications, overlooking the varying dynamics of health disorder severities and their distinct economic and animal welfare

[11] SOM was constituted as mobility scores ≥3 in management scenarios 2 and 3, and mobility scores ≥2 in management scenarios 4 and 5.

impacts (Alsaaod et al., 2019; Bausewein et al., 2022) as discussed in section 6.2.1. Future PLF technologies should adopt a more nuanced approach, considering non-binary health class classifications, which would enable tailored intervention procedures for different health disorder severities. This is crucial for effective health disorder management because of the different economic and animal welfare impacts due to the different health disorder severity dynamics; as demonstrated in Chapter 2 and Chapter 3 and discussed in section 6.2.1. Therefore, treating all health severities as equal, as in binary classification often seen in current PLF technologies (Alsaaod et al., 2019; Bausewein et al., 2022), undermines the potential for unique intervention procedures respective of health disorder severity. Results from Chapter 4 strongly suggest that future PLF technological developments should adopt a non-binary health disorder classification procedure to facilitate more nuanced intervention procedures respective of health disorder severity to effectively mitigate their negative impacts (Chapter 2, Chapter 3, and section 6.2.1).

When mobility scores ≥3 were grouped together to constitute SOM as binary, which is typically done (see review by Alsaaod et al., 2019), the economic benefits were minimal or did not exist. This was because daily alerts were indistinguishable with respect to the underlying mobility scores ≥3 and incurred large labour costs when checked. In contrast, in the non-binary health class classification approach when mobility score 3 was separated from mobility scores ≥4 to allow for prolonged alert generation, larger economic benefits were achieved. In addition, including mobility score 2 into the intervention procedure showed that significant reductions in the welfare impact due to SOM could be achieved while maintaining the economic benefits (Chapter 5). This further emphasises the need to account for mobility score as a form of SOM (Chapter 2 and Chapter 3). More importantly it emphasises the need to include mobility score 2 into the non-binary SOM classification procedure because currently it is not at all considered as SOM in the classification procedure (Alsaaod et al., 2019). These economic and animal welfare benefits were achieved because the more nuanced non-binary classification and intervention approach that considered the economic and animal welfare impacts associated with different SOM dynamics allowed for the customisation of intervention procedures specific to different mobility scores. Hence, this customisation included a novel time dimension whereby alerts apropos less severe SOM (i.e., mobility score 2 and 3) could be prioritised and generated at predefined intervals to reduce the opportunity cost of checking false positive alerts while ensuring production losses and animal welfare impacts associated with these mobility scores were avoided in a timely manner. Few alert prioritisation methods exist (Dominiak & Kristensen, 2017) to reduce the number of potentially overwhelming number of alerts (Eckelkamp & Bewley, 2020). The alert prioritisation method proposed and used in this study is an original methodological contribution to the literature because no alert prioritisation method like the one in Chapter 4 exists. Moreover, clear economic and animal welfare benefits are associated with this alert prioritisation contribution. Therefore, results from Chapter 4 and Chapter 5 provide compelling evidence that future developments in PLF technology for health management should focus on non-binary health classification because the dynamics of animal health disorders and their consequential economic and welfare impacts can be better accounted for through tailored animal health disorder severity intervention procedures.

The alert's information quality depends on the technology's performance in distinguishing between health classes and is based on the respective distribution of diagnostic marker values. In turn, the quality of information can influence the added value of the technology (Rojo-Gimeno et al., 2019). In a binary health class classification context, the quality of information is positively influenced in general by greater separation between the two distributions of health class diagnostic marker values (Nakas et al., 2023). However, value adding separations between the distributions in diagnostic marker values for non-binary health classes becomes more complex. This is because more than one separation between the distributions of health class diagnostic marker values is required. Chapter 5 provides valuable evidence, in the context of non-binary SOM classification, apropos separations between diagnostic marker values suggesting that larger separations between the distribution of non-SOM (i.e., health class K_1) and other SOM (i.e., health classes K_2 and K_3) diagnostic marker values can positively influence the added economic and animal welfare value of digitally supported animal health management. This is because such separations can ensure the increased feasibility of generating alerts with information characteristics pertaining to low false positive and high true positive probabilities. Furthermore, these information characteristics are aligned with the preferences of farmers (Van De Gucht et al., 2017b).

6.2.3 Understanding synergies and antagonisms in digitally supported animal health management and implications for farmer preferences

Farmers are undoubtedly heterogeneous towards animal health management (e.g., Biesheuvel et al., 2021; de Lauwere et al., 2020; Doidge et al., 2021; Sok et al., 2016; van Soest et al., 2015). For individual farmers to obtain the promising economic and animal welfare benefits from digitally supported animal health management, as presented in section 6.2.2, it is crucial to consider the factors that contribute to this heterogeneity. This involves understanding the complex interplay between synergies and antagonisms emerging within digitally supported animal health management that can influence animal health decision making alongside animal health management preferences. This section explores the synergistic and antagonistic interactions, focusing on economic factors, animal welfare, labour time, and alert frequencies. By shedding light on these interplays that potentially influence animal health decision making, a deeper understanding is gained to ensure that the preferences of individual farmers are accurately considered, thus further promoting the successful and optimal implementation of digitally supported animal health management tailored to their specific needs.

Overall, the results from Chapter 5 show promising evidence that synergies between economic and animal welfare benefits exist[12]. This evidence is incredibly valuable to stimulate the implementation of animal welfare enhancing management strategies because farmers are sensitive to economic factors in the context of animal welfare enhancements (Balzani & Hanlon, 2020; Läpple & Osawe, 2022; Latacz-Lohmann & Schreiner, 2019; Schröter & Mergenthaler, 2021; Wimmer & Frick, 2021). This entails promising implications in encouraging more farmers to invest in animal welfare measures without feeling that they are compromising their economic viability (Balzani & Hanlon, 2020). In addition, while some farmers are willing to pay for enhanced animal welfare (Läpple & Osawe, 2022) the results from Chapter 5 demonstrate that with digitally supported animal health management this antagonism between economic and welfare benefits is generally not needed.

Despite the overall and promising synergy between economic and animal welfare benefits achievable with digitally supported animal health management, a more nuanced view is required on certain antagonisms. By enhancing our understanding on potential antagonistic aspects found in digitally supported animal health management, it becomes possible to further tailor digitally supported animal health management strategies and solutions uniquely to consider individual farmer preferences. The following discussion highlights specific antagonisms between aspects such as labour time and production losses, labour time and animal welfare, and false alerts and animal welfare. The insights derived from examining the specific antagonistic aspects mentioned above provide valuable insights for PLF technology developers and external animal health advisors, enabling them to work alongside farmers and ensure that individual preferences regarding animal health management are met.

Reduced labour time is an expected benefit through the use of PLF technology (Berckmans, 2015) and is often associated with the adoption of similar technologies (Gabriel & Gandorfer, 2023) However, in Chapter 4, higher labour time[13] was

[12] This evidence is based on the assumption that farmers' cognitive framework will change so that their constitution of SOM is aligned with the golden standard.

[13] Labour time was not directly measured in Chapter 4 but can be inferred from labour related costs whereby higher labour costs are indicative of higher labour time required.

required to manage SOM but these increases were generally associated with larger reductions in production losses. The antagonism between labour time and production losses are important to note because while reduced labour time can be achieved when considering the total labour hours over multiple livestock farming activities (e.g., Morgan-Davies et al., 2021, 2018), labour time can increase when considering some specific activities such as those found in digitally supported animal health management. This is important to note because farmers have shown higher preferences for technological investments compared to additional labour requirements for animal health management in the case of mastitis (Huijps et al., 2009). On one hand, making farmers aware of the additional labour time required to mitigate the production losses is crucial because labour could remain as an important factor in a PLF-based animal health management approach. On the other hand, the significance of the antagonism between labour time and production losses is shaped by how farmers value their time when labour is constrained with respect to the commensurate reductions in production losses. Therefore, making farmers aware of this interplay will permit farmers to make more informed decisions apropos optimising labour demands while using PLF technology in the face of fluctuating market prices (Wageningen Economic Research, 2020, 2022) that have substantial effects on the cost of production losses due to animal health disorders (sensitivity analysis; Chapter 2).

Without repeating too much in the context of labour time, it is also an important factor concerning animal welfare enhancements (Balzani & Hanlon, 2020). Results from Chapter 4 showed that scenarios with increased labour time (indicated by higher labour costs) were associated with improved cow mobility, and ultimately improved animal welfare (Chapter 5). Again, this antagonism will be influenced by how farmers value an increase in the additional time required with respect to the commensurate gains in animal welfare. Making farmers aware of the additional time required for improved animal welfare, in combination with the previously discussed reductions in production losses, can further contribute to optimal and personalised digitally supported animal health management strategies.

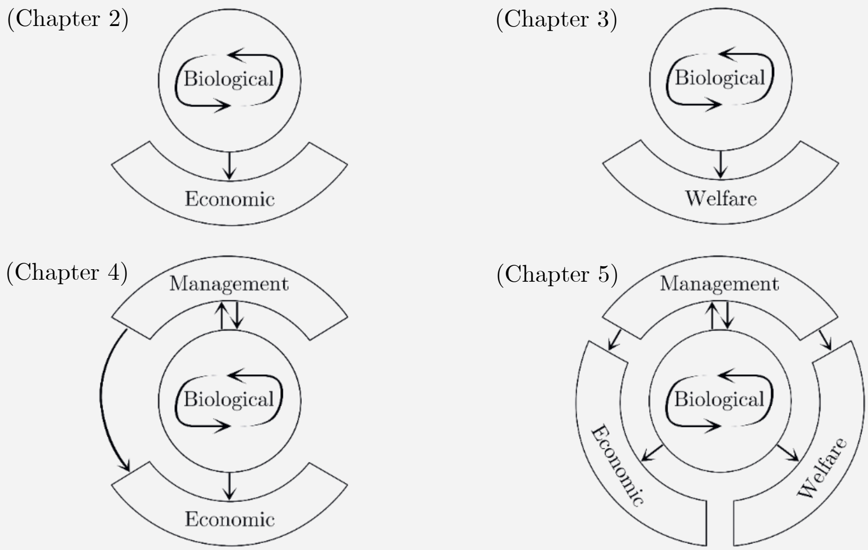
Farmers have exhibited a preference for PLF technology that have lower false alert probabilities (Mollenhorst et al., 2012; Van De Gucht et al., 2017b). Farmers are also known to value animal welfare (Hansson & Lagerkvist, 2016; Owusu-Sekyere et al., 2021) and have thus expressed positive views towards the use of PLF technology to enhance animal welfare (Schillings et al., 2023b). Low false alert probability and enhanced animal welfare are two aspects that can contradict each other in the context of digitally supported animal health management. Chapter 5 provides evidence of this. Under the simulated management strategies, when the false alert probability decreased (increased), the animal welfare benefits were also decreased (increased). This is because more false alerts consequentially mean that more true positive alerts occur (Nakas et al., 2023), thereby prompting intervention for cows with SOM and reductions in the associated animal welfare impact. These results are valuable for farmers because they can help identify what false alert probabilities are required to obtain the farmer's preference for enhanced animal welfare. These results are also valuable for future PLF technology developments. This is especially true in a participatory development approach because the implications of farmer preferences apropos these two aspects in conjunction with their antagonistic nature can be illustrated to provide better insights on how to design suitable PLF technology that considers the needs of farmers (Schillings et al., 2023a).

6.3 Methodological reflections

It is important to recognise that the majority of the insights gained from this thesis are based on a simulation model. Simulation models, and their outputs, are seen as more or less useful, rather than more or less true, and are developed as tools within specific context to study, describe and explore phenomena of a system understudy (Sismondo, 1999). Thus, simulation models are simplifications of the real system they represent that often require assumptions within context to study, describe, and explore these system phenomena.

The simulation model described within the contents of this thesis was developed as a necessary tool to understand the relative, rather than actual, economic and welfare impact of different constitutions of SOM severity as described by various mobility scores (Chapter 2 and Chapter 3). With a better understanding on the relative economic and welfare impacts of different constitutions of SOM severity, the model was further used as a tool to evaluate the economic outcomes of digitally supported animal health management strategies (Chapter 4) and how the underlying information phenomenon of PLF technologies used in digitally supported animal health management would affect the economic and welfare outcomes (Chapter 5). Hence, the simulation model is composed of multiple components with complex interactions. Box 6.1 presents a high-level schematic illustration and description of the simulation model components and the interactions between the components. It is presented to provide visual support for points discussed withing this section on methodological reflections.

Box 6.1 Schematic illustration of bio-economic simulation model components, interactions, and extensions.



Description:

This box illustrates the evolution of the simulation model per research chapter as components were added and linked. At the core of the simulation model is a biological component (developed in Chapter 2) that includes production factors, such as fertility and lactation, as well as epidemiological factors, such as incidence of hoof disorders and their effect on cow mobility. There are interactions between the biological factors depicted by arrows that reciprocally influence production and epidemiological factors. For example, lactation stage affects the incidence of hoof disorders, which in turn, through sub-optimal mobility, affects lactation quantity. Using the biological component as the core permitted linkages between it and the economic, welfare and management components in the respective chapters. By doing so, the biological processes and corresponding interactions were allowed to manifest into consequential economic and welfare impacts, and management events. For example, biological factors and their interactions affected factors such as milk revenue losses and functional impairment in the economic and welfare components, respectively. Furthermore, biological factors also influence factors in the management component, which in turn affects factors in the biological, economic, and welfare components. For instance, the incidence of a hoof disorder that affects cow mobility prompts intervention to cure the underlying hoof disorder and mitigate further milk revenue losses and functional impairment. Additionally, management factors directly impact factors in the economic and welfare components, such as treatment costs and cow-human interactions when hooves are trimmed. Ultimately, each extension while maintaining interactions between components permitted a more holistic evaluation of the negative health disorder effects to be studied for a range of different management strategies.

6.3.1 Challenges

This section presents a discussion on the methodological challenges encountered through the development of the simulation model and other closely related methods. The implications of model simplifications and assumptions made to overcome these challenges, and alternative solutions for future research specific to overcoming these challenges are also discussed.

In Chapter 2 an extensive epidemiological modelling procedure was undertaken, in the biological component of the model, to simulate the incidence of eight common hoof disorders in the Netherlands (DigiKlauw, 2020). Of the three infectious hoof disorders, two of them (interdigital dermatitis and heel horn erosion, and interdigital phlegmon) were not modelled as contagious hoof disorders because their transmission dynamics are unknown. This imposed a secondary data challenge ultimately leading to the two hoof disorders being modelled as environmental infections with a Greenwood model. This approach assumes that the probability of infection is independent on the concentration of the infectious agent in the herd (Becker, 1989). Input parameters apropos their incidence were validated in accordance with evidence on their prevalence in dairy farms in the Netherlands with a typical SOM management strategy as simulated in Chapters 2 and 3 (DigiKlauw, 2020; Somers et al., 2003). However, these input parameters remained unchanged in Chapters 4 and 5. Because the SOM management strategies simulated in Chapters 4 and 5 differ considerably compared to the SOM management strategy simulated in the former two chapters, the "true" incidence of these hoof disorders is not captured by the model because the effect of a change in SOM management on their transmission dynamics are not accounted for since they are yet to be known. Accounting for their transmission dynamics consequential of changes in SOM management could provide a better understanding of their specific contribution towards the dynamics of SOM, and, moreover, a better understanding of their specific contribution to the SOM economic and animal welfare impacts. For example, it may be that positive associations between the hoof disorders and short hoof trimming intervals exist, as observed for the infectious hoof disorder digital dermatitis (Holzhauer et al., 2006). If a similar case for interdigital dermatitis and heel horn erosion, or interdigital phlegmon exists, then their underlying economic and welfare impacts may have been underestimated in Chapters 4 and 5 because the model is blind to their transmission dynamics under changes in SOM management (Thompson & Smith, 2019). Increasing data collection efforts apropos their transmission dynamics will contribute towards modelling them as contagious hoof disorders. The same argument applies to the incidence of the non-infectious hoof disorders as their "true" incidence are unknown following a change in SOM management. Acquiring new information on the incidence following changes in SOM management will provide more insight on their SOM economic and welfare impacts.

While acquiring new data can generate new information and enhance our understanding of a phenomenon within a system, such as the transmission dynamics of a contagious hoof disorder, incorporating such information into the simulation model may alter the model structure and increase its complexity. However, model complexification could lead to greater uncertainty in model outputs as it's propagated through the uncertainty surrounding the new information, which may arise due to factors such as measurement errors, inherent variability, random processes, or subjective expert judgements (Puy et al., 2022a). In other cases, model complexification may impose structural model errors, such as incorrectly specifying relationships between variables, that may promote inaccurate model output (Thompson & Smith, 2019). Therefore, careful consideration and evaluation of the quality and relevance of the new information and its potential impact on the model are necessary before incorporating it into the model and ultimately drawing conclusions from new simulations. Balancing model complexity and uncertainty at each stage of model complexification can be achieved by calculating the model's effective dimensions that ultimately ensures that the model remains within context and fits the initial purpose of application (Puy et al., 2022a).

Following the incidence of hoof disorders (Chapter 2), their progression in terms of impact on cow mobility as defined by mobility scores (Sprecher et al., 1997) were modelled. Although certain hoof disorders have stronger associations with various mobility scores (Blackie et al., 2013; Tadich et al., 2010), general mobility score transitional risks were specified due to data constraints apropos hoof disorder specific mobility score transitional risks and were calibrated on mobility score prevalence at herd-level (Frankena et al., 2009). Despite this, the results from the model produced trends between hoof disorders – digital dermatitis, interdigital phlegmon, and white line disease - and mobility scores similar to those based on empirical data (Charfeddine & Pérez-Cabal, 2017; Tadich et al., 2010). However, for some hoof disorders, sole ulcer specifically, the trends between mobility scores produced by the model did not correlate with results based on empirical data (Blackie et al., 2013). Additional data on hoof disorder specific mobility score transitional risks could improve the model's representation of trends between specific hoof disorders and mobility scores. More refined calibration techniques that focus on mobility score trends within hoof disorders as well as at herd-level could also contribute to improved trends. However, the choice of calibration technique depends on model complexity. Some examples include grid search, simulated annealing (e.g., Dowsland & Thompson, 2012), Bayesian optimisation (e.g., Lunderman et al., 2021), and a suite of evolutionary algorithms (e.g., Petrowski & Ben-Hamida, 2017).

An innovative approach was developed to quantify the welfare impact of SOM in Chapter 3 by first deriving welfare impairment weights associated with physical effects of SOM on welfare indicators with expert knowledge elicitation using ACA.

This unique approach offers a more detailed understanding of the impact of SOM on animal welfare. It achieves this by examining the physical effects of SOM on various welfare indicators, while experts implicitly reveal their beliefs apropos the welfare impairments arising from different combinations of these effects by making trade-off decisions. Five welfare indicators affected by SOM were included due to the available scientific literature concerning these effects, while it can be expected that SOM can affect many more welfare indicators considering the number of welfare indicators described by Mellor et al. (2020). Increasing the number of welfare indicators in the ACA could potentially increase the cognitive burden of expert respondents and affect the quality of responses (Watson et al., 2017). While it is important to limit cognitive burden, it should not be done by omitting welfare indicators from the ACA based on prior assumptions that they are not important. Doing so may conceal welfare impairment weights that are unknowingly important for the actual assessment of SOM welfare impacts. This was demonstrated by the sensitivity analysis where the total welfare impact per maximum mobility score SOM case were consistently influenced by welfare impairment weights apropos the less important welfare indicators body condition score and behavioural change, suggesting that additional research efforts are required to gain a better understanding on how animal welfare is impacted through these welfare indicators. If welfare indicators are assumed to be unimportant and omitted from the ACA to reduce cognitive burden, the corresponding welfare impairment weights will not be captured and neither their influence on the total welfare impact of SOM. Therefore, including as many welfare indicators is important to gain better insight on the effects of SOM on animal welfare that can also guide future research. Albeit a balance between the number of welfare indicators and cognitive burden must still be considered. Combining ACA capabilities with blocked fractional factorial designs, which distribute subsets of welfare indicators among multiple respondents (Louviere et al., 2000), can address all relevant welfare indicators while reducing cognitive burden for each respondent.

After the welfare impairment weights were derived, the impact of SOM on animal welfare was then quantified (Chapter 3). The model quantifying this impact assumes a linear relationship between welfare disutility and duration per mobility score. This might not be the case in reality as a cow may learn to cope with a mobility score over time to reduce the welfare impact of the mobility score (Wechsler, 1995). Therefore, when this information becomes available, the model will have to be respecified whereby welfare impairment weights can be dynamically adjusted as a function of dynamic changes in physical affects congruent to mobility score and mobility score duration to better reflect the welfare impact of SOM in light of coping mechanisms.

6.3.2 Opportunities

Although methodological challenges can lead to opportunities (if you see the glass half full), this section delves beyond the opportunities arising in light of challenges as it is evident that methodological challenges are not the only factors at play. This section presents a discussion on the potential opportunities for future research that can be explored utilising the methods employed in this study in and out the context of digitally supported animal health management.

As discussed in the methodological challenges with reference to Chapter 2, data apropos the transmission dynamics of certain hoof disorders were not available. However, the presence of digital technologies in PLF offers opportunities for improved data collection on the transmission dynamics of health disorders in general due to their advantageous autonomous, continuous, and diverse data collection capabilities. One exciting possibility enabled by these technologies is the study of how health disorders spread through animal social networks (de Freslon et al., 2019; Neethirajan & Kemp, 2021b). With an enhanced understanding on the transmission dynamics of health disorders through social networks, novel digitally supported animal health management approaches can be designed. For instance, these approaches could provide valuable insights for making more informed decisions regarding both the economic and animal welfare implications of quarantining an infected animal based on its social network. Here, the risk of spreading health disorders to peers, subsequent impacts on production and animal welfare, and the compound effects through subsequent infections can be taken into account. These data types can help in developing more informative bio-economic simulation models, like the one described in this thesis, to assess the economic and animal welfare benefits of alternative digitally supported animal health management strategies.

In Chapter 3, the innovative approach proposed to quantify the welfare impact of SOM provides an exciting opportunity to be extended towards assessing the welfare impact of multiple health disorders and their respective severities. By using ACA and decomposing animal welfare into individual welfare indicators (i.e., welfare attributes) and considering the varying measurable physical effects on the welfare indicators, this approach allows for the calculation of welfare impairment weights per physical effect. Furthermore, this approach focuses solely on the physical effects of welfare indicators irrespective of health disorder, ensuring an objective assessment of welfare impairment. Ultimately, welfare impairment weights for all physical effects on welfare indicators can be obtained. Aggregating the welfare impairment weights, in conjunction with the physical effects on welfare indicators per health disorder severity, will yield a welfare disutility score indicative of the overall welfare impact per health disorder severity. In summary, this approach involves considering the impact of different health conditions on the welfare of animals, akin to how disability weights capture the severity of health states in the context of disability adjusted life years (DALY) - a metric concerning burden of disease on human populations (Devleesschauwer et al., 2014; Salomon et al., 2012).

With respect to the simulated sensor-based SOM management scenarios in Chapter 4, the alert prioritisation criterion is composed of a predefined alert threshold respective of mobility score. This threshold was kept constant at 0.5 for the number of classifications that occurred of the alert notification interval, respective of mobility score. It would be interesting to test the economic and animal welfare effects of other threshold values for different mobility score that vary over different alert notification intervals. For example, it may, or may not, be more economically beneficial to increase the threshold value to 0.7 over a 30-day alert notification interval for mobility scores 2 and 3 in comparison to the 0.5 threshold value over a 7-day alert notification interval for mobility scores 2 and 3 as simulated in Chapter 4 and Chapter 5. The simulation model described in this thesis will easily allow for additional scenarios to be tested that can further support sensor development and implementations decisions.

The results from Chapter 4 suggest that bi-annal whole herd professional hoof trimming should be replaced with weekly cow specific professional hoof trimming. This is of course based on the assumption that professional hoof trimmers will radically change their hoof trimming practices while in reality it may not be as simple as the simulation model suggests. Future scenario-based simulation studies that involve multiple stakeholders in animal health management services should be engaged in the design of scenarios.

As highlighted earlier, farmers are heterogeneous regarding animal health management (e.g., Biesheuvel et al., 2021; de Lauwere et al., 2020; Doidge et al., 2021; Sok et al., 2016; van Soest et al., 2015). In conjunction with economic (Huijps et al., 2010, 2009) and animal welfare (Owusu-Sekyere et al., 2021) factors that influence animal health management, farmers may be heterogenous in the valuation of economic and animal welfare gains. For example, Läpple and Osawe (2022) found that farmers in different groups of social value orientation differed in terms of the economic value they placed on animal welfare enhancements. In Chapter 5 the economic and animal welfare value of digitally supported animal health management was studied. However, because of the heterogeneity between farmers towards the valuation of economic and animal welfare gains it may mean that farmers make different decisions following an alert, especially when there is a probability that the alert is for a cow that does not need to be checked. In Chapter 5 all alerts were checked, while this very strict decision making may not be the case in practice (Eckelkamp & Bewley, 2020) and may be because of the information uncertainty the alert encapsulates. To simulate empirically observed decisions following an alert one approach would entail incorporating a farmer's risk preferences apropos the expected economic and animal welfare outcomes for different decisions made following an alert under an expected utility framework (Von Neumann & Morgenstern, 1947).

Chapter 5 presented an original approach in describing the behaviour of classification probabilities in 3-class classification problems. However, this approach was limited to describing the behaviour of classification probabilities defined by normally distributed diagnostic marker values. It would be interesting to expand the approach to describe non-normal distributions of diagnostic marker values. Hence, additional insights on the economic and welfare implications can be obtained for health class classifiers that have non-normal diagnostic marker value distributions. These opportunities should not be limited to 3-class classification problems, as there is potential to study the economic and animal welfare implications across the range of classification probabilities for >3-class classifiers used in digitally supported animal health management.

6.3.3 Extending the animal health economics framework in animal health management

The term economics when applied to the context of animal health economics encompasses a broader scope that extends beyond the conventional boundaries of the field. Traditional animal health economics textbooks predominantly focus on the economic consequences of animal health disorders, primarily emphasising monetary losses experienced by farmers (i.e., Hennessy & Marsh, 2021; Rushton, 2009). As discussed in section 1.1 the theoretical underpinning of animal health economic research is the two-dimensional expenditure-loss frontier put forward by McInerny et al. (1992) and later adapted by van Soest et al. (2016) and Hogeveen and van der Voort (2017). However, the two-dimensional expenditure-loss frontier limits our understanding to monetary effects associated with animal health and production while it is imperative to acknowledge that the ramifications of health disorders extend beyond these mere monetary effects.

Animal health disorders have profound impacts on animal welfare (Broom & Corke, 2002; Nielsen et al., 2021; Whay & Shearer, 2017) and the environment (Mackenzie & Kyriazakis, 2021; Özkan et al., 2022), making it imperative to incorporate these aspects more comprehensively into bio-economic models. Transforming the scope of traditional bio-economic models to ***bio-burden*** models whereby the term *burden* encapsulates, amongst others, economic, animal welfare and environmental burdens (i.e., negative effects) of animal health disorders. By doing so, the traditional two-dimensional expenditure-loss frontier can be extended to a multi-dimensional “expenditure-burden” frontier. Hence, these bio-burden models can better capture and quantify the true impact and value of animal health management strategies aimed at addressing animal health issues with an ultimate goal to promote economically, ethically, and environmentally sustainable animal husbandry systems (Chemineau, 2016; FAO, 2018; Keeling et al., 2019; Özkan et al., 2022).

This thesis makes a pioneering contribution to the field of animal health economics by extending the traditional bio-economic model (Box 6.1; Chapter 2), which mostly consider the economic impacts only under status quo management. The model described within this thesis expands the traditional bio-economic model by including an original component aimed at quantifying the animal welfare impact of animal health disorders (Box 6.1; Chapter 3). In addition, the traditional bio-economic model is enhanced by including an incredibly flexible management component to test the economic effects of novel sensor-based management strategies (Box 6.1; Chapter 4). By ultimately combining all these components together, the model in Chapter 5 (Box 6.1) fostered a thorough evaluation of the welfare impact congruent to preventive and failure costs within different animal health management strategies. Overall, this integrated *bio-burden* approach in this thesis allowed for a more holistic assessment of the economic and animal welfare aspects and helped identify win-win solutions apropos management strategies aimed at mitigating the economic and animal welfare impact of SOM.

Although not explicitly done in this thesis, the bio-burden model serves as an example apropos how the traditional two-dimensional expenditure-loss frontier can be extended. There are two possible extensions.

The first extension could include the welfare impact of an animal health disorder into failure costs. This will require the market value of animal welfare to be known and more importantly how a unit of market valued animal welfare is affected by an animal health disorder. If this is known, then the expenditure-loss frontier remains two-dimensional, and the optimal solution is still at the point where the sum of preventive and failure costs are minimised. However, capturing the market value of animal health disorder induced welfare impact has its challenges. Moreover, “economising” animal welfare as by this approach may have implications for the meaning and assessment of actual animal welfare. This is because this market value based approach detracts from the interests of solely improving actual animal welfare (Buller & Roe, 2014), rather it caters to consumer preferences for animal welfare often reflected by the price premium they are willing to pay for it (Buller & Roe, 2014; Clark et al., 2017; Yang & Renwick, 2019).

The second extension requires animal welfare to be valued solely as a difference between two animal health disorder induced animal welfare impacts. This approach avoids "economising" animal welfare as it focusses solely on improvements of animal welfare (Buller & Roe, 2014). Hence, animal welfare impacts of a health disorder are kept separate from the associated preventive and failure costs of various animal health management strategies, yet the costs associated with mitigating animal welfare impacts are still accounted for. This transforms the traditional two-dimensional expenditure-loss frontier to a three dimensional "expenditure-burden" frontier whereby the x-, y-, and z-axis represent the values of failure costs, preventive costs, and the welfare impact of different animal health management strategies. Navigating the minimization problem across these three dimensions poses potential challenges, depending on the resulting shape and complexity of the data within the three-dimensional space. However, this approach presents a starting point in analysing these three dimensions in animal health management.

In conclusion, the contribution of this thesis towards advancing the animal health economic framework in animal health management is not the panacea to animal health disorders. However, this thesis serves as an important steppingstone towards addressing the multifaceted nature of animal health management and the associated burdens. Future research can build upon the foundation this thesis provides to develop more effective and sustainable solutions for promoting animal well-being, economic prosperity, and environmental stewardship through managing animal health disorders in animal husbandry systems.

6.4 Future research

Future research recommendations are put forward in Chapters 2 – 5, while section 6.3 provide indications for future research specific to methodological components of this thesis. Furthermore, this section goes beyond the scope of future research concerning methodological components by introducing suggestions for future research on specific topics that have not been previously addressed.

To gain a better understanding on the impact of SOM on animal welfare additional welfare indicators are needed for the ACA (Chapter 3). This will require additional studies that assess the physical effects of SOM, preferably at the mobility score level, on additional welfare indicators. Ideally, these studies should be longitudinal to assess how the physical effects of SOM at mobility score level affect the welfare indicators. This may provide insight on how a cow afflicted with SOM copes over time given the mobility score she is afflicted with. Hence, a more accurate estimation of the SOM impact on animal welfare could be achieved. With this information and by using ACA, a more holistic understanding on how the physical effects of SOM affect animal welfare indicators that can be studied.

As intervention for SOM increases with a sensor-based SOM management approach the proportion of cows in the herd without SOM will increase. This means that the underlying classification model used will generate denser distributions of diagnostic marker values for the class of cows without SOM. Hence, a fixed classification probability (as defined by the cut-off threshold value) apropos cows without SOM will generate higher false alert frequencies (Chapter 4 and Chapter 5). Therefore, with an objective concerning the economic and animal welfare effects, it will be beneficial to study what dynamic changes in classification probabilities are required to reduce the frequency in false alerts while maintaining appropriate classification probabilities to ensure cows with SOM are correctly classified in order for appropriate treatment to be provided.

Hopefully future research conducted by the PLF research community concerning the development of 3-class classification model for SOM management will be stimulated by the research presented in Chapter 5. If it is, a recommendation to prospective researchers is to report distribution of diagnostic marker values instead of only the performance metrics (i.e., sensitivity, specificity, and the area under the curve) of their classification models. By reporting the distribution of diagnostic marker values, the implications of their classification models can be better tested alongside the design of sensor-based SOM management scenarios that explore the full potential of their classification models.

6.5 Implications for animal welfare assessors and the environment

6.5.1 Animal welfare assessors

The potential utilisation of PLF technology to assess animal welfare has been widely discussed (Buller et al., 2020; Gómez et al., 2021; Hogeveen & van der Voort, 2021; Silva et al., 2021; Stygar et al., 2022; van Erp-van der & Rutter, 2020). A common theme in these discussions is the ability for continuous animal-based measurements with PLF to provide insights on the overall health of the herd or flock that is congruent, for example, to the animal welfare principle of good health apropos the Welfare Quality® protocols (2009a, 2009b) as opposed to annual assessment (e.g., Heinola et al., 2021).

Considering the data interoperability problem (Bahlo et al., 2019; Rose et al., 2022), careful interpretation of data from farmers to welfare assessors is necessary to obtain a representative understanding of the actual health status of the herd or flock, and thus the animal welfare implications related to animal health. Relying solely on the final health class classification output from PLF technology may not provide an accurate representation of actual animal welfare as it may depend on the farmer's animal welfare management preferences. Previously, it was demonstrated in Chapter 5 that higher animal welfare enhancements were achieved with higher classification probabilities for SOM cows in conjunction with lower classification probabilities for non-SOM cows. Thus, generally speaking, farmers who prioritise high levels of animal welfare can achieve this by selecting classification probabilities for different health classes. Farmers with a strong preference for high animal welfare may want all animals with poor health to be accurately detected so that proper treatment can be provided. Depending on the performance of the sensor, this preference may result in a high number of animals without poor health being classified as having poor health as well. Consequently, the frequency of poor health classification data may not accurately represent actual animal welfare because the health class classification performance is tailored to align with a farmer's animal welfare management preferences. Therefore, it is crucial for animal welfare assessors to consider appropriate ways to evaluate the actual quality of animal welfare as accurately as possible, without solely relying on the final classification output data provided by PLF technology from farmers. Algorithms for this type of interpretation do not exist yet. One approach is to begin with the raw diagnostic marker values, as this would provide a better estimate of actual animal welfare regardless of the farmer's animal welfare management preferences. This would allow for a more representative evaluation of animal welfare, taking into account the full range of relevant factors beyond the final classification output.

In the instance that algorithms exist to evaluate the actual quality of animal welfare irrespective of farmers' animal welfare management preferences, additional data interoperability implications exist for welfare assessors that shift towards data driven welfare assessments. This lies in the possibility that farmers adopt different types PLF technology each with different classification performances (Alsaaod et al., 2019; Bausewein et al., 2022) thereby having different separations between distributions of diagnostic marker values. The effects of these separations were already discussed in relation to Chapter 5. Hence, if different farmers have different sensors, each with varying underlying classification models, the data animal welfare assessors receive from farmers may vary in quality as a result. Therefore, algorithms developed to evaluate the actual quality of animal welfare will also have to consider these differences in PLF technology generated data. On the other hand, a simple approach towards reducing data interoperability issues across different PLF technologies would be for welfare assessors to initiate a standardisation in technology requirements to ensure consistent data exchanges. Although farmers have expressed interest in consistent data for animal welfare assessments (Schillings et al., 2023b), such a standardisation may impose additional implications for the farmers. This is because the costs associated with the standardised PLF technology requirements may inhibit farmers to participate in the welfare quality schemes given their budget constraints (Silva et al., 2021).

6.5.2 Environment

More and more in stakeholder dialogues across diverse topics an additional chair is provided for the stakeholders. However, this chair does not seat a human stakeholder. Rather it is provided as a symbolic gesture towards the environment; it seats the environment as a stakeholder. By doing so it helps facilitate a dialogue considering the environmental implications in the context of the topic discussed among stakeholders. This section is that chair in the context of digitally supported animal health management.

Although the environmental implications of digitally supported animal health management were not studied in this thesis, the results suggest that digital animal health management may be environmentally beneficial. Research shows that cows afflicted with ketosis (Mostert et al., 2018a), hoof disorders (Mostert et al., 2018b), and mastitis (Mostert et al., 2019) produce more greenhouse gas emissions per output unit compared to cows not afflicted with these health disorders. Thus, reducing the incidence and prevalence of health disorders could potentially benefit the environment. Chapter 4 and Chapter 5 demonstrate that the prevalence of SOM – congruent to hoof disorders – can be drastically reduced with digitally supported animal health management. Therefore, these results suggest digitally supported animal health management also has positive implications for the environment and further contribute the discussion apropos digital agriculture and the environmental benefits (e.g., Niloofar et al., 2021). Future research is required to explore and quantify the specific environmental benefits of digitally supported animal health management. This can be done by building on the foundations set by the research found within this thesis whereby the simulation model (Box 6.1) is further extended with an environmental component to effectively capture the environmental burden of animal health disorders. Moreover, it will facilitate the exploration and quantification of the environmental benefits that digitally supported animal health management provides.

6.6 Main conclusions

The general objective of this thesis is to offer economic and animal welfare decision support in the utilisation of digital technologies (i.e., sensors) found in PLF, to enhance animal health management by adding economic and animal welfare value to the farming operation. Four research questions were addressed in Chapters 2 – 5 as follows:

1) What do the different dynamics of SOM contribute to the total economic cost of SOM?
2) What do the different dynamics of SOM contribute to the total animal welfare impact of SOM?
3) What changes in SOM management are required to obtain additional economic value from a sensor-based SOM management approach?
4) How do changes in the underlying settings of sensors influence the economic and animal welfare outcomes apropos sensor-based SOM management?

Based on the findings congruent to addressing the research questions, the following conclusions are drawn:

- Mild and moderate suboptimal mobility (SOM) account for a substantial proportion (~47 percent) of the total annual direct costs of SOM under a typical SOM management strategy. (Chapter 2)
- SOM has an important indirect effect on fertility related culling, resulting in additional fertility related costs. (Chapter 2)
- The physical effects of SOM on animal welfare indicators can be used to derive mobility score associated welfare impediment weights. (Chapter 3)
- Moderate SOM, respectfully maximum mobility score 3 SOM cases, has the largest impact on animal welfare at case- and herd-level under a typical SOM management strategy. (Chapter 3)
- The use of sensors to automatically detect SOM can generate additional economic value but radical (cognitive framework) shifts apropos SOM management are required to achieve the benefits of sensor-based SOM management. (Chapter 4)
- Using, PLF, twice yearly whole herd routine hoof trimming could be replaced by more frequent cow specific hoof trimming to obtain economic and welfare benefits. (Chapter 4 and Chapter 5).

- Prolonged information generation apropos mobility scores 2 and 3 is economically beneficial in sensor-based SOM management opposed to immediate information generation. (Chapter 4)
- Simple frequency based alert prioritisation method can be used to reduce the number of false alerts that ultimately add economic value to a sensor-based SOM management strategy. (Chapter 4)
- Mobility score 2 must be considered as SOM due to the associated economic and welfare consequences and treating cows with this mobility score results in highest overall economic and welfare benefits. (Chapters 2, 3, 4, and 5)
- 3-class classification models are more economically and welfare beneficial compared to binary classification models for SOM classification. (Chapter 5)
- 3-class classification model generated diagnostic marker value distributions for the non-SOM class should be the most separated from diagnostic marker value distributions for SOM classes to ensure higher economic and welfare outcomes of sensor-based SOM management. (Chapter 5)
- Economic and animal welfare trade-offs exist in sensor-based SOM management. (Chapter 4 and Chapter 5)
- Bio-economic simulation models provide substantial opportunities to test a wide range of digitally supported animal health management strategies and associated technological innovations that would be impossible to test in practice due to, amongst others, time and financial constraints. By doing so, unattractive scenarios can be identified and ruled out without running the risk of implementing them in practice with potential negative implications. (Chapter 4 and Chapter 5)

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Summary

Poor animal health in animal husbandry systems has significant implications for both the economic viability of farms and the welfare of the animals. Addressing and mitigating animal health disorders is crucial to limit the negative economic effects and enhance the overall well-being of animals. Proactive animal health management is essential to mitigate these negative effects. Precision livestock farming (PLF) offers promising solutions for animal health management. Combining PLF technologies, such as sensors, with statistical models, can enable objective and continuous monitoring of individual animals with the potential for early warning signals apropos the onset of animal health disorders. By detecting and treating animal health disorders sooner, a sensor-based animal health management approach could minimise production losses and improve animal welfare. However, research quantifying the added economic and animal welfare value of such an approach is limited. Thus, an understanding of how technologies in PLF (i.e., sensors) can be effectively implemented at the farm-level is imperative to ensure economic and animal welfare value is harnessed by limiting as best as possible the negative effects of animal health disorders on economic and animal welfare outcomes. The overall objective of this thesis is to investigate the economic and animal welfare value sensor-based animal health management. The animal health disorder sub-optimal mobility (SOM) in dairy cows is used as an animal health disorder case in a Dutch dairy context.

Chapter 2 describes the development of a novel bio-economic simulation model to analyse the effects of hoof disorders on cow mobility and estimate the economic impact of SOM in a Dutch dairy herd of 125 dairy cows under a typical SOM management strategy. The model considered eight different hoof disorders and their role in SOM, utilising a Reed-Frost model for digital dermatitis and a Greenwood model for the other seven disorders. SOM is described by a 5-point mobility scoring method (1 = perfect mobility; 5 = severely impaired mobility). Per day, for every cow spent with one of five mobility scores, production- and management-based economic calculations were computed. The total annual economic loss due to SOM resulting from the hoof disorders understudy was €15,342, equivalent to €122 per cow per year. Maximum mobility score 2 – 5 SOM cases respectfully contributed 13, 34, 48 and 5 percent to the total annual direct economic loss (€9,061) of SOM. The total annual indirect economic losses encompassed additional culling due to SOM (~65 percent) and changes in overall herd milk production (~35 percent), with the mean total annual indirect economic loss amounting to €6,281. These results highlight the economic significance of lower mobility scores and indirect economic losses arising from SOM and emphasise the need for better SOM management practices especially with respect to lower mobility scores.

In Chapter 3 the animal welfare impact of SOM was quantified. Due to the lack of methods available to quantify the animal welfare impact of health disorders, a novel expertise-based method to quantify the animal welfare impact of health disorders is proposed. Expert knowledge was elicited and used to quantify animal welfare impairment weights apropos the physical effects of SOM on animal welfare indicators. These weights congruent to animal welfare indicators were linked to mobility scores to obtain an animal welfare disutility per mobility score. Following, the animal welfare impairment weights were then used to simulate the animal welfare impact of SOM at both individual case- and herd-level using the bio-economic simulation model developed in the preceding research chapter. Findings from the study reveal that although the animal welfare disutility increase in mobility scores, the simulations reveal that SOM cases with lower mobility scores have a greater overall animal welfare impact due to their longer duration and higher frequency. Maximum mobility score 2 – 5 SOM cases respectfully contributed 16, 70, 12 and 1 percent to the total animal welfare impact of SOM. The study suggests that early detection and treatment of lower mobility scores can lead to improved animal welfare outcomes for dairy cows. Moreover, this research introduces an innovative and unique approach to quantifying the influence of health disorders on animal welfare that can be extended beyond the context of SOM.

Chapter 4 focuses on the economics of sensor-based SOM management. To evaluate the added economic value, a bio-economic simulation model is used to compare a farm without automatic SOM detection sensors to a farm with automatic SOM detection sensors. Eighty original sensor-based SOM management strategies were designed that included combinations of different sensor performances, a novel yet simple alert prioritisation method, prolonged verses immediate alert generations for different constitutions of SOM, and different interventions apropos treatments. The results of the study provide valuable insights into the trade-offs between production losses and additional labour costs associated with different sensor-based management strategies, sensor performances, and alert prioritisation methods. The simulations demonstrate that the economic value added by automatic SOM detection sensors is sensitive to the sensor-based management strategies apropos: sensor performance, interval of prolonged alert generation for lower mobility scores (mobility scores 2 and 3) and interventionists apropos treatment. Based on the evidence from the scenarios, the study suggests that the current practice of twice-yearly routine hoof trimming should be replaced with cow-specific hoof trimmer treatments following SOM detection by the sensors. Early detection and treatment of mild SOM cases resulted in economic gains when combined with the introduction of the novel alert prioritisation method. Furthermore, the alert prioritisation criterion that allowed an intervention interval of seven days proved economically beneficial because costly false alerts could be avoided while maintaining earlier mitigations of production losses. The implementation of automatic SOM detection sensor systems offers various options to improve SOM management and achieve better farm economic performance along with enhanced cow mobility.

In Chapter 5 components of the preceding research chapters were cumulated to evaluate the effect of 3-class classification models and the various classification outcomes on economic and animal value. Eight classifiers each with 600 different classification outcomes were defined for SOM classification and management. Mobility scores were grouped into various SOM classes depending on the classifier. A bio-economic simulation model was used to simulate the economic and welfare effects of the various classifiers and respective classification outcomes. The simulated output data was first analysed using an exploratory approach to explore the general effects of classifiers and classification outcomes on economic and animal welfare outcomes. Second, a novel method accounting for the highly interactive classification outcomes was developed to quantify the trade-offs in classification outcomes and how these trade-offs affected the economic and welfare gains. All tested classifiers showed economic and welfare gains on average. Classifiers with larger separations between non-SOM and SOM classes showed the highest average economic gains. Including mobility score 2 into a SOM class showed meaningful animal welfare gains on average as opposed to when mobility score 2 was included in a non-SOM class. Larger increases in economic gains were often achieved at the cost of smaller reductions in animal welfare gains in conjunction with trade-offs in classification outcomes. This chapter provides valuable insights on designing appropriate 3-class SOM classifiers that could also be beneficial when designing classifiers for health disorders other than SOM.

In Chapter 6 a general discussion apropos the research within the thesis is presented. Overall, as a collection of four research questions addressed in Chapters 2 – 5, this thesis contributes to the literature in various ways. It provides insights on methodological approaches that *i*) capture indirect costs of health disorders *ii*) quantify expertise based welfare impacts of health disorders, *iii*) highlight the importance of less severe but prevalent levels of animal health disorders, *iv*) demonstrate significant opportunities for sensor supported animal health management that includes novel sensor-based management strategies, *v*) incorporates economics and animal welfare into the animal health decision making framework, and *vi*) propose a tractable approach to understand the complex and interdependent nature of 3-class classification models.

In conclusion, economic and animal welfare value can be achieved through the utilisation of sensors in animal health management. However, this requires sensor-based animal health management strategies to be designed and adhered to, as well as further technological developments. Based on the findings congruent to addressing the research questions, the following conclusions are drawn:

- Mild and moderate suboptimal mobility (SOM) account for a substantial proportion (~47 percent) of the total annual direct costs of SOM under a typical SOM management strategy. (Chapter 2)
- SOM has an important indirect effect on fertility related culling, resulting in additional fertility related costs. (Chapter 2)
- The physical effects of SOM on animal welfare indicators can be used to derive mobility score associated welfare impediment weights. (Chapter 3)
- Moderate SOM, respectfully maximum mobility score 3 SOM cases, has the largest impact on animal welfare at case- and herd-level under a typical SOM management strategy. (Chapter 3)
- The use of sensors to automatically detect SOM can generate additional economic value but radical (cognitive framework) shifts apropos SOM management are required to achieve the benefits of sensor-based SOM management. (Chapter 4)
- Using, PLF, twice yearly whole herd routine hoof trimming could be replaced by more frequent cow specific hoof trimming to obtain economic and welfare benefits. (Chapter 4 and Chapter 5).

- Prolonged information generation apropos mobility scores 2 and 3 is economically beneficial in sensor-based SOM management opposed to immediate information generation. (Chapter 4)
- Simple frequency based alert prioritisation method can be used to reduce the number of false alerts that ultimately add economic value to a sensor-based SOM management strategy. (Chapter 4)
- Mobility score 2 must be considered as SOM due to the associated economic and welfare consequences and treating cows with this mobility score results in highest overall economic and welfare benefits. (Chapters 2, 3, 4, and 5)
- 3-class classification models are more economically and welfare beneficial compared to binary classification models for SOM classification. (Chapter 5)
- 3-class classification model generated diagnostic marker value distributions for the non-SOM class should be the most separated from diagnostic marker value distributions for SOM classes to ensure higher economic and welfare outcomes of sensor-based SOM management. (Chapter 5)
- Economic and animal welfare trade-offs exist in sensor-based SOM management. (Chapter 4 and Chapter 5)
- Bio-economic simulation models provide substantial opportunities to test a wide range of digitally supported animal health management strategies and associated technological innovations that would be impossible to test in practice due to, amongst others, time and financial constraints. By doing so, unattractive scenarios can be identified and ruled out without running the risk of implementing them in practice with potential negative implications. (Chapter 4 and Chapter 5)

Scientific publications

This thesis

Edwardes, F., van der Voort, M., Halasa, T., Holzhauer, M. and Hogeveen, H. (2022). Simulating the mechanics behind sub-optimal mobility and the associated economic losses in dairy production. *Preventive Veterinary Medicine*, 199, p.105551. DOI: https://doi.org/10.1016/j.prevetmed.2021.105551 (Chapter 2)

Edwardes, F., van der Voort, M. and Hogeveen, H. (2022). The economics of sensor-based management of dairy cow suboptimal mobility. *Journal of Dairy Science*, 105(12), pp.9682-9701. DOI: https://doi.org/10.3168/jds.2021-21726 (Chapter 4)

Edwardes, F., van der Voort, M., Rodenburg, T.B., and Hogeveen, H. (2023). A new approach and insights on modelling the impact of production diseases on animal welfare. *Animal* (revised and resubmitted). (Chapter 3)

Edwardes, F., van der Voort, M. and Hogeveen, H. (2023). Quantifying the economic and animal welfare trade-offs of classification models in precision livestock farming for sub-optimal mobility management. *Computers and Electronics in Agriculture* (revised and resubmitted). (Chapter 5)

Other

Wicaksono, A., Edwardes, F., Steeneveld, W., van den Borne, B.H.P., Pinho, P., Randi, F. and Hogeveen H. (2023). The economic effect of cow-based fertility programs with an intensive use of reproductive hormones. *Journal of Dairy Science.* (submitted).

William Francis Ivor Edwardes
Wageningen School of Social Sciences (WASS)
Completed Training and Supervision Plan

Name of the learning activity	Department/Institute	Year	ECTS*
A) Project related competences			
A1 Managing a research project			
WASS Introduction Course	WASS	2019	1
Writing PhD research proposal	WUR	2019	6
PhD meetings BEC	WUR	2019 - 2023	2
'What's the value in sensors detecting sub-optimal mobility in dairy cows: a simulation model'	The Dutch Society for Veterinary Epidemiology and Economics (VEEC), online	2020	1
'The economic value of precision dairy farming'	PLF workshop	2021	1
'My sensor beeped: The economic and animal welfare gains in dairy cow sub-optimal mobility management'	International Symposium of Veterinary Epidemiology and Economics (ISVEE), Halifax	2022	1
'My sensor beeped: The economic and animal welfare gains'	European Conference on Precision Livestock Farming (ECPLF), Vienna	2022	1
A2 Integrating research in the corresponding discipline			
Agent based modelling, INF34806	WUR	2019	6
Advanced Microeconomics, UEC51806	WUR	2020	6
Advanced choice modelling (summer school)	Leeds CMC (online due to COVID-19)	2021	0.9

B) General research related competences			
B1 Placing research in a broader scientific context			
R and Big Data	PE&RC	2021	0.6
Machine learning A-Z	Udemy	2023	2
Statistical Uncertainty of Dynamic Models	PE&RC	2022	1.5
Environmental and Resource Economics – Module: Circular Economy	WASS, WIMEK & SENSE	2021	2
B2 Placing research in a societal context			
Workshop organisation: *'The economic and welfare impact of sub-optimal mobility and hoof health in dairy cows'*	International Society for Applied Ethology (ISAE), online	2021	2
Conference organisation	EU Precision Livestock Farming Workshop Conference (EUPLFC), Wageningen	2021	2
C) Career related competences/personal development			
C1 Employing transferable skills in different domains/careers			
Supervision: BSc and MSc thesis students	BEC	2021/2022	2
Start to supervise BSc and MSc thesis students	WGS	2021	0.3
Brain friendly working and writing	WGS	2019	0.3
Brain Training	WGS	2019	0.3
Scientific Writing	Wageningen in'to Languages	2021	1.8
Total			**39.8**

*One credit according to ECTS is on average equivalent to 28 hours of study load

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A large reason for pursuing a PhD was to prove to myself that I could achieve the highest level of academic training. Now four years after embarking on this academic quest, and as the time to defend my PhD thesis approaches, I begin to realise that this goal is about to be reached. However, it certainly would not have been achievable without the people I met and walked with along the way. The variety of support these individuals provided are no doubt a significant contribution towards the completion of my PhD. I would like to thank all of them for their continued support and contributions towards making my goal achievable, and just as importantly – incredibly enjoyable!

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Tariq Halasa, a very special thank you for taking me under your wing while I visited your group at the University of Copenhagen. I learned a great deal on developing a bio-economic simulation models, which laid invaluable foundations for the work that followed and my personal development as a simulation modeller. I am grateful to have you as a mentor.

Now, I would like to turn to the people outside the academic circle. To my friends and family, you all provided the love and laughter I needed to ensure my energy reserves were always full. I knew that with you all by my side I could take a forward step along my academic pursuit each day. I am forever thankful for your company along the way.

A large portion of this adventure was spent during the COVID-19 lockdowns. The silver lining to this difficult and confined period were the friendships I developed with my Hoevestein corridor mates. Qifa Yao, Dace Udrovska, Javi Huerta, Nicole Ceccinato, Vladislavs Šing, and Cornelia Rommens, I am so grateful to have been living with you all in such a challenging time. Wouter Kraakman, although we did not live together, I am glad you moved into my room after me and quickly integrated into the crew of friends. Thank you all for your continued friendship.

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About the author

Francis Edwardes (born March 23rd, 1993) was raised by his loving parents on their extensive, veld grazing, Brangus beef farm in the Kwa-Zulu Natal Midlands of South Africa. Francis' farm-oriented childhood instilled a constant connection and curiosity with agriculture, especially livestock farming.

Post-schooling, Francis headed south to Stellenbosch University in the Western Cape, South Africa, to pursue a bachelor's degree in agricultural economics. During his honour's degree (a one year post-bachelor and pre-master degree) Francis developed a keen interest in animal health economics. This path led him to delve further, pursuing a master's degree at the same institution.

For his thesis, Francis explored the economic feasibility of developing endemic stability towards bovine babesiosis as an intervention strategy opposed to the conventional intensive acaricide dipping strategies. His work was hugely inspired by the ongoing bovine babesiosis incidences on his parent's farm. Seeking broader perspectives, he spent six months at Wageningen University and Research, The Netherlands, in the Business and Economics (BEC) on exchange where he developed a bio-economic simulation model to reach his research objectives.

His experience abroad instilled a yearning for scientific research. Not long after returning to South Africa to complete his master's thesis, he found himself at the BEC group again. This time to pursue a PhD in a topic closely related to animal health economics. While completing his PhD, Francis acquired an extensive understanding on how to study the effects of animal health issues on farm economics and animal welfare.

Having now concluded his PhD, Francis is redirecting his focus from academia to his true passion—documentary photography. While his ties to agriculture, especially livestock farming, remain strong, he's focusing his lens on capturing positive animal welfare. This initial project sets the stage for his broader ambition: documenting diverse agricultural and food systems through a lens that blends societal, environmental, and political perspectives. Francis aspires to weave together a life where imagery meets inquiry, embodying the fusion of passion and purpose.

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