Technische Universität München
TUM School of Life Sciences

Toward a systems-oriented evaluation of data-driven agriculture – the case of wearable sensors in dairy farming

Johanna Pfrombeck

Vollständiger Abdruck der von der TUM School of Life Sciences der Technischen Universität München zur Erlangung einer

Doktorin der Agrarwissenschaften (Dr. agr.)

genehmigten Dissertation.

Vorsitz: Prof. Dr. Kurt-Jürgen Hülsbergen

Prüfer*innen der Dissertation:

1. Priv.-Doz. Dr. Markus Gandorfer
2. Prof. Dr. Heinz Bernhardt

Die Dissertation wurde am 13.10.2022 bei der Technischen Universität München eingereicht und durch die TUM School of Life Sciences am 11.04.2023 angenommen.

Es ist nicht genug zu wissen,
man muss es auch anwenden;
es ist nicht genug zu wollen,
man muss es auch tun.

*[Knowing is not enough;
we must apply.
Willing is not enough;
we must do.]*

Johann Wolfgang von Goethe (1907). *Maximen und Reflexinen: nach den Handschriften des Goethe- und Schiller-Archivs* (Vol. 21). Goethe-Gesellschaft.

Acknowledgements

When I started working at the Bavarian State Research Center for Agriculture after my master's degree in 2017, I had not given much thought to doing a PhD. Fairly quickly, however, I realized how much fun science can be, and a few months later I had myself enrolled as a PhD student at the Technical University of Munich. I would like to express my sincere thanks to the many people who motivated and supported me on my way to my doctorate:

First of all, my greatest thanks go to my supervisor PD Dr. Markus Gandorfer, who supported me in conceptualizing the topic of my dissertation, providing the necessary scientific input to focus on the dimensions of sustainability. Markus Gandorfer enriched the path of my dissertation with valuable strategic and scientific input and contributed to the improvement of the research results with each of our discussions. Thanks to his support throughout the process, three internationally published articles on current research topics have emerged, with which we have definitely struck a chord with the agricultural research community.

Further, I would like to thank Prof. Dr. Heinz Bernhardt for co-refereeing my dissertation, as well as Prof. Dr. Kurt-Jürgen Hülsbergen for chairing my dissertation defense. I really appreciate your time and expertise.

Furthermore, special thanks go to the (former) heads of the Institute for Agricultural Engineering and Animal Husbandry of the Bavarian State Research Center for Agriculture, Dr. Georg Wendl, Dr. Markus Demmel, and Dr. Stefan Neser, for ensuring a pleasant working atmosphere, which contributed considerably to my motivation to do a PhD.

Many thanks also go to my colleagues Olivia, Andreas G., Andreas H., Beat, Marvin, Stefan, Stephan, Sven, and Xaver, who contributed to the necessary motivation for my dissertation. You are as good a team as one could wish for. With you, scientific work is always fun.

A big thanks from the bottom of my heart goes to my family that is my constant reminder that real life is better than simulation. I am so incredibly grateful that you have given me so much support throughout my doctoral years and have always been understanding of the time needed to complete my dissertation.

Schelchenvils, 10.10.2022

Table of contents

List of figures

List of tables

Zusammenfassung

Digitalisierung und Robotik haben ihren Weg in die landwirtschaftliche Praxis gefunden. Damit verbunden sind Chancen und Risiken, aber auch spezifische Herausforderungen. Es sind mitunter ökonomische Aspekte, aber auch Aspekte des Tierwohls, des Umweltschutzes, der Akzeptanz von Landwirtinnen und Landwirten und der gesellschaftlichen Akzeptanz, die über die weitere Entwicklung der digitalen Landwirtschaft bestimmen. Während bei technischen Innovationen in der Vergangenheit oftmals technisch-funktionale Bewertungen oder Aspekte der Wirtschaftlichkeit im Vordergrund standen, wurden Rufe nach einer multiperspektivischen Betrachtung lauter. Das System Landwirtschaft ist ein Komplex aus verschiedenen Subsystemen, welche zueinander in Abhängigkeiten und Wechselbeziehungen stehen und sich in einem ständigen Veränderungsprozess befinden. Um diese Komplexität zu erkennen und zu verstehen, gewinnen systemorientierte Forschungsansätze an Bedeutung. Ein möglicher Ansatz, das System Landwirtschaft aus mehreren Perspektiven zu bewerten, ist die Orientierung an einer Nachhaltigkeitsbewertung.

Die vorliegende publikationsbasierte Dissertation umfasst eine Bewertung von digitalen Technologien in der Landwirtschaft und fokussiert dabei auf Sensorsysteme an der Kuh zur Verhaltensüberwachung. Die Dissertation umfasst drei die Technologie hinsichtlich verschiedener Gesichtspunkte bewertende Publikationen. Während zwei der Publikationen ausschließlich Sensorsysteme an der Kuh adressieren, wirft eine dritte Publikation neben den Sensorsystemen im Speziellen einen umfangreicheren Blick auf eine größere Bandbreite an digitalen Technologien in der Landwirtschaft. Den Ansatz einer multiperspektivischen Betrachtung verfolgend, nähert sich die Dissertation einem systemorientierten Forschungsansatz. Weg von einer eindimensionalen Bewertung berühren die drei Publikationen die drei Dimensionen der Nachhaltigkeit „Soziales“, „Ökologie“ und „Ökonomie“. Sie liefern damit einzelne Bausteine für eine Nachhaltigkeitsbewertung digitaler Landwirtschaft. Neben einer Pluralität an Perspektiven zur Bewertung von digitalen Technologien in der Landwirtschaft stützen sich die drei Publikationen der Dissertation dabei auch auf eine Pluralität an methodischen Ansätzen.

Die erste Publikation fokussiert auf die Nachhaltigkeitsdimension „Soziales“ und stellt die gesellschaftliche Akzeptanz von digitalen Technologien in der Landwirtschaft in den Mittelpunkt. Auf das Potential von digitalen Technologien in der Landwirtschaft hinsichtlich Tierwohl und Umweltschutz stützend, gibt es Stimmen, welche eine Aufwertung des Images der Landwirtschaft aus gesellschaftlicher Sicht erwarten. Die Datenbasis der Studie bildete eine im Jahr 2018 mit einem Verbraucherpanel durchgeführte Online-Umfrage unter der Bevölkerung in Deutschland, welche in 2.012

auswertbaren Datensätzen resultierte. Methodisch stützte sich die Umfrage zur Einstellungsakzeptanz sowohl auf quantitative (z. B. Abfrage von Items zur Einstellung mittels Likert-Skalen) als auch qualitative (Spontanassoziationen zu gezeigten Bildern) Ansätze. Die Ergebnisse aus den quantitativen Abfragen zeigten eine im Durchschnitt positive Einstellung der Befragten zu einem Einsatz von digitalen Technologien in der Landwirtschaft und zu deren staatlicher Förderung. Verglichen damit fiel die Bewertung von einer Auswahl spezifischer Einzeltechnologien anhand der Spontanassoziationen kritischer aus, insbesondere für die beiden gezeigten Bilder mit Robotertechnologien aus der Milchviehhaltung (Melkroboter und Fütterungsroboter). Da viele der spontan genannten negativ konnotierten Assoziationen sich mehr auf das bestehende landwirtschaftliche Produktionssystem im Allgemeinen als auf die abgebildeten digitalen Technologien im Speziellen bezogen, wird schlussgefolgert, dass eine Aufwertung des gesellschaftlichen Images durch digitale Technologien in der Landwirtschaft als unwahrscheinlich anzusehen ist, da einzelne positive Aspekte der Digitalisierung (Tierwohl, Umweltschutz) im Schatten allgemeiner Kritik am aktuellen Produktionssystem stehen.

Die zweite Publikation fokussiert auf Tierwohlaspekte von Kalbesensoren, welche als Thema der Nachhaltigkeitsdimension „Ökologie“ zugeschrieben werden. Sie untersuchte, ob das Befestigen eines praxisüblichen Kalbesensors am Schwanz der Tiere zu Verhaltensänderungen beim Tier führt. Der Datensatz stammte aus der Milchviehherde des Staatsguts Achselschwang (Bayern, Deutschland), bei der im kalbenahen Zeitraum Kalbesensoren am Schwanz mehrere Tiere befestigt wurden. Die Tiere waren ebenfalls mit einem Pansenbolus ausgestattet, welcher kontinuierlich die Bewegungsaktivität der Tiere erfasst. Der erste von zwei methodischen Ansätzen stützte sich auf eine Analyse der Variabilität der Bewegungsaktivität (Pansenbolus). Der zweite methodische Ansatz umfasste eine visuelle Verhaltensbeobachtung über Videoanalyse, bei welcher eine Vielzahl an Verhaltensweisen erfasst wurden: Dauer des Stehens, Gehens, Liegens, der Futteraufnahme, des Trinkens, von sozialer Interaktion, dem Scheuern des Schwanzes an Gegenständen sowie die Häufigkeit des Schwanzhebens und der Anzahl an Steh- und Liegeperioden. Bei beiden methodischen Ansätzen wurden die Analysezeiträume in 4-Stunden-Blöcke unterteilt und mit einem Referenzzeitraum verglichen. Bei der Analyse der Variabilität der Bewegungsaktivität konnte im Mittel über alle analysierten Tiere keine Zunahme der Anzahl an 4-Stunden-Blöcken mit einer signifikanten Zunahme der Variabilität der Bewegungsaktivität festgestellt werden. Bei der visuellen Verhaltensanalyse zeigte ein Mittelwertvergleich über alle analysierten Tiere keine signifikante Veränderung nach Anlegen eines Kalbesensors für die Mehrheit der Verhaltensweisen. Jedoch war zu beobachten, dass einzelne Tiere auf das Befestigen eines Kalbesensors unter anderem mit einer erhöhten Häufigkeit des Schwanzhebens oder Scheuern des

Schwanzes an Gegenständen (z. B. Wassertrog) reagierten. Diese tierindividuellen Reaktionen sollten in einem größeren Rahmen weiter beforscht werden.

Schließlich beschäftigt sich die dritte Publikation der Dissertation mit der Nachhaltigkeitsdimension „Ökonomie". Um den Gewinnbeitrag einer Investition in Aktivitätssensoren zur automatischen Brunsterkennung zu ermitteln, wurde ein stochastisches Modell angewandt, welches Unsicherheiten sowohl für Brunsterkennungsraten (visuell, sensorgestützt) als auch den Zeitaufwand zur Tierkontrolle (visuell, sensorgestützt) mittels Monte-Carlo-Simulation modelliert. Den jährlichen Kosten der Investition lagen drei marktverfügbare Sensorsysteme zugrunde. Der Deckungsbeitrag für visuelle und sensorgestützte Brunsterkennung wurde jeweils mittels SimHerd (SimHerd A/S, Viborg, Dänemark) berechnet. SimHerd ist ein dynamisches, mechanistisches und stochastisches Simulationsmodell für Milchviehherden, welches mit über 2.000 Parametern verschiedene Ereignisse der Milchkuh wie beispielsweise Fruchtbarkeit und Gesundheit berücksichtigt. Um eine Vielzahl an möglichen betrieblichen Gegebenheiten abzudecken, umfasste die Studie verschiedene Szenarien: die Rassen Fleckvieh (Milchleistungen 7.000 kg und 9.000 kg) und Holstein (Milchleistungen 9.000 kg und 11.000 kg), Herdengrößen von 70 und 210 Kühen, eine Ausstattung von nur Kühen oder Kühen und Jungvieh und Lohnkosten von 10 €/h und 20 €/h. Der Erwartungswert für den Gewinnbeitrag bei einer Investition in Aktivitätssensoren zur automatischen Brunsterkennung lag über alle analysierten Szenarien hinweg bei +7 € bis +46 € je Kuh und Jahr. Betrachtet man alle analysierten Szenarien, so lag die ermittelte Wahrscheinlichkeit für einen positiven Gewinnbeitrag über alle Szenarien hinweg bei 74 % bis 99 % der Simulationsläufe. Da die Mehrheit der Aktivitätssensoren die Funktion der Brunsterkennung mit einer Gesundheitsüberwachung und teils sogar einer Früherkennung von Kalbungen vereint, sind weitere neben den in der Studie berechneten ökonomische Effekte zu erwarten.

Als Synthese der drei Publikationen der Dissertation kann festgehalten werden, dass wichtige Erkenntnisse für eine systemorientierte Bewertung digitaler Technologien in der Landwirtschaft erarbeitet wurden. An den drei Nachhaltigkeitsdimensionen orientierend, bilden sie einzelne Bausteine zur Bewertung der sozialen, ökonomischen und ökologischen Auswirkungen des Einsatzes digitaler Technologien in der Landwirtschaft. Basierend auf den Ergebnissen der drei Publikationen als auch der zusätzlich einbezogenen Literatur wird schlussgefolgert, dass Sensorsysteme an der Kuh zur Verhaltensüberwachung einen Beitrag zu einer nachhaltigeren Milchproduktion leisten können. So liefern die Sensorsysteme für den Großteil der analysierten betrieblichen Konstellationen einen positiven Gewinnbeitrag, obwohl bei der Studie zur ökonomischen Bewertung nur die Leistung der Brunsterkennung bewertet wurde. Da die ökonomischen Vorteile der Funktionen zum Gesundheits- und Kalbemanagement nicht bewertet und berücksichtigt wurden, handelt es sich um eine konservative Betrachtung. Gerade diese Funktionen bieten neben dem zusätzlichen ökonomischen Potential auch positive Auswirkungen auf die Tiergesundheit. Aufgrund der Potentiale hinsichtlich Arbeitsentlastung und -flexibilisierung leisten die Sensorsysteme in gewissem Maße auch einen positiven Beitrag im Sinne sozialer Nachhaltigkeit. In diesem Kontext ist auch die gesellschaftliche Akzeptanz der Technologien von zentraler Bedeutung. Hier zeigen die Ergebnisse, dass zumindest keine grundsätzliche Abneigung gegenüber dem Einsatz digitaler Systeme in der Landwirtschaft beobachtet werden kann.

Auf den Publikationen der Dissertation basierend ergibt sich weiterer Forschungsbedarf, mitunter zur gesellschaftlichen Akzeptanz digitaler Technologien in der Landwirtschaft. Mittels den Spontanassoziationen wurden Gründe für eine Ablehnung von Tierhaltungssystemen identifiziert, wobei sich jedoch nicht in allen Fällen feststellen ließ, ob und in welchem Ausmaß die gennannten kritischen Begriffe tatsächlich in der Tatsache der Digitalisierung der auf den Bildern gezeigten Technologien begründet waren. Darüber hinaus können weitere Forschungsansätze darüber Aufschluss geben, welche digitalen Technologien kritischer gesehen werden als andere. Eine interdisziplinäre Zusammenarbeit mit anderen wissenschaftlichen Disziplinen wie der Soziologie scheint hierbei zukünftig zielführend. Weiterhin gilt es nun, das Potential der Sensorsysteme hinsichtlich Tiergesundheit mit einer Erfassung geeigneter Parameter und einer Vernetzung mit weiteren gesundheitsrelevanten Datenquellen auszuschöpfen. Schließlich wurde im Gesamtkontext des Dissertationsthemas ein bestehender Forschungsbedarf zu möglichen negativen externen Auswirkungen von digitalen Technologien (in der Milchviehhaltung) identifiziert. So wären zukünftig weitere Untersuchungen wie beispielsweise zu Rebound-Effekten beim Einsatz digitaler Technologien anzustreben.

Es wird künftig geeignete Strategien der betroffenen Stakeholder bedürfen, damit jene digitalen Technologien mit einem Potential für eine nachhaltigere Landwirtschaft Akzeptanz finden und damit auch in der Praxis angewandt werden. Die Herausforderung, Tierhaltungssysteme so weiterzuentwickeln, dass sie sowohl von der Gesellschaft als auch von Milchviehhaltern akzeptiert werden, zeigt die Bedeutung eines systemorientierten Ansatzes auf. Bereits bei der Entwicklung von digitalen Technologien für die Landwirtschaft ist es unabdingbar zu berücksichtigen, dass es sich hierbei nicht nur um einen rein technischen Prozess handelt, sondern dass dieser auch weitreichende Veränderungen auf soziale, ökologische und wirtschaftliche Aspekte des gesamten landwirtschaftlichen Systems haben kann.

Summary

Digitalization and robotics have found their way into agricultural practice, presenting many opportunities and risks, but also specific challenges. Economic aspects, but also aspects of animal welfare, environmental protection, and the acceptance by farmers and the public are factors that determine the future viability of digital agriculture. Whereas the focus was on technical-functional evaluation of technological innovations or aspects of economic viability in the past, nowadays the need for a multi-perspective view is becoming increasingly apparent in the interests of sustainable agriculture. The agricultural system is a complex of different subsystems that are interdependent and interrelated and are in a constant process of change. To recognize and understand this complexity, systems-oriented research approaches are gaining more and more importance. One possible approach to evaluate the agricultural system from several perspectives is to follow the structure of a sustainability assessment.

This publication-based dissertation focuses on an evaluation of digital farming technologies, especially on wearable sensor systems for behavioral monitoring in dairy farming. It comprises three publications evaluating the technology with respect to different aspects. While two of the publications exclusively address wearable sensor systems on cows, a third publication takes a broader look at a wider range of digital technologies in agriculture. Following the objective of a multi-perspective view, the dissertation takes a systems-oriented research approach. Moving away from a one-dimensional assessment, the three publications touch on the three dimensions of sustainability "social", "ecological" and "economic". They thus provide individual building blocks for a sustainability assessment of digital farming technologies. In addition to a plurality of perspectives on the assessment of digital technologies in agriculture, the three publications of the dissertation also rely on a plurality of methodological approaches.

The first publication touches on the sustainability dimension "social" and focuses on the public acceptance digital farming technologies. Relying on the potential of digital farming technologies in terms of animal welfare and environmental protection, there are voices that postulate an enhancement of the social image of agriculture through digitalization. The data basis of the first publication was an online survey conducted in 2018 among a German consumer panel, which resulted in 2,012 analyzable data sets. Methodologically, the attitudinal acceptance survey relied on both quantitative (e.g., querying items on attitude using Likert scales) and qualitative (spontaneous associations with pictures shown) approaches. The results from the quantitative queries showed an on average positive attitudinal acceptance toward a use of specific digital farming technologies and also toward state subsidies for farmers investing in these technologies. Compared to this result, the spontaneous associations brought out

the perception that digital farming technologies (milking robot, feeding robot) are seen more critically in connection with animals than when applied in crop production. Also, many of the spontaneously mentioned associations related more to the existing farming system in general than to the depicted digital farming technologies in particular. It is, therefore, concluded that an improvement of the public image through digitalization is to be regarded as unlikely, since individual positive aspects of digitalization are too strongly overshadowed by general criticism of the current farming system.

The second publication focuses on animal welfare aspects of calving sensors, a topic attributed to the sustainability dimension "ecology". It analyzed whether attaching a calving sensor to the tail of the animals leads to behavioral changes. The data set originates from the dairy herd at Achselschwang state farm (Bavaria, Germany), of which several animals had calving sensors attached to their tails in the pre-calving period. These animals were also equipped with a rumen bolus, which continuously records the animals' activity. The first of two methodological approaches analyzed the variability of activity (rumen bolus). The second methodological approach involved visual behavioral observation via video analysis, during which a variety of behaviors were recorded: duration of standing, walking, lying, feed intake, drinking, social interaction, rubbing the tail on objects, and frequency of tail raising and number of standing and lying bouts. In both methodological approaches, periods were divided into 4-hour blocks and compared with a reference period. When analyzing the variability of activity, no increase in the number of 4-hour blocks with a significant increase in the variability of locomotor activity was detected on average across all animals analyzed. In the visual behavior analysis, a comparison of means across all animals analyzed showed no significant change after attachment of a calving sensor for the majority of behaviors. However, it was observed that individual animals responded to the attachment of a calving sensor with, among other things, an increased frequency of tail raising or rubbing the tail on objects (e.g., water trough). These animal-specific responses should be further researched on a larger scale.

Finally, the third publication of the dissertation covers the sustainability dimension "economics". To determine the net return of investment in activity sensor for automated estrus detection, a stochastic model was applied, which modeled uncertainties for both estrus detection rates (visual, sensor-based) and the time required for animal control (visual, sensor-based) using Monte Carlo simulation. Annual investment costs were based on three commercially available wearable sensor systems. The gross margin for visual and sensor-based estrus detection was calculated in each case using SimHerd (SimHerd A/S, Viborg, Denmark). SimHerd is a dynamic, mechanistic, and stochastic simulation model for dairy herds that involves over 2,000 parameters to account for various dairy cow events such as fertility and health. To cover a wide range of possible farm situations, the study included different scenarios: the Simmental (milk yields of 7,000 kg and 9,000 kg) and Holstein (milk yields of 9,000 kg and 11,000 kg) breeds, herd sizes of 70 and 210 cows, an equipment of only cows or cows and heifers, and labor costs of 10 €/h and 20 €/h. The mean net return of investment in activity sensors for estrus detection was +7 € to +46 € per cow and year across all analyzed scenarios. Considering all analyzed scenarios, the determined probability for a positive net return of investment was 74% to 99% of the simulation runs. Since the majority of activity sensors combine the function of estrus detection with health monitoring and in some cases even early detection of calving, further economic effects can be expected in addition to those analyzed in the study.

As a synthesis of the three publications of the dissertation, it can be stated that important findings for a systems-oriented assessment of digital farming technologies have been developed. Based on the three sustainability dimensions, they form individual building blocks for evaluating the social, economic and ecological impacts of the use of digital farming technologies. Based on the results of the three publications as well as the additional literature included, it is concluded that wearable sensor systems in dairy farming can contribute to more sustainable milk production. Thus, the sensor systems provide a positive net return of investment for the majority of the analyzed farm situations, although only the function of estrus detection was evaluated in the economic study. Since the economic benefits of the health and calf management functions were not evaluated and considered, this is a conservative view. In addition to the additional economic potential, these functions in particular also offer positive effects on animal health and can thus serve animal welfare. Due to the potential in terms of reduced workload and flexibility for the farmer, the sensor systems also make a positive contribution toward social sustainability to a certain extent. In this context, the public acceptance of the technologies is also of central importance. The respective results show that at least no fundamental aversion to the use of digital farming technologies can be observed.

The publications of the dissertation highlight areas in need of further research, including on the public acceptance of digital farming technologies. By means of the spontaneous associations, reasons for a rejection of animal husbandry systems were identified, although it was not in all cases possible to determine whether and to what extent the critical terms named were actually rooted in the digital nature of the technology shown in the pictures. In addition, further research may shed light on which digital technologies are viewed more critically than others. Interdisciplinary cooperation with other scientific disciplines such as sociology would seem a promising approach in the future. Furthermore, it is now necessary to exploit the potential of the sensor systems with regard to animal health by recording suitable parameters as part of a network of other health-relevant data sources. Finally, in the overall context of the dissertation topic, a need for research on possible negative external effects of digital technologies (in dairy farming) was identified. Thus, further studies on rebound effects, for example, in the use of digital technologies should be considered in the future.

In the future, appropriate strategies will be required from the stakeholders concerned to ensure that those digital technologies with a potential for more sustainable agriculture find acceptance and are thus also applied in practice. The challenge of further developing animal husbandry systems in such a way that they are accepted by both society and dairy farmers highlights the importance of a systems-oriented approach. Already in the development of digital farming technologies, it is essential to consider that this is not just a purely technical process, but that it can also have far-reaching changes on social, ecological, and economic aspects of the entire agricultural system.

1 Structure and objectives of the dissertation

This cumulative dissertation is based on three studies published in peer-reviewed scientific journals. It is devoted to an evaluation of wearable sensor systems in dairy farming. The dissertation follows a systems-oriented research approach. Therefore, an orientation toward the social, economic, and ecological sustainability dimensions was chosen as the approach for evaluation. To evaluate the digital technologies from different perspectives, the three studies focus on aspects of the three dimensions of sustainability. Similarly, a plurality of methodological approaches was applied. Regarding the "social" sustainability dimension, quantitative as well as qualitative methods of empirical social research were applied to address the question of public acceptance of digital farming technologies. Addressing the sustainability dimension "environment" and considering aspects of animal welfare of digital calving sensors, behavior of dairy cows after calving sensor attachment was analyzed. Both visual evaluation and analysis of activity data were performed to assess potential changes in dairy cow behavior. In the third publication, an economic evaluation of activity sensors for estrus detection was conducted, methodically based on applying an economic simulation model for dairy herds and stochastic modeling. This study thus covers the sustainability dimension "economy".

The dissertation is structured as follows: First, an overview of systems-oriented research and sustainability assessment is presented, forming the framework of the dissertation. Then, an insight into digital technologies in dairy farming and in particular wearable sensor systems for behavior monitoring is given and research fields on the evaluation of these technologies are classified. A literature review of the specific topics covered in the three publications follows. The methodological approaches are outlined, and the results of the publications are presented. The dissertation ends with a discussion of the results and methods and resulting implications.

2. The systems-oriented research approach for technology assessment

2.1 The need for a comprehensive technology assessment

Regarding digital farming technologies, the focus of the literature has been mainly on technical functionality and economics so far. Indeed, technical functionality represents a relevant basis for successful adoption on farms. However, sustainable use of technologies requires much more than a purely technical functionality assessment. The relationship between technology and sustainability is described as ambivalent (Grunwald 2010). The history of technology use is characterized by a long-lasting positive association of technological innovations with progress and prosperity. During the Industrial Revolution, the use of technology was advocated as an enabler of emerging ideals of the European Enlightenment, such as the relief of physical labor. Gradually, however, and seriously only in recent decades, also unintended consequences of technology use have been recognized. Previously, these unintended consequences did not receive much attention because their solution was seen in an extended use of (even more advanced) technology and because they were judged to be negligible compared to the technologies' benefits. In addition, environmental damage still received comparatively little attention. This tension necessitated the need for approaches to assess technology use more comprehensively. One of these approaches is "Technology Assessment", which deals with a comprehensive assessment of the consequences of technology use and with the analysis and evaluation of perspectives of those potentially affected by the consequences of technology (Grunwald 2010). The term "Technology Assessment" describes a nonspecific collection of different approaches to analyzing the multiple consequences of technology use. For instance, communicating risks of a technology and observing sustainability are gathered under this term (Grunwald 2009). Public criticism of modern agri-food technologies has also often been underestimated in the agricultural sector, although it may be a relevant barrier to the future commercialization of food produced (Shaw 2002, König et al. 2010, Gupta et al. 2012). Pesticides, nanotechnology, cloning, and genetic engineering are striking examples that have raised public concerns (Shaw 2002, König et al. 2010, Gupta et al. 2012, Frewer 2017), leading to policy interventions (e.g., ban on the cultivation of genetically modified plants), or to a deterioration of the image of agriculture in general. Therefore, there is a need to move away from a pure technology assessment and toward a holistic view of digital farming, thus looking at digital technologies for farming from a broader perspective.

2.2 The systems-oriented research approach in agricultural sciences

Agricultural science has already been characterized as a systems science by Mayer and Mayer in 1974. Many years later, in 2005, the German Research Foundation dedicated its memorandum to the question of how agricultural research defines itself. Since the framework conditions for research are constantly changing over time, a critical scrutiny and realignment of topics being dealt with and methodologies being applied in research is reasonable. For example, changing public demands made on agriculture and technological innovations require adaptive capabilities of agricultural research. Thus, the memorandum of the German Research Foundation (2005) again emphasized that a systems-oriented approach is indispensable in agricultural sciences.

"Even in oral traditions, agriculture has always been perceived as a system… More than ever, the science of agriculture stands at the center of a broader system integrating human society and its physical environment".

(Mayer and Mayer 1974)

Although Mayer and Mayer described agricultural sciences as systems science as early as 1974, agricultural sciences still have not arrived at following a fully systems-oriented approach. Gradually, it has been recognized that farms operate not necessarily according to the principles of "rational decision-making" or the logic that research suggested as guiding principles. It was thus realized that farms cannot be represented in a monocausal manner, since external effects such as ecological and social impacts influence their decision making (Bellon and Hemptinne 2012, Darnhofer et al. 2012). The need to consider this ecological and social context has not only been recognized for decisions made by farmers, but also when it comes to the development of agricultural technologies (Biggs 1995, Collinson and Lightfoot 2000).

In systems-oriented agricultural research, the farm is seen as a whole, embedded in a natural, social, economic, and technological context (Gilbert et al. 1980, Darnhofer et al. 2010, Darnhofer et al. 2012). Thus, the subject of research is the agroecosystem including its subsystems "soil", "plants", "animals", and "humans", on which technology, economy, and the public have an impact. All these subsystems are constantly evolving due to mutual influence and changing conditions of the environment in which the farming system is embedded (German Research Foundation 2005). According to Gilbert et al. (1980), farming systems research "*also recognizes the interdependencies and interrelationships between the natural and human environments*". Since humans play a decisive role in the agroecosystem as farmers and the public alike, they have an influence on inputs, outputs, and interactions within the system. This implies and highlights the need to look at the agroecosystem with all its facets to understand it comprehensively. Pursuing a farming systems research approach means capturing dynamics and interactions between the different elements of the system, thus focusing on a larger number of causal relationships instead of a monocausal scheme (German Research Foundation 2005, Darnhofer et al. 2012). In other words, links between (sub)systems may provide even more decisive information than the (sub)systems themselves. It is in the nature of a farm to be subject to a constant process of adaptation to new, sometimes even unpredictable circumstances (Darnhofer et al. 2010), which may be driven, for example, by changes in the legal framework, changes in the demands of society, or modified production conditions. These dynamics of the farming systems have to be captured. The need for a systems-oriented research approach has also been acknowledged in livestock farming (Gibon et al. 1999). Since a farming systems research approach appears so plausible, the first assumption is that one can adhere to proven and established methodical procedures. However, the reality is sobering: There is no "one size fits all" approach to farming systems research, which is probably one reason why systems-oriented research has not yet established itself as a standard in agricultural research.

2.3 Sustainability assessment

A possible methodological approach to achieve a holistic view is, for instance, a sustainability assessment that analyzes the different dimensions of "social", "ecological", and "economic" sustainability and their trade-offs. A comprehensive sustainability assessment requires the analysis of a large number of sustainability indicators of these three dimensions (see Food and Agriculture Organization of the United Nations (FAO) 2014, Latruffe et al. 2016).

What does "sustainability" mean? It was mentioned for the first time in the context of forestry. In 1713, Hans-Carl von Carlowitz published his book "Sylvicultura Oeconomica" (Carlowitz 2000), describing as a principle of forestry that only as much wood may be harvested as the forest yields in new growth. Thus, he had recognized a certain connection between ecological factors and economic and social concerns (Klöpffer and Renner 2007). The current definition of "sustainability" stems from a global development context and received its inspiration from the Brundtland Report, according to which sustainable development is development that *"meets the needs of present without compromising the ability of future generations to meet their own needs*" (World Commission on Environment and Development 1987). The Brundtland Report, also known as "Our Common Future", was published by the World Commission on Environment and Development in 1987 and represents the starting point of a worldwide discourse on the importance of sustainability and sustainable development. In its definition, sustainability now comprises three dimensions: an ecological, an economic, and a social one, of which the social dimension has received the least attention (Bitsch

2016). The initially strongly ecological-economic understanding of sustainability by von Carlowitz has thus been expanded over time to include a social dimension, as can now be found in the Brundtland Report. In 1990, Francis and Youngberg defined "Sustainable agriculture" as "*a philosophy based on human goals and on understanding the long-term impact of our activities on the environment and on other species. These [farming] systems reduce environmental degradation, maintain agricultural productivity, promote economic viability in both the short and long term, and maintain stable rural communities and quality of life*." (Francis and Youngberg 1990). The idea of viewing sustainability in three dimensions has also gained ground in German politics. The German Parliament set up the Enquete Commission "Protection of People and the Environment", which developed the three-pillar model of "social", "economic", and "ecological" sustainability in 1995. According to its understanding, the three pillars are of equal importance; they are interdependent and cannot be optimized partially (Flora 1992, Bartol and Herkommer 2004). John Elkington coined the term "triple bottom line" to describe the interaction of the three dimensions of sustainability (Elkington 1998). The three dimensions of the "triple bottom line"-concept are also known as "people – planet – profit" (Kuhlman and Farrington 2010).

Approaches and instruments applied to assess sustainability following the three dimensions are broad and come from different disciplines. A difficulty in measuring agricultural sustainability is that it is "*a dynamic rather than static concept*" (Hayati et al. 2010, p.95). Indicators are applied as points of reference to assess sustainability. Economic, ecological, and social indicators allow farmers to assess achievements in terms of sustainable farming, both for their own farm and against a benchmark with other farms. But also for other stakeholders such as politics, industry, or science, indicators provide information to assess the state of sustainability and its changes. A variety of indicators can be found in the literature (Hayati et al. 2010). Due to the increasing relevance of environmental issues (Bockstaller et al. 2008), many indicators have been added in recent years (Riley 2001, Rosnoblet et al. 2006), especially for evaluating the ecological dimension. Not all indicators are directly measurable. Bockstaller et al. (2011) therefore classified ecological indicators into "simple indicators" (based on a causal variable), "predictive indicators" (based on outputs from models of varying complexity), and "measured indicators" (based on field measurement or observation). Examples of ecological indicators are "soil health", "nitrate content of groundwater and crops", and "yield trends" (Becker 1997, Zhen and Routray 2003). Ecological integrity also includes animal welfare aspects, including animal health and freedom from stress (see FAO 2014). Economic sustainability describes the economic viability of a farm, focusing on whether a "*farming system can survive in the long term in a changing economic context*" (Latruffe et al. 2016). In this context, profitability, liquidity, stability, and productivity are relevant aspects. Zhen and Routray (2003) cite “net farm income”, “benefit-cost ratio of production”, and “crop productivity” as examples of indicators of economic sustainability. Social sustainability puts people at the center, encompassing both the welfare of the farmer and his family as well as the demands of society. Social indicators analyzed in this context address e.g., working conditions, quality of life, education, multifunctionality, quality of products, and acceptable agricultural practices (Van Cauwenbergh et al. 2007, Lebaq et al. 2013, Terrier et al. 2013).

In their review, Lovarelli et al. (2020) stated that precision livestock farming brings benefits on all three dimensions of sustainability. Considering the social sustainability dimension, they mentioned farmer and animal welfare as potential benefits of precision livestock farming. However, they pointed to the need of quantifying the benefits being generated and of demonstrating not only positive but also negative impacts of precision livestock farming on ecological, economic, and social sustainability (Lovarelli et al. 2020). Eastwood et al. (2004) also let it be known that they are taking a holistic view of precision dairy farming by defining it as “*the use of information technologies* […] *aimed at improved management strategies for optimizing economic, social, and environmental farm performance*”. So did Spilke and Fahr (2003): Their way of thinking is characterized by considering the three dimensions of sustainability, as they stated that precision dairy farming “*aims for an ecologically and economically sustainable production of milk with secured quality, as well as a high degree of consumer and animal protection*” (Spilke and Fahr 2003).

As a sustainable farming system does not aim to optimize single aspects of the three sustainability dimensions if this might have a negative impact on other sustainability dimensions (Flora 1992 ,Bartol and Herkommer 2004), the focus is rather on finding an appropriate balance between ecological, economic, and social targets (Flora 1992). This way of thinking thus poses new challenges to research, as research approaches have to be rethought and boundaries between research disciplines have to be broken down. People from different disciplines have to collaborate to meet the various objectives of sustainability. Systems-oriented agricultural research represents an approach which considers farming operations in their complexity, having to cope with the balance of various sustainability criteria.

The approach and thematic structure of the dissertation is based on three studies covering selected aspects of the social, economic, and ecological sustainability dimensions. Together with further analyses, they form relevant building blocks for a sustainability analysis of sensor systems in dairy farming. The three studies in the context of evaluating wearable sensor systems in dairy farming not only address the three sustainability dimensions but are also based on a plurality of methodological approaches (see Figure 1). The social sustainability dimension is covered by a study on the public attitudinal acceptance of digital farming technologies in Germany. According to the literature, *“[S]ocial acceptance is a prerequisite to social sustainability [because] if a technology is rejected by a society or its members, it is not viable*” (Wood et al. 2016). Quantitative as well as qualitative methods of empirical social research were chosen as methodological approach for the study on the public attitudinal acceptance. The second study deals with an assessment of dairy cow behavior after calving sensor attachment to their tail, thus analyzing aspects of animal welfare as topic of the ecological sustainability dimension. The data of the study originates from a dairy research and demonstration farm (on-farm experiment) and includes both visual assessment of behavior and analysis of automatically recorded activity data. Finally, the third publication addresses “economy“ as the third sustainability dimension. Applying a farm systems modeling approach, sensors for automated estrus detection are evaluated with respect to their profitability.

sustainability dimension	people social	planet ecological	profit economic
publication	publication I Public attitudinal acceptance of digital farming technologies in Germany	publication II Dairy cow behavior after calving sensor attachment to their tail	publication III Economic evaluation of activity meters for estrus detection
methodological approach	empirical social research	on-farm experimentation	farm systems modeling

Figure 1. Thematic and methodological approach of the dissertation

This cumulative thesis is based on the following international published and peer-reviewed journal publications:

I. Pfeiffer, J., Gabriel, A., Gandorfer, M. (2021a). Understanding the public attitudinal acceptance of digital farming technologies: a nationwide survey in Germany. *Agriculture and Human Values*, *38*(1), 107-128.

II. Pfeiffer, J., Spykman, O., Gandorfer, M. (2021b). Sensor and video: two complementary approaches for evaluation of dairy cow behavior after calving sensor attachment. *Animals, 11*(7), 1917.

III. Pfeiffer, J., Gandorfer, M., Ettema, J. F. (2020). Evaluation of activity meters for estrus detection: A stochastic bioeconomic modeling approach. *Journal of Dairy Science*, *103*(1), 492-506.

3 Literature review of the research fields of the dissertation

Chapter 3 provides an overview of digital technologies in dairy farming and a compact review of the literature on their evaluation. It additionally focuses on the research fields of the three publications. Specifically, it includes a literature review on the public acceptance of digital farming technologies, on calving sensors in dairy farming, and on economics of sensor-assisted estrus detection. Information on the methodological approaches is found in the respective sections of the three publications.

Data-driven dairy farming: an overview of available digital technologies

In recent years, digitalization has found its way into dairy farming, now affecting the whole production process: milking (milking process, milk yield, milk component analysis), feeding (feed supply, feed pushing), hygiene management (slat cleaning, bedding, udder care), and herd management (fertility, calving, health monitoring) (see e.g., Bewley 2010, Da Borso et al. 2017, Grodkowski et al. 2018). Sensor systems on or in dairy cows enable monitoring of individual animals, specifically identifying them, determining their position, and monitoring their behavior and health condition (see Rutten et al. 2013). Digital scales for continuous weight monitoring and camera-based sensors for body condition recording (Peiper et al. 1993, O'Leary et al. 2020, Zin et al. 2020) complete the range of sensor systems to monitor animal-specific parameters. Collecting data automatically, in particular at the level of the individual animal, for more precise animal management is described as "Precision Dairy Farming". It comprises "*technologies to measure physiological, behavioral, and production indicators*" (Bewley 2010) or "*the use of information technologies for assessment of fine-scale animal and physical resource variability*" (Eastwood et al. 2004). Precision Dairy Farming involves continuous monitoring of milk yield and milk components as well as parameters such as activity, feeding and rumination behavior, and physiological parameters such as body temperature or pH value in the stomach (see e.g., Bewley 2010, Rutten et al. 2013, Borchers and Bewley 2015) to make more informed decisions at individual animal level. Besides hardware-based technologies, digitalization in dairy farming also involves software applications supporting the dairy farmer in decision making. Farm management information software (e.g., documentation, herd management), apps (health assessment, market information), and digital marketplaces (e.g., marketing platform, used machinery exchange platform) are also part of digitalization.

Wearable sensor systems to manage dairy cows

Activity, step count, rumination, eating time, number of drinking cycles, pH-value in the stomach, rumen motility, and body temperature – all these are examples of parameters already being measured automatically and continuously by means of sensor technology either on or in the dairy cow (see Bewley 2010, Rutten et al. 2013, Borchers and Bewley 2015). The beginnings of wearable sensor systems date back to the 1980s (Mottram 2016). After the development of sensors for individual animal identification, the first pedometers for attachment to the animal's leg entered the market. The first generations of pedometers were technically based on simple position sensors to record parameters such as the number of steps taken by an animal. Gradually, sensors have been developed to be attached on the neck, in the ear, or to be orally administered and reside in the reticulum, while the use of 3D accelerometers enabled a more precise measurement of activity at the same time (Rutten et al. 2013, Mottram 2016). These sensor systems aim at three main functions: the detection of estrus, monitoring the cow's health, and an early detection of calving. After a sensor system has been attached to the cow, it determines her individual behavior, which is continuously adapted as reference behavior over time. Algorithms detect changes in the parameters recorded and issue, depending on frequency, duration, and intensity of deviation from the reference behavior, a message to the farmer. Estruses are recognized by an increase in activity (Saint-Dizier and Chastant-Maillard 2012). In the case of calving, a decrease in body temperature, a decrease in rumination, or typical activity patterns in advance of calving support sensor-assisted detection (Cooper-Prado et al. 2011, Miedema et al. 2011, Ouellet et al. 2016, Rutten et al. 2017). The various parameters recorded by the wearable sensor systems also provide decisive indications for health monitoring. For instance, indications of febrile diseases based on an increase in body temperature (Benzaquen et al. 2007, Kim et al. 2019) or metabolic diseases based on a decrease in rumination (Kaufman et al. 2016, Goff et al. 2020) may be provided.

Amid the growing number of parameters measured by wearable sensor systems on or in the dairy cow, the vision is clear: the automation of processes and even the automation of decisions. Rutten et al. (2013) have already dealt with the current and visionary use of parameters that are recorded by sensor systems in dairy farming. In their review of the literature from 2002 to 2012 on 139 sensor systems, they characterized the development of sensor systems in dairy farming into four levels: While level 1 describes a mere recording of parameters (e.g., activity), level 2 already includes interpretation of the recorded data, thus revealing changes in the measured parameters (e.g., an increase of activity, indicating estrus). In Level 3, Rutten et al. (2013) see an additional integration of external information such as economic information. Level 4 finally characterizes the decision-making process, e.g., whether insemination should be performed or not. While this decision is still made by the farmer today, the vision is an automatic decision made by the sensor system. The sensor systems of the publications included in the review of Rutten et al. (2013) were assigned only levels 1 and 2 of the described levels of development. Their review thus illustrates that the sensor systems are so far still more of a decision support than providing actual decision recommendations to dairy farmers.

Literature on the evaluation of digital dairy farming technologies

The evaluation of digital dairy farming technologies has already been a topic of research for some time. This section provides an overview of aspects having been researched to date, referencing specific research findings in the discussion section. So far, research has been focusing on the technical functionality of various digital dairy farming technologies. As a result, there is, for example, a large number of studies evaluating estrus detection rate of activity-measuring sensor systems (e.g., Firk et al. 2002, Hockey et al. 2010, Dela Rue et al. 2012, Chanvallon et al. 2014). Additionally, evaluating functionality of sensors for an early detection of calving (Marchesi et al. 2013, Saint-Dizier and Chastant-Maillard 2015), of automated body condition scoring systems (O'Leary et al. 2020, Zin et al. 2020), and of automated in-line milk analysis (Caria et al. 2019) has been playing a major role in research so far. The potential of automated and continuous recording of parameters on or in the animal, such as activity, rumination, and body temperature, by means of sensor systems has also been exploited in research. The parameters recorded are not only applied to describe the cows' behavior during events such as disease (Alsaaod et al. 2012, Stangaferro et al. 2016), calving (Jensen 2012, Saint-Dizier and Chastant-Maillard 2015), or stress (Abeni and Galli 2017, Kovács et al. 2019). Rather, due to the larger database enabled by the sensor systems, models are being created for an early detection of these events mentioned. Automated milking systems have also been subjected to assessments of their functionality and impact on performance and health of cows (e.g., Sørensen et al. 2016, Bach and Cabrera 2017). Economic evaluations have already been carried out for digital technologies such as robotic milking (Hyde and Engel 2002, Rotz et al. 2002), automated body condition scoring systems (Bewley et al. 2010a), and information technology applications on a dairy farm (activity meter, automated concentrate feeders, and automated recording of milk yield and temperature) (Van Asseldonk et al. 1999), finding a certain economic potential of these technologies, that, however, depended on the scenarios considered. While literature on the assessment of digital dairy farming has a strong focus on the technologies and their functionality themselves, only a small number of studies has dealt with impacts of digital dairy farming on farmers and their families. Studies on adoption rates as well as on promoting and inhibiting factors for the adoption of digital dairy farming technologies (Jago et al. 2013, Groher et al. 2020), on the characterization of dairy farms applying digital technologies (Steeneveld and Hogeveen 2015), and on impacts of digital dairy farming technologies on the dairy farmers' work (Michaelis et al. 2013) and human-animal interactions (Hostiou et al. 2017) are examples to cite in this regard. The literature shows that digital dairy farming technologies are still far from being standard, that they tend to be applied more often in larger herds, and that their non-adoption is often justified by economic considerations (Jago et al. 2013, Steeneveld and Hogeveen 2015, Groher et al. 2020). Studies on the public perception of digital farming technologies, especially in animal husbandry, are, however, rare.

The public acceptance of digital farming technologies

With regard to digitalization in agriculture, scientific analysis of topics being assigned to the social dimension has emerged late. And yet, although the topic has been addressed partially, literature focuses on the farmer as a user of digital technologies and thus on the adoption of technologies (e.g., Jago et al. 2013, Steeneveld and Hogeveen 2015, Groher et al. 2020) and their effects on farm work (e.g., Michaelis et al. 2013). However, such benefits are not sufficient for newly developed technologies or innovations to succeed. Rather, also the public perspective has to be taken into account. Investigations of the public perspective of digital agriculture are, however, rare.

Apart from digital farming technologies, research on the public acceptance of technologies and innovations in general has a slightly longer history. Public controversies and concerns about technologies being implemented in the past have led to a gradual increase not only in the number of studies on the public acceptance of technologies, but also in the diversity of the determinants investigated (see Gupta et al. 2012). Gupta et al. (2012) date the starting point of investigations on the public acceptance of technologies to 1977, when the first study on nuclear technology was published. Another socially controversial topic is the use of pesticides, leading to first empirical studies being conducted in 1988. The review by Gupta et al. (2012) also revealed that genetic modification is one of the most intensively analyzed technologies in terms of public acceptance (first paper in 1988, see Gupta et al. 2012), possibly due to its controversial public discussion.

With regard to agriculture, pesticides and genetic engineering were thus among the first technologies to be analyzed from a public perspective. Gradually, various agricultural topics have been in the focus of the public, which is why one tried to understand their perception in the public more comprehensively (see Figure 2): animal cloning (e.g., Garnier et al. 2003, Butler 2009), agrifood technologies such as nanotechnology or cultured meat (e.g., Frewer et al. 2011), renewable energy innovations such as biomass cogeneration heat and power plants (e.g., Stiehler et al. 2011), and production methods in and on urban buildings (e.g., Specht et al. 2016). The studies analyzing food technologies revealed that the public weighs perceived risks and benefits against each other, with the benefits of e.g., genetically modified food and food irradiation seen predominantly for the industry. It also plays a role in public acceptance whether the impacts emanating from a (new) technology have been comprehensively assessed and whether people can retain control over the extent of consumption of food produced this way (see Frewer et al. 2011). Regarding animal production, numerous studies have been devoted not only to (modern) livestock farming with a focus on different husbandry systems (Kühl et al. 2019), large-scale facilities (Sharp and Tucker 2005), or modern production methods (Boogaard et al. 2011), but also to the public relevance of animal welfare more generally (e.g., Bennett 1997, Kendall et al. 2006, Deemer and Lobao 2011). Public acceptance of (modern) animal husbandry systems correlated positively with the relevance attributed to animals being able to perform their behavior in accordance with nature as well as with stronger trust in farmers (Sharp and Tucker 2005, Boogaard et al. 2011, Kühl et al. 2019). Although the need to investigate the public socio-ethical implications of digital farming technologies has been addressed several times (Wathes et al. 2008, Stilgoe et al. 2013, Rose and Chilvers 2018, Eastwood et al. 2019, Klerkx et al. 2019), literature is scarce. To the best of the author's knowledge, there are only two studies on public acceptance of digital dairy farming technologies. Millar et al. (2002) analyzed consumer attitudes toward automated milking systems and found that 38.3 % of respondents rated them as "ethically acceptable", with higher awareness of the technology being associated with more positive attitudes. In a study by Krampe et al. (2021), consumers indicated that they see potential for precision livestock farming technologies in pork and dairy farming to improve animal health. However, they also feared that these would lead to more industrialization, and that information about the technologies would be inadequately communicated to consumers (Krampe et al. 2021). The dissertation's study (Pfeiffer et al. 2021a) thus complements this still little-researched area (highlighted in black in Figure 2). While the societal view of digitalization has already been examined from several angles in non-agricultural contexts, this is not the case in agricultural research. Since the question of public acceptance of digitalization more generally has already attracted attention in non-agricultural contexts, these findings can possibly be transferred to digital agricultural innovations or at least provide suggestions for relevant determinants of acceptance. While the public acceptance of autonomous driving (e.g., Fraedrich and Lenz 2016) has already been researched in the automotive industry, this is not the case for agricultural machinery. Also, possible fields of robot application in social life, especially for care (e.g., Broadbent et al. 2009, Eurobarometer 2012, De Graaf and Allouch 2013), have already been analyzed. However, in the aforementioned studies on the public acceptance of various non-agricultural digital technologies, the majority of the public is a potential user of these technologies. Since this is not the case for digital farming technologies, different approaches are required to measure public acceptance.

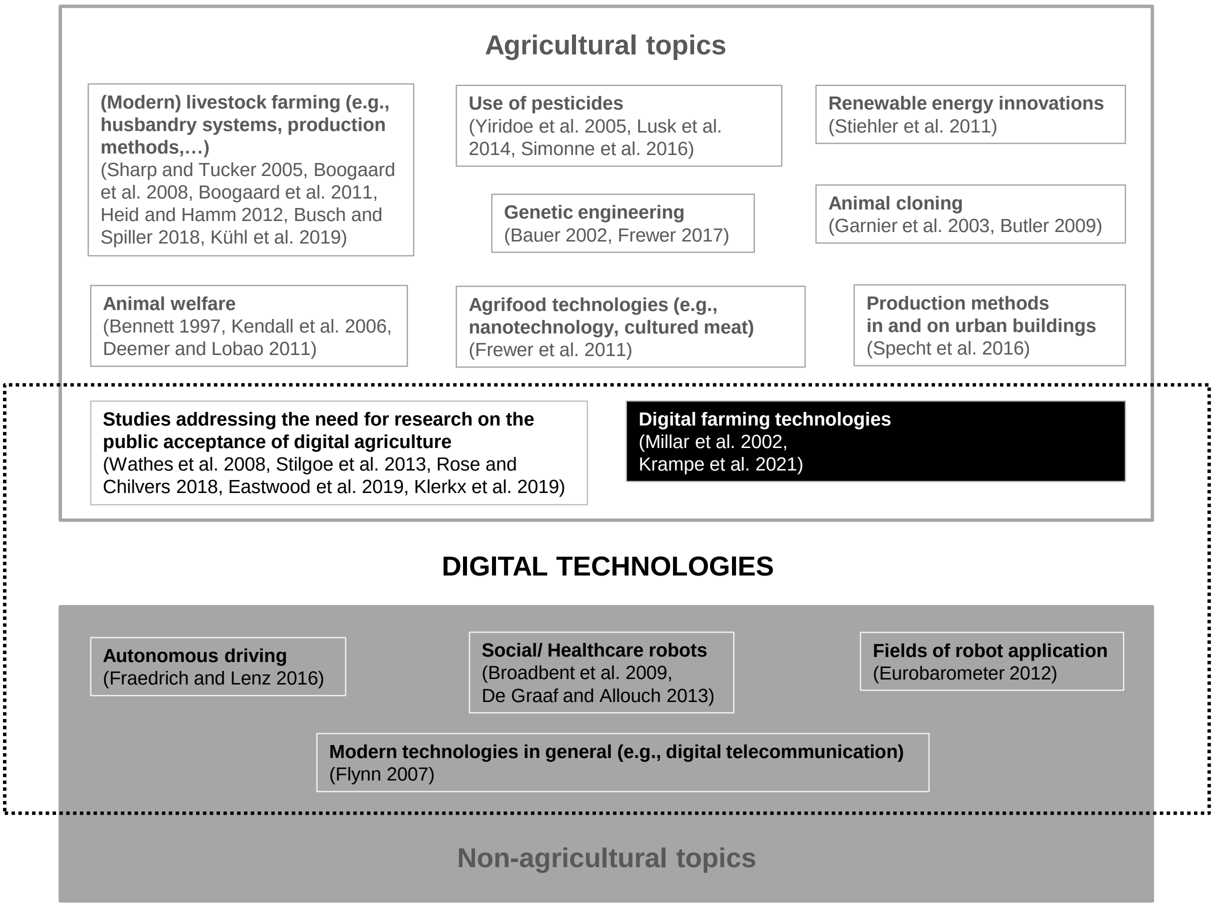

Figure 2. Research on public acceptance in agricultural and non-agricultural topics with regard to digital technologies (exemplary research topics and studies, no claim to completeness)

Calving sensors in dairy farming

Animal welfare in livestock farming has taken center stage with consumers (Clark et al. 2016, Cornish et al. 2016, Kühl et al. 2019). The public discussion about dairy farming focuses on topics such as husbandry systems, production intensity, and the handling of calves (Kühl et al. 2019, Simons et al. 2019, Placzek et al. 2021). Indeed, sustainable dairy farming begins with appropriate calving management. Mee (2008) summarized several international studies, finding a dystocia rate of 2 to 7 % (cows and heifers) or 3 to 10 % (heifers) in dairy farming. According to Gevrekci et al. (2006), dairy farms in the United States have an even higher dystocia rate. As a result of dystocia, calf mortality may occur. Calves born under dystocia often suffer from lower passive immunity transfer and physiological stress (Barrier et al. 2013). According to Lombard et al. (2007), heifer calves born under dystocia are also more susceptible to respiratory and digestive disorders. Consequently, negative impacts on animal health and corresponding treatment costs arise. The data on many calvings have shown that calving monitoring and assistance, if appropriate, have the potential to reduce incidence of stillbirths and post-partum endometritis and uterine infections with cows.

Similarly, the effects on reproductive performance, measured by the calving to conception interval and the number of required inseminations per conception, were positive (Paolucci et al. 2010, Palombi et al. 2013). In order to ensure the welfare of both calves and cows, monitoring of calving should thus be a high priority. This is difficult for farmers to achieve, however, due to uncertainty about exact calving times.

Sensors for early detection of calving are therefore applied as a technical solution to improve calving management. Currently, there are three commercially available calving sensors to be attached to the cows' tail to detect the onset of calving based on an increase in the frequency and duration of tail raising (Miedema et al. 2011, Giaretta et al. 2021): Moocall (Moocall Ltd., Ireland: attached with a ratchet), CalveSense (Allflex Group Germany GmbH: attached with an adhesive and tape), and Calving Alert Set (Patura KG: attached with a clamp and tape). In studies, sensors for attachment on the cows' tail detected up to 95% of calvings (see Giaretta et al. 2021), offering great potential for the health of cow and calf and reducing calf mortality (Lombard et al. 2007, Mee 2008, Barrier et al. 2013). Although these sensor systems showed the potential of early calving detection with a high accuracy (Giaretta et al. 2021, Horváth et al. 2021, Voss et al. 2021), studies provide first evidence that attaching sensors to the animals' tail may cause changes in animal behavior, or that these sensors are being dropped (Lind and Lindahl 2019, Giaretta et al. 2021, Voss et al. 2021). However, the literature landscape on potential changes in the behavior of cows after attachment of a calving sensor to their tail is sparse.

The economics of sensor-assisted estrus detection

A glance at the literature revealed that studies on the economic evaluation of sensor-assisted estrus detection are barely researched – despite sensors for estrus detection already having entered the market in the 1980s (Mottram 2016). Although it has often been emphasized that good reproductive performance has a crucial economic relevance in dairy farming (e.g., Groenendaal et al. 2004, Giordano et al. 2012, Galvão et al. 2013), only few studies have addressed the economics of automated estrus detection. While Rutten et al. (2014) and Bekara et al. (2017) did include investment costs in their economic analyses of activity sensors for estrus detection, the studies by Van Asseldonk et al. (1999) and Inchaisri et al. (2010) focused on a more general comparison of economic effects of different estrus detection rates (without considering investment costs for automated estrus detection). All these four studies chose stochastic dynamic simulation models to assess economic effects in dairy herds. To better understand the observed economic effects, several variables and scenarios (e.g., herd size, milk yield, reproductive performance) were included in these studies. The authors of the studies concluded that high estrus detection rates as well as investing in activity sensors for estrus detection are, on average, profitable for dairy farms (Van Asseldonk et al. 1999, Inchaisri et al. 2010, Rutten et al. 2014, Bekara et al. 2017). However, the average values determined for a limited number of scenarios did not yet provide sufficient information about the percentage of dairy farmers for whom an investment in automated estrus detection would be profitable. As fixed values were assumed for estrus detection rates (visual, sensor-assisted) in the aforementioned studies, the results were limited to individual farm-specific situations in dairy herds. Thus, the existing literature does not fully account for the heterogeneity of dairy farms in the economic evaluation of sensor-assisted estrus detection.

The underlying reasons for this limited number of studies on the economics of automated estrus detection are plausible: A dairy herd is a complex system. It consists of many individual living beings that react differently to changes, e.g., in fertility management. Changes in fertility management continue to involve a variety of adaptations in the dairy herd (e.g., demography or health status of the herd), which are difficult and very costly to capture in a real experiment conducted on a farm (Shalloo et al. 2004). Furthermore, changes in the fertility management of a dairy herd can only be detected comprehensively and reliably after a certain time, which would require a long period of on-farm experimentation. Further influencing factors that are gradually implemented, such as advancements in breeding, husbandry systems, or feeding, complicate the evaluation of the effects of changes in fertility management caused by sensors for automated estrus detection in isolation, particularly in a complex system such as a herd. Various operational situations such as breed, size, and milk yield of a dairy herd furthermore imply a need to consider many variables and would, therefore, result in very extensive on-farm experimentation.

4 Publications

4.1 Understanding the public attitudinal acceptance of digital farming technologies: a nationwide survey in Germany

Pfeiffer, J., Gabriel, A., Gandorfer, M. (2021). Understanding the public attitudinal acceptance of digital farming technologies: a nationwide survey in Germany. *Agriculture and Human Values*, *38*(1), 107-128.

(see Appendix for full text)

Contributions

The contributions of the authors to the publication were as follows:

Johanna Pfeiffer took the lead in writing the first draft of the manuscript as well as in editing the manuscript in the review process. She also performed the literature review and discussion of the results of the study. Johanna Pfeiffer analyzed the data together with Andreas Gabriel. Andreas Gabriel developed the questionnaire with substantial input from Sebastian Schleicher. Andreas Gabriel also conducted the online survey and contributed valuable input to the manuscript, in particular to the material and methods section. Markus Gandorfer developed the research idea and improved the study with suggestions throughout the whole process.

Methodological approach

That technology acceptance plays a relevant role worth investigating was first recognized in Germany in the mid-1970s. It was triggered by critical voices rising in the population against an increasing technization of the living and working world, and initially particularly against nuclear energy (Gupta et al. 2012). A change in the attitude of the public was expected and technology acceptance research became increasingly important from then on (Hüsing et al. 2002, Petermann und Scherz 2005).

Per se, “acceptance“ is an elastic and multifaceted term, a dynamic, complex construct, lacking a uniform definition (Renn and Zwick 1997, Kollmann 2004). In general, “acceptance“ describes “approval“, “appreciation“, “endorsement“, “confirmation“, or “agreeing with something“ (Lucke 1995). In the midst of this ambiguity, a wide variety of definitions and delimitations of the concept of acceptance is given in the literature. Lucke (1995) described three dimensions of acceptance: a cognitive (having knowledge of an issue), a normative-evaluative (considering the issue to be good or not good), and a conative (explicit agreement or disagreement with the issue) dimension. Another approach to defining “acceptance“ found in the literature is to differentiate between attitudinal and behavioral acceptance. For example, Kollmann

(2004) coined the definition of “acceptance“ this way: According to his definition, “acceptance“ is seen in three phases: “attitude“, “adoption“, and “acceptance“. “Attitude“ describes the level of assessment before purchasing a product (“assessment acceptance“), “adoption“ describes the level of action, i.e. purchase of a product (“action acceptance“), and “acceptance“ itself describes the level of use, i.e. active use of a product (“use acceptance“). Thus, capturing passive (attitude) and active (purchase and use) components of acceptance requires different approaches in acceptance research.

As acceptance is a complex construct lacking a uniform definition, there are some aspects to consider in acceptance research:

- Acceptance cannot be measured directly. Therefore, there is no single valid methodological way to measure acceptance.
- As great as the diversity of definitions of acceptance, so, too, will be the diversity of what has been measured as “acceptance“ in studies (see Renn and Zwick 1997, Hüsing et al. 2002).

Since acceptance cannot be measured directly, suitable indicators are needed to indirectly capture relevant dimensions of acceptance (Renn and Zwick 1997). Adell (2009) gave some examples of different ways to assess acceptance: Assessment of the usefulness of and satisfaction with a product, assessment of the willingness to buy/ pay/ have/ keep/ use a product, assessment of the voluntary use of a product combined with the frequency of use, or assessment of physiological reactions.

Nowadays, a comprehensive range of models for assessing acceptance and use of technologies in general is available to the scientific community: Theory of Reasoned Action (Ajzen and Fishbein 1980), Technology Acceptance Model (TAM) (Davis 1989), Theory of Planned Behaviour (TPB) (Ajzen 1991), Motivational Model (Davis et al. 1992), Social Cognitive Theory (Compeau and Higgins 1995), Innovation Diffusion Theory (Rogers 1995), Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al. 2003), and the Dynamic Acceptance Model (Kollmann 1998), to name just a few of them. These models have in common that they include an active behavioral component of acceptance in terms of using a technology. However, public acceptance of digitalization in agriculture is characterized by the fact that the technology to be assessed (digital farming technologies) is not even considered for use by the public. Determining an adoption rate or frequency of use is thus not a suitable approach to assess public acceptance. Therefore, an attitude-oriented approach was chosen for the study on public acceptance by basing it on the construct “assessment acceptance“ from Kollmann’s (1998) Dynamic Acceptance Model.

To get to the bottom of the public's view on digital farming technologies, the study in this dissertation draws its methodology from empirical social research. Empirical social research describes a systematic collection of data aiming to understand human behavior (Schnell et al. 2005). Therefore, it combines different methods, techniques, and instruments. The three basic methods of data collection are surveys, observations, and content analysis (Häder 2010, Punch 2013). Empirical social research combines both quantitative and qualitative methods. Since the focus of the study on the public acceptance of digital farming technologies was not only on making generalizable statements, but also on approaching to understand what thoughts the public associates with these technologies, it includes quantitative and qualitative research approaches. An online survey was conducted to answer the research question. Specifically, Likert scales for statements concerning digital farming technologies (quantitative approach) and subsequently spontaneous associations with four pictures showing digital farming technologies in action (qualitative approach) complemented each other. However, as the spontaneous associations mentioned were finally grouped into categories and their frequency of naming was quantified, the procedure combines qualitative with quantitative approaches. The two approaches represent two successive parts of the online questionnaire, which were both answered by the same sample. This resulted in a high sample size for both the quantitative and qualitative approaches.

Empirical data on the attitudinal acceptance of digital farming technologies were collected in a nationwide survey in Germany. Since 90 % of the population living in Germany use the internet (Federal Statistical Office Germany (Destatis) 2018), an online survey was determined as the method of choice to achieve a high sample size across the whole country. This approach allowed for the assessment of a geographically distributed sample within a short time, thus being time- and cost-effective (see also Lefever et al. 2007, Sue and Ritter 2012). There is a hypothesis of differences in rural-urban attitudes toward agriculture (e.g., Van Liere and Dunlap 1980, Freudenburg 1991, Sharp and Tucker 2005). These differences could thus not only apply to agriculture per se, but also potentially to digital farming technologies. Since the respondents had to indicate the size of their place of residence (divided into three size categories), rural-urban differences in the attitudinal acceptance of digital farming technologies could be assessed. In this regard, a sample distributed across Germany provided reliable results. Although internet usage is comparatively more limited among older generations (Destatis 2018), the sample of the study is representative in terms of e.g., age due to pre-quotation. Thus, this does not represent a significant limitation in the interpretation of the data.

Summary

The aim of the study was to assess the general attitudes of the German public toward the use of digital farming technologies and their effects on farmers, consumers, animal husbandry, and crop production. An additional objective of the study was to identify indications of concerns about digital farming technologies. The attitudinal acceptance of digital farming technologies was assessed as the first phase (assessment phase) in the acceptance process of Kollmann's (2004) acceptance model. A nationwide online survey in 2018 combined quantitative and qualitative approaches of empirical social research and yielded 2,012 analyzable questionnaires. Likert scales were applied to capture the respondents' general attitudes toward benefits of digital farming technologies, their consent to the use of digital farming technologies, and their consent to state subsidies for farmers investing in digital farming technologies as target variables. The latter two target variables were assessed based on four examples of digital farming technologies: spot spraying, digital hoeing, near-infrared spectroscopy sensor technology, and sensors for animal husbandry. The respondents' socio-demographics, connection to agriculture, knowledge about present-day agriculture, trust in farmers, and general attitudes toward farming were queried as factors potentially influencing the target variables. A multivariate regression model was applied to identify factors influencing the target variables. As a second methodological approach, respondents could voluntarily write down up to three spontaneous associations for each of four pictures showing digital farming technologies: a milking robot, a feeding robot, an autonomous tractor, and a swarm of small field robots.

In their general attitudes toward digital farming technologies, respondents were, on average, more positive than negative. Also, there was, on average, more consent than disapproval to the use of the four specific digital farming technologies and on state subsidization for farmers investing in them. Some factors were found to influence the target variables. Respondents having more positive general attitudes toward farming (e.g., animal welfare and environmental protection are considered very important) and more trust in farmers rated all three target variables on digital farming technologies significantly more positive. Comparatively smaller, but also positive influences on some of the target variables were identified for knowledge of present-day agriculture, gender, age, and education level. Only work experience in the agricultural sector of the surveyed participants had a significant negative influence on the two target variables of general attitudes toward the benefits of digital farming technologies and consent to the use of the specific four digital farming technologies. From the spontaneous associations with the four pictures showing digital farming technologies, categories were formed for each technology. Categories such as "future and progress", "efficiency and reduced workload", "industrial agriculture", and "costs of technology" were

associated with all four digital farming technologies. In the case of the milking robot and feeding robot, additionally terms belonging to the categories “dairy farming/milking“, “cow“, “hygiene“, and “animal cruelty“ were mentioned, and in the case of the swarm of field robots and the autonomous tractor, terms belonging to the categories “field cultivation“, “nature and plants“, “environmental protection“, “concerns for environmental protection“, “animal protection“, “safety“, and “human health“ were mentioned. In general, more negative terms were associated with the milking robot and feeding robot than with the swarm of field robots and the autonomous tractor. For both the milking robot and feeding robot, a particularly high number of negative terms belonging to the categories “animal cruelty“, “industrial agriculture“, and “terms of rejection” (e.g., “awful”) were noted by the respondents. The spontaneous associations thus provided relevant clues as to the concerns on which a potential rejection, or non-acceptance, of digital farming technologies is based.

The study showed a positive public attitudinal acceptance of digital farming technologies when their potential in terms of environmental protection and animal welfare was briefly explained. However, the spontaneous associations evoked comparatively more negative attitudes toward digital farming technologies, as emotions were aroused by the pictures. Since more negative terms were associated with the milking robot and feeding robot than with the two digital farming technologies applied in crop production, it is assumed that applying digital technologies on animals is viewed more critically. Another conclusion of the study is that it is unlikely that digital farming technologies will improve the image of agriculture per se. If a system is generally called into question (e.g., indoor housing in livestock farming or conventional crop production applying pesticides), the use of digital farming technologies that may contribute to environmental protection or animal welfare will not significantly attenuate this overall criticism.

4.2 Sensor and video: two complementary approaches for evaluation of dairy cow behavior after calving sensor attachment

Pfeiffer, J., Spykman, O., Gandorfer, M. (2021). Sensor and video: two complementary approaches for evaluation of dairy cow behavior after calving sensor attachment. *Animals, 11*(7), 1917.

(see Appendix for full text)

Contributions

The contributions of the authors to the publication were as follows:

Johanna Pfeiffer developed the conceptualization of the study and methodological approaches applied. She was responsible for the collection of the entire data set. She also performed data analysis (in particular video observations) and literature review. Johanna Pfeiffer wrote the original draft of the manuscript and led the review process. Olivia Spykman made important contributions to the paper by developing and executing the methodology of analyzing the variability of activity index. She also performed reviewing and editing of the manuscript. Markus Gandorfer provided valuable input to the paper with the development of the research idea and conceptualization of the study design and methodology. He provided relevant comments on the manuscript and interpretation of the results.

Methodological approach

Various parameters have been analyzed and different approaches have been applied in literature to assess behavioral changes or even stress in dairy cows. When assessing stressors, behavioral and physiological parameters can be distinguished (see Table 1), which may be influenced simultaneously (Ratnakaran et al. 2017) and may consequently impact animal performance.

Table 1. Parameters applied in the literature to measure stress response in dairy cattle (no claim to completeness)

Parameter	**Source**
Behavioral	
Intake of feed and water, rumination	Gorewit et al. 1985, Ominski et al. 2002, Reinemann et al. 2004, Abeni and Galli 2017, Kovács et al. 2019
Defecation, urination	Rushen et al. 1999, Rushen et al. 2001, Müller and Schrader 2005
Vocalization	Rushen et al. 1999, Watts and Stookey 2000, Rushen et al. 2001, Müller and Schrader 2005
Activity *(stepping, leg lifting, kicking, tail lifting, fidgeting, overall activity level)*	
Visual (video/live observation)	Gorewit et al. 1985, Winter and Hillerton 1995, Boissy and Le Neindre 1997, Rushen et al. 2001, Wenzel et al. 2003, Müller and Schrader 2005, Cook et al. 2007, Stewart et al. 2017, Kovács et al. 2019, Pilatti et al. 2019
Activity sensor	Rigalma et al. 2010, Abeni and Galli 2017, Stewart et al. 2017, Heinicke et al. 2019
Physiological	

Endocrine hormones (e.g., in milk, blood)	Lefcourt et al. 1986, Wise et al. 1988, Lay et al. 1992, Wenzel et al. 2003, Rigalma et al. 2010
Heart rate	Hopster and Blokhuis 1994, Lefcourt et al. 1999, Wenzel et al. 2003, Kovács et al. 2019
Respiration	Gaughan et al. 2000, Schütz et al. 2010, Schütz et al. 2014
Temperature	Hillman et al. 2005, Schütz et al. 2010, Stewart et al. 2017
Pain sensitivity	Rushen et al. 1999

Stressors for cows having been analyzed in the literature include, for instance, isolation from the herd (Boissy and Le Neindre 1997, Rushen et al. 1999, Rushen et al. 2001, Müller and Schrader 2005), confrontation with novelties such as a milking system (Winter and Hillerton 1995, Wenzel et al. 2003, Kovács et al. 2019), exposure to stray voltage (Gorewit et al. 1985, Lefcourt et al. 1986, Reinemann et al. 2004, Rigalma et al. 2010), and heat (Wise et al. 1988, Kadzere et al. 2002, Ominski et al. 2002, Hillman et al. 2005, Cook et al. 2007, Schütz et al. 2010, Schütz et al.2014, Abeni and Galli 2017, Heinicke et al. 2019, Pilatti et al. 2019). In many of these studies, activity behavior has been analyzed to assess the onset of discomfort or stress response (see Table 1). Activity was evaluated either visually (e.g., by means of an ethogram) or with recording devices such as activity sensors.

The study combines two methodological approaches to assess dairy cow behavior after calving sensor attachment to the tail. The first methodological approach is a behavioral classification based on video analysis, which is frequently applied in dairy behavior research (e.g., Gorewit et al. 1985, Winter and Hillerton 1995, Boissy and Le Neindre 1997, Rushen et al. 2001). As a second, innovative methodological approach, the study relies on activity data measured by a rumen bolus to evaluate the cows' behavior. Specifically, the second methodological approach is an analysis of the variability of activity values around the mean. Studies have revealed that the scattering of values around a mean provide relevant information (Alsaaod et al. 2012, Van Nuffel et al. 2013, Thorup et al. 2015) as an increase in mean does not necessarily go along with an increase in the variability around this mean (and vice versa). Analyzing the variability around a mean value (testing for homogeneity of variance) is well known from economics, as it is a commonly applied approach to describe the impact of specific shocks on price volatility (e.g., Gandorfer et al. 2017). The scattering of values around a mean was shown to provide also valuable information in animal behavior research. In this context, analyzing the variability of cow activity has become established for the detection of diseases. In a study by Edwards and Tozer (2004), additional insight provided by analyzing the variability of activity became apparent for the detection of cows with metabolic or digestive disorders: The variability of activity, recorded with pedometers, was higher in sick compared to healthy cows (Edwards and Tozer 2004). Analyzing variability of cow activity has also become established for the detection of lameness (Chapinal et al. 2010, Thorup et al. 2015). Alsaaod et al. (2012) concluded a low adequacy of single analysis of thresholds and absolute values for an early detection of lameness in dairy cattle. Instead, more precise results were obtained with both positive and negative deviations from normal behavior of the cows. Van Nuffel et al. (2013) analyzed the variability of gait variables such as step width or stance time for early detection of lameness in dairy cattle. Based on standard deviations, a coefficient of variation for gait variables of different legs was calculated to detect cows suffering from lameness. Following these findings, the methodological approach of analyzing the variability of activity was also applied in this study.

Summary

The study aim was to analyze cow behavior after attaching two commercial calving sensors (Moocall (Moocall Ltd., Dublin, Ireland) and CalveSense (Allflex Group Germany GmbH, Bad Bentheim, Germany)) to the tail. The data stem from 18 animals on a dairy research and demonstration farm (state farm Achselschwang, Bavaria, Germany) where they were separated into a maternity pen littered with straw prior to calving and had one of the two calving sensors attached. Two methodological approaches were chosen to answer the research question. As all 18 animals of the sample were equipped with a rumen bolus (smaXtec animal care GmbH, Graz, Austria) to continuously record their activity, the first methodological approach was an analysis of activity behavior (activity index of the rumen bolus) before and after calving sensor attachment. In a period from five days before to 24 hours after calving sensor attachment, variability of automatically recorded activity was analyzed using the Brown-Forsythe test. The second, more established methodological approach was a behavioral observation via video analysis in a subgroup of nine animals. The behaviors walking, standing, lying, eating, drinking, social interaction, tail raising, rubbing the tail on objects, and the number of standing and lying bouts were observed visually. These behaviors were analyzed twelve hours immediately after calving sensor attachment and twelve hours at the same time of day the day before. The periods considered on the day(s) before and on the day of calving sensor attachment were divided into time slots of four hours each for both methodological approaches.

In the first methodological approach, no change in the absolute number of time slots showing a significant increase in the variability of activity was found on average across all 18 cows. In the second methodological approach, no significant changes in most visually analyzed behaviors, namely walking, eating, drinking, social interaction, tail

raising, rubbing the tail on objects, and the number of standing and lying bouts was found on average. On average, cows spent more time lying and less time standing during the first hours after calving sensor attachment. However, this could be sourced to one single cow and was rather interpreted as a shift in lying and standing time. Inspecting the cows individually, it appeared that in some of them there was a greater number of time slots showing a significant increase in the variability of activity and an increased frequency of tail raising and rubbing the tail on objects after calving sensor attachment. Although these changes were only observed in individual cows, it would be relevant to analyze these findings on a larger scale.

From the findings obtained in both methodological approaches in the study, it was concluded that attaching a calving sensor to the tail is not generally perceived as disturbing by cows. However, as some cows showed an increased frequency of tail raising and rubbing the tail on objects after calving sensor attachment, they could have tried to drop the sensor. Because these observations were only made in the first hours after calving sensor attachment, a short adaptation period may be assumed, which should be weighed against the positive effects of calving sensors on the welfare of cow and calves due to the prevention of dystocia.

4.3 Evaluation of activity meters for estrus detection: A stochastic bioeconomic modeling approach

> Pfeiffer, J., Gandorfer, M., Ettema, J. F. (2020). Evaluation of activity meters for estrus detection: A stochastic bioeconomic modeling approach. *Journal of Dairy Science*, *103*(1), 492-506.
>
> (see Appendix for full text)

Contributions

The contributions of the authors to the publication were as follows:

Johanna Pfeiffer developed the conceptualization of the study together with Markus Gandorfer. She parameterized the SimHerd model and performed all analyses of the study (SimHerd and @RISK). She also conducted the literature review, wrote the original draft of the manuscript, and led the review process of the manuscript. Markus Gandorfer contributed decisively to the study conceptualization and methodological development of the net return model. His feedback on the manuscript led to improvements throughout the whole writing and editing process. Jehan Ettema, as co-developer of SimHerd, gave important comments on the parameterization of SimHerd. He contributed to the manuscript with the description of SimHerd in the material and methods section.

Methodological approach

Simulation experiments are established in science, expanding the spectrum of methodological approaches in addition to real experiments. Simulation experiments are performed applying agricultural system models that include relevant farm system components and their interactions. Jones et al. (2017) date the beginnings of agricultural system models back to the 1950s. Starting with the simulation of plant and soil processes (Van Bavel 1953, De Wit 1958), the development of herd dynamics simulation models followed in the 1970s (Jones et al. 2017). To transfer the knowledge gained in this way to the real system, it is important that the model represents the system as closely to reality as possible. With an increasing number of variables and their interactions considered in a model, its potential to represent a farm as realistically as possible increases (Jalvingh 1992). To answer a scientific question, either new models are developed, or existing models are adapted. The establishment of model-based simulation experiments in agricultural research is demonstrated by the large number of farm models applied in studies (see e.g., Berentsen and Giesen 1995, Herrero et al. 1999, Hansen et al. 2000, Keating et al. 2003, Cabrera et al. 2006, Modin-Edman et al. 2007, Schils et al. 2007, Crosson et al. 2011, Doole et al. 2013).

Considering dairy herds in a model is expedient when it comes to decisions regarding herd management or technology investments. In the literature, dynamic stochastic simulation models of dairy herds for this purpose exist, mostly based on Microsoft Excel (Microsoft Corporation, Redmond, WA, USA). Such a model of a dairy herd has been used by Bewley et al. (2010b) to assess the economic impact of investments in technologies such as an automated body condition scoring system. Stochastic dairy herd models have also been applied in studies evaluating different strategies of reproduction management (Inchaisri et al. 2010), or calving management (Jalvingh et al. 1993). Bekara et al. (2017) and Rutten et al. (2014) have even applied dairy herd models for their economic evaluation of technologies to improve estrus detection.

For the study on the economic evaluation of automated estrus detection, the dairy herd model SimHerd (SimHerd A/S, Viborg, Denmark) was parameterized. SimHerd is a dynamic, mechanistic, and stochastic simulation model for dairy herd management decision support. It takes into account more than 2,000 parameters that describe a plethora of aspects of a dairy herd, including parameters of fertility management (Sørensen et al. 1992). The biological parameters are specified at cow level, embedded in management strategies at herd level. Therefore, changes in estrus detection rates (e.g., due to automated estrus detection) and their effects on gross margin per cow and year are simulated. The idea of SimHerd was born at Aarhus University (Denmark) in 1989, from when it was continuously developed. Initially, it was used solely for research purposes, but its field of application was extended to consulting and veterinary medicine. Meanwhile, analyses on animal health economics and herd management, methodically based on the SimHerd model, have been published in several studies. These studies based on SimHerd dealt with different dairy herd breeding strategies such as crossbreeding (Clasen et al. 2020) or the use of sexed semen (Ettema and Østergaard 2015, Ettema et al. 2017). SimHerd was also applied to address animal health issues, as comprehensive analyses have already been carried out on mastitis (Østergaard et al. 2005a), milk fever (Østergaard et al. 2003), ketosis (Østergaard et al. 2000), and lameness (Ettema and Østergaard 2006). Also changes in the incidence of diseases that may result from the use of technologies such as an inline progesterone indicator (Østergaard et al. 2005b) have been simulated with SimHerd.

In the few existing studies on the economics of automated estrus detection, different herd sizes, labor costs, and milk yields were simulated, and sometimes even stochastic simulation models for dairy herds were applied (Van Asseldonk et al. 1999, Rutten et al. 2014, Bekara et al. 2017). A closer look at the studies reveals that they assumed a deterministic value for the visual and sensor-assisted estrus detection rate, respectively. Thus, the results of these studies were limited to a single mean value for each scenario, respectively. However, quite a variation in both estrus detection rates (visual and sensor-assisted) (see Rutten et al. 2013) and time spent for estrus detection (visual and sensor-assisted) exists. The study in this dissertation differs from previous economic studies especially in that the latter were limited to individual farm-specific situations in dairy herds. Applying a stochastic dynamic simulation model for dairy herds and analyzing different scenarios (as in previous studies), the study in this dissertation additionally modeled estrus detection rates (visual, sensor-assisted) with distributions using the Monte Carlo method in @RISK (Palisade Corporation, Ithaca, NY) to account for the heterogeneity observed on dairy farms. In contrast to previous studies, the study also considered probability distributions for the time spent for estrus detection (visual, sensor-assisted) (see Table 2). Thus, a probability distribution for the net return of investment in activity meters for estrus detection was modeled.

Monte Carlo simulation is a stochastic method that allows taking uncertainties of variables into account, thus being a tool for quantitative risk analysis. Underlying distributions of variables represent the probabilities of occurrence of values the variable can take and form the basis for a large number of random experiments. The principle of Monte Carlo simulation is based on drawing many random samples from the distributions while at the same time making the resulting combinations traceable (Harrison 2010). Thus, it allows understanding the behavior of a sampling distribution in random samples. For the target variable, a relative frequency distribution is given, which could also be observed in the simulated populations (see Mooney 1997, Casella and Robert 1999). This makes Monte Carlo simulation a scientific tool for questions that are analytically intractable and too costly, time-consuming, or impractical to conduct experiments (Harrison 2010).

Table 2. Studies with a focus on the economic evaluation of (automated) estrus detection

Approach	Variables/ Scenarios	Sensor	Estrus detection rate [%]	Labor costs [€/h]	Key findings	Study
Stochastic dynamic simulation model described by Inchaisri et al. (2010)	Herd size Culling strategy Voluntary waiting period	Activity meter	50 (30; 40; 60; 70) (visual) 80 (65; 75; 85; 95) (automated)	0; 9; 18; 36	Baseline scenario: Marginal financial effect 2,827 €/year, Internal rate of return: 11%, investment generally profitable	Rutten et al. (2014)
Stochastic dynamic model	7 herds (differ in breed, herd size, milk yield, calving management, milk price) 6 scenarios each: Type of sensor system Equipment rate	Pedometer Activity meter	50 (visual) 90 (automated)	---	Internal rate of return: up to 33.8%, investment profitable in two-thirds of scenarios	Bekara et al. (2017)
Stochastic dynamic simulation model described by Jalvingh et al. (1993)	Conception rate Milk yield	--- (no investment costs)	50 (visual) 90 (automated)	---	Increased gross margin Dfl. 0.54 to 1.91 per 100 kg FPCM per year	Van Asseldonk et al. (1999)
Stochastic dynamic simulation model	Reproductive performance scenarios: poor, average, good	--- (no investment costs)	30; 50; 70 (visual)	---	Sensitivity analysis in average reproductive performance scenario: improvement in estrus detection rate from 30% to 50% and 50% to 70% resulted in reduction of net economic loss of, respectively, 53€ and 11€ per cow per year	Inchaisri et al. (2010)
Stochastic dynamic simulation model (SimHerd)	Herd size Equipment rate Breed Milk yield	Activity meter	**modeled with probability distributions**	10; 20	Average net return of investment over all scenarios ranges from +7€ to +46€ per cow per year, positive annual net return for majority of simulation runs	Pfeiffer et al. (2020)

Summary

The aim of this study was a comprehensive economic evaluation of automated estrus detection by means of activity meters. As methodological approach, a stochastic model was applied with the net return of investment in activity meters for estrus detection being the target variable. The net return of investment quantifies the economic benefit of sensor-assisted compared to visual estrus detection. The model included the gross margin, expressed as a function of estrus detection rate (visual, sensor-assisted), the time spent for estrus control (visual, sensor-assisted), labor costs, and all costs associated with the investment in activity meters. As both estrus detection rate (visual, sensor-assisted) and time spent for estrus control (visual, sensor-assisted) are subject to heterogeneity on farms, they were modeled using the Monte Carlo method in @RISK (Palisade Corporation, Ithaca, NY). The gross margin was calculated using SimHerd (SimHerd A/S, Viborg, Denmark). In SimHerd, average production prices of the years 2016 to 2019 were assumed. As uncertainty was considered for estrus detection rates and time spent for estrus control, probability distributions for the net return of investment in activity meters for estrus detection were given as results. The scenarios analyzed included the Simmental and Holstein breed, milk yields of 7,000, 9,000, and 11,000 kg/year, herd sizes of 70 and 210, labor costs of 10 and 20 €/h, and an equipment with activity meters of only cows or cows and heifers.

The net return of investment was calculated for 32 different scenarios, which included many constellations of dairy farms and thus gave a realistic range for the economic benefit when investing in activity meters for estrus detection. The first step was analyzing the change in gross margin with increasing estrus detection rate. The relationship between estrus detection rate and gross margin could be described with a polynomial function. An increase in the gross margin by optimizing the estrus detection rate is largely attributed to increased revenues from calves and heifers. Since fewer cows have to leave the herd due to poor fertility when estrus detection rate increases, the number of productive years per cow increases. This is accompanied by a change in herd demographics: Cows are getting older and are therefore more susceptible to disease, which also increases expenses for disease treatment. However, revenues increased faster than expenses in all scenarios analyzed, leading to an increase in gross margin with improved estrus detection rate.

The average net return of investment in activity meters for estrus detection was between +7 and +46 € per cow and year for all scenarios analyzed. The values for the 10th percentile were between -11 and +13 € per cow and year and for the 90th percentile between +17 and +95 € per cow and year. Considering all scenarios analyzed,

investing in activity meters for estrus detection would be profitable for 74 to 99 % of dairy farms (i.e., net return of investment > 0 € per cow and year).

Due to fixed cost degression effects, the net return of investment in activity meters for estrus detection was higher for herd sizes of 210 compared to 70. Equipping not only cows but also heifers resulted in a higher average net return of investment and higher values for the 90th percentile. The net return of investment also increased with higher labor costs. With higher milk yield level, the average net return of investment generally increased as well. However, this increase was more pronounced from 7,000 to 9,000 kg (Simmental breed) than from 9,000 to 11,000 kg (Holstein breed).

The study results revealed a certain economic potential of activity meters for automated estrus detection. This economic potential has been quantified for the first time in this study for a comprehensive range of dairy farm constellations. As activity meters nowadays combine other functions besides estrus detection, such as an early detection of diseases and an early detection of calving, their economic potential will be even higher. This additional benefit needs to be evaluated and quantified in future research studies.

5 Discussion, conclusions, and implications

In the three publications of the dissertation, new valuable findings on a systems-oriented evaluation of digital technologies in dairy farming were developed. The results form important elements for closing the research gaps described in the respective literature reviews of the three research fields of the dissertation. The aspects analyzed in the studies give a predominantly positive assessment of the digital technologies analyzed: Activity sensors for automated estrus detection showed certain economic potential for the majority of scenarios analyzed, calving sensors attached to the tail of animals did not lead to significant behavioral changes on average across all animals analyzed, and analysis of public acceptance did not reveal a major fundamental aversion to digital farming technologies per se.

5.1 Discussion of main findings

Following a systems-oriented view of dairy farming, it has to be considered that a dairy farmer is influenced in his actions by the environment in which he is embedded (Darnhofer et al. 2012). Animal welfare has been playing an increasingly important role in the last two decades, especially in North-West Europe (Te Velde et al. 2002, Boogaard et al. 2006, María 2006, Miele et al. 2011, TNS Emnid 2012), but also in other regions of the world such as North America (e.g., Sharp and Tucker 2005, Kendall et al. 2006, Deemer and Lobao 2011, Ventura et al. 2016). Although similar results to the study on the public attitudinal acceptance of digital farming technologies among the German public might be obtained in other North-West European countries, the results cannot be transferred one to one to other countries or regions in the world. The results have to be seen in the context of region and culture. In particular, the public acceptance study (Pfeiffer et al. 2021a) only represents a momentum for Germany and thus also cannot necessarily be transferred in time.

The results of the online survey among the German public show a lack of acceptance of current animal husbandry systems in general. This is in line with findings from other studies showing a similar mood in the German public toward animal husbandry (e.g., Helmle 2010, Rovers et al. 2018). Reasons explaining this lack of acceptance, which emerged both in the spontaneous associations of the study (Pfeiffer et al. 2021a) and in further literature, include for instance factory farming, industrial farming, a dwindling contact between animal and farmer, the use of antibiotics, and a perceived lack of animal welfare (see Vanhonacker et al. 2012, Simons et al. 2019, Wolfram et al. 2019). These are critical aspects of agriculture that are frequently addressed in the German media (Helmle 2010, Wolfram et al. 2019) and therefore exert a relevant influence on the public, for whom the media are one of the most important sources of information (TNS Emnid 2012).

To develop approaches for increasing public acceptance and put efforts in the right place, knowledge of most decisive influencing factors in this respect is relevant. A frequently postulated reason for the lack of public acceptance of (digital) animal husbandry is the public's low level of agricultural knowledge, due to a great spatial distance from primary agricultural production. The factual situation on this is not yet clear, but there are indications, including the data of the study in this dissertation (Pfeiffer et al. 2021a), to refute this hypothesis. Studies among urban and rural population on the public acceptance of agriculture in terms of animal welfare and environmental aspects did not demonstrate a clear direction of influence (see e.g., Van Liere and Dunlap 1980, Freudenburg 1991, Sharp and Tucker 2005). Among the survey respondents in Germany (Pfeiffer et al. 2021a), neither the size of place of residence (as potential indicator of spatial proximity to agriculture) nor the level of knowledge of present-day agriculture nor personal contact with farmers and discussion about agricultural topics had a clear positive influence on the attitudinal acceptance of digital farming technologies. It has already been investigated whether providing more information or more insights (e.g., by means of a farm visit) lead to greater public acceptance. However, there are studies on genetically modified food (Wuepper et al. 2019), biotechnology (Scholderer and Frewer 2003), and dairy cattle welfare (Ventura et al. 2016, Weary and Von Keyserlingk 2017) that do not find any positive correlation in this respect, but in some cases even negative influences. An underlying reason for this is that opinions are not only based on experience and knowledge, but rather on one's own values (Te Velde et al. 2002). Although it was not directly observable in the model applied in the public acceptance study (Pfeiffer et al. 2021a), it is advocated that personal contact and face-to-face conversation between farmer and consumer is a more important step than solely providing information to strengthen public acceptance (see also Boogaard et al. 2011, Weary and Von Keyserlingk 2017, Wildraut et al. 2019). Furthermore, the results of the study (Pfeiffer et al. 2021a) call for further well-founded analyses on a larger basis of whether the hypothesis that public acceptance of agriculture is particularly low in urban areas can be confirmed.

The literature on dairy cow behavior after calving sensor attachment is limited to a few studies, all of which focus on the Moocall sensor (Lind and Lindahl 2019, Giaretta et al. 2021, Voss et al. 2021). The findings of the study in this dissertation (Pfeiffer et al. 2021b) reveal similar tendencies as the previous studies on the Moocall sensor, but also provide information that goes beyond these previous findings. As the behavioral analysis study (Pfeiffer et al. 2021b) did not show a generally altered ethological pattern of the dairy cows analyzed after attachment of a Moocall or CalveSense sensor, it reinforces the findings of the Giaretta et al. (2021) study focusing on the Moocall sensor. While the study in the dissertation (Pfeiffer et al. 2021b) and the Giaretta et al. (2021) study did not show any significant changes in tail raising after calving sensor attachment on average across the cows analyzed, 80% of dairy farmers interviewed by Lind and Lindahl (2019) reported increased tail raising. In the Giaretta et al. (2021) study, however, the visual behavioral observation was performed with time gaps (three times a day, with 15 min per observation). The study in this dissertation (Pfeiffer et al. 2021b) supports the findings of Lind and Lindahl (2019) to some extent, as individual animal analysis showed that three of nine cows responded to calving sensor attachment (Moocall or CalveSense) with a temporarily increased frequency of tail raising. Also, the rubbing of the tail on objects observed in two of these three cows strengthens the indications of a reaction of individual cows after calving sensor attachment, which may be interpreted as discomfort or an attempt to drop the calving sensor. Rubbing the tail attenuated over the time period analyzed, suggesting an adaption process of behavior, as also reported in Lind and Lindahl (2019). Thus, larger samples are needed to provide the scientific evidence for the behavioral changes found in individual animals.

The study in the dissertation on a comprehensive behavioral evaluation after attachment of the two calving sensors Moocall and CalveSense (Pfeiffer et al. 2021b) provides valuable insights into animal welfare aspects of calving sensors. Per definition, appropriate behavior is an animal welfare principle, in addition to good feeding, good housing, and good health (absence of pain) (Welfare Quality 2009). Apart from the unaffectedness of the usual behavior pattern (Giaretta et al. 2021, Pfeiffer et al. 2021b), increases in tail raising and rubbing the tail observed in individual cows (Pfeiffer et al. 2021b) need to be analyzed more deeply in terms of frequency and impact on animal welfare. It is also relevant to avoid pressure marks or swellings of the tail observed in some animals (Lind and Lindahl 2019, Pfeiffer et al. 2021b, Voss et al. 2021) by an appropriate design of calving sensors.

In addition to a sufficiently high sensitivity of the sensor systems and acceptance of the sensor systems by the animals, cost-effectiveness plays a central role in the future dissemination on dairy farms. The economic potential of activity meters for estrus detection determined in the study in the dissertation (Pfeiffer et al. 2020) underscores the economic relevance of good fertility performance in dairy herds (see Van Asseldonk et al. 1999, Groenendaal et al. 2004, Inchaisri et al. 2010, Giordano et al. 2012, Galvão et al. 2013). The study demonstrated that this economic potential can be exploited by sensor systems. Due to considered probability distributions and a diversity of analyzed scenarios, the economic study in the dissertation (Pfeiffer et al. 2020) covers a wide range of dairy farm situations when investing in activity meters for estrus detection. The results of the few previous studies on profitability of automated estrus detection can be placed in this resulting range for the net return of investment in activity meters for estrus detection. Rutten et al. (2014) demonstrated an average marginal financial effect of 2,827 € for the baseline scenario when increasing estrus detection rates from 50 to 80 % by investing in estrus detection sensors. Considering the assumed herd size of 130 cows, this would result in an average marginal financial effect of 22 € per cow, which is in line with the mean value for the net return of investment of 7 to 46 € (depending on scenario) calculated in the study in the dissertation (Pfeiffer et al. 2020). Bekara et al. (2017) demonstrated even greater economic potential for an investment in automated estrus detection with a calculated increase in annual gross margin per cow by 8 to 92 €, assuming that estrus detection rate increases from 50 to 90 %. An economic advantage of this amount is also found in the results of the study in this dissertation (Pfeiffer et al. 2020) for particularly favorable scenarios, especially since in one scenario (herd size 210, cows and heifers, milk yield 11,000, and labor costs of 20 €/h) even the value for the 90th percentile already amounts to 95 €. The 74 to 99 % probability of an investment having a positive economic effect (depending on scenario) obtained in the study (Pfeiffer et al. 2020) has also been found in previous studies: In Rutten et al. (2014), an investment was profitable for most of the analyzed scenarios, and in Bekara et al. (2017) for two-thirds of the analyzed situations. The results gained in the dissertation’s study are also consistent with the assessment by dairy farmers. Out of 219 dairy farmers surveyed in Germany, only 18 % denied that they were saving money after installing a collar sensor for automated estrus detection (Michaelis et al. 2013). The positive economic effects of larger herd size (Rutten et al. 2014, Bekara et al. 2017), higher labor costs (Rutten et al. 2014), higher milk yield level (Van Asseldonk et al. 1999), and optimization of fertility performance in heifers (Ettema and Santos 2004) observed in the study (Pfeiffer et al. 2020) has also been found in previous studies.

5.2 Methodological discussion

It is methodologically challenging to grasp the public acceptance of technologies that are not directly intended for use by consumers. Therefore, it was not possible to apply common models for measuring technology acceptance such as the Technology Acceptance Model (Davis et al. 1989), Theory of Planned Behavior (Ajzen 1991), or Unified Theory of Acceptance and Use of Technology (Venkatesh et al. 2003). The construct “attitudinal acceptance” according to Kollmann (2004) was therefore chosen as a possible approach, knowing that it does not cover any action (e.g., purchase of technology) or use components, which are integral parts of “acceptance” by definition (Lucke 1995, Schäfer and Keppler 2013).Thus, the results are not to be interpreted as overall acceptance of digital farming technologies, but are nevertheless a basis for assessing the attitudinal acceptance.

An important finding regarding the methodology of the public acceptance study (Pfeiffer et al. 2021a) is that it is purposeful to rely on different methodological approaches to draw reliable conclusions about the public acceptance. As the spontaneous associations led to a more negative evaluation of the digital technologies, on the one hand, the pictures evoked “affective resonances” (Shouse 2005), feelings and emotions (Cvetkovich 2003) and thus appealed to a further level of meaning, and, on the other hand, it is suggested that the spontaneous associations reflect a somewhat more subconscious assessment of attitudinal acceptance. Relying on multiple methodological approaches to capture attitudinal acceptance was a valuable approach as they all provided multifaceted results, whereby a consideration of the statements that are rated on Likert scales alone would have rather overestimated the public attitudinal acceptance.

Regarding the questionnaire, it can be stated that although examples of digital farming technologies were briefly explained, it remains open to what extent the respondents were able to gain an idea of the inherently comprehensive and complex topic of digital farming technologies that is not very tangible for respondents. It remains unclear whether providing more information on digital farming technologies would have led to a different assessment of the statements rated on Likert scales. Also, showing other pictures of the four digital farming technologies chosen could have led to different spontaneous associations.

As recognizing behavioral changes or even stress in animals is such a relevant issue, the behavioral analysis study (Pfeiffer et al. 2021b) highlights the potential to automate the process of animal behavior analysis to increase efficiency of behavioral research. The combination of the two methodological approaches applied for the first time to evaluate dairy cow behavior after calving sensor attachment provided precise information. So far, behavior in cows is assessed to a large extent visually via live observation or video analysis. As visual assessment of animal behavior is very time-consuming (Müller and Schrader 2003), studies relying on visual observation of behavior often use small sample sizes (e.g., Gorewit et al. 1985, Winter and Hillerton 1995, Boissy and Le Neindre 1997, Rushen et al. 2001). To increase sample size and thus efficiency of video analysis, it is argued for the need to automate the process of visually assessing animal behavior. Automation of video analysis can be achieved through progress in artificial intelligence (see e.g., Jingqiu et al. 2017, Li et al. 2018). Thus, an efficient and at the same time objective and reliable (Winckler and Willen 2001, O’Callaghan et al. 2003, Weary et al. 2006) behavioral assessment would be realized in animals.

Regarding the methodological implementation of the study on evaluating dairy cow behavior after calving sensor attachment (Pfeiffer et al. 2021b), it has to be noted that the study contains some limitations in terms of parameters and variables analyzed. The small sample size does not yet allow any conclusions on a potential influence of breed, or age of the cows on the behavior of dairy cows after calving sensor attachment to their tail. Due to the small sample size, conclusions about potential differences between the two calving sensors, Moocall and CalveSense, cannot yet be drawn based on the study in this dissertation. Besides the limited sample size, limitations of the measured parameters also have to be discussed. Some of the behaviors observed in the study, such as standing, lying, and intake of food or water, are maintenance behavior (Giaretta et al. 2021), meaning that they are characterized by high resilience (Weary et al. 2006). As a result, they may not be the most sensitive indicators of changes in the animals' state. Building on the findings on behavioral changes analyzed in the study (Pfeiffer et al. 2021b), the question of a potential stress response of the animals to the attachment of calving sensors arises. Stress situations trigger hormonal changes that would have provided deeper insights into the animals' state. Additional measurements of endocrine hormones (e.g., in milk, blood) (Lay et al. 1992, Wenzel et al. 2003, Rigalma et al. 2010) could potentially react more quickly or sensitively to calving sensor attachment. Thus, there are a variety of parameters and variables, the analysis of which on a larger scale would provide more in-depth insights into the animal welfare assessment of calving sensors.

The primary objective of the third study (Pfeiffer et al. 2020) was to comprehensively assess the economic viability of an investment in activity sensors for automated estrus detection for dairy farms in Germany. Combining the application of a stochastic model with the simulation of gross margin with SimHerd (A/S) proved to be an appropriate methodological approach to answer the research question. In comparison to the few previous economic studies on automated estrus detection, the study in the dissertation (Pfeiffer et al. 2020) did not determine an average value for the economic gain or loss for only a limited range of dairy farm situations (Rutten et al. 2014, Bekara et al. 2017), but rather a variety of dairy farm scenarios. Both the results of the economic studies on individual dairy farm situations (Inchaisri et al. 2010, Rutten et al. 2014, Bekara et al. 2017) and German dairy farmers' assessment of the profitability of sensor systems for automated estrus detection (Michaelis et al. 2013) confirm the plausibility of the generated results and thus verify the suitability of the chosen methodological approach. The SimHerd (A/S) model was confirmed to be an appropriate tool for the simulation of dairy herds, having shown its applicability for analyzing a wide range of research questions in other research (e.g., Østergaard et al. 2003, Ettema and Østergaard 2015, Ettema et al. 2017, Clasen et al. 2020) due to the numerous parameters it takes into account. Therefore, compared to previous economic studies, side effects of improved estrus detection rate such as changes in herd demographics and thus higher disease incidences could be automatically accounted for in a scientifically sound manner.

In terms of the methodological approach, it also has to be noted that the stochastic net return model applied takes aspects of working time into account only to a limited extent. It does include savings in time for estrus control and, considered in the annual cost of investment, also labor time for installation of the sensor system. However, in most cases, adoption of an estrus detection system results in further changes in labor time required that were not included in the economic model: impacts on labor time requirements due to changes in dry cow, calving, calf, and disease management. Investment in a sensor system, mostly leading to an increase in estrus detection rates of a dairy farm, entails that more cows are dry at herd level, resulting in a higher time requirement for dry cow management, and lower time requirement for milking. As there are more calvings at herd level, the time required to control calving cows and feed and care for the larger calf herd also increases. Furthermore, there is an increased time requirement for disease management as, firstly, cows stay in the herd for longer (i.e., get older) and are therefore more susceptible to diseases (Gröhn et al. 1995) and, secondly, more cows are in transition period, which is a very sensitive period for the occurrence of diseases (Redfern et al. 2021). A resulting implication for the methodological approach of the study (Pfeiffer et al. 2020) is to account for these additional labor time effects.

The net return model only included sensitivity of the estrus detection systems, but not their specificity. High sensitivity is more easily realized at the expense of specificity (Mottram 2016). Low specificity may result in increased insemination of animals not in estrus and increased time spent on animal control with estrus alerts issued by the sensor system (Rutten et al. 2014). Rutten et al. (2014) did already include this aspect in their economic analysis and found that blind insemination of all animals for which an estrus alert was issued might not be profitable, depending on specificity. Including specificity of the sensor systems in the net return model, in addition to the sensitivity already considered, can therefore be recommended for further specification of the economic evaluation.

In summary, the methodological approach of considering specific aspects of the three sustainability dimensions presented an appropriate way for a multi-perspective evaluation of wearable sensor systems in dairy farming. The three studies in the dissertation resulted in relevant aspects and partially also hypotheses, which have to be verified in further steps. In particular, the quantitative study on the public attitudinal acceptance gave a first impression of the prevailing situation. However, a stronger focus on qualitative approaches could have provided more insight into the results determined. This could include, for example, in how much detail the topic is understood by the public at all and what the critical arguments are with regard to the use of digital farming technologies. Overall, the selected foci of the three studies in the context of the pursued research approach resulted in the dissertation containing only a few aspects representing the dairy farmers' view on wearable sensor systems in dairy farming. However, these will be crucial for the acceptance and future diffusion of the technology. Again, qualitative interviews (e.g., focus groups) could contribute to get detailed feedback from dairy farmers, e.g., on practical suitability of the sensors (sensitivity, specificity, handling), which may be even more decisive than economic aspects with regard to future dissemination.

5.3 Development potential of sensor systems in dairy farming and their future adoption

A glance into the future: How will the sensor systems evolve?

In recent years, there has been a trend toward wearable sensor systems not only recording activity, but also additional parameters such as rumination, body core temperature, feeding behavior, rumen activity, or heart rate (Bewley 2010, Saint-Dizier and Chastant-Maillard 2012). Since these parameters provide decisive indications for estrus (e.g., Mottram 2016), calving (e.g., Miedema et al. 2011, Saint-Dizier and Chastant-Maillard 2015), and disease (e.g., Vickers et al. 2010, Kim et al. 2019), their application will continue to gain importance in future dairy farming. Monitoring several parameters with one sensor system may even increase precision of the alerts given by the sensor systems (e.g., Cavero et al. 2008, Miedema et al. 2011, Ouellet et al. 2016). To develop sensor systems holding many functions with high sensitivities and specificities at the same time, one will need to rely on the combination of different parameters. It is therefore purposeful to further develop the sensor systems in such a way that they cover many functions (estrus detection, calving, and health monitoring) and thus do not require multiple sensors to be attached to the animal at the same time.

The data recorded by wearable sensor systems on or in the dairy cow are increasingly linked to further data recorded in the barn. In the future dairy barn, digital technologies such as automated milking systems, automated feeding systems, and sensor systems to monitor individual animals (e.g., behavior, body condition, weight) will be interconnected and will collect large amounts of data detailing the daily routine of each individual animal. Thus, linking data recorded by the sensor systems on or in the dairy cow (e.g., activity, rumination, core body temperature) with data on milk yield, milk components, body condition, body weight, or retrieved concentrate feed results in a pool of comprehensive information on each individual animal. Algorithms may thus be applied that incorporate large amounts of data from multiple sources in the barn. By analyzing this data pool, conclusions may be drawn about the animals’ state and events such as estrus, calving, and disease may be identified at an early stage with even higher precision (see e.g., Cavero et al. 2008). In their review on the development of sensor systems, Rutten et al. (2013) have even described an automated initiation of a decision-making process by the technology as an advanced stage of development. This would allow automatic notification of the veterinarian or insemination technician when an event such as estrus or disease is detected by the sensor systems.

Adoption and future adoption potential of sensor systems in dairy farming

Based on the largely positive results obtained in the studies in this dissertation evaluating wearable sensor systems on dairy cattle, the question arises as to the acceptance of this technology by dairy farmers. A Germany-wide survey (Gabriel et al. 2021) provides information with regard to the adoption and future adoption potential of the sensor systems: In the survey conducted between November 2019 and January 2020, 20% of livestock farmers indicated having already invested in a sensor system for behavior monitoring (Gabriel et al. 2021). In a 2013 study conducted by the University of Kentucky, 41% of dairy farmers surveyed reported using sensors to measure cow activity (Borchers and Bewley 2015). In Switzerland in 2018, 6% of dairy farmers surveyed indicated that they apply activity sensors (Groher et al. 2020). In pasture-based countries such as New Zealand or Australia, sensors for activity measuring play a minor role, as patches are frequently used for estrus detection (e.g., Gargiulo et al. 2018). There are reasonable aspects that explain future investment interest in the sensor systems and suggest a high adoption potential in the future: e.g., the given profitability of the sensor systems, reduced workload, and combined purchase of the sensor systems when investing in new milking technology. In terms of adopting digital technologies, aspects of profitability (initial investment, questionable profitability, running costs) are cited by dairy farmers as a key barrier (e.g., Borchers and Bewley 2015, Gabriel et al. 2021). This dissertation demonstrates a given profitability of investing in sensor systems for automated estrus detection for dairy farms in Germany. Further economic effects are to be expected from their application in early calving detection (Crociati et al. 2020) and health management (Hogeveen et al. 2011), thus probably increasing dairy farmers' future interest in investing in the technology. Investment subsidies such as the "Bayerisches Sonderprogramm Landwirtschaft Digital (BaySL Digital)" in Bavaria, Germany, are further accelerating the adoption process. The majority of dairy farmers already using such sensor systems indicate being satisfied with the technology and also describe them as useful (e.g., Michaelis et al. 2013, Borchers and Bewley 2015). In particular, they report time and cost savings, reduced workload, and easy handling of the sensor systems (Michaelis et al. 2013). As these sensor systems are often also used for animal identification in the milking system (e.g., for automated animal-specific recording of milk quantity), some dairy farmers purchase them along with new milking technology. This gives an additional boost to investment, which will be reinforced with further digitalization of milking technology. Thus, although sensor systems for automated measurement of activity and other parameters on the cow are not yet widespread in all countries, relevance of the technology is expected to further increase in the future.

Based on the results of the studies in this dissertation and from the literature, it is concluded that wearable sensor systems in dairy farming are a viable digital technology for the future, due to an identified economic benefit and a positive evaluation of selected calving sensors with regard to animal behavior. The dissertation also showed that increasing “mechanization” and “industrialization” of animal husbandry systems are sensitive issues from the public's point of view. However, it can be assumed that small sensors on dairy cows will not primarily drive this criticism. It is, nevertheless, necessary to fully exploit the sensors’ potential regarding animal health by recording appropriate parameters and linking the sensors to other health-relevant data sources in the barn to force the future viability of the technology.

5.4 Further research requirements

In the three studies in the dissertation, distinct aspects of social, ecological, and economic sustainability were analyzed. However, each of the three sustainability dimensions is assessed by looking at a variety of individual aspects captured by different indicators. Thus, a sustainability assessment becomes complete only when additional indicators are considered and analyzed. In this regard, questions regarding labor conditions, satisfaction among farmers (and their families), internal family situations including equality between men and women, animal health, and quality of food, to name just a few, should be considered in an expanded assessment scheme.

Since the “dairy farming system” integrates various subsystems and their interactions, there is a need for further research in the overall system. The different actors and influencing factors in the dairy farming system call for a comprehensive assessment of the technologies. For example, further research has to be conducted on the economics of sensor-assisted health monitoring and early detection of calving, as these two functions are frequently combined with the estrus detection function. Furthermore, this dissertation analyzed the economics of sensor-assisted estrus detection for different farm situations (e.g., breed, herd size, milk yield). Future research should also analyze the effect of risk and farmers risk aversion on the economic evaluation and adoption process. Ackoff (1999) described the farming system as purposeful, meaning that it pursues a purpose (e.g., profit maximization) and may achieve this purpose in different ways. Thus, individual parts of the farming system may have own, possibly contradictory purposes, resulting in a dynamic in the behavior of the whole farming system. Thus, although profit maximization is a goal pursued by the farmer, it is not the only explanatory variable of his actions (see Norton 1976, Colin and Crawford 2000).

In addition to different farm situations considered in the economic study in this dissertation, there is a need for better understanding the adoption of sensor technology in dairy farming. For instance, the farmer's knowledge, his previous experience with digital technologies, his family situation, or his extra-familial activities may have a decisive influence on the adoption of digital farming technologies. Thus, aspects that are difficult to evaluate in monetary terms, such ease of work or a gain in flexibility, can also be a motivation for dairy farmers to act in a way that is not purely rational in monetary terms. Also in the context of digital farming technology adoption, sequential adoption has been little analyzed so far (e.g., Khanna 2001, Schimmelpfennig and Ebel 2016, Gabriel and Pfeiffer 2021). Therefore, there is a need for more research regarding whether the presence of specific machinery or technologies (e.g., milking robot, automated feeding system) has an impact on the adoption of sensor systems on dairy cows.

Particularly with regard to public acceptance, there is a continuous need for research in the future. This dissertation revealed that different methodological approaches to capture public acceptance elicited diverse perspectives of the public on digital farming technologies. In addition to quantitative research approaches, qualitative research approaches will play an increasingly important role in the future, also when it comes to identifying reasons for a lack of acceptance of digital farming technologies. Building on the results gained on public acceptance, the focus is now on identifying and initiating appropriate measures to strengthen public acceptance of (digital) dairy farming. In the sense of a systems-oriented approach, it is pointed out that cooperation with other disciplines such as sociology is important for this process. This process is made complex due to the results on public acceptance representing only a snapshot for a specific region. Public acceptance will remain subject to rapid change due to a strong influence of media and culture, which poses and will continue to pose great challenges for research.

Sensor systems in dairy farming have the potential to positively influence health, reproduction, and calving management of a dairy farm. However, from a systems-oriented perspective, it is important to consider not only potential positive external effects, but also negative ones and trade-offs associated with the technologies. Possible negative external effects may include direct negative environmental impacts such as the emission of greenhouse-active gases (Herzog et al. 2018) or rebound effects (Berkhout et al. 2000, Sorrell et al. 2009). The application of many digital technologies for dairy farming occurs under the umbrella of improving herd management and thus animal welfare. In the literature, potentially positive effects of digital technologies on animal health and thus animal welfare are described several times (see e.g., Bewley 2010, Kim et al. 2019). Herzog et al. (2018) devoted their review to the greenhouse gas and NH_3 emission mitigation potential of, for example, improved fertility (Garnsworthy 2004), improved longevity (Bell et al. 2015), and improved health (Chen et al. 2016). Such improvements may occur when sensor systems are applied, as they may improve estrus detection rate, reduce fertility-related cullings, and detect diseases and calvings earlier. Further, rebound effects may occur as a result of technological progress. Rebound effects are known and well researched in economics (Berkhout et al. 2000, Sorrell et al. 2009) and have already been analyzed in the context of digitalization (e.g., Coroamă and Mattern 2019) or agriculture (e.g., Song et al. 2018). With regard to digital (dairy) farming technologies, however, rebound effects have so far received only scant attention (e.g., Weller von Ahlefeld 2019). As a concrete example, sensor systems in dairy farming have the potential to detect cases of disease early – in some cases even earlier than humans (Kim et al. 2019). However, the resulting increase in the likelihood of disease cases being detected in the dairy herd could thereby potentially increase the use of medications in dairy farming. Potentially positive effects on animal health, animal welfare, or emissions could thus be reduced or, in the worst case, even completely eliminated. To date, there is still too little evidence on these side effects.

5.5 Further implications for research, farmers, and technology development

This dissertation follows aspects of a systems-oriented research approach and emphasizes the need to have a look at the various stakeholders in the dairy farming system, including the public. Capturing spontaneous associations in the public acceptance study, a great deal of general criticism of current animal husbandry systems emerged. These spontaneous associations are an indication that systems-oriented research approaches should be given more relevance, knowing well that it is in no way trivial to realize an animal husbandry system accepted by both farmers (practicable and economic solutions) and the public alike. However, it is now a matter of intercepting the public criticism of animal husbandry and integrating and taking it into account as well as possible in further research and development processes in agriculture, such as digitalization – this can be stimulated through a systems-oriented research approach. “Traditional“ research, being based on reductionist approaches, analyzes specific parts of the whole farming system (e.g., animal nutrition, or milk yield), looks for linear cause-effect relationships, and considers the farmer as a person making decisions independently (Röling and Jiggins 1998). Thus, there is an increasing need for scientists to also think of a livestock farming systems approach. It is essential to recognize the complexity of the livestock farming system, to pursue interdisciplinary approaches, and to consider other actors besides animals and farmers as subjects to research (e.g., environment, product quality, society). Systems thinking is, thus, not to be seen as an isolated sub-project in a research project, but rather as "*the foundation, starting point from which to explore and analyse a complex problem in a holistic way*" (Darnhofer et al. 2012). Although beginnings of livestock farming systems research date back to the 1980s in Western Europe (Gibon et al. 1999), this approach has not yet been fully internalized in current research. In the Netherlands, for example, transformation of agricultural research toward a systems-oriented way of thinking was initiated by politics (Spiertz and Kropff 2011). In Germany, the 2005 memorandum "Perspektiven der agrarwissenschaftlichen Forschung" reiterated the need for an agricultural systems science. It was addressed to decision-makers in research institutions, politics, and administration.

The profession of farmer is subject to a constant process of change. Initially driven by a demand to increase production efficiency in the past, farmers now have to pursue more diverse functions and goals at the same time. In addition to primary agricultural production, farmers have to cope with various actors and challenges: the public (debates on applied working methods and technologies, increased demands on product quality), climate change (environmental protection), animal welfare (increasing priority of animal welfare and societal perception as a living being to be protected instead of a mere farm animal), politics (changing framework conditions such as documentation requirements to prove regulations of environmental protection), and at the same time maintaining competitiveness. Digitalization can have an impact on this field of tension in various ways: It can enable more environmentally friendly management, increase animal health and thus animal welfare, facilitate documentation, generate more transparency in the value chain, reduce the workload of farmers, and increase profitability of the farm. Digitalization can therefore contribute to overcoming the current challenges facing agriculture. At the same time, however, it can also be a challenge for some farmers who, for instance, lack IT affinity and for whom the adoption of digital technologies therefore represents a major hurdle. Thus, in addition to sound technical knowledge, farmers will need further skills to enhance sustainability of their farming system, such as a constant adaptive capacity (see Darnhofer et al. 2010). In this context, digital technologies are also supposed to expand the range of measures available to farmers. Still, it is important to keep in mind that the process of adaptability involves transaction costs and therefore inevitable trade-offs with farm efficiency that have to be weighed (see Darnhofer et al. 2010).

In the process of developing technologies for agriculture, it is indispensable to keep in mind that this does not only involve a purely technical process but may also have far-reaching changes on social and economic aspects of the whole farming system (Klerkx et al. 2012). Thus, development can rarely be described as a mere technical process (Diedrich et al. 2011, Scott 2011). As the field of digital agriculture is very fast-moving, many new (digital) technologies are being developed and entering the market in a short time. In order not to reduce this fast-moving development to a purely technical process, the relevance of a responsible, sustainable development process has already been emphasized in literature. Rose and Chilvers (2018) emphasized the need for a structured involvement of the public in the innovation process. Also, consumers should participate in socio-ethical discussions, not after an innovation has been launched, but from the very beginning. Driven by this motivation to guide technology development socially and ethically acceptably, responsible research and innovation (RRI) (see Von Schomberg 2011, Stilgoe et al. 2013) is one of the concepts described in literature: "*A transparent, interactive process by which societal actors and innovators become mutually responsive to each other with a view to the (ethical) acceptability, sustainability and societal desirability of the innovation process and its marketable products (in order to allow a proper embedding of scientific and technological advances in our society)*." (definition by Von Schomberg 2011, p. 11). According to Von Schomberg (2011), the framework of responsible research and innovation combines four dimensions: anticipation, reflexivity, inclusion, and responsiveness. Anticipation describes the call to think in advance about possible consequences of technology innovation, their probability and plausibility. Reflexivity means being self-critical with one's own activity and commitments and acknowledging the limits of one's knowledge. Inclusion refers to the inclusion of voices from the public in the innovation process. Finally, responsibility in this context stands for acknowledging outside criticism of an innovation and adapting the development process to the lessons learned. Responsible research and innovation thus turns away for an innovation process mainly focusing on productivity and efficiency aims and addresses socio-ethical challenges. The beginnings of responsible research and innovation lie in Europe and North America and refer to technology development in a general context (Eastwood et al. 2019). Therefore, the task now is extending it to other countries as well as to digital technologies for agriculture (see also Eastwood et al. 2019) to ensure economically, ecologically, and socially sustainable digital agriculture in the future.

6 Literature

Abeni, F., & Galli, A. (2017). Monitoring cow activity and rumination time for an early detection of heat stress in dairy cow. *International Journal of Biometeorology*, *61*(3), 417-425.

Ackoff, R. L. (1999). *Ackoff's best: His classic writings on management*. John Wiley & Sons.

Ajzen, I. & Fishbein, M. (1980). Understanding Attitudes and Predicting Social Behavior. Englewood Cliffs, NJ: Prentice-Hall.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179-211.

Alsaaod, M., Römer, C., Kleinmanns, J., Hendriksen, K., Rose-Meierhöfer, S., Plümer, L., & Büscher, W. (2012). Electronic detection of lameness in dairy cows through measuring pedometric activity and lying behavior. *Applied Animal Behaviour Science*, *142*(3-4), 134-141.

Bach, A., & Cabrera, V. (2017). Robotic milking: Feeding strategies and economic returns. *Journal of Dairy Science*, *100*(9), 7720-7728.

Barrier, A. C., Haskell, M. J., Birch, S., Bagnall, A., Bell, D. J., Dickinson, J., Macrae, A. I. & Dwyer, C. M. (2013). The impact of dystocia on dairy calf health, welfare, performance and survival. *The Veterinary Journal*, *195*(1), 86-90.

Bartol, A., & Herkommer, E. (2004). Der aktuelle Begriff: Nachhaltigkeit. *Wissenschaftliche Dienste des Deutschen Bundestages*, (6).

Bauer, M. W. (2002). Controversial medical and agri-food biotechnology: a cultivation analysis. *Public Understanding of Science*, *11*(2), 93.

Becker, B. (1997). Sustainability assessment: a review of values, concepts, and methodological approaches. Consultative Group on International Agricultural Research, The World Bank, Washington, DC, USA, 70.

Bekara, M. E. A., Bareille, N., Bidan, F., Allain, C., & Disenhaus, C. (2017). An ex ante analysis of the economic profitability of automatic oestrus detection devices in different dairy farming systems in France. In *8. European Conference on Precision Livestock Farming (ECPLF)*, Nantes, France. D. Berckmans and A. Keita (Eds.), pp. 333-339.

Bell, M. J., Garnsworthy, P. C., Stott, A. W., & Pryce, J. E. (2015). Effects of changing cow production and fitness traits on profit and greenhouse gas emissions of UK dairy systems. *The Journal of Agricultural Science*, *153*(1), 138-151.

Bellon, S., & Hemptinne, J.-L. (2012). Redefining frontiers between farming systems and the environment. In I. Darnhofer, D. Gibbon, & B. Dedieu (Eds.), *Farming Systems Research into the 21st century: The new dynamic* (pp. 307-333). Springer, Dodrecht.

Bennett, R.M. 1997. Farm animal welfare and food policy. *Food Policy* 22 (4), 281–288.

Benzaquen, M. E., Risco, C. A., Archbald, L. F., Melendez, P., Thatcher, M. J., & Thatcher, W. W. (2007). Rectal temperature, calving-related factors, and the incidence of puerperal metritis in postpartum dairy cows. *Journal of Dairy Science*, *90*(6), 2804-2814.

Berentsen, P. B. M., & Giesen, G. W. J. (1995). An environmental-economic model at farm level to analyse institutional and technical change in dairy farming. *Agricultural Systems*, *49*(2), 153-175.

Berkhout, P. H., Muskens, J. C., & Velthuijsen, J. W. (2000). Defining the rebound effect. *Energy Policy*, *28*(6-7), 425-432.

Bewley, J. (2010). Precision dairy farming: advanced analysis solutions for future profitability. In *Proceedings of the first North American Conference on Precision Dairy Management, Toronto, Canada* (p. 16).

Bewley, J. M., Gray, A. W., Hogeveen, H., Kenyon, S. J., Eicher, S. D., & Schutz, M. M. (2010a). Assessing the potential value for an automated dairy cattle body condition scoring system through stochastic simulation. *Agricultural Finance Review*.

Bewley, J. M., Gray, A. W., Hogeveen, H., Kenyon, S. J., Eicher, S. D., & Schutz, M. M. (2010b). Stochastic simulation using@ Risk for dairy business investment decisions. *Agricultural Finance Review*.

Biggs, S. D. (1995). Farming systems research and rural poverty: Relationships between context and content. *Agricultural Systems*, *47*(2), 161-174.

Bitsch, V. (2016). Sustainability as innovation: Challenges and perspectives in measurement and implementation. In C. Huyghe, P. Bergeret, & U. Svedin (Eds.), *Diffusion and Transfer of Knowledge in Agriculture* (pp. 15-20).

Bockstaller, C., Guichard, L., Makowski, D., Aveline, A., Girardin, P., & Plantureux, S. (2008). Agri-environmental indicators to assess cropping and farming systems. A review. *Agronomy for sustainable development*, *28*(1), 139-149.

Bockstaller, C., Lasserre-Joulin, F., Slezack-Deschaumes, S., Piutti, S., Villerd, J., Amiaud, B., & Plantureux, S. (2011). Assessing biodiversity in arable farmland by means of indicators: an overview. *Oléagineux, Corps gras, Lipides*, *18*(3), 137-144.

Boissy, A., & Le Neindre, P. (1997). Behavioral, cardiac and cortisol responses to brief peer separation and reunion in cattle. *Physiology & Behavior*, *61*(5), 693-699.

Boogaard, B. K., Bock, B. B., Oosting, S. J., Wiskerke, J. S., & van der Zijpp, A. J. (2011). Social acceptance of dairy farming: The ambivalence between the two faces of modernity. *Journal of Agricultural and Environmental Ethics*, *24*(3), 259-282.

Boogaard, B. K., Oosting, S. J., & Bock, B. B. (2006). Elements of societal perception of farm animal welfare: A quantitative study in The Netherlands. *Livestock Science*, *104*(1-2), 13-22.

Boogaard, B. K., Oosting, S. J., & Bock, B. B. (2008). Defining sustainability as a socio-cultural concept: Citizen panels visiting dairy farms in the Netherlands. *Livestock Science* 117 (1): 24-33.

Borchers, M. R., & Bewley, J. M. (2015). An assessment of producer precision dairy farming technology use, prepurchase considerations, and usefulness. *Journal of Dairy Science*, *98*(6), 4198-4205.

Broadbent, E., Stafford, R., & MacDonald, B. (2009). Acceptance of healthcare robots for the older population: Review and future directions. *International Journal of Social Robotics*, *1*(4), 319.

Busch, G., & Spiller, A. (2018). Consumer acceptance of livestock farming around the globe. *Animal Frontiers*, *8*(1), 1-3.

Butler, J. E. (2009). Cloned animal products in the human food chain: FDA should protect American consumers. *Food and Drug Law Journal*, 64(3), 473-501.

Cabrera, V. E., Hildebrand, P. E., Jones, J. W., Letson, D., & De Vries, A. (2006). An integrated North Florida dairy farm model to reduce environmental impacts under seasonal climate variability. *Agriculture, Ecosystems & Environment*, *113*(1-4), 82-97.

Caria, M., Todde, G., & Pazzona, A. (2019). Evaluation of automated in-line precision dairy farming technology implementation in three dairy farms in Italy. *Frontiers of Agricultural Science and Engineering*, *6*, 181-187.

Carlowitz, H. V. (2000). Sylvicultura oeconomica: Anweisung zur wilden Baum-Zucht. *Leipzig*, *1713*, 84.

Casella, G., & Robert, C. P. (1999). Monte Carlo statistical methods. Springer, New York.

Cavero, D., Tölle, K. H., Henze, C., Buxadé, C., & Krieter, J. (2008). Mastitis detection in dairy cows by application of neural networks. *Livestock Science*, *114*(2-3), 280-286.

Chanvallon, A., Coyral-Castel, S., Gatien, J., Lamy, J. M., Ribaud, D., Allain, C., Clément, P., & Salvetti, P. (2014). Comparison of three devices for the automated detection of estrus in dairy cows. *Theriogenology*, *82*(5), 734-741.

Chapinal, N., De Passille, A. M., Rushen, J., & Wagner, S. (2010). Automated methods for detecting lameness and measuring analgesia in dairy cattle. *Journal of Dairy Science*, *93*(5), 2007-2013.

Chen, W., White, E., & Holden, N. M. (2016). The effect of lameness on the environmental performance of milk production by rotational grazing. *Journal of Environmental Management*, *172*, 143-150.

Clark, B., Stewart, G. B., Panzone, L. A., Kyriazakis, I., & Frewer, L. J. (2016). A systematic review of public attitudes, perceptions and behaviours towards production diseases associated with farm animal welfare. *Journal of Agricultural and Environmental Ethics*, *29*(3), 455-478.

Clasen, J. B., Fikse, W. F., Kargo, M., Rydhmer, L., Strandberg, E., & Østergaard, S. (2020). Economic consequences of dairy crossbreeding in conventional and organic herds in Sweden. *Journal of Dairy Science*, *103*(1), 514-528.

Colin, J. P., & Crawford, E. W. (2000). Economic perspectives in agricultural systems analysis. *Applied Economic Perspectives and Policy*, *22*(1), 192-216.

Collinson, M., & Lightfoot, C. (2000). The future of Farming Systems Research. In M. Collinson (Ed.), *A history of Farming Systems Research* (pp. 391–419). Oxon: CABI.

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly*, 189-211.

Cook, N. B., Mentink, R. L., Bennett, T. B., & Burgi, K. (2007). The effect of heat stress and lameness on time budgets of lactating dairy cows. *Journal of Dairy Science*, *90*(4), 1674-1682.

Cooper-Prado, M. J., Long, N. M., Wright, E. C., Goad, C. L., & Wettemann, R. P. (2011). Relationship of ruminal temperature with parturition and estrus of beef cows. *Journal of Animal Science*, *89*(4), 1020-1027.

Cornish, A., Raubenheimer, D., & McGreevy, P. (2016). What we know about the public's level of concern for farm animal welfare in food production in developed countries. *Animals*, *6*(11), 74.

Coroamă, V. C., & Mattern, F. (2019). Digital rebound–why digitalization will not redeem us our environmental sins. In *Proceedings 6th international conference on ICT for sustainability. Lappeenranta. http://ceur-ws. org* (Vol. 2382).

Crociati, M., Sylla, L., van Straten, M., Stradaioli, G., & Monaci, M. (2020). Estimating the net return of a remote calving alarm system in a dairy farm. *Journal of Dairy Science*, *103*(10), 9646-9655

Crosson, P., Shalloo, L., O'brien, D., Lanigan, G. J., Foley, P. A., Boland, T. M., & Kenny, D. A. (2011). A review of whole farm systems models of greenhouse gas emissions from beef and dairy cattle production systems. *Animal Feed Science and Technology*, *166*, 29-45.

Cvetkovich, A. (2003). *Archive of feelings* (Vol. 2008). Durham, NC: Duke University Press.

Da Borso, F., Chiumenti, A., Sigura, M., & Pezzuolo, A. (2017). Influence of automatic feeding systems on design and management of dairy farms. *Journal of Agricultural Engineering*, *48*(s1), 48-52.

Danziger, K. (1985). The methodological imperative in psychology. *Philosophy of the social sciences*, *15*(1), 1-13.

Darnhofer, I., Bellon, S., Dedieu, B., & Milestad, R. (2010). Adaptiveness to enhance the sustainability of farming systems. A review. *Agronomy for Sustainable Development*, *30*(3), 545-555.

Darnhofer, I., Gibbon, D., & Dedieu, B. (2012). Farming systems research: an approach to inquiry. In *Farming systems research into the 21st century: The new dynamic* (pp. 3-31). Springer, Dordrecht.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13, 319–340.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, *35*(8), 982-1003.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of Applied Social Psychology*, 22(14), 1111–1132.

Deemer, D. R., & Lobao, L. M. (2011). Public concern with farm-animal welfare: Religion, politics, and human disadvantage in the food sector. *Rural Sociology*, *76*(2), 167-196.

De Graaf, M. M., & Allouch, S. B. (2013). Exploring influencing variables for the acceptance of social robots. *Robotics and Autonomous Systems*, *61*(12), 1476-1486.

Dela Rue, B., Kamphuis, C., Burke, C. R., & Jago, J. G. (2012). Field evaluation of automated estrus detection systems – Meeting farmers' expectations. In *Proc. 11th International Conference on Precision Agriculture (ICPA), Indianapolis, IN*. Springer, New York, NY.

De Wit, C. T. (1958). *Transpiration and crop yields* (No. 64.6).

Diedrich, A., Upham, P., Levidow, L., & van den Hove, S. (2011). Framing environmental sustainability challenges for research and innovation in European policy agendas. *Environmental Science & Policy*, *14*(8), 935-939.

Doole, G. J., Romera, A. J., & Adler, A. A. (2013). An optimization model of a New Zealand dairy farm. *Journal of Dairy Science*, *96*(4), 2147-2160.

Eastwood, C., Chapman, D., & Paine, M. (2004). Precision dairy farming-taking the microscope to dairy farm management. In *Current Topics in Dairy Production, edited by: Fulkerson, W., Dairy Research Foundation Symposium, Camden, Australia*.

Eastwood, C., Klerkx, L., Ayre, M., & Rue, B. D. (2019). Managing socio-ethical challenges in the development of smart farming: from a fragmented to a comprehensive approach for responsible research and innovation. *Journal of Agricultural and Environmental Ethics*, *32*(5), 741-768.

Edwards, J. L., & Tozer, P. R. (2004). Using activity and milk yield as predictors of fresh cow disorders. *Journal of Dairy Science*, *87*(2), 524-531.

EG-Kommission (1991): Die künftige Entwicklung der gemeinsamen Agrarpolitik. *Agra-Europe*, 7/91.

Elkington, J. (1998). Partnerships from cannibals with forks: The triple bottom line of 21st-century business. *Environmental Quality Management*, *8*(1), 37-51.

Ettema, J. F., & Østergaard, S. (2006). Economic decision making on prevention and control of clinical lameness in Danish dairy herds. *Livestock science*, *102*(1-2), 92-106.

Ettema, J. F., & Østergaard, S. (2015). Economics of sex-biased milk production. *Journal of Dairy Science*, *98*(2), 1078-1081.

Ettema, J. F., & Santos, J. E. P. (2004). Impact of age at calving on lactation, reproduction, health, and income in first-parity Holsteins on commercial farms. *Journal of Dairy Science*, *87*(8), 2730-2742.

Ettema, J.F., Thomasen, J. R., Hjortø, L., Kargo, M., Østergaard, S., & Sørensen, A. C. (2017). Economic opportunities for using sexed semen and semen of beef bulls in dairy herds. *Journal of Dairy Science*, *100*(5), 4161-4171.

Eurobarometer. 2012. *Public attitudes towards robots*. European Commission.

Federal Statistical Office Germany (Destatis). 2018. Press release No. 330 of 5 September 2018. Accessed 10 March 2020.

Firk, R., Stamer, E., Junge, W., & Krieter, J. (2002). Automation of oestrus detection in dairy cows: a review. *Livestock Production Science*, *75*(3), 219-232.

Flora, C. B. (1992). Building sustainable agriculture: a new application of farming systems research and extension. *Journal of Sustainable Agriculture*, *2*(3), 37-49.

Flynn, R. (2007). Risk and the public acceptance of new technologies. In *Risk and the public acceptance of new technologies* (pp. 1-23). Palgrave Macmillan, London.

Food and Agriculture Organization of the United Nations (FAO) (2014). SAFA guidelines (Sustainability Assessment of Food and Agriculture Systems. Version 3.0, retrieved from: https://www.fao.org/3/i3957e/i3957e.pdf. Accessed 01 April 2022.

Fraedrich, E., & Lenz, B. (2016). Societal and individual acceptance of autonomous driving. In *Autonomous driving* (pp. 621-640). Springer, Berlin, Heidelberg.

Francis, C. A., & Youngberg, G. (1990). *Sustainable agriculture: An overview*. In Francis, C. A., Flora, C. B., and King, L. D. (Eds.) Sustainable Agriculture in Temperature Zones (pp. 1-23). John Wiley and Sons, New York, United States of America, Chichester, England.

Freudenburg, W. R. (1991). Rural-urban differences in environmental concern: A closer look. *Sociological Inquiry*, *61*(2), 167-198.

Frewer, L. J., Bergmann, K., Brennan, M., Lion, R., Meertens, R., Rowe, G., Siegrist, C., & Vereijken, C. M. J. L. (2011). Consumer response to novel agri-food technologies: Implications for predicting consumer acceptance of emerging food technologies. *Trends in Food Science & Technology*, *22*(8), 442-456.

Frewer, L. J. (2017). Consumer acceptance and rejection of emerging agrifood technologies and their applications. *European Review of Agricultural Economics*, *44*(4), 683-704.

Gabriel, A., Gandorfer, M., & Spykman, O. (2021). Nutzung und Hemmnisse digitaler Technologien in der Landwirtschaft. *Berichte über Landwirtschaft-Zeitschrift für Agrarpolitik und Landwirtschaft*.

Gabriel, A., & Pfeiffer, J. (2021). Adoption potential of digital and automation technologies in smaller-scale livestock farming. *Agri-Tech Economics for Sustainable Futures*, *20*, 3.

Galvão, K. N., Federico, P., De Vries, A., & Schuenemann, G. M. (2013). Economic comparison of reproductive programs for dairy herds using estrus detection, timed artificial insemination, or a combination. *Journal of Dairy Science*, *96*(4), 2681-2693.

Gandorfer, M., Porsch, A., & Bitsch, V. (2017). Producer price volatility in the German fruit and vegetable industry. *European Journal of Horticultural Science*, *82*(3), 149-154.

Gargiulo, J. I., Eastwood, C. R., Garcia, S. C., & Lyons, N. A. (2018). Dairy farmers with larger herd sizes adopt more precision dairy technologies. *Journal of Dairy Science*, *101*(6), 5466-5473.

Garnier, J. P., Klont, R., & Plastow, G. (2003). The potential impact of current animal research on the meat industry and consumer attitudes towards meat. *Meat Science*, 63(1), 79-88.

Garnsworthy, P. C. (2004). The environmental impact of fertility in dairy cows: a modelling approach to predict methane and ammonia emissions. *Animal Feed Science and Technology*, *112*(1-4), 211-223.

Gaughan, J. B., Holt, S., Hahn, G. L., Mader, T. L., & Eigenberg, R. (2000). Respiration rate: Is it a good measure of heat stress in cattle?. *Asian-Australasian Journal of Animal Sciences*, *13*(Supplement Vol C), 329-332.

German Research Foundation. (2005). *Future perspectives of agricultural science and research: memorandum*. Wiley-VCH.

Gevrekci, Y., Chang, Y. M., Kızılkaya, K., Gianola, D., Weigel, K. A., & Akbaș, Y. (2006). Bayesian inference for calving ease and stillbirth in Holsteins using a bivariate threshold sire-maternal grandsire model. In *Proceedings of the 8th World Congress on Genetics Applied to Livestock Production, Belo Horizonte, Minas Gerais, Brazil, 13-18 August, 2006* (pp. 01-26). Instituto Prociência.

Giaretta, E., Marliani, G., Postiglione, G., Magazzù, G., Pantò, F., Mari, G., Formigoni, A., Accorsi, P. A., & Mordenti, A. (2021). Calving time identified by the automatic detection of tail movements and rumination time, and observation of cow behavioural changes. *Animal*, *15*(1), 100071.

Gibon, A., Sibbald, A. R., Flamant, J. C., Lhoste, P., Revilla, R., Rubino, R., & Sørensen, J. T. (1999). Livestock farming systems research in Europe and its potential contribution for managing towards sustainability in livestock farming. *Livestock Production Science*, *61*(2-3), 121-137.

Gilbert, E. H., Norman, D. W., & Winch, F. E. (1980). Farming systems research: a critical appraisal. *MSU Rural Development Paper-Michigan State University, Department of Agricultural Economics (USA)*.

Giordano, J. O., Kalantari, A. S., Fricke, P. M., Wiltbank, M. C., & Cabrera, V. E. (2012). A daily herd Markov-chain model to study the reproductive and economic impact of reproductive programs combining timed artificial insemination and estrus detection. *Journal of dairy science*, *95*(9), 5442-5460.

Goff, J. P., Hohman, A., & Timms, L. L. (2020). Effect of subclinical and clinical hypocalcemia and dietary cation-anion difference on rumination activity in periparturient dairy cows. *Journal of Dairy Science*, *103*(3), 2591-2601.

Gorewit, R. C., Scott, N. R., & Czarniecki, C. S. (1985). Responses of dairy cows to alternating electrical current administered semirandomly in a nonavoidance environment. *Journal of Dairy Science*, *68*(3), 718-725.

Grodkowski, G., Sakowski, T., Puppel, K., & Baars, T. (2018). Comparison of different applications of automatic herd control systems on dairy farms–a review. *Journal of the Science of Food and Agriculture*, *98*(14), 5181-5188.

Groenendaal, H., Galligan, D. T., & Mulder, H. A. (2004). An economic spreadsheet model to determine optimal breeding and replacement decisions for dairy cattle. *Journal of Dairy Science*, *87*(7), 2146-2157.

Groher, T., Heitkämper, K., & Umstätter, C. (2020). Digital technology adoption in livestock production with a special focus on ruminant farming. *Animal*, *14*(11), 2404-2413.

Gröhn, Y. T., Eicker, S. W., & Hertl, J. A. (1995). The association between previous 305-day milk yield and disease in New York State dairy cows. *Journal of Dairy Science*, *78*(8), 1693-1702.

Grunwald, A. (2009). Technology assessment: concepts and methods. In *Philosophy of technology and engineering sciences* (pp. 1103-1146). North-Holland.

Grunwald, A. (2010). *Technikfolgenabschätzung: Eine Einführung* (Vol. 1). edition sigma.

Gupta, N., Fischer, A. R., & Frewer, L. J. (2012). Socio-psychological determinants of public acceptance of technologies: a review. *Public Understanding of Science*, *21*(7), 782-795.

Häder, M. (2010). *Empirische Sozialforschung*. Wiesbaden: VS Verlag für Sozialwissenschaften.

Hansen, B., Kristensen, E. S., Grant, R., Høgh-Jensen, H., Simmelsgaard, S. E., & Olesen, J. E. (2000). Nitrogen leaching from conventional versus organic farming systems—a systems modelling approach. *European Journal of Agronomy*, *13*(1), 65-82.

Harrison, R. L. (2010). Introduction to monte carlo simulation. In *AIP conference proceedings* (Vol. 1204, No. 1, pp. 17-21). American Institute of Physics.

Hayati, D., Ranjbar, Z., & Karami, E. (2010). Measuring agricultural sustainability. *Biodiversity, Biofuels, Agroforestry and Conservation Agriculture*, 73-100.

Heid, A., & Hamm, U. (2012). Consumer attitudes towards alternatives to piglet castration without pain relief in organic farming: qualitative results from Germany. *Journal of Agricultural and Environmental Ethics*, *25*(5), 687-706.

Heinicke, J., Ibscher, S., Belik, V., & Amon, T. (2019). Cow individual activity response to the accumulation of heat load duration. *Journal of Thermal Biology*, *82*, 23-32.

Helmle, S. (2010). Images are communication: empirical survey and modeling of the image of agriculture in Germany. *OGA Jahrbuch-Journal of the Austrian Society of Agricultural Economics*, *19*(1), 51-60.

Herrero, M., Fawcett, R. H., & Dent, J. B. (1999). Bio-economic evaluation of dairy farm management scenarios using integrated simulation and multiple-criteria models. *Agricultural Systems*, *62*(3), 169-188.

Herzog, A., Winckler, C., & Zollitsch, W. (2018). In pursuit of sustainability in dairy farming: A review of interdependent effects of animal welfare improvement and environmental impact mitigation. *Agriculture, Ecosystems & Environment*, *267*, 174-187.

Hillman, P.E.; Lee, C.N.; Willard, S.T. 2005. Thermoregulatory responses associated with lying and standing in heat stressed dairy cows. *Transactions of the ASAE* 2005, *48(2),* 795–801.

Hockey, C. D., Morton, J. M., Norman, S. T., & McGowan, M. R. (2010). Evaluation of a neck mounted 2-hourly activity meter system for detecting cows about to ovulate in two paddock-based Australian dairy herds. *Reproduction in Domestic Animals*, *45*(5), e107-e117.

Hogeveen, H., Huijps, K., & Lam, T. J. G. M. (2011). Economic aspects of mastitis: new developments. *New Zealand Veterinary Journal*, *59*(1), 16-23.

Hopster, H., & Blokhuis, H. J. (1994). Validation of a heart-rate monitor for measuring a stress response in dairy cows. *Canadian Journal of Animal Science*, *74*(3), 465-474.

Horváth, A., Lénárt, L., Csepreghy, A., Madar, M., Pálffy, M., & Szenci, O. (2021). A field study using different technologies to detect calving at a large-scale hungarian dairy farm. *Reproduction in Domestic Animals*, *56*(4), 673-679.

Hostiou, N., Fagon, J., Chauvat, S., Turlot, A., Kling-Eveillard, F., Boivin, X., & Allain, C. (2017). Impact of precision livestock farming on work and human-animal interactions on dairy farms. A review. *Biotechnologie, Agronomie, Société et Environnement/Biotechnology, Agronomy, Society and Environment*, *21*(4), 268-275.

Hüsing, B., Bierhals, R., Bührlen, B., Friedewald, M., Kimpeler, S., Menrad, K., Wengel, J., Zimmer, R., & Zoche, P. (2002). Technikakzeptanz und Nachfragemuster als Standortvorteil. *Abschlussbericht an das Bundesministerium für Bildung und Forschung, Fraunhofer-Institut für Systemtechnik und Innovationsforschung (Fraunhofer ISI), Karlsruhe*.

Hyde, J., & Engel, P. (2002). Investing in a robotic milking system: A Monte Carlo simulation analysis. *Journal of Dairy Science*, *85*(9), 2207-2214.

Inchaisri, C., Jorritsma, R., Vos, P. L., Van der Weijden, G. C., & Hogeveen, H. (2010). Economic consequences of reproductive performance in dairy cattle. *Theriogenology*, *74*(5), 835-846.

Jago, J., Eastwood, C., Kerrisk, K., & Yule, I. (2013). Precision dairy farming in Australasia: adoption, risks and opportunities. *Animal Production Science*, *53*(9), 907-916.

Jalvingh, A. W. (1992). The possible role of existing models in on-farm decision support in dairy cattle and swine production. *Livestock Production Science*, *31*(3-4), 351-365.

Jalvingh, A. W., Van Arendonk, J. A. M., Dijkhuizen, A. A., & Renkema, J. A. (1993). Dynamic probabilistic simulation of dairy herd management practices. II. Comparison of strategies in order to change a herd’s calving pattern. *Livestock Production Science*, *37*(1-2), 133-152.

Jensen, M. B. (2012). Behaviour around the time of calving in dairy cows. *Applied Animal Behaviour Science*, *139*(3-4), 195-202.

Jingqiu, G., Zhihai, W., Ronghua, G., & Huarui, W. (2017). Cow behavior recognition based on image analysis and activities. *International Journal of Agricultural and Biological Engineering*, *10*(3), 165-174.

Jones, J. W., Antle, J. M., Basso, B., Boote, K. J., Conant, R. T., Foster, I., Charles, H., Godfray, J., Herrero, M., Howitt, R. E., Janssen, S., Keating, B. A., Munoz-Carpena, R., Porter, C. H., Rosenzweig, C., & Wheeler, T. R. (2017). Brief history of agricultural systems modeling. *Agricultural Systems*, *155*, 240-254.

Kadzere, C. T., Murphy, M. R., Silanikove, N., & Maltz, E. (2002). Heat stress in lactating dairy cows: a review. *Livestock Production Science*, *77*(1), 59-91.

Kaufman, E. I., LeBlanc, S. J., McBride, B. W., Duffield, T. F., & DeVries, T. J. (2016). Association of rumination time with subclinical ketosis in transition dairy cows. *Journal of Dairy Science*, *99*(7), 5604-5618.

Keating, B. A., Carberry, P. S., Hammer, G. L., Probert, M. E., Robertson, M. J., Holzworth, D., Huth, N. I., Hargreaves, J. N. G., Meinke, H., Hochman, Z., McLeam, G., Verburg, K., Snow, V., Dimes, J. P., Silburn, M., Wang, E., Brown, S., Bristow, K. L., Asseng, S., Chapman, S., McCown, R. L., Freebairn, D. M., & Smith, C. J. (2003). An overview of APSIM, a model designed for farming systems simulation. *European Journal of Agronomy*, *18*(3-4), 267-288.

Kendall, H. A., Lobao, L. M., & Sharp, J. S. (2006). Public concern with animal well-being: Place, social structural location, and individual experience. *Rural Sociology*, *71*(3), 399-428.

Khanna, M. (2001). Sequential adoption of site-specific technologies and its implications for nitrogen productivity: A double selectivity model. *American Journal of Agricultural Economics*, *83*(1), 35-51.

Kim, H., Min, Y., & Choi, B. (2019). Real-time temperature monitoring for the early detection of mastitis in dairy cattle: Methods and case researches. *Computers and Electronics in Agriculture*, *162*, 119-125.

Klerkx, L., Jakku, E., & Labarthe, P. (2019). A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. *NJAS-Wageningen Journal of Life Sciences*, *90*, 100315.

Klerkx, L., Van Mierlo, B., & Leeuwis, C. (2012). Evolution of systems approaches to agricultural innovation: concepts, analysis and interventions. *Farming Systems Research into the 21st century: The new dynamic*, 457-483.

Klöpffer, W., & Renner, I. (2007). Lebenszyklusbasierte Nachhaltigkeitsbewertung von Produkten. *TATuP-Zeitschrift für Technikfolgenabschätzung in Theorie und Praxis*, *16*(3), 32-38.

Kollmann, T. (1998). Akzeptanz innovativer Nutzungsgüter. *Konsequenzen für die Einführung von Telekommunikations-und Multimediasystemen. Gabler. Wiesbaden*.

Kollmann, T. (2004). Attitude, adoption or acceptance? Measuring the market success of telecommunication and multimedia technology. *International Journal of Business Performance Management*, *6*(2), 133-152.

König, A., Kuiper, H. A., Marvin, H. J., Boon, P. E., Busk, L., Cnudde, F., Cope, S., Davis, H. V., Dreyer, M., Frewer, L. J., Kaiser, M., Kleter, G. A., Knudsen, I., Pascal, G., Prandini, A., Renn, O., Smith, M. R., Traill, B. W., Van der Voet, H., Van Trijp, H., Vos, E., & Wentholt, M. T. (2010). The SAFE FOODS framework for improved risk analysis of foods. *Food Control*, *21*(12), 1566-1587.

Kovács, L., Kézér, F. L., Póti, P., Jurkovich, V., Szenci, O., & Nagy, K. (2019). Heart rate variability, step, and rumination behavior of dairy cows milked in a rotary milking system. *Journal of dairy science*, *102*(6), 5525-5529.

Krampe, C., Serratosa, J., Niemi, J. K., & Ingenbleek, P. (2021). Consumer perceptions of precision livestock farming—a qualitative study in three European countries. *Animals*, *11*(5), 1221.

Kühl, S., Gauly, S., & Spiller, A. (2019). Analysing public acceptance of four common husbandry systems for dairy cattle using a picture-based approach. *Livestock Science*, *220*, 196-204.

Kuhlman, T., & Farrington, J. (2010). What is sustainability?. *Sustainability*, *2*(11), 3436-3448.

Latruffe, L., Diazabakana, A., Bockstaller, C., Desjeux, Y., Finn, J., Kelly, E., Ryan, M., & Uthes, S. (2016). Measurement of sustainability in agriculture: a review of indicators. *Studies in Agricultural Economics*, *118*(3), 123-130.

Lay Jr, D. C., Friend, T. H., Randel, R. D., Bowers, C. L., Grissom, K. K., & Jenkins, O. C. (1992). Behavioral and physiological effects of freeze or hot-iron branding on crossbred cattle. *Journal of Animal Science*, *70*(2), 330-336.

Lebacq, T., Baret, P. V., & Stilmant, D. (2013). Sustainability indicators for livestock farming. A review. *Agronomy for Sustainable Development*, *33*(2), 311-327.

Lefcourt, A. M., Erez, B., Varner, M. A., Barfield, R., & Tasch, U. (1999). A noninvasive radiotelemetry system to monitor heart rate for assessing stress responses of bovines. *Journal of Dairy Science*, *82*(6), 1179-1187.

Lefcourt, A. M., Kahl, S., & Akers, R. M. (1986). Correlation of indices of stress with intensity of electrical shock for cows. *Journal of Dairy Science*, *69*(3), 833-842.

Lefever, S., Dal, M., & Matthíasdóttir, Á. (2007). Online data collection in academic research: advantages and limitations. *British Journal of Educational Technology*, *38*(4), 574-582.

Li, Z., Ge, C., Shen, S., & Li, X. (2018). Cow individual identification based on convolutional neural network. In *Proceedings of the 2018 International Conference on Algorithms, Computing and Artificial Intelligence,* Sanya, China, 21-23 December, 2018 (pp. 1-5). Association for Computing Machinery, New York, United States of America.

Lind, A. K., & Lindahl, C. (2019). Calving alert system—A helping technique or a welfare problem. In *9. European Conference on Precision Livestock Farming (ECPLF),* Cork, Ireland, 26-29 August, 2019. B. O'Brien, D. Hennnessy, & L. Shalloo (Eds.) (pp. 385-388).

Lombard, J. E., Garry, F. B., Tomlinson, S. M., & Garber, L. P. (2007). Impacts of dystocia on health and survival of dairy calves. *Journal of Dairy Science*, *90*(4), 1751-1760.

Lovarelli, D., Bacenetti, J., & Guarino, M. (2020). A review on dairy cattle farming: Is precision livestock farming the compromise for an environmental, economic and social sustainable production?. *Journal of Cleaner Production*, *262*, 121409.

Lucke, D. (1995). *Akzeptanz: Legitimität in der 'Abstimmungsgesellschaft'. Opladen: Leske+ Budrich,* Wiesbaden: VS Verlag für Sozialwissenschaften.

Lusk, J. L., Roosen, J., & Bieberstein, A. (2014). Consumer acceptance of new food technologies: Causes and roots of controversies. *Annual Review of Resource Economics*, *6*(1), 381-405.

Marchesi, G., Leonardi, S., Tangorra, F. M., Calcante, A., Beretta, E., Pofcher, E., & Lazzari, M. (2013). Evaluation of an electronic system for automatic calving detection on a dairy farm. *Animal Production Science*, *53*(10), 1112-1114.

María, G. A. (2006). Public perception of farm animal welfare in Spain. *Livestock Science*, *103*(3), 250-256.

Mayer, A., & Mayer, J. (1974). Agriculture, the island empire. *Daedalus*, 83-95.

Mee, J. F. (2008). Prevalence and risk factors for dystocia in dairy cattle: A review. *The Veterinary Journal*, *176*(1), 93-101.

Michaelis, I., Hasenpusch, E., & Heuwieser, W. (2013). Estrus detection in dairy cattle: Changes after the introduction of an automated activity monitoring system?. *Tierärztliche Praxis Ausgabe G: Großtiere/Nutztiere*, *41*(03), 159-165.

Miedema, H. M., Cockram, M. S., Dwyer, C. M., & Macrae, A. I. (2011). Changes in the behaviour of dairy cows during the 24 h before normal calving compared with behaviour during late pregnancy. *Applied Animal Behaviour Science*, *131*(1-2), 8-14.

Miele, M., Veissier, I., Evans, A., & Botreau, R. (2011). Animal welfare: establishing a dialogue between science and society. *Animal Welfare*, *20*(1), 103.

Millar, K. M., Tomkins, S. M., White, R. P., & Mepham, T. B. (2002). Consumer attitudes to the use of two dairy technologies. *British Food Journal*, *104* (1), 31-44.

Modin-Edman, A. K., Öborn, I., & Sverdrup, H. (2007). FARMFLOW—A dynamic model for phosphorus mass flow, simulating conventional and organic management of a Swedish dairy farm. *Agricultural Systems*, *94*(2), 431-444.

Mooney, C.Z. (1997). *Monte Carlo Simulation*. Sage University Paper series on Quantitative Applications in the Social Sciences, 07-116. Thousand Oaks, CA: Sage.

Mottram, T. (2016). Animal board invited review: precision livestock farming for dairy cows with a focus on oestrus detection. *Animal*, *10*(10), 1575-1584.

Müller, R., & Schrader, L. (2005). Behavioural consistency during social separation and personality in dairy cows. *Behaviour*, *142*(9-10), 1289-1306.

Norton, G. A. (1976). Analysis of decision making in crop protection. *Agro-ecosystems*, *3*, 27-44.

O'Callaghan, K. A., Cripps, P. J., Downham, D. Y., & Murray, R. D. (2003). Subjective and objective assessment of pain and discomfort due to lameness in dairy cattle. *Animal Welfare*, *12*(4), 605-610.

O'Leary, N., Leso, L., Buckley, F., Kenneally, J., McSweeney, D., & Shalloo, L. (2020). Validation of an Automated Body Condition Scoring System Using 3D Imaging. *Agriculture*, *10*(6), 246.

Ominski, K. H., Kennedy, A. D., Wittenberg, K. M., & Nia, S. M. (2002). Physiological and production responses to feeding schedule in lactating dairy cows exposed to short-term, moderate heat stress. *Journal of Dairy Science*, *85*(4), 730-737.

Østergaard, S., Sørensen, J. T., & Kristensen, A. R. (2000). A stochastic model simulating the feeding-health-production complex in a dairy herd. *Journal of Dairy Science*, *83*(4), 721-733.

Østergaard, S., Sørensen, J. T., & Houe, H. (2003). A stochastic model simulating milk fever in a dairy herd. *Preventive Veterinary Medicine*, *58*(3-4), 125-143.

Østergaard, S., Chagunda, M. G. G., Friggens, N. C., Bennedsgaard, T. W., & Klaas, I. C. (2005a). A stochastic model simulating pathogen-specific mastitis control in a dairy herd. *Journal of Dairy Science*, *88*(12), 4243-4257.

Østergaard, S., Friggens, N. C., & Chagunda, M. G. G. (2005b). Technical and economic effects of an inline progesterone indicator in a dairy herd estimated by stochastic simulation. *Theriogenology*, *64*(4), 819-843.

Ouellet, V., Vasseur, E., Heuwieser, W., Burfeind, O., Maldague, X., & Charbonneau, É. (2016). Evaluation of calving indicators measured by automated monitoring devices to predict the onset of calving in Holstein dairy cows. *Journal of Dairy Science*, *99*(2), 1539-1548.

Palombi, C., Paolucci, M., Stradaioli, G., Corubolo, M., Pascolo, P. B., & Monaci, M. (2013). Evaluation of remote monitoring of parturition in dairy cattle as a new tool for calving management. *BMC Veterinary Research*, *9*(1), 1-9.

Paolucci, M., Sylla, L., Di Giambattista, A., Palombi, C., Elad, A., Stradaioli, G., Pascolo, P., & Monaci, M. (2010). Improving calving management to further enhance reproductive performance in dairy cattle. *Veterinary Research Communications*, *34*(1), 37-40.

Peiper, U. M., Edan, Y., Devir, S., Barak, M., & Maltz, E. (1993). Automatic weighing of dairy cows. *Journal of Agricultural Engineering Research*, *56*(1), 13-24.

Petermann, T., & Scherz, C. (2005). TA und (Technik-) Akzeptanz (-forschung). *TATuP-Zeitschrift für Technikfolgenabschätzung in Theorie und Praxis*, *14*(3), 45-53.

Pilatti, J. A., Vieira, F. M. C., Rankrape, F., & Vismara, E. S. (2019). Diurnal behaviors and herd characteristics of dairy cows housed in a compost-bedded pack barn system under hot and humid conditions. *Animal*, *13*(2), 399-406.

Placzek, M., Christoph-Schulz, I., & Barth, K. (2021). Public attitude towards cow-calf separation and other common practices of calf rearing in dairy farming—a review. *Organic Agriculture*, *11*(1), 41-50.

Punch, K. F. (2013). *Introduction to social research: Quantitative and qualitative approaches*. Sage.

Ratnakaran, A. P., Sejian, V., Jose, V. S., Vaswani, S., Bagath, M., Krishnan, G., Beena, V., Devi, I., Varma, G., & Bhatta, R. (2017). Behavioral responses to livestock adaptation to heat stress challenges. *Asian Journal of Animal Science*, *11*(1), 1-13.

Redfern, E. A., Sinclair, L. A., & Robinson, P. A. (2021). Why isn't the transition period getting the attention it deserves? Farm advisors' opinions and experiences of managing dairy cow health in the transition period. *Preventive Veterinary Medicine*, *194*, 105424.

Reinemann, D. J., Stetson, L. E., & LeMire, S. D. (2004). Comparison of dairy cow aversion to continuous and intermittent current. *Transactions of the ASAE*, *47*(4), 1257.

Renn, O., & Zwick, M. M. (1997). *Risiko- und Technikakzeptanz* (pp. 15-73). Springer, Berlin.

Rigalma, K., Duvaux-Ponter, C., Barrier, A., Charles, C., Ponter, A. A., Deschamps, F., & Roussel, S. (2010). Medium-term effects of repeated exposure to stray voltage on activity, stress physiology, and milk production and composition in dairy cows. *Journal of Dairy Science*, *93*(8), 3542-3552.

Riley, J. (2001). The indicator explosion: local needs and international challenges. *Agriculture, Ecosystems and Environment*, *2*(87), 119-120.

Rogers, E. M. (1995). Diffusion of innovations (4th edn) (NewYork, NY, Free Press).

Röling, N., & Jiggins, J. (1998). The ecological knowledge system. In N. Röling, & M. A. Wagermakers (Eds.), *Facilitating sustainable agriculture. Participatory learning and adaptive management in times of environmental uncertainty* (pp. 283–311). Cambridge: Cambridge University Press.

Rose, D. C., & Chilvers, J. (2018). Agriculture 4.0: Broadening responsible innovation in an era of smart farming. *Frontiers in Sustainable Food Systems*, *2*, 87.

Rosnoblet, J., Girardin, P., Weinzaepflen, E., & Bockstaller, C. (2006). Analysis of 15 years of agriculture sustainability evaluation methods. In *9th ESA Congress, Warsaw, Poland* (pp. 707-708).

Rotz, C. A., Coiner, C. U., & Soder, K. J. (2001). Economics of robotic milking on a dairy farm in the United States. In *Farm work science facing the challenges of the XXI century. Proceedings XXIX CIOSTA-GIGR V Congress, Krakow, Poland, 25-27 June, 2001* (pp. 115-122). Wageningen Pers.

Rovers, A., Sonntag, W. I., Brümmer, N., & Christoph-Schulz, I. (2018). Citizens' perception of recent livestock production systems in Germany. *German Journal of Agricultural Economics*, *67*(670-2021-584), 223-233.

Rushen, J., Boissy, A., Terlouw, E. M. C., & De Passillé, A. M. B. (1999). Opioid peptides and behavioral and physiological responses of dairy cows to social isolation in unfamiliar surroundings. *Journal of Animal Science*, *77*(11), 2918-2924.

Rushen, J., Munksgaard, L., Marnet, P. G., & DePassillé, A. M. (2001). Human contact and the effects of acute stress on cows at milking. *Applied Animal Behaviour Science*, *73*(1), 1-14.

Rutten, C. J., Kamphuis, C., Hogeveen, H., Huijps, K., Nielen, M., & Steeneveld, W. (2017). Sensor data on cow activity, rumination, and ear temperature improve prediction of the start of calving in dairy cows. *Computers and Electronics in Agriculture*, *132*, 108-118.

Rutten, C. J., Steeneveld, W., Inchaisri, C., & Hogeveen, H. (2014). An ex ante analysis on the use of activity meters for automated estrus detection: To invest or not to invest?. *Journal of Dairy Science*, *97*(11), 6869-6887.

Rutten, C. J., Velthuis, A. G. J., Steeneveld, W., & Hogeveen, H. (2013). Invited review: Sensors to support health management on dairy farms. *Journal of Dairy Science*, *96*(4), 1928-1952.

Saint-Dizier, M., & Chastant-Maillard, S. (2012). Towards an automated detection of oestrus in dairy cattle. *Reproduction in Domestic Animals*, *47*(6), 1056-1061.

Saint-Dizier, M., & Chastant-Maillard, S. (2015). Methods and on-farm devices to predict calving time in cattle. *The Veterinary Journal*, *205*(3), 349-356.

Schäfer, M., & Keppler, D. (2013). Modelle der technikorientierten Akzeptanzforschung. Discussion paper. Technical University of Berlin.

Schils, R. L. M., De Haan, M. H. A., Hemmer, J. G. A., Van den Pol-van Dasselaar, A., De Boer, J. A., Evers, A. G., Holshof, G., Van Middelkoop, J. C., & Zom, R. L. G. (2007). DairyWise, a whole-farm dairy model. *Journal of Dairy Science*, *90*(11), 5334-5346.

Schimmelpfennig, D., & Ebel, R. (2016). Sequential adoption and cost savings from precision agriculture. *Journal of Agricultural and Resource Economics*, 97-115.

Schnell, R., Hill, P. B., & Esser, E. (2005). Methoden der empirischen Sozialforschung, 9., akt. *Aufl., München [ua]*.

Scholderer, J., & Frewer, L. J. (2003). The biotechnology communication paradox: Experimental evidence and the need for a new strategy. *Journal of Consumer Policy*, *26*(2), 125-157.

Schütz, K. E., Rogers, A. R., Poulouin, Y. A., Cox, N. R., & Tucker, C. B. (2010). The amount of shade influences the behavior and physiology of dairy cattle. *Journal of Dairy Science, 93(1),* 125–133.

Schütz, K. E., Cox, N. R., & Tucker, C. B. (2014). A field study of the behavioral and physiological effects of varying amounts of shade for lactating cows at pasture. *Journal of Dairy Science*, *97*(6), 3599-3605.

Stewart, M., Wilson, M. T., Schaefer, A. L., Huddart, F., & Sutherland, M. A. (2017). The use of infrared thermography and accelerometers for remote monitoring of dairy cow health and welfare. *Journal of Dairy Science*, *100*(5), 3893-3901.

Scott, D. (2011). The technological fix criticisms and the agricultural biotechnology debate. *Journal of Agricultural and Environmental Ethics*, *24*(3), 207-226.

Shalloo, L., Dillon, P., Rath, M., & Wallace, M. (2004). Description and validation of the Moorepark dairy system model. *Journal of Dairy science*, *87*(6), 1945-1959.

Sharp, J. S., & Tucker, M. (2005). Awareness and Concern about Large-Scale Livestock and Poultry: Results from a Statewide Survey of Ohioans. *Rural Sociology*, *70*(2), 208-228.

Shaw, A. (2002). 'It just goes against the grain' *Public Understanding of Science*, *11*, 273-291.

Shouse, E. (2005). Feeling, emotion, affect. *M/c journal*, *8*(6).

Simonne, A., Ozores-Hampton, M., Treadwell, D., & House, L. (2016). Organic and conventional produce in the US: examining safety and quality, economic values, and consumer attitudes. *Horticulturae*, *2*(2), 5.

Simons, J., J. Luy, I. Birkle, J. Klink-Lehmann, A. Rovers, M. von Meyer-Höfer, C. Vierboom, I. Härlen, N. Brümmer, W. Sonntag, S. Saggau, M. Hartmann, A. Spiller, & Christoph-Schule, I. (2019). Wahrnehmung und Akzeptanz. In *SocialLab - Nutztierhaltung im Spiegel der Gesellschaft*. *Agra Europe, 13*(19), 1-7.

Song, J., Guo, Y., Wu, P., & Sun, S. (2018). The agricultural water rebound effect in China. *Ecological Economics*, *146*, 497-506.

Sørensen, L. P., Bjerring, M., & Løvendahl, P. (2016). Monitoring individual cow udder health in automated milking systems using online somatic cell counts. *Journal of Dairy Science*, *99*(1), 608-620.

Sørensen, J. T., Kristensen, E. S., & Thysen, I. (1992). A stochastic model simulating the dairy herd on a PC. *Agricultural Systems*, *39*(2), 177-200.

Sorrell, S., Dimitropoulos, J., & Sommerville, M. (2009). Empirical estimates of the direct rebound effect: A review. *Energy Policy*, *37*(4), 1356-1371.

Specht, K., Siebert, R., & Thomaier, S. (2016). Perception and acceptance of agricultural production in and on urban buildings (ZFarming): a qualitative study from Berlin, Germany. *Agriculture and Human Values*, *33*(4), 753-769.

Spiertz, J. H. J., & Kropff, M. J. (2011). Adaptation of knowledge systems to changes in agriculture and society: The case of the Netherlands. *NJAS-Wageningen Journal of Life Sciences*, *58*(1-2), 1-10.

Stangaferro, M. L., Wijma, R., Caixeta, L. S., Al-Abri, M. A., & Giordano, J. O. (2016). Use of rumination and activity monitoring for the identification of dairy cows with health disorders: Part III. Metritis. *Journal of Dairy Science*, *99*(9), 7422-7433.

Steeneveld, W., & Hogeveen, H. (2015). Characterization of Dutch dairy farms using sensor systems for cow management. *Journal of Dairy Science*, *98*(1), 709-717.

Stilgoe, J., Owen, R., & Macnaghten, P. (2013). Developing a framework for responsible innovation. *Research Policy, 42*(9), 1568–1580.

Spilke, J., & Fahr, R. (2003). Decision support under the conditions of automatic milking systems using mixed linear models as part of a precision dairy farming concept. In *EFITA 2003 conference,* Debrecen, Hungary, 5-9 July, 2003 (pp. 5-9).

Stiehler, W., Decker, T., & Menrad, K. (2011). *Public acceptance of biomass cogeneration heat (and power) plants (BCH (P) P's) in Bavaria* (No. 1780-2016-141792).

Sue, V. M., & Ritter, L. A. (2012). *Conducting online surveys*. Sage.

Terrier, M., Gasselin, P., & Blanc, J. L. (2013). Assessing the sustainability of activity systems to support households' farming projects. In *Methods and procedures for building sustainable farming systems* (pp. 47-61). Springer, Dordrecht.

Te Velde, H., Aarts, N., & Van Woerkum, C. (2002). Dealing with ambivalence: farmers' and consumers' perceptions of animal welfare in livestock breeding. *Journal of Agricultural and Environmental Ethics*, *15*(2), 203-219.

Thorup, V. M., Munksgaard, L., Robert, P. E., Erhard, H. W., Thomsen, P. T., & Friggens, N. C. (2015). Lameness detection via leg-mounted accelerometers on dairy cows on four commercial farms. *Animal*, *9(10),* 1704-1712.

TNS Emnid. (2012). Das Image der deutschen Landwirtschaft. *URL: http://www. ima-agrar. de/fileadmin/redaktion/download/image-studie/2012/ima-imagestudie-landwirtschaft_bericht-2012. Pdf.* Accessed 10 March 2020.

Van Asseldonk, M. A. P. M., Jalvingh, A. W., Huirne, R. B. M., & Dijkhuizen, A. A. (1999). Potential economic benefits from changes in management via information technology applications on Dutch dairy farms: a simulation study. *Livestock Production Science*, *60*(1), 33-44.

Van Bavel, C. H. M. (1953). A Drought Criterion and Its Application in Evaluating Drought Incidence and Hazard 1. *Agronomy Journal*, *45*(4), 167-172.

Van Cauwenbergh, N., Biala, K., Bielders, C., Brouckaert, V., Franchois, L., Garcia Cidad, V., Hermy, M., Mathijs, E., Muys, B., Reijnders, J., Sauvenier, X., Valckx, J., Vanclooster, M., van der Veken, B., Wauters, E. & Peeters, A. (2007). SAFE—A hierarchical framework for assessing the sustainability of agricultural systems. *Agriculture, Ecosystems & Environment*, *120*(2-4), 229-242.

Vanhonacker, F., Verbeke, W., Van Poucke, E., Pieniak, Z., Nijs, G., & Tuyttens, F. (2012). The concept of farm animal welfare: Citizen perceptions and stakeholder opinion in Flanders, Belgium. *Journal of Agricultural and Environmental Ethics*, *25*(1), 79-101.

Van Liere, K. D., & Dunlap, R. E. (1980). The social bases of environmental concern: A review of hypotheses, explanations and empirical evidence. *Public Opinion Quarterly*, *44*(2), 181-197.

Van Nuffel, A., Vangeyte, J., Mertens, K. C., Pluym, L., De Campeneere, S., Saeys, W., Opsomer, G., & Van Weyenberg, S. (2013). Exploration of measurement variation of gait variables for early lameness detection in cattle using the GAITWISE. *Livestock Science*, *156*(1-3), 88-95.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478.

Ventura, B. A., Von Keyserlingk, M. A., Wittman, H., & Weary, D. M. (2016). What difference does a visit make? Changes in animal welfare perceptions after interested citizens tour a dairy farm. *PLoS One*, *11*(5), e0154733.

Vickers, L. A., Burfeind, O., Von Keyserlingk, M. A. G., Veira, D. M., Weary, D. M., & Heuwieser, W. (2010). Comparison of rectal and vaginal temperatures in lactating dairy cows. *Journal of Dairy Science*, *93*(11), 5246-5251.

Von Ahlefeld, P. J. W. (2019). Rebound Effekte in der Präzisionslandwirtschaft - Ein Kommentar. *Berichte über Landwirtschaft - Zeitschrift für Agrarpolitik und Landwirtschaft*.

Von Schomberg, R. (2011). Towards responsible research and innovation in the information and communication technologies and security technologies fields. *Available at SSRN 2436399*.

Voss, A. L., Fischer-Tenhagen, C., Bartel, A., & Heuwieser, W. (2021). Sensitivity and specificity of a tail-activity measuring device for calving prediction in dairy cattle. *Journal of Dairy Science*, *104*(3), 3353-3363.

Wathes, C. M., Kristensen, H. H., Aerts, J. M., & Berckmans, D. (2008). Is precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall?. *Computers and Electronics in Agriculture*, *64*(1), 2-10.

Watts, J. M., & Stookey, J. M. (2000). Vocal behaviour in cattle: the animal's commentary on its biological processes and welfare. *Applied Animal Behaviour Science*, *67*(1-2), 15-33.

Weary, D. M., Niel, L., Flower, F. C., & Fraser, D. (2006). Identifying and preventing pain in animals. *Applied Animal Behaviour Science*, *100*(1-2), 64-76.

Weary, D. M., & Von Keyserlingk, M. A. G. (2017). Public concerns about dairy-cow welfare: how should the industry respond?. *Animal Production Science*, *57*(7), 1201-1209.

Welfare Quality (2009). *Assessment protocol for cattle*. Welfare Quality®.

Wenzel, C., Schönreiter-Fischer, S., & Unshelm, J. (2003). Studies on step–kick behavior and stress of cows during milking in an automatic milking system. *Livestock Production Science*, *83*(2-3), 237-246.

Wildraut, C., Meyer-Höfer, M. V., Rovers, A., Mergenthaler, M., Sonntag, W., Spiller, A., & Christoph-Schulz, I. (2019). Landwirte und Verbraucher im Dialog. In *SocialLab—Nutztierhaltung im Spiegel der Gesellschaft. Agra Europe*, *13*(19), 12-16.

Winckler, C., & Willen, S. (2001). The reliability and repeatability of a lameness scoring system for use as an indicator of welfare in dairy cattle. *Acta Agriculturae Scandinavica, Section A-Animal Science*, *51*(S30), 103-107.

Winter, A., & Hillerton, J. E. (1995). Behaviour associated with feeding and milking of early lactation cows housed in an experimental automatic milking system. *Applied Animal Behaviour Science*, *46*(1-2), 1-15.

Wise, M. E., Armstrong, D. V., Huber, J. T., Hunter, R., & Wiersma, F. (1988). Hormonal alterations in the lactating dairy cow in response to thermal stress. *Journal of Dairy Science*, *71*(9), 2480-2485.

Wolfram, J., Brümmer, N., Mergenthaler, M., & Christoph-Schulz, I. (2019). Landwirtschaftliche Tierhaltung in den Medien. *Social-Lab—Nutztierhaltung im Spiegel der Gesellschaft. Agra Europe*, *13*(19), 16-18.

Wood, A., Blackhurst, M., & Lawler, D. (2016). Social acceptance as a prerequisite for social sustainability. In *World Environmental and Water Resources Congress,* Florida, United States of America, 22-26 May, 2016 (pp. 190-196).

World Commission on Environment and Development. (1987). Our Common Future Oxford. *UK: Oxford University Press*.

Wuepper, D., Wree, P., & Ardali, G. (2019). Does information change German consumers' attitudes about genetically modified food?. *European Review of Agricultural Economics*, *46*(1), 53-78.

Yiridoe, E. K., Bonti-Ankomah, S., & Martin, R. C. (2005). Comparison of consumer perceptions and preference toward organic versus conventionally produced foods: A review and update of the literature. *Renewable Agriculture and Food Systems*, *20*(4), 193-205.

Zhen, L., & Routray, J. K. (2003). Operational indicators for measuring agricultural sustainability in developing countries. *Environmental Management*, *32*(1), 34-46.

Zin, T. T., Seint, P. T., Tin, P., Horii, Y., & Kobayashi, I. (2020). Body Condition Score Estimation Based on Regression Analysis Using a 3D Camera. *Sensors*, *20*(13), 3705.

7 Appendix

Pfeiffer, J., Gabriel, A., Gandorfer, M. (2021). Understanding the public attitudinal acceptance of digital farming technologies: a nationwide survey in Germany. Agriculture and Human Values, 38(1), 107-128. [https://link.springer.com/article/10.1007/s10460-020-10145-2] [Publisher: Springer Nature]

Agriculture and Human Values
https://doi.org/10.1007/s10460-020-10145-2

Understanding the public attitudinal acceptance of digital farming technologies: a nationwide survey in Germany

Johanna Pfeiffer[1,2] · Andreas Gabriel[1,3] · Markus Gandorfer[1]

Accepted: 21 August 2020

Abstract
The magnitude of public concerns about agricultural innovations has often been underestimated, as past examples, such as pesticides, nanotechnology, and cloning, demonstrate. Indeed, studies have proven that the agricultural sector presents an area of tension and often attracts skepticism concerning new technologies. Digital technologies have become increasingly popular in agriculture. Yet there are almost no investigations on the public acceptance of digitalization in agriculture so far. Our online survey provides initial insights to reduce this knowledge gap. The sample (n = 2012) represents the German population in terms of gender, age (minimum 18 years), education and size of place of residence. Results showed that if the potential of digital farming technologies (DFT) regarding animal welfare and environmental protection was described, respondents reacted positively. Thus, the general attitudes of respondents toward the benefits of DFT were mostly positive. The approval to increasing adoption rates of particular DFT by providing subsidies was also high. Linear regression models showed that the dominant positive influences on respondents' attitudes toward the benefits of DFT were a generally positive attitude toward farming and a strong trust in farmers in Germany. Confronting respondents with pictures showing DFT resulted in many spontaneous negative associations and general criticism of agricultural production. The latter holds true for DFT in animal husbandry in particular. However, as agriculture as a whole is criticized by many groups in Germany, it is unlikely that benefits from digitalization will significantly increase the public acceptance of agriculture as a whole.

Keywords Spontaneous associations · Precision livestock farming · Precision crop farming · Dairy · Robot

Abbreviations
DFT Digital farming technology

✉ Johanna Pfeiffer
johanna.pfeiffer@lfl.bayern.de

Andreas Gabriel
andreas.gabriel@lfl.bayern.de

Markus Gandorfer
markus.gandorfer@lfl.bayern.de

[1] Institute for Agricultural Engineering and Animal Husbandry, Bavarian State Research Center for Agriculture, Voettinger Strasse 36, 85354 Freising, Germany

[2] Technical University of Munich, 85354 Freising, Germany

[3] Chair of Economics of Horticulture and Landscaping, Technical University of Munich, Alte Akademie 16, 85354 Freising, Germany

Introduction

Public acceptance of digital farming technologies

In recent years, digitalization has found its way into agriculture and is now increasingly used in both animal husbandry and crop production. Digital farming technologies (DFT) include, for example, the application of sensors, automation, and robots in production systems (Banhazi et al. 2012; Shamshiri et al. 2018). Currently, stakeholders in the sector confirm that digitalization may increase public acceptance of agriculture because of its potential regarding animal welfare and more environmentally-friendly production. However, increased agricultural efficiency through digitalization is not necessarily accepted by the public as these technologies may also be perceived as a threat (Driessen and Heutinck 2015; Pfeiffer et al. 2019). In the past, it has been shown that innovative technologies have often been met with little or no acceptance in the public, and in some cases have even had to endure far-reaching criticism as a result (Frewer et al. 1997; Bauer 2002). Indeed, public concerns about the introduction of modern technologies, especially in the food and

Published online: 02 September 2020

agricultural system, have often been underestimated (Shaw 2002; König et al. 2010; Gupta et al. 2012). Thus, it is essential to analyse the public acceptance of innovations right at the beginning of their developmental process in order to ensure a successful implementation later on (Millar et al. 2002; Verbeke et al. 2007; Gupta et al. 2012).

Although public acceptance of DFT is of paramount importance, little research has been conducted in this area. Often, the economic and environmental impacts of farming systems are analyzed while the social component is neglected. In a recent review of the literature on digitalization in agriculture the authors concluded that the topic has gradually entered social science (Klerkx et al. 2019). Klerkx et al. confirmed that studies published so far have focused on topics such as adoption and adaptation of technologies, effects on farm work as well as ownership, privacy, and ethics in digital agriculture. However, no comprehensive studies have been listed for the research field of public perception of DFT. Nevertheless, the necessity of analyzing possible social resistance in the establishment of new technologies has been acknowledged (Stilgoe et al. 2013; Asveld et al. 2015; Rose and Chilvers 2018). Wathes et al. (2008) emphasized that new farming technologies may have a wider impact not only on farmers and animals, but also on society, which should be evaluated objectively to identify ethical issues. Along this line, Eastwood et al. (2019) pointed out that too much emphasis was placed on the development and adoption of smart farming technologies on farms while socio-ethical implications of society were neglected.

Studies on public acceptance in general provide first impressions of factors, which may also play a putative role in the public acceptance of DFT. Analyzing 292 research papers regarding determinants influencing public acceptance of technologies (e.g., pesticides, nanotechnology, cloning), Gupta et al. (2012) showed that six major determinants accounted for about 60% of all determinants mentioned: perceived risk, trust, perceived benefit, knowledge, individual differences and attitudes. In the literature, intra-personal, inter-personal, but also technology-related characteristics appear to form public acceptance of innovative food technologies (Bearth and Siegrist 2016). More precisely, Bearth and Siegrists' (2016) meta-analysis provided evidence of predictors such as socio-demographics, knowledge of food technology, trust in the regulators of the technologies, perceived naturalness of the food technology as well as risk and benefit perception. Regarding technologies in the food sector, perceived risks and benefits are often characterized as decisive determinants of public acceptance (Ronteltap et al. 2007; Gupta et al. 2012; Bearth and Siegrist 2016). If the public associates too little benefit with a technology, the fundamental need for an innovative technology is called into question (Gaskell 2000). Communicable, perceived benefits that increase the potential for public acceptance of a new technology can be triggered, for example, by a reduction in the final product price or an increase in product health (Spence and Townsend 2008). At present, there is only superficial knowledge of the publicly perceived risks and benefits of DFT, and even less knowledge of their influence on public acceptance.

Some studies investigated the public acceptance of agriculture and modern farming in general (e.g., Sharp and Tucker 2005; Boogaard et al. 2011a; Kühl et al. 2019), new agrifood technologies such as genetic engineering or nanotechnology (e.g., Frewer 2017), renewable energy innovations (e.g., Devlin 2005; Wüstenhagen et al. 2007; Stiehler 2015), and novel agricultural production methods in and on urban buildings (Specht et al. 2016). In the context of agriculture and modern farming, research on public acceptance has focused on individual aspects of animal husbandry such as animal welfare (e.g., Kendall et al. 2006; Deemer and Lobao 2011). Public concern about animal welfare is mainly associated with modern animal husbandry and, in particular, with increasing farm sizes as shown by studies in North-West Europe and the US (Bennett 1997; Winter et al. 1998; Sharp and Tucker 2005; Boogaard et al. 2011a). A study conducted by Boogaard et al. (2011a) revealed that modern dairy farming is viewed critically by Dutch society as it is associated with a loss of family farms and growing herd sizes, and thus contradicts the desired image of dairy farming. Here, modern dairy farming was considered as a whole, with no focus on specific innovations or technologies. The survey of Boogaard et al. (2011a) provided evidence that public acceptance of modern dairy farming (e.g., farm practices, farm animals) is determined by the following factors: values and convictions, knowledge, relation to agriculture regarding explicit working experience and farm visits, and socio-demographics. This relationship is supported by Sharp and Tucker (2005) who analyzed public opinion about large-scale livestock farming using livestock welfare concern and livestock environmental concern as target variables. Their survey among inhabitants of the US state of Ohio revealed an influence of socio-demographics, physical and social distance from agriculture, agricultural attitudes, and trust in farmers.

Further studies on the public acceptance, without a focus on agriculture, provide additional information on possible influencing factors. In the field of renewable energy, research has been carried out on the public acceptance of new technologies such as biomass plants or wind turbines, revealing an influence of factors such as socio-demographics, knowledge, working experience in the sector, trust in key actors, perceived benefit and costs, and general attitudes (e.g., toward environmental protection) (Devlin 2005; Devine-Wright 2008; Stiehler 2015).

Even technological developments overlapping with other industries such as autonomous driving find little attention in agricultural literature. While the public acceptance of autonomous driving has already been researched in the automotive industry (e.g., Fraedrich and Lenz 2016), the public acceptance of autonomous machines for agricultural practice have never been studied in-depth. A recent study carried out across the EU provided information on public attitudes toward robotics as one of several technological developments in digital agriculture. In general and regardless of the field of application, a majority (70%) of EU citizens indicated to feel positive about robotics. While the positive attitude toward robotics varied between individual countries, ranging from 54 to 88%, German respondents showed a general positive attitude (69%) toward the application of robotics in agriculture. In the study, the majority of all respondents (88%) agreed with a need for robotics for dangerous work previously carried out by humans (Eurobarometer 2012). However, as the acceptance of autonomous vehicles in general draws a heterogeneous picture, with skepticism certainly being present, the public's attitude toward autonomous agricultural machinery remains to be investigated.

Considering the above cited studies, public acceptance has been studied with regard to various agricultural topics. However, with regard to DFT specifically, the findings were limited to the milking robot so far. As the milking robot is one of the first autonomous machines in dairy farming, it has been the subject of analyses on social aspects of technologies in dairy farming. However, the focus in this respect is mostly on animals and farmers, covering topics such as human-animal-technology interaction or impacts on animal welfare (e.g., Wenzel et al. 2003; Holloway et al. 2014; Driessen and Heutinck 2015), neglecting the overall social perspective. In their study on consumer attitudes toward the use of dairy technologies, Millar et al. (2002) demonstrated social concerns about DFT in terms of the milking robot, as only 39.3% of participants of a UK postal survey rated the milking robot as "ethically acceptable" and only roughly 30% would have welcomed its use in practice. In addition to the questionnaire, a short description of the milking robot was provided to the participants. Apart from demographic and household information as well as awareness of the technology, only little information on further factors possibly influencing the acceptance was included in the study (Millar et al. 2002).

In summary, so far results of the existing literature have shown that agriculture is certainly situated in an area of social tension. However, it is unclear to what extent the public accepts new DFT in different fields of application and whether concerns will potentially lead to future public debates.

Research methods and concept of acceptance

Modern acceptance research comprises a multitude of approaches to a variety of research objects (e.g., consumer products, technologies, political decisions). Many of these objects are judged by people in their roles as users, consumers, or citizens. Accordingly, the literature provides a plethora of characterizations for numerous concepts of acceptance, which differ not only in extent (individual, group attitude), level of observation (specific, general), and detectable effects. The term acceptance itself also has a versatile character. Endruweit (1986) defined the goal of acceptance research as determining the probability of a positive reaction to a certain stimulus. Thus, acceptance can be seen as the result of an interaction process (Hofinger 2001), as the adoption of an object or idea (Dethloff 2004) or as the mere allegorization of an opinion expressed at a certain point in time (Lucke 1995).

It turns out that several studies apply a purely attitude-based understanding of acceptance, as *public attitude* is used as a measure of advocacy or rejection in public (e.g., Devine-Wright 2008; Amin et al. 2011) and attitude-oriented approaches are used to survey opinions on technologies in the population. Schäfer and Keppler (2013) noted that an attitude-oriented understanding of acceptance may also include intention or willingness to act, but not action itself (see Lucke 1995). They considered several studies on acceptance and concluded that the majority that treats acceptance as a comprehensive construct includes not only an attitude component but also an action component (see e.g., Huijts et al. 2012).

Our research approach to determine public acceptance leans on the acceptance process described by Kollmann (2004), who based his studies about the acceptance process of innovative consumer products on three subsequent behavioral phases. He determines the first phase in the acceptance process as the attitude toward a product prior to purchase or use (assessment phase). The second phase in the acceptance process is described as action phase and is characterized by the purchase and adoption of a product. Building on the first two phases, the use phase of the purchased product follows as the third phase and is understood as completion of the acceptance process.

When looking at new technologies that directly benefit separate groups (farmers, animals) and only indirectly affect the respondent personally (e.g., through health benefits and quality of life, improving animal welfare, preservation of the natural environment), it is difficult to determine public acceptance, as is the case with DFT. Therefore, we do not analyze acceptance as a complete construct including a use phase, but follow the approach of attitude-oriented acceptance research and measure the first phase of

Kollmann's acceptance model (attitude); hence the term *attitudinal acceptance*.

The focus in acceptance research was on the cognitive component for a long time, but the relevance of affect in decision making has gradually been recognized. It has been postulated that relying solely on cognitive components is not effective (see Mowrer 1960; Shafir et al. 1993). Initially it was unclear whether attitudes are also directly influenced by non-cognitive factors. Over time, however, studies have increasingly shown that affect can be independent of cognitive structures and thus influences attitudes directly (Onur Bodur et al. 2000). People give affective responses rapidly and automatically, thus representing spontaneous, rather than deliberate, associations. They express an emotional state and reflect a negative or positive stimulus that may be connected to pictures created in the mind. Reliance on such feelings is described as the "affect heuristic" (Collier 1957). People rely on their "affective pool", which contains both positive and negative connotations. Regarding affects, people refer to events in the past that have remained in their memory, including emotional states associated with them (Zajonc 1980; Epstein 1994; Finucane et al. 2000; Slovic et al. 2007; Spence and Townsend 2008). According to Slovic et al. (2007), incorporating affective impressions is easy and efficient, especially when the assessment is complex or knowledge is limited, as is the case with DFT.

Although the majority of studies described above rely on quantitative approaches, methods of acceptance research go far beyond quantitative analyses. As qualitative research approaches can make a valuable contribution to measuring acceptance, they are increasingly being used on agricultural topics to clarify a wide range of questions regarding the acceptance of agriculture. To measure acceptance, pictures and videos have already been used to stimulate spontaneous associations of survey respondents (Harper 2002; Kühl et al. 2019). Media, such as pictures, can evoke "affective resonances" (Shouse 2005) as well as being "repositories of feelings and emotions" (Cvetkovich 2003). Thus, affect and emotions are elicited by the targeted use of media. Suchar (1989) described the revealing of aspects of "social psychology" as one of the reasons for the application of photo-elicitation. Especially in comparison to a purely text-based survey, the benefits of photo-elicitation are the stimulation of latent memory, the awakening of deeper elements of human consciousness and the release of emotional statements, thus eliciting additional information (Collier 1957; Harper 2002; Richard and Lahman 2015). Analysis of elicited emotions, in addition to assessing given statements, serves to capture determinants of attitudes and acceptance such as risk perception (Sjöberg 2007; Gupta et al. 2012).

Research fields

In the current context of agriculture as a field of social tension, questions arise regarding the extent to which a use of modern DFT will be supported by the public as a whole. We conducted a survey among the German public to gather insights into their opinion on the digitalization of farming. To better elucidate the opinion of respondents, we employed a mixed method approach, as recommended by Weary and Keyserlingk (2017). The following research fields (1), (2) and (3) were queried by Likert scales to gain information on the public attitudinal acceptance of DFT (quantitative approach). For research field (4), a qualitative approach was employed including spontaneous associations with pictures showing specific DFT.

(1) General attitudes of respondents toward the use of DFT and evaluation of the effects of DFT on farmers, consumers, animal husbandry and crop production. Respondents' consent to the use of selected DFT in animal husbandry- and crop production-practice.
(2) Extent of the respondents` agreement to a provision of a state subsidy to farmers as a means to disseminate DFT in practice.
(3) Influence of the factors *socio-demographics, connection to agriculture, knowledge of present-day agriculture, trust in farmers*, and *general attitudes toward farming* on the attitudinal acceptance of DFT.
(4) Respondents' spontaneous associations with pictures showing specific DFT to gain first insights into concerns and benefits being associated with the technologies.

Materials and methods

Empirical model to measure public attitudinal acceptance of digital farming technologies

We developed a specific model to evaluate the public attitudinal acceptance of various DFT and to detect the relevant factors responsible for shaping these attitudes. An online survey was elaborated to collect first-time empirical data from a representative sample of the German adult population.

According to Kollmann (2004), the attitude toward a product (assessment phase) is composed of awareness, interest, and expectations. Addressing the subordinate indication of consumer expectations and assessment of the use of a new technology, we measured the general attitudes toward the benefits of DFT, the consent to the use of DFT,

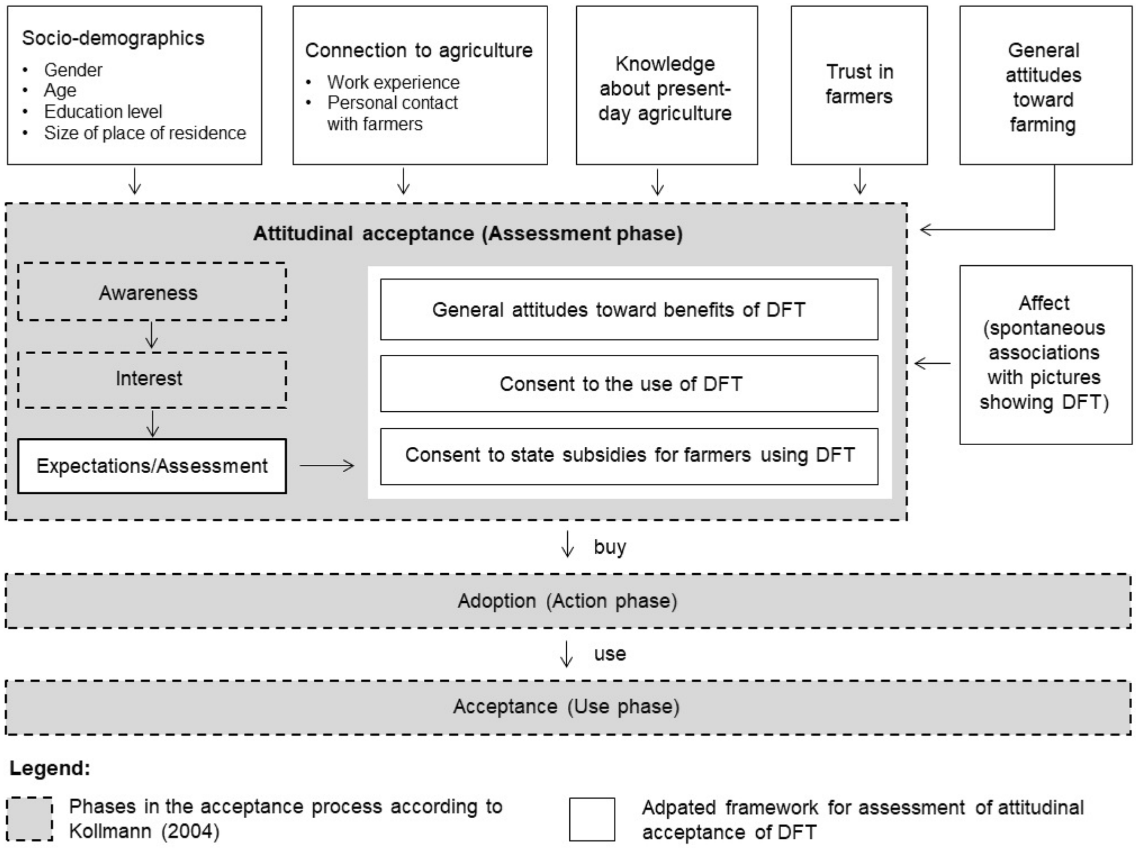

Fig. 1 Framework for measuring acceptance. Adapted from Kollmann (2004). *DFT* digital farming technology

and the consent to state subsidies for farmers using DFT as target variables of attitudinal acceptance (see Fig. 1). The two other phases in Kollmann's acceptance model relate to the decision and final use of the new technology. Since in our case the population does not purchase and use the technology itself, but chooses the products resulting from it, an investigation that goes beyond attitudinal acceptance was omitted.

Questionnaire structure

In the first part of the study, information on consumers' socio-demographics was gathered and Likert scales were applied to assess attitudes toward DFT. Relevant literature on thematically similar acceptance studies was used to compile the influencing factors and scale items included. Based on the review by Gupta et al. (2012), we used the determinants described as the most relevant ones of public acceptance of technologies to gain information about influences on the attitudinal acceptance of DFT. In our model, individual differences were covered as the factors *socio-demographics* and *connection to agricultural sector*. Knowledge, trust and attitudes are further determinants of public acceptance of technologies integrated into the model (see Gupta et al. 2012). We queried them as the factors *knowledge of present-day agriculture, trust in farmers,* and *general attitudes toward farming*. To measure both latent predictors and target variables for the objectives on the analysis, Likert scales were used as essential components. To prevent skewed results due to certain answering patterns, the order of the items in each of the surveyed scales was randomly distributed for each respondent. In a further part of the questionnaire, photo-elicitation was used to gather spontaneous associations with pictures showing different DFT. Scale items from the first survey part do not allow us to identify reasons that are seen by the public as promoting or inhibiting attitudinal acceptance of DFT. Therefore, we applied photo-elicitation as a second methodological approach to elicit affect-based thoughts from the respondents.

Socio-demographics and quota control

Based on recent studies, socio-demographics were expected to potentially play a role in the attitudinal acceptance of DFT (Haartsen et al. 2003; Sharp and Tucker 2005; María 2006; Devine-Wright 2008; Boogaard et al. 2011a). Therefore, we evaluated the socio-demographic distribution of the survey sample by assessing four variables: age, gender, education and size of place of residence. Regarding the size of place of residence, we included three categories, due to the hypothesis of different rural–urban attitudes toward agriculture and environmental issues (Van Liere and Dunlap 1980; Freudenburg 1991; Sharp and Tucker 2005; Boogaard et al. 2011a). The categories of the variables were classified on the basis of official population statistics and literature-based considerations. This resulted in the classification of the variables of age (five categories, minimum 18 years), education (five categories), size of place of residence (three categories), and gender (two categories).

Connection to agricultural sector

In addition to socio-demographics, contact with agriculture or farmers can have an impact on the respondents' acceptance of agriculture and of innovative technologies specifically (Devlin 2005; Sharp and Tucker 2005; Delezie et al. 2006; Devine-Wright 2008; Boogaard et al. 2011a). Personal contact with farmers in the social environment, exchange about agricultural topics, or professional experience in the areas of agribusiness and food supply allows people to gain expertise and consolidate points of view. Therefore, we included scales on work experience in the agricultural sector and on personal contact with a farmer as independent variables. Within the scale of personal contact with a farmer, we differentiated whether or not conversations also covered agricultural topics.

Predictors from Likert scales

General attitudes toward the subject context may transpire to be an acceptance-relevant factor or a basic prerequisite for acceptance (Lucke 1995; Grunert et al. 2003; Kollmann 2004). In our study, the scale *general attitudes toward farming* was rated via five items. Since public acceptance may be determined by inherent characteristics of technologies as well as by their impact on humans, nature and animals, the items refer to relevant topics confirmed in previous studies to be decisive regarding public acceptance. Since these aspects were rated by the majority of respondents in the study by Boogaard et al. (2011a) as desired image of agriculture, the two items "Preservation of the environment for future generations" and "Welfare of farm animals is important" were included in the scale of our survey. Additionally, the item "I have a fundamentally positive attitude toward agriculture in Germany" was integrated, following previous results of scale measurement of consumer attitudes toward livestock welfare and environmental concerns (Sharp and Tucker 2005) and toward the use of renewable energies in the direct environment (Stiehler 2015). As the support of small farming structures was positively associated with livestock welfare concerns and environmental concerns in the study by Boogaard et al. (2011a), we included the item "Family farming structures seem valuable and should be preserved" as an item on the scale. As a further item, "Farmers should get more free time" was added. The scale was supplemented by three additional items to quality-check participants' response behavior after completion and the plausibility of the answers. These additional items were not included in the analysis.

Since knowledge can be a decisive determinant of the public acceptance of a new food technology (Bearth and Siegrist 2016) it was included in our model. According to Te Velde et al. (2002), the construction of perceptions in individuals is influenced by factors such as experience- and impression-based knowledge. Along this line, a survey by Stiehler (2015) found supportive empirical evidence, revealing that public acceptance of biomass cogeneration heat (and power) plants significantly depended on the degree of information in this field. However, a review on public acceptance of renewable energy technologies by Devine-Wright (2008) has suggested that a higher level of knowledge is not necessarily correlated with higher public acceptance. Whether there is a connection between the level of knowledge of present-day agriculture and the public acceptance of DFT is, to date, unclear. Therefore, the analysis of the relationship between knowledge of agricultural processes and public attitudinal acceptance of DFT can provide initial indications as to whether providing information on agriculture can influence public attitudinal acceptance of DFT. In our study, cognitive knowledge, in terms of having knowledge of a fact, was assessed by the scale *knowledge of present-day agriculture*. Survey respondents were asked to self-assess their level of knowledge on animal husbandry, crop production and modern agricultural equipment.

Besides the *general attitudes toward farming* and *knowledge of present-day agriculture* scales, the scale *trust in farmers* was included in the model. Studies on the acceptance of new technologies often focus on inherent characteristics of technologies, although several studies provide solid empirical evidence that trust in the user of a new technology is also a crucial influencing factor in public acceptance (Dunlap et al. 1993; Slovic 1993; Cvetkovich and Lofstedt 1999; Eiser et al. 2002; Roosen et al. 2015; Stiehler 2015; Bearth and Siegrist 2016). Siegrist et al. (2000) explicitly described trust as "social trust", i.e. relying on people who are in charge of handling a technology, and emphasized that the group of people being trusted is usually not known personally. Especially when one's own knowledge and interest in a technology is limited, trust in people using the technology appears all the more relevant (Siegrist et al. 2000; Bearth and Siegrist 2016). Wüstenhagen et al. (2007) illustrated public acceptance of renewable energy innovation as a triangle, consisting of the three dimensions of socio-political, market, and community acceptance, of which the latter represents a central component of trust. In addition, Sharp and Tucker (2005) demonstrated that elevated trust in farmers is associated with less concern about livestock welfare and environmental aspects of large-scale livestock and poultry operations. To take social trust into account, we surveyed the items "German farmers pay great attention to the welfare of their animals" and "German farmers protect our environment".

Target variables from Likert scales

Since digitalization in agriculture is per se an abstract topic for many of the respondents, we introduced them to DFT by means of some general information and the presentation of examples of DFT. Four individual DFT were illustrated and briefly explained in the questionnaire as specific examples: spot spraying (selective application of pesticides in crop production), digital hoeing (alternative chemical weed control), near-infrared spectroscopy (NIR) sensor technology (measuring nutrient content in manure), and sensors for animal husbandry (early detection of problems and diseases in animals in livestock farming). Respondents gave their approval or disapproval on five-point Likert scales. The scale *general attitudes toward the benefits of DFT* was used to assess public acceptance of DFT on a general level. The rating of DFT was conducted not only at a general level, but also at a technology-specific level. With regard to each of the four specific DFT mentioned, the respondents stated their level of *consent to the use of specific DFT* and their level of *consent to state subsidization for farmers using DFT* as target variables.

Spontaneous associations with digital farming technologies

In the second part of the online survey, respondents were asked for voluntary spontaneous associations with pictures showing DFT. For animal husbandry, pictures of a cow during the milking process in a milking robot and of cows in a barn being fed by a feeding robot were selected.[1,2] For crop production, pictures of an autonomous tractor and of a swarm of small robots, both during the sowing process on the field, were shown.[3,4] We deliberately chose pictures of these four technologies from the internet to obtain feedback on widespread media-based pictures of DFT. For each of the two digital technologies in dairy farming and crop production, up to three spontaneous associations could be stated. Survey participants were not given any additional information about the respective pictures. The spontaneous associations helped to identify further reasons for attitudinal acceptance of DFT (or a lack thereof).

While the rating of given statements with Likert scales in the first part of the questionnaire served to provide a cognitive evaluation of DFT by the respondents, the affect- and thus emotion-based approach provided another dimension of determining attitudinal acceptance, as cognitive and emotional responses do not necessarily align. As emotions serve to capture risk perception, the spontaneous associations were supposed to obtain initial indications of the risks and benefits that respondents associate with some examples of DFT. This should pave the way for further analyses of perceived benefits and risks in order to optimize communication with the public on the subject of DFT.

Data collection: nationwide online-survey

The questionnaire was handed to a professional field service provider with an extensive nationwide online consumer panel, thus facilitating sample determination (German residents aged at least 18 and with internet access) and enabling a pre-set quota control of the sample for representativeness regarding selected socio-demographics. For representative evaluation of the German adult population in terms of age, gender, education level, and size of place of residence, statistical data from the "b4p- Best for planning 2017" dataset were used to pre-select the quota in this survey. b4p is a long-term market media study program in Germany that has been analyzing media use and consumer behavior (random sample of more than 30,000 participants older than 13 years) since 2013. This enables target group-specific distribution quotas via queries at associated counting services.

In 2018, 90% of the German population used the internet, with the proportion of internet users being lowest among the older generations (Federal Statistical Office Germany (Destatis) 2018a). However, as our sample is representative in terms of age, we can ensure that age groups are covered by the respective shares of the entire sample (see Table 1). Collecting data online enabled us to obtain a large and geographically distributed sample within a short time, thus saving time and costs (see also Stanton 1998; Ilieva et al. 2002; Lefever et al. 2007). Nevertheless, it can be critically noted that our survey on digital technology only addressed people who are familiar with the internet.

Furthermore, choosing an online survey as data collection method enabled an adaptive course of the survey, depending on the information provided by the interviewees, and therefore an effective and user-friendly procedure. The integration

[1] https://www.schweizerbauer.ch/landtechnik/firmen--personen/20000-melkroboter-von-lely-in-betrieb-19341.html (accessed on June 15, 2018).

[2] https://melktechnik-center.com/Fuetterungstechnik/FMR-Roboter/ (accessed on 15 June, 2018).

[3] https://www.caseih.com/emea/de-at/News/Pages/2016-08-30-Case-IH-stellt-auf-der-Farm-Progress-Show-neues-Traktorkonzept-vor.aspx (accessed on June 15, 2018).

[4] https://www.fendt.com/int/fendt-mars (accessed on June 15, 2018).

Table 1 Socio-demographic distribution of survey sample (n = 2012)

	Variable	Category	Absolute frequency	Relative frequency (%)
Socio-demographic characteristics	Gender[a]	Female	1011	50.2
		Male	1001	49.8
	Age[a]	18–29 years old	340	16.9
		30–39 years old	364	18.1
		40–49 years old	395	19.6
		50–59 years old	459	22.8
		60 years and older	454	22.6
	Size of place of residence[a]	Less than 5000 inhabitants	284	14.1
		5000 to 99,999 inhabitants	1075	53.4
		100,000 and more inhabitants	653	32.5
	Education level[a]	No general school-leaving qualification (yet) or basic secondary school[b] without vocational qualification	94	4.7
		Basic secondary school[b] with vocational qualification	487	24.2
		Higher secondary school-leaving qualification[c] or upper secondary school[d]	686	34.1
		University entrance qualification[d] without university degree	327	16.3
		University degree (university, college, technical college, academy, polytechnic)	418	20.8
Connection to agricultural sector	Work experience	Work experience in agricultural sector	165	8.2
		No work experience in agricultural sector	1847	91.8
	Personal contact with farmers	Yes, with conversations about agricultural topics	387	19.2
		Yes, without conversations about agricultural topics	285	14.2
		No	1340	66.6

[a]Representative distribution of the German population according to b4p dataset 2017 (German residents over 18 with permanent access to the internet)

[b]Basic secondary school (*Mittelschule*), leading to basic school-leaving qualification (*Qualifizierender Abschluss*)

[c]Higher secondary school (*Realschule*), leading to higher school-leaving qualification (*Mittlere Reife*)

[d]Upper secondary school (*Gymnasium*), leading to University entrance qualification (*Abitur*)

of additional information (short information on the purpose and function of specific DFT) and visual material (pictures showing selected DFT) into the online questionnaire supported the conduct of the survey and provided more clarity to the respondents for better responsiveness. The online questionnaire was pre-tested by a subsample of the online panel of 10% of the desired total sample size concerning comprehensibility and technical procedure of the survey. Subsequently, the main survey was carried out from July 13 to 23, 2018. In total, more than 4,000 online interviews were initiated, with 2215 completely answered data sets remaining due to lack of target group affiliation or quota fulfilment. After final quality control, 2012 data sets could be used for the analysis.

Analyzing methods

In order to use the individual scales for further calculations, homogeneity and internal consistency of the overall constructs (scales) and reliability of the items were checked by Cronbachs α (Cα).[5] Using the Spearman-Brown test, the contribution of each item to scale reliability could be determined to obtain the overall scale quality and, if necessary,

[5] While Cα test values above 0.7 are assumed to be acceptable (“acceptable” ≥ 0.7, “good” ≥ 0.8, “excellent” ≥ 0.9), measures below this limit cast doubt on the homogeneity of the scale (“questionable” < 0.7, “poor” < 0.6, “unacceptable” < 0.5) (see Field 2017).

to decide whether individual items should be excluded from a scale (Field 2017).

Reliability analyses can be equated with a confirmatory one-dimensional factor analysis, allowing for the assignment of an individual, metric-scale value (factor value) to each data set. The metric values for each of the scales were applied in the subsequent multivariate regression model to identify their impacts on respondents' attitudes concerning DFT, consent to the use of specific DFT, and consent to a state subsidy for DFT. Further predictor co-variables (socio-demographics, respondents' connection to agricultural sector) were dummy-coded and added to the three linear regression models.

Regarding the spontaneous associations affected by the respective pictures of DFT, statements not suitable for evaluation (e.g., "I have no idea", "I don't know") were removed from the data set. After that step, depending on the specific technology, 3982 (swarm robots), 4035 (feeding robot), 4397 (autonomous tractor), and 4649 (milking robot) associations were included for further analysis. Categories including similar terms and expressions were formed allowing a categorization of associations. Nine categories were applicable to all shown technologies (e.g., *Future and Progress*). Besides, the formation of five animal- (e.g., *Animal Cruelty*) and seven crop-specific (e.g., *Concerns for Environmental Protection*) categories was necessary. For illustrating the result of the analysis, the ten categories most frequently associated with each of the four pictures, respectively, were compiled. Within each category, the connotation of the individual associations was evaluated as negative ("−"), neutral ("0") or positive ("+"). If associations with different connotations were found in a category, multiple connotations were assigned. By assigning connotations, our approach resembles that of Kühl et al. (2019), who categorized associations with pictures of different husbandry systems for dairy cattle and classified them as negative or positive.

Results

Socio-demographic distribution and connection to agriculture of survey sample

The distribution of the survey sample (n = 2012) represents the German population with regard to the socio-demographic characteristics of gender, age (minimum 18 years), size of place of residence, and level of education (see Table 1). With regard to their connection to agriculture, 8.2% of respondents stated that they have some work experience in the agricultural sector, while 91.8% have none. 19.2% of respondents know a farmer and discuss agricultural topics with him or her, while 14.2% of respondents know a farmer with whom they do not talk about agricultural topics, however (Table 1).

Descriptive analysis of response scales

The response scales concerning general attitudes toward farming, knowledge of present-day agriculture as well as trust in farmers were used as predictors for the subsequent multivariate evaluation (independent variables). The scales concerning general attitudes toward the benefits of DFT (D1), consent to the use of specific DFT (D2), and consent to a state subsidy for farmers using DFT (D3) represent the dependent variables. The results of the individual items of the scales are expressed as mean values and standard deviations (Table 2). The responses range between the scale poles of "1 = I fully agree" and "5 = I fully disagree", or "1 = very high", and "5 = very low" for the scale of knowledge of present-day agriculture. The literature-based selection of the items provided "acceptable" to "excellent" quality criteria of the composed scales.

General attitudes toward farming, knowledge, and trust in farmers

The general attitudes toward farming-scale revealed that values linked to agriculture play a relevant role. The preservation of the environment for future generations ($\mu = 1.55$), family farming structures ($\mu = 1.64$), and welfare of farm animals ($\mu = 1.65$) are valued most highly by respondents. On average, respondents indicated that they have a fundamentally positive attitude toward agriculture in Germany ($\mu = 2.06$) and that farmers should get more free time ($\mu = 2.11$). Respondents rated their knowledge of present-day agriculture as mediocre to rather low. In particular, the self-assessment covered production methods in animal husbandry processes ($\mu = 3.33$), crop production ($\mu = 3.53$), and the latest machinery and equipment used in agriculture ($\mu = 3.57$). For all three items of this scale, a substantial proportion of respondents indicated to have very good or good knowledge of present-day agriculture (13.6%, 20.3%, and 12.6%, respectively). Considering that 8.2% of the respondents claimed to have work experience in the agricultural sector, these proportions are high. It is interesting to note that especially those respondents who stated that they have already personally talked to farmers about agricultural issues also claimed a significantly higher level of knowledge of present-day agriculture (T value 20.67; $p = 0.000$) compared to those who have no contact with acquaintances in this sector. This also applies to those respondents who already had their own experiences in the agricultural sector, as opposed to those who have never been in contact with agriculture (T value 12.59, $p = 0.000$).

Table 2 Scales for independent and dependent (D) variables (n = 2012)

Scales *Scale reliability*[a]	Items	Mean (μ)[b]	*SD*
General attitudes toward farming *Cα = 0.72*	Preservation of the environment for future generations	1.55	0.72
	Welfare of farm animals is important; this influences my actions	1.65	0.74
	Family farming structures seem valuable and should be preserved	1.64	0.74
	I have a fundamentally positive attitude toward agriculture in Germany	2.06	0.83
	Farmers should get more free time	2.11	0.78
Knowledge of present-day agriculture *Cα = 0.90*	Knowledge of animal husbandry processes	3.33	1.03
	Knowledge of production methods in crop production	3.53	0.99
	Knowledge of the latest machinery and equipment used in agriculture	3.57	0.99
Trust in farmers *Cα = 0.80*	German farmers pay great attention to the welfare of their animals	2.73	0.90
	German farmers protect our environment	2.77	0.89
General attitudes toward the benefits of DFT (D1) *Cα = 0.75*	Bring farmers and consumers closer together	2.80	0.92
	Enable a more environmentally-friendly production	2.31	0.82
	Lead to the alienation of the farmer from his soil and animals[(−)]	2.91	1.01
	Improves the quality of life of the farming family	2.10	0.76
	Improves animal welfare and animal health	2.39	0.87
Consent to the use of specific DFT (D2) *Cα = 0.76*	Digital hoeing technology	1.82	0.88
	Sensors for livestock farming	1.92	0.88
	NIR sensors for organic fertilization	1.96	0.89
	On-field spot spraying	2.22	1.00
Consent to state subsidization for farmers using DFT (D3) *Cα = 0.85*	State subsidization of digital hoeing technology	2.09	1.02
	State subsidization of sensors for livestock farming	2.16	1.03
	State subsidization of NIR sensors for organic fertilization	2.28	1.04
	State subsidization of spot spraying	2.36	1.07

DFT digital farming technologies

[a]Cronbach's α (Cα) of full-item scale

[b]5-point scale: minimum 1 = I fully agree/very high; 3 = undecided/mediocre; maximum 5 = I fully disagree/very low

[(−)]Original question with negative polarization; Cα and mean refer to *ex-post* reversion of item

As a third scale, trust in farmers in Germany was surveyed, which, in contrast to the general attitudes, dealt directly with information on the applied practice of farmers. The results revealed that trust in farmers was rated less positive than the general attitudes toward farming indicated. The agreement that German farmers pay great attention to the welfare of their animals (μ = 2.73) and protect our environment (μ = 2.77) in their practice was modest. For the two items, a high proportion of undecided respondents (44.2%, and 45.4%, respectively) emerged.

Attitudes toward the benefits of digital farming technologies (D1, D2, D3)

Regarding the general attitudes toward the benefits of DFT (D1), respondents primarily saw an improvement in the quality of life of the farming family through relieving the farmer (μ = 2.10). More environmentally-friendly production (μ = 2.31) and improvement of animal welfare and animal health (μ = 2.39) were seen as further areas of potential benefits from DFT. The respondents' agreement that DFT bring consumers and farmers closer together was only moderate (μ = 2.80). Likewise, a high share of undecided respondents (23.0% to 44.3%) was found for all items on this scale.

The overall consent to the use of sensors for livestock farming, digital hoeing technology, NIR sensors for organic fertilization, and spot spraying (D2) was very high. The mean values for the agreement to their use ranged from μ = 1.82 to μ = 2.22, with 63.0% to 78.3% of the respondents fully agreeing or agreeing. The consent to the use of spot spraying, however, was markedly lower than that of the other three DFT. Not only was the consent to the use of the DFT in practice high, but also the consent to a state subsidy for farmers using DFT (D3). Here, the averages ranged from

Table 3 Determinants for peoples' attitudes concerning digital farming technologies (n = 2012)

Independent variables[b]	Dependent variables (standardized coefficients)		
	Model D1 General attitudes toward benefits of digital farming technologies	*Model D2* Consent to the use of specific digital farming technologies	*Model D3* Consent to state subsidies for farmers using digital farming technologies
Constant	0.045	0.138	– 0.028
Scales variables (metric scaled)			
General attitudes toward farming	0.183***	0.298***	0.308***
Knowledge of present-day agriculture	0.116***	0.044[a]	0.030
Trust in farmers	0.385***	0.097***	0.237***
Socio-demographics (dummy-coded, standardized)			
Gender (1 = male)	0.096*	0.177***	– 0.076[a]
Age (1 < 40 years)	– 0.011	– 0.018	0.154***
Education level (1 = *university entrance qualification or higher*)	0.063	0.205***	– 0.061
Size of place of residence (1 ≤ 5000)	– 0.055	– 0.108[a]	– 0.080
Connection to agricultural sector (dummy-coded, standardized)			
Work experience in agricultural sector (1 = yes)	– 0.201**	– 0.179*	– 0.114
Personal contact with farmers & discussion about agricultural topics (1 = yes)	0.006	0.029	– 0.001
R	0.497	0.363	0.443
R^2-adj	0.244	0.128	0.193

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

[a]$p < 0.1$

[b]Testing on multicollinearity shows independence between predictors

$\mu = 2.09$ to $\mu = 2.36$, with 59.5% to 66.7% of the respondents fully agreeing or agreeing, depending on the technology. Again, spot spraying experienced the lowest approval and digital hoeing technology the highest. The statistics showed significantly higher consent to state subsidization of digital hoeing technology and sensors for livestock farming than to NIR sensors and spot spraying.

Determinants for peoples' attitudes concerning digital farming technologies

The linear regression models revealed influence of the independent variables (socio-demographics, connection to agricultural sector, general attitudes toward farming, knowledge of present-day agriculture, trust in farmers) on the dependent variables (digitalization in agriculture models D1, D2, and D3) (Table 3). The main influences on respondents' attitudes toward the benefits of digitalization in agriculture appeared to be general attitudes toward farming as well as trust in farmers. With more positive general attitudes toward farming, the respondents' general attitudes toward the benefits of DFT (D1) were more positive, and the consent to the use of specific DFT (D2) and to state subsidy for farmers using DFT (D3) was increased. This positive influence on D1, D2, and D3 applied equally to the trust in farmers-scale. It turned out that there were further independent variables influencing the attitudinal acceptance of DFT, but their influence was comparatively low. Respondents who claimed to have better knowledge of present-day agriculture had significantly more positive general attitudes toward the benefits of DFT (D1). There was evidence of a statistically significant influence of gender on the agreement to DFT (D1 and D2). Men had slightly more positive general attitudes toward the benefits of DFT (D1), and their consent to the use of specific DFT (D2) was slightly increased compared to women. In terms of age, it appeared that consent to state subsidy for farmers using DFT (D3) was higher among younger respondents (age classes under 40 years). With higher education (university degree and university entrance qualification without university degree), the consent to the use of specific

Table 4 Partial correlations (Pearson correlation coefficient) between dependent variables

	D1	D2	D3
D1	1	0.478**	0.457**
D2	0.478**	1	0.602**
D3	0.457**	0.602**	1

D1 General attitudes toward the benefits of digital farming technologies; D2 Consent to the use of specific digital farming technologies; D3 Consent to state subsidy for farmers using digital farming technologies

**Correlation at the level of 0.01 (2-sided) significant

DFT (D2) was significantly higher. For the size of place of residence, no significant effect on the attitudes toward digitalization in agriculture could be shown. Respondents claiming to have worked in the agricultural sector had more negative general attitudes toward DFT (D1) and showed less consent to the use of specific DFT (D2). However, the results did not reveal any impact of work experience on the general consent to a state subsidy for farmers using DFT. The three models that address digitalization in agriculture do not show a statistically significant correlation with personal contact with farmers (with and without conversations on agricultural topics).

In addition to the regression model results, partial correlations among the three dependent study variables provide information about their coherences (Table 4). A highly significant positive correlation was found between the consent to the use of the four selected DFT (D2) and the consent to state subsidies of their use in agricultural practice (D3). They are closely linked due to the respective questions being placed consecutively for each technology in the survey. A significant correlation, however, could also be found between these two variables and D1 (general attitudes toward the benefits of DFT), confirming the reliability of the results and the successful choice of measurement methods.

Spontaneous associations with pictures showing digital farming technologies

The ten most frequent aggregate categories of spontaneous associations with the pictures showing specific DFT in crop production and dairy farming are shown in Table 5. Categories that could be formed with all four pictures are *Future and Progress; Efficiency and Reduced Workload; Technology; Digitalization, Autonomy and Automation*; *Industrial agriculture/Size dimension; Costs of Technology; Farmer; Terms of Agreement* and *Terms of Rejection*. Animal-specific categories included *Dairy Farming/Milking*; *Cow*; *Hygiene; Animal Cruelty; Agriculture.* Crop-specific categories included *Field Cultivation*; *Nature and Plants; Environmental Protection*; *Concerns for Environmental Protection; Animal Protection; Safety; Human Health.*

The positively connoted category *Future and Progress* appeared for each picture, as respondents assigned attributes such as “futuristic” or “innovative” to each of the presented technologies. Another frequent category was increased *Efficiency and Reduced Workload* for the farmer by means of DFT. In this regard, a high number of respondents stated terms such as “effective”, “fast”, and even “higher precision” of agriculture (for example, in the distribution of feed in the barn). However, as “loss of jobs” was also mentioned several times in this category, the overall rating is mainly positive, but also partially negative. Neutral categories such as *Digitalization*, *Autonomy and Automation*; *Dairy Farming;* and *Field Cultivation* played a crucial role in the associations with all four pictures. We merged terms such as “machine” and “high-tech” into the neutral category *Technology*, which consistently polled a large proportion of the aforementioned spontaneous associations in all four pictures.

In general, we saw that the most commonly mentioned categories for the animal-related technologies were more negative than those for the crop production technologies. This was especially true for the picture of the milking robot, for which three negative categories were among the five most common. Negative terms with regard to the issue of *Animal Cruelty* such as “animal suffering”, “tight”, “poor cow”, “not animal-appropriate”, and “imprisoned” were associated most frequently with the picture of the milking robot. The issue of *Animal Cruelty* was also mentioned in the context of the feeding robot, but at a lower frequency.

The aspect of *Industrial Agriculture* played a relevant role in the case of the two animal husbandry technologies. Respondents were worried, for example, about “exploitation of the animals”, “alienation”, “factory farming” and “animal as an object” (negative). The picture of the autonomous tractor also led survey participants to think of *Industrial Agriculture*, but at a lower frequency than the dairy farming technologies. In this case, terms such as “impersonal” were noted, but also “mass production”, “large-scale farmers”, and “monster”. Often, however, only the *Size Dimension* was described with terms such as “big” or “large area”, which is why we included this aspect in the category *Industrial Agriculture*. For the picture of the autonomous tractor, this resulted in a combination of neutral and negative associations. Swarm robotics was also associated with words such as “mass production” and “industrial” (negative), but with regards to the *Size Dimension*, it was described as “small”, “toy”, and “cute” (positive). For the picture of the autonomous tractor, many respondents expressed *Concerns for Environmental Protection* (negative), using words like “environmental pollution”, “soil compaction”, “chemistry”, “poison”, and “monoculture”. In relation to the picture of the swarm robots, this category also applied, but only a few

Table 5 Frequently mentioned categories in spontaneous associations with four pictures of digital farming technologies

Picture 1 Autonomous tractor sowing in the field Total number of mentions suitable for evaluation: 4397				Picture 2 Swarm robots sowing in the field Total number of mentions suitable for evaluation: 3982			
Rank	Aggregate categories	Mentions	Connotation	Rank	Aggregate categories	Mentions	Connotation
1	Future and Progress	737	+	1	Digitalization, Autonomy and Automation	667	0
2	Efficiency and Reduced Workload	635	+/(−)	2	Efficiency and Reduced Workload	643	+/(−)
3	Digitalization, Autonomy and Automation	605	0	3	Future and Progress	591	+
4	Field cultivation	493	0	4	Field Cultivation	357	0
5	Technology	452	0	5	Industrial Agriculture/ Size Dimension	333	−/0/+
6	Terms of rejection (e.g., “creepy”)	303	−	6	Technology	284	0
7	Terms of agreement (e.g., “good”)	235	+	7	Terms of Rejection (e.g., “creepy”)	275	−
8	Concerns for environmental protection	173	−	8	Terms of Agreement (e.g., “good”)	267	+
9	Industrial agriculture/size dimension	170	−/0	9	Costs of Technology	142	−/(0)/(+)
10	Nature and plants	156	0	10	Environmental Protection	76	+
Picture 3 Cow-feeding robot during feed provision in the barn Total number of mentions suitable for evaluation: 4035				Picture 4 Cow in milking robot during milking process Total number of mentions suitable for evaluation: 4649			
Rank	Aggregate categories	Mentions	Connotation	Rank	Aggregate categories	Mentions	Connotation
1	Efficiency and Reduced Workload	572	+/(−)	1	Animal Cruelty	754	−
2	Digitalization, Autonomy and Automation	478	0	2	Dairy Farming/Milking	687	0
3	Dairy farming/feeding	475	0	3	Terms of Rejection (e.g., “awful”)	546	−
4	Industrial agriculture	380	−	4	Technology	470	0
5	Animal cruelty	370	−	5	Industrial Agriculture	427	−
6	Future and Progress	360	+	6	Digitalization, Autonomy and Automation	385	0
7	Terms of rejection (e.g., “awful”)	317	−	7	Future and Progress	359	+
8	Terms of agreement (e.g., “useful”)	255	+	8	Efficiency and Reduced Workload	307	+/(−)
9	Hygiene	233	0	9	Hygiene	250	0
10	Technology	213	0	10	Cow	177	0

Ranking of the ten most frequent categories for each of the shown pictures

Assignments of connotation: “+” = positive; “0” = neutral; “−” = negative

terms could be assigned to it. For the pictures of the milking and feeding robots, we assigned a similar number of terms to the category *Hygiene*, which was mainly composed of words like “hygiene”, “clean”, and “sterile” and rated as neutral. Strikingly, many of the mentioned spontaneous associations did not explicitly target the DFT depicted, but rather criticized agricultural production processes per se. For example, associations such as “factory farming” and “locked up” call the animal husbandry system in general into question. Likewise, terms such as “monoculture”, “environmental pollution”, and “pesticide” are a criticism of agronomic practices in agriculture, with no specific reference to the DFT depicted.

Discussion

Classification of results

The connection to the agricultural sector and general attitudes toward agriculture

With regard to the connection to agriculture, the sample showed a high proportion of respondents with work experience in the agricultural sector (8.2%) compared to the current share of employed persons in agriculture of about 1.1% in Germany (Federal Statistical Office Germany (Destatis) 2018b). This may be explained, on the one hand, by the fact that some of the respondents' work experience in the agricultural sector lies in the past. On the other hand, the question asked for work experience in the agriculture sector or a related field, which also includes the upstream and downstream sectors (such as food retailing).

The mediocre to rather low knowledge of present-day agriculture in Germany can be explained by increasingly fewer points of contact between farmers and the public (Weber et al. 1995; Holloway 2004). The higher proportion of people who claimed to have good or very good knowledge of agricultural production compared to those who have work experience in agriculture may be attributed to overconfidence (Moore and Healy 2008). The spontaneous associations confirmed a partially low level of knowledge of present-day agricultural production of the German public (see also Simons et al. 2019) as, for example, the milking robot, was often not recognized as such.

In general, the level of trust in farmers in Germany was only moderate. The agreement that farmers contribute to the protection of the environment and pay close attention to the welfare of their animals behaved similarly moderately in other studies conducted in Germany (Helmle 2010), but also in the Netherlands (Boogaard et al. 2011a) and the US-State of Ohio (Sharp and Tucker 2005). The fact that respondents rated the items of trust in German farmers better than those reflecting their knowledge of present-day agriculture showed that a comprehensive knowledge of current agricultural production methods among the public is not the only prerequisite for a positive perception of agriculture in the public. The formation of opinions on agricultural topics and thus trust in farmers is largely influenced by how a topic is presented in the media. Throughout the past 20 years, the majority of the German public obtained information on agriculture from television (TNS Emnid 2012). The majority of the German public considers media reports on agriculture to be balanced (TNS Emnid 2012), implying that the image of agriculture is strongly influenced by its representation in the media. Studies analyzing the effect of the type of communication on the image of agriculture among German residents revealed that while direct contact with agriculture through conversation with farmers had a positive influence on the image, contact with agriculture via media (media-mediated agriculture) had a negative influence. Agricultural topics often discussed in German media include rising meat prices, meat scandals, animal husbandry conditions (associated with so-called factory farming), and the use of antibiotics (Helmle 2010; Wolfram et al. 2019). Thus, these critical portrayals at least partly explain the moderate level of trust in German farmers observed in our survey.

Rating of digital farming technologies

Regarding studies on the public acceptance, one has to bear in mind that the results have to be seen in the context of cultural and geographical differences (e.g., societal values, religion) shaping public attitudes (Srite and Karahanna 2006; Costa-Font and Gil 2009; Bearth and Siegrist 2016). The literature reveals that research on the public acceptance of technologies is mainly concentrated on the developed world (especially North America and North-Western Europe) and does not provide sufficient insight into the situation in developing countries (see also Gupta et al. 2012; Bearth and Siegrist 2016). Thus, it has to be considered that this study was conducted in Germany, a country with a low share of the population being employed in the agricultural sector.

The respondents' evaluation of the statements to DFT was quite positive—both in the general statements and in the four specific DFT. Given our explanations of DFT, most agreed that they show potential in the areas of animal welfare as well as environmental protection and advocated their use in practice. The similarly high level of agreement on the use of DFT in practice and on subsidies for farmers using them, underlines the seriousness of respondents' answers, as they were well aware that taxpayers' money would be used for this purpose. Since we asked about the consent to the use of taxpayers' money in the survey, our attitude-oriented approach also included an intention or willingness to act-component (see Schäfer and Keppler 2013). In the Dutch survey by Boogaard et al. (2011a), agreement on a higher willingness to pay for both environmental and landscape care and subsidies to farmers (if they can only stay in business with governmental subsidies) was more subdued compared to our results, but still more supportive than negative. Also in studies conducted in the UK (Bennett 1997), Spain (María 2006), and Germany (Weinrich et al. 2014), the majority of respondents indicated a willingness to pay for improved animal welfare standards (e.g., phase-out use of cages in egg production, pasture-raised milk). However, a meta-analysis by Lagerkvist and Hess (2011) on consumer willingness to pay for farm animal welfare showed that French and German consumers exhibited higher, and Danish consumers lower willingness to pay for farm animal welfare than consumers from other countries such as the US, UK and Sweden. The result of this meta-analysis highlights once again that the results concerning the consent to state subsidies for farmers using DFT, have to be seen in the context of the country of survey of the study.

The influence of socio-demographic factors (Devlin 2005; Sharp and Tucker 2005; Devine-Wright 2008; Boogaard et al. 2011a), knowledge (Devlin 2005; Devine-Wright 2008; Boogaard et al. 2011a; Stiehler 2015), general attitudes (Lucke 1995; Grunert et al. 2003; Kollmann 2004; Sharp and Tucker 2005; Boogaard et al. 2011a; Stiehler 2015), and trust (Dunlap et al. 1993; Slovic 1993; Cvetkovich and Lofstedt 1999; Eiser et al. 2002; Roosen et al. 2015; Stiehler 2015; Bearth and Siegrist 2016) on acceptance has already been revealed many times. Socio-demographic variables such as gender, age, and education not only influence general views of agriculture (Haartsen et al. 2003; Sharp and Tucker 2005; María 2006) but partly also the attitudes toward the benefits of DFT, as shown in our study. For instance, Boogaard et al. (2011a) showed that older people were more positive about contemporary agricultural production methods, more open-minded toward modern production processes, and had a higher willingness to pay for added values such as maintaining nature. María (2006) showed that younger people were more critical than older ones in terms of animal welfare on farms and found a higher willingness to pay a surcharge to improve animal welfare among younger or middle aged people than among older ones. However, Kühl et al. (2019) applied a picture-based approach to analyze the overall acceptance of different husbandry systems for dairy cattle, with socio-demographics such as gender, age, and education not driving any significant differences in acceptance. Although there were also a few studies to the contrary, a review of the social basis of environmental concerns by Van Liere and Dunlap (1980) confirmed that age is predominantly negatively correlated with environmental concerns. Our results point in a similar direction as the findings of María (2006), showing that younger (< 40 years old) rather than older people agreed to a state subsidy for farmers using DFT.

Although points of contact between the population and agriculture are becoming fewer, our results did not reveal a significant effect of the size of place of residence on the attitudinal acceptance of DFT. Numerous studies have dealt with the hypothesis of a difference in agricultural and environmental attitudes between rural and urban populations (e.g., Van Liere and Dunlap 1980; Freudenburg 1991; Sharp and Tucker 2005). Yet there appears to be no clear overall tendency. For example, in their survey, Sharp and Tucker (2005) did not identify a clear pattern between the place of residence on the one hand and livestock welfare and environmental concerns on the other hand. Similarly, our results did not demonstrate any significant impact of the size of place of residence on the attitudinal acceptance of DFT. A possible explanation for this is the declining number of farmers in rural areas and the simultaneously increasing influx of urban population into rural areas, resulting in a growing proportion of rural residents without agricultural ties. Therefore, our chosen limit for the size of place of residence (5000) may have been still too high to recognize significant differences in the attitude toward agricultural issues.

The literature shows that personal contact with farmers as well as work experience in agriculture can have a positive effect on an individual's image of agriculture (Sharp and Tucker 2005; Helmle 2010; Wildraut et al. 2019), including attitudes toward modern animal husbandry and willingness to pay for values such as maintaining nature and landscape (Boogaard et al. 2011a). Sharp and Tucker (2005) found that people who grew up on farms had fewer livestock welfare and environmental concerns. However, their study did not reveal an impact of a mere visit to rural areas (e.g., for recreational purposes) on concerns about livestock welfare and the environment. Kühl et al. (2019) also did not identify significant differences in the overall acceptance of different husbandry systems for dairy cattle between respondents who had already visited a farm and those who had not. However, our results are not in line with the findings of Sharp and Tucker (2005), Helmle (2010), Boogaard et al. (2011a) and Wildraut et al. (2019), as our study did not show an effect of personal contact with farmers, including conversations on agricultural topics, on the attitudes toward DFT. We even found a slightly negative effect of work experience in the agricultural sector on the general attitudes toward the benefits of DFT and consent to the use of specific DFT. Thus, our results regarding the influence of personal contact with farmers on the public acceptance of DFT cannot yet be clearly explained and require further studies to substantiate them. The increased negative general attitudes toward the benefits of DFT and lower consent to the use of DFT by respondents with work experience in the agricultural sector could partly be explained by negative experiences with using DFT. It is not known how many of the respondents with work experience in the agricultural sector had explicit experience with DFT. However, there exists well-founded evidence that the use of DFT still poses certain challenges that could be reflected in our results. Challenges of digital agriculture, are, amongst others, high complexity of interpretation of the collected data and thus a lack of decision support for the average user, and too high costs to implement them nation-wide (Reichardt and Jürgens 2009; Weersink et al. 2018). For the public to be convinced of technologies such as DFT, first and foremost, its users must be convinced so that they can convey this positive image to the public.

According to the findings of our survey study conducted in Germany, accepting DFT and agreeing to their subsidization is mainly based on positive general attitudes toward farming and trust in farmers. Altogether, these determinants had a greater impact on the attitudinal acceptance of DFT than other variables such as socio-demographics. Thus, our results confirmed the role of values and beliefs shaping peoples' attitudes and decisions (Lusk et al. 2014), including agricultural issues. To alter values and beliefs, however, is not easy to realize in practice: Trust in risk regulators is difficult to build, but is quickly lost (Frewer and Salter 2002). Using the example of novel food technologies, Siegrist (2008) emphasized that advantages and disadvantages of technologies may not always be obvious, thus being difficult for the public to evaluate. About 87% of the EU population has never worked with a robot, regardless of its field of application (Eurobarometer 2012). This reinforces the explanation that it is difficult to assess the risks and benefits of technologies without respective experience. In addition, to form a well thought out and balanced opinion on agricultural topics can be difficult with a low level of knowledge of present-day agriculture. Therefore, trust in the user of a technology is a relevant factor for the public acceptance of agricultural innovations. In this context, it is important to keep in mind that the topic of digitalization in agriculture is rather specific and new. Therefore, especially when decisions cannot be made on the basis of sound knowledge, values and trust are central factors in making decisions that are not fully rationally justified (Sparks et al. 1994; Siegrist 2008).

As our results showed, the public values some positive aspects of modern agriculture such as food quality and low prices and perceives the sector to be innovative and technically advanced (see also Boogaard et al. 2008). The spontaneous associations confirmed that the addressed DFT are considered to be innovative and relevant to the future by many. However, the public attitude toward modern agriculture, including modern animal farming, is ambivalent as there are also many negative impressions in the public. Modernity and technical progress in agriculture are not considered to be negative in general, but the loss of values, traditions, and naturalness (Alrøe and Kristensen 2002; Lassen et al. 2006) often accompanying technological innovations are not appreciated. This dilemma is a reason why modern agricultural production is often criticized by the public as it contradicts the deeply rooted vision of romantic, idyllic family farms and museum agriculture in European society (Boogaard et al. 2011b; Simons et al. 2019).

Looking at the categories of spontaneous associations, it seemed that some of the respondents impulsively referred to events in the past that have remained in their memory due to media coverage, as issues such as concerns for environmental protection, industrial agriculture, or animal cruelty are often addressed in German media (see Helmle 2010; Wolfram et al. 2019). In group discussions on the understanding of modern agriculture in Germany by Simons et al. (2019), terms such as "mass production" and "less contact between humans and animals" were mentioned by the respondents, similar to participants in our study. There, many individuals spontaneously associated the idea of *Industrialization* with the two pictures of the milking robot and the feeding robot that we showed them. It was noticeable that the spontaneous associations with the two DFT for dairy farming were more negative compared to the ones for crop production. The negative connotation of DFT in dairy farming may be shaped by the high level of concern for animal welfare in the Germany public. This was confirmed by previous studies conducted in Germany, showing that animal welfare was consistently ranked the highest among a multitude of public demands and wishes for agriculture (see TNS Emnid 2012; Luy et al. 2019). A survey among EU citizens on their attitudes toward possible fields of application of robotics (Eurobarometer 2012) provides further explanations. While priority was given to space exploration and manufacturing, citizens were more empathic about the use of robotics for the care of people. When asked about a ban on robotics in application areas, care of children, elderly, and disabled people (60%) led the way, while only 6% voted for a ban in agriculture. It may be possible to draw parallels between the EU survey and our survey: when using robotics in the handling of living beings (human or animal), the views are comparatively critical. Comparing the two dairy farming technologies, the milking robot was associated with more negative terms than the feeding robot. This was mainly due to a more frequent association of the milking robot with *Animal Cruelty* and *Industrial Agriculture*. Therefore, it can be assumed that the milking robot was perceived as a technology used with the aim of increasing herd size and milk yield (performance-oriented), thus counteracting the wishful thinking about small family farms. In sum, the share of negative connotations associated with the milking robot (35%) in our study was consistent with the share of respondents in the UK study by Millar et al. (2002), who rated the milking robot as "not ethically acceptable" (32%). It is striking that in the general attitudes toward the benefits of DFT, the potential was seen primarily in an increase in the farmer's wellbeing. In comparison, the perceived potential for improving animal welfare was lower. This tendency was also evident in the evaluation of a milking robot by citizens of the UK (Millar et al. 2002). A reason for a critical attitude toward DFT may therefore be that benefits are seen more relevant to the farmer than to the animal or nature. With regard to the size dimension of agricultural robotics for sowing, the survey participants graded small swarm robots more positively than the large autonomous tractor, largely due to increased safety and environmental concerns related to the large and thus heavy machine.

The more general criticism of the animal husbandry technologies shown included year-round indoor housing as opposed to free-range and pasture systems as a concept of ideal animal husbandry (Miele et al. 2011; Weinrich et al. 2014; Cardoso et al. 2016). Surveys in Germany revealed that animal husbandry of other species (pork, poultry) is judged at least as critically as cattle farming. This assessment was made by farmers and the broader public alike (Simons et al. 2019; Wildraut and Mergenthaler 2019). Likewise, crop production is often met with criticism in the German public. Aspects such as decreasing biodiversity, nitrate leaching, and the desire to reduce pesticide use are just a few examples of the many points of criticism of agriculture in Germany. Consequently, DFT may be well accepted as a building block for improving animal welfare and a more environmentally-friendly production. However, the impact of these positive effects on the general acceptance of agriculture will probably be limited due to a lot of general criticism of agriculture in Germany, particularly in the case of animal husbandry.

Methodical considerations

Our study provides relevant results on public attitudinal acceptance of DFT in the German population. Consumer studies carried out on innovations in the food sector so far have measured various forms of acceptance. Willingness to pay, or acceptance, were measured as target variables in a large number of studies on, for example, gene technology, or nanotechnology (Bearth and Siegrist 2016). The fact that the use of DFT has a direct influence on farmers and animals, and only an indirect one on consumers, makes it harder to grasp public acceptance at the action and usage levels. Therefore, an approach based on models such as the technology acceptance model (Davis et al. 1989) was not appropriate for our study. Moreover, as our study did not cover any action component (e.g., purchase of a product), our measured target variables cannot be interpreted as "acceptance", as defined in the literature (see Lucke 1995; Schäfer and Keppler 2013). However, it has to be noted that the construct "attitudinal acceptance" by Kollmann has been mainly applied to innovation in use, although it is described as an independent construct that precedes the purchase of a product (Kollmann 2004).

The evaluation of the consent to state subsidies for farmers who purchase DFT, however, provides first relevant indications. Further studies on the actual willingness of consumers to pay for improving environmental and livestock conditions by means of DFT (action phase) should be pursued, for which choice experiments would be a suitable methodological approach (see also Lagerkvist and Hess 2011). Presumably, in terms of willingness to pay for higher animal welfare or environmental protection standards, there might be a different outcome, depending on the study being methodologically based on a choice experiment or on Likert scales for provided statements, as was the case in our study. Thus, the results of our study are not yet sufficient for evaluating the overall acceptance of DFT. Nevertheless, with our study we are taking a necessary step that enables an initial assessment of the situation in Germany, on the basis of which further methodological procedures can be developed.

The combination of the two methodological approaches emerged to be particularly valuable. Based on the results of our study, we recommend that surveys on the acceptance of technologies that are not comprehensively known to the general public should not be structured purely text-based. The results demonstrated that asking for the evaluation of provided statements (Likert scales), on the one hand, and spontaneous associations with pictures showing DFT, on the other hand, leads to a multi-faceted assessment. As described in the literature, the pictures showing DFT contributed to the release of feelings and emotions (Cvetkovich 2003), as evidenced by emotional references such as "animal suffering", "poor cow", or "poison". Our results confirmed the finding of Slovic et al. (2007) that integrating affective impressions may lead to higher efficiency, especially if the assessment of a given issue is complex. In fact, whereas the evaluation of DFT was largely positive in the given statements, the spontaneous associations revealed a much more differentiated picture. Asking for spontaneous associations proved to be a suitable methodical approach to obtain valuable indications of perceived benefits and risks of DFT from the public. Therefore, spontaneous associations provide a sound basis for determining concerns in the public, which need to be addressed for developing approaches to strengthen public acceptance.

Public acceptance is to be considered against a cultural and also media background in which public perceptions arise. Since the general image of agriculture varies from country to country, it can be assumed that this heterogeneity also applies to the public acceptance of DFT. The results of our study conducted among the German population revealed that general attitudes and values influence acceptance of DFT. However, attitudes and values are to a considerable extent anchored in a cultural and socio-economic context. Therefore, we suggest similar future studies in further countries in order to gain insights that are not limited to the German public. Furthermore, integrating respective components into the framework of the survey could provide valuable indications of the extent to which public opinions on agriculture are influenced by its representation in the media (e.g., type of media used).

Implications and conclusions

The high share of undecided respondents in questions concerning general attitudes toward agriculture, trust in farmers, and the assessment of DFT shows that there is a need to inform the public in an objective way. However, more comprehensive, balanced information on a topic may not necessarily always result in greater acceptance of an issue (Scholderer and Frewer 2003; Weary and Keyserlingk 2017; Wuepper et al. 2019), as opinions are based not only on experience and knowledge but also, and very importantly, on values and beliefs (Te Velde et al. 2002). Since opinions on a topic are thus very deeply rooted, simply providing information in order to change them will most likely be insufficient (Grunert et al. 2003). In the study by Millar et al. (2002) on the consumer acceptance of the milking robot in the UK, a short description of the technology was provided. However, 29% of respondents answered they were unable to judge whether the milking robot was "ethically acceptable"—a similar proportion of undecided consumers could be found in our study regarding the general attitudes toward the benefits of DFT, although Millar et al. did provide more background information in their survey. Ventura et al. (2016) have already addressed the question of whether a self-guided farm visit (carried out on a 500-head dairy farm in North America) can contribute to changing perceptions, concerns, and values about dairy cattle. In their study, a farm visit helped to resolve some concerns of the public, while at the same time other concerns arose. Studies carried out in Germany on the acceptance of animal husbandry systems confirmed that merely providing information does not necessarily lead to greater acceptance in the public. In comparison, a personal dialogue between the public and farmers had a stronger, positive effect regarding some issues, such as conditions under which farm animals are kept. In this context, it is interesting to note that the effect of a personal dialogue was particularly strong in the statement "Technology makes the work of animal owners easier and farm animals can be better cared for" (Wildraut et al. 2019). Although personal contact with a farmer had no significant impact on the attitudes toward the benefits of DFT in our study, the dialogue between farmers and consumers is essential and an important step in the process of building trust between farmers and the public. In line with the literature, we see that public acceptance of DFT is not only determined by the characteristics of technologies and the associated impacts on animals or nature. Rather, the public must have trust in the farmer, who is seen as the person responsible for the most appropriate use of DFT, thus deciding on a possible improvement of animal welfare and environmental protection. Weary and Keyserlingk (2017) analyzed various strategies for dealing with public concerns about dairy-cow welfare. They concluded that engagement with the public is more successful than efforts to educate the public. Two-way conversations in particular are effective when addressing the most concerned people, possibly directly on a farm that is being opened up to the public. These conversations may also help farmers understand the concerns of the public, and help the public put itself in the farmers' shoes. Regarding farmer-consumer dialogues, public interest in technical details of agricultural processes is probably limited. Information should be focused on fundamental values and take into account emotional components. To this end, the potential of DFT for animal welfare and environmental protection may serve as a supportive argument. Importantly, in this context, farmers, and especially trainees in agricultural education, should be trained in communication strategies with the public. For farmers, it is becoming increasingly necessary to recognize and develop social communication skills as an entrepreneurial competence.

Our study revealed that the need for considering the public acceptance of an increasing use of DFT should not be neglected. Although our results are limited to the German public, they indicate the urgent need for other countries to involve the social component at an early stage when evaluating DFT. Regarding the social component, not only research and farmers should become active when establishing technologies on the market. Also innovators and developers have to involve the public as early as possible in a development process. Initial studies on responsible research and innovation (RRI) aiming to guide socially and ethically acceptable innovation (Stilgoe et al. 2013) are already addressing relevant points in this regard (see Rose and Chilvers 2018; Bronson 2019; Eastwood et al. 2019). To this end, in agriculture, more intensive and coordinated cooperation between public, private, and civil society actors involved in the development of technical innovations needs to be established (Rose and Chilvers 2018). End-users and consumers should be involved in a socio-ethical discussion, for example relating to farmer-technology interaction or animal-technology interaction, using workshops or citizen panels, so that critical feedback can be taken into account early on. The beginnings of RRI lie in a social and political European setting, which is why the focus of its application lies in the European and North American context, without previous application to DFT (Eastwood et al. 2019). Therefore, an extension of RRI to digital agriculture as well as to other countries is indispensable.

In summary, the results of our study prove that future research on digital agriculture must put more emphasis on the analysis of public response to agricultural modernization and its dynamics in order to ensure an appropriate image of increasingly automated agriculture.

Acknowledgements We thank Sebastian Schleicher for his substantial input regarding the development of the survey. We would also like to thank Olivia Spykman for proofreading the paper.

Funding This work was funded by the Bavarian State Ministry for Food, Agriculture and Forestry. Open Access funding provided by Projekt DEAL.

Compliance with ethical standards

Conflict of interest No personal rights are affected and no third-party conflicts of interest exist.

Informed consent All persons and institutions involved in the production of this manuscript are informed and familiar with the provided results and this publication. The data was collected via a closed consumer panel. The participation of the panel members is based on their explicit consent, whereby a separation of personal and factual data was always guaranteed. It is not possible to draw any conclusions about the personal data of panel members involved in data collection. The rights to the factual data used for this publication lie exclusively with the authors and their institution.

References

Alrøe, H.F., and E.S. Kristensen. 2002. Towards a systemic research methodology in agriculture: Rethinking the role of values in science. *Agriculture and Human Values* 19: 3–23.

Amin, L., H. Hashim, N.M. Sidik, Z.A. Zainol, and N. Anuar. 2011. Public attitude towards modern biotechnology. *African Journal of Biotechnology* 10 (58): 12409–12417.

Asveld, L., J. Ganzevles, and P. Osseweijer. 2015. Trustworthiness and responsible research and innovation: The case of the bioeconomy. *Journal of Agricultural and Environmental Ethics* 28: 571–588.

Banhazi, T.M., H. Lehr, J.L. Black, H. Crabtree, P. Schofield, M. Tscharke, and D. Berckmans. 2012. Precision livestock farming: An international review of scientific and commercial aspects. *International Journal of Agricultural and Biological Engineering* 5 (3): 1–9.

Bauer, M.W. 2002. Controversial medical and agri-food biotechnology: A cultivation analysis. *Public Understanding of Science* 11 (2): 93–111.

Bearth, A., and M. Siegrist. 2016. Are risk or benefit perceptions more important for public acceptance of innovative food technologies: A meta-analysis. *Trends in Food Science & Technology* 49: 14–23.

Bennett, R.M. 1997. Farm animal welfare and food policy. *Food Policy* 22 (4): 281–288.

Boogaard, B.K., B.B. Bock, S.J. Oosting, J.S.C. Wiskerke, and A.J. van der Zijpp. 2011a. Social acceptance of dairy farming: The ambivalence between the two faces of modernity. *Journal of Agricultural and Environmental Ethics* 24 (3): 259–282.

Boogaard, B.K., S.J. Oosting, B.B. Bock, and J.S.C. Wiskerke. 2011b. The sociocultural sustainability of livestock farming: An inquiry into social perceptions of dairy farming. *Animal* 5 (9): 1458–1466.

Boogaard, B.K., S.J. Oosting, and B.B. Bock. 2008. Defining sustainability as a socio-cultural concept: Citizen panels visiting dairy farms in the Netherlands. *Livestock Science* 117 (1): 24–33.

Bronson, K. 2019. Looking through a responsible innovation lens at uneven engagements with digital farming. *NJAS-Wageningen Journal of Life Sciences* 90: 100294.

Cardoso, C.S., M.J. Hötzel, D.M. Weary, J.A. Robbins, and M.A. von Keyserlingk. 2016. Imagining the ideal dairy farm. *Journal of Dairy Science* 99: 1663–1671.

Collier, J. 1957. Photography in anthropology: A report on two experiments. *American Anthropologist* 59: 843–859.

Costa-Font, M., and J.M. Gil. 2009. Structural equation modelling of consumer acceptance of genetically modified (GM) food in the Mediterranean Europe: A cross country study. *Food Quality and Preference* 20 (6): 399–409.

Cvetkovich, A. 2003. *An archive of feelings: Trauma, sexuality, and lesbian public cultures*. Durham: Duke University Press.

Cvetkovich, G., and R.E. Lofstedt (eds.). 1999. *Social trust and the management of risk*. London: Earthscan.

Davis, F., P. Bagozzi, and P. Warshaw. 1989. User acceptance of computer technology—a comparison of two theoretical models. *Management Science* 35 (8): 982–1003.

Deemer, D.R., and L.M. Lobao. 2011. Public concern with farm-animal welfare: Religion, politics, and human disadvantage in the food sector. *Rural Sociology* 76 (2): 167–196.

Delezie, E., W. Verbeke, J. De Tavernier, and E. Decuypere. 2006. Consumers' preferences toward techniques for improving manual catching of poultry. *Poultry Science* 85 (11): 2019–2027.

Dethloff, C. 2004. *Akzeptanz und Nicht-Akzeptanz von technischen Produktinnovationen [Acceptance and non-acceptance of technical product innovations]*. Lengerich, Berlin, Bremen, Miami, Riga, Viernheim, Wien, Zagreb: Pabst Science Publishers.

Devlin, E. 2005. Factors affecting public acceptance of wind turbines in Sweden. *Wind Engineering* 29 (6): 503–511.

Devine-Wright, P. 2008. Reconsidering public acceptance of renewable energy technologies: a critial review. In *Delivering a low-carbon electricity system: Technologies, economics and policy*, ed. M. Grubb, T. Jamasb, and M.G. Pollitt, 443–461. Cambridge: Cambridge University Press.

Driessen, C., and L.F.M. Heutinck. 2015. Cows desiring to be milked? Milking robots and the co-evolution of ethics and technology on Dutch dairy farms. *Agriculture and Human Values* 32: 3–20.

Dunlap, R.E., M.E. Kraft, and E.A. Rosa (eds.). 1993. *Public reactions to nuclear waste: Citizens' views of repository siting*. Durham: Duke University Press.

Eastwood, C., L. Klerkx, M. Ayre, and B.D. Rue. 2019. Managing socio-ethical challenges in the development of smart farming: From a fragmented to a comprehensive approach for responsible research and innovation. *Journal of Agricultural and Environmental Ethics* 32 (5–6): 741–768.

Eiser, J.R., S. Miles, and L.J. Frewer. 2002. Trust, perceived risk, and attitudes toward food technologies. *Journal of Applied Social Psychology* 32: 2423–2433.

Endruweit, G. 1986. Sozialverträglichkeits- und Akzeptanzforschung als methodologisches Problem. In *Die Analyse der*

Sozialverträglichkeit für Technologiepolitik: Perspektiven und Interpretationen [Social compatibility and acceptance research as a methodological problem], ed. H. Jungermann et al., 80–91. München: High-Tech-Verlag.

Epstein, S. 1994. Integration of the cognitive and psychodynamic unconscious. *American Psychologist* 49: 709–724.

Eurobarometer. 2012. *Public attitudes towards robots*. European Commission.

Federal Statistical Office Germany (Destatis). 2018a. Press release No. 330 of 5 September 2018. Accessed 10 March 2020.

Federal Statistical Office Germany (Destatis). 2018b. *Statistisches Jahrbuch [Statistical yearbook].* Germany.

Field, A. 2017. *Discovering statistics using IBM SPSS statistics*, 5th ed. London: Sage.

Finucane, M.L., A. Alhakami, P. Slovic, and S.M. Johnson. 2000. The affect heuristic in judgments of risks and benefits. *Journal of Behavioral Decision Making* 13 (1): 1–17.

Fraedrich, E., and B. Lenz. 2016. Societal and individual acceptance of autonomous driving. In *Autonomous driving: Technical, legal and social aspects*, ed. M. Maurer, J.C. Gerdes, B. Lenz, and H. Winner, 621–640. London: Springer.

Freudenburg, W.R. 1991. Rural-urban differences in environmental concern: A closer look. *Sociological Inquiry* 61 (2): 167–198.

Frewer, L.J. 2017. Consumer acceptance and rejection of emerging agrifood technologies and their applications. *European Review of Agricultural Economics* 44 (4): 683–704.

Frewer, L., C. Howard, and R. Shepherd. 1997. Public concerns in the United Kingdom about General And Specific Applications of genetic engineering: Risk, benefit, and ethics. *Science, Technology, & Human Values* 22 (1): 98–124.

Frewer, L.J., and B. Salter. 2002. Public attitudes, scientific advice and the politics of regulatory policy: The case of BSE. *Science and Public Policy* 29 (2): 137–145.

Gaskell, G. 2000. Agricultural biotechnology and public attitudes in the European Union. *AgBioForum* 3: 87–96.

Grunert, K.G., L. Bredahl, and J. Scholderer. 2003. Four questions on European consumers' attitudes toward the use of genetic modification in food production. *Food Science and Emerging Technologies*. 4 (4): 435–445.

Gupta, N., A.R. Fischer, and L.J. Frewer. 2012. Socio-psychological determinants of public acceptance of technologies: A review. *Public Understanding of Science* 21 (7): 782–795.

Haartsen, T., P. Groote, and P.P.P. Huigen. 2003. Measuring age differentials in representations of rurality in the Netherlands. *Journal of Rural Studies* 19: 245–252.

Harper, D. 2002. Talking about pictures: A case for photo elicitation. *Visual Studies* 17 (1): 13–26.

Helmle, S. 2010. Images are communication: Empirical survey and modeling of the image of agriculture in Germany. *OGA Jahrbuch-Journal of the Austrian Society of Agricultural Economics* 19 (1): 51–60.

Hofinger, G. 2001. Formen von "Akzeptanz": Sichtweisen auf ein Biosphärenreservat [Forms of "acceptance": Perspectives on a biosphere reserve]. *Umweltpsychologie* 5 (1): 10–27.

Holloway, L. 2004. Showing and telling farming: Agricultural shows and re-imaging British agriculture. *Journal of Rural Studies* 20: 319–330.

Holloway, L., K. Wilkinson, and C. Bear. 2014. Robotic milking technologies and renegotiating situated ethical relationships on UK dairy farms. *Agriculture and Human Values* 31 (2): 185–199.

Huijts, N.M., E.J. Molin, and L. Steg. 2012. Psychological factors influencing sustainable energy technology acceptance: A review-based comprehensive framework. *Renewable and Sustainable Energy Reviews* 16 (1): 525–531.

Ilieva, J., S. Baron, and N.M. Healey. 2002. Online surveys in marketing research. *International Journal of Market Research* 44 (3): 1–14.

Kendall, H.A., L.M. Lobao, and J.S. Sharp. 2006. Public concern with animal well-being: Place, social structural location, and indicidual experience. *Rural Sociology* 71 (3): 399–428.

Klerkx, L., E. Jakku, and P. Labarthe. 2019. A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. *NJAS-Wageningen Journal of Life Sciences* 90: 100315.

Kollmann, T. 2004. Attitude, adoption or acceptance? Measuring the market success of telecommunication and multimedia technology. *International Journal of Business Performance Management* 6 (2): 133–152.

König, A., H.A. Kuiper, H.J.P. Marvin, P.E. Boon, L. Busk, F. Cnuddle, S. Cope, H.V. Davies, M. Dreyer, L.J. Frewer, M. Kaiser, G.A. Kleter, I.B. Knudsen, G. Pascal, A. Prandini, O. Renn, M.R. Smith, B.W. Traill, H. van der Voet, H. van Trijp, E. Vos, and M.T.A. Wentholt. 2010. The SAFE FOODS framework for improved risk analysis of foods. *Food Control* 21: 1566–1587.

Kühl, S., S. Gauly, and A. Spiller. 2019. Analysing public acceptance of four common husbandry systems for dairy cattle using a picture-based approach. *Livestock Science* 220: 196–204.

Lagerkvist, C.J., and S. Hess. 2011. A meta-analysis of consumer willingness to pay for farm animal welfare. *European Review of Agricultural Economics* 38 (1): 55–78.

Lassen, J., P. Sandøe, and B. Forkman. 2006. Happy pigs are dirty!–conflicting perspectives on animal welfare. *Livestock Science* 103 (3): 221–230.

Lefever, S., M. Dal, and A. Matthiasdottir. 2007. Online data collection in academic research: Advantages and limitations. *British Journal of Educational Technology* 38 (4): 574–582.

Lucke, D. 1995. *Akzeptanz: Legitimität in der „Abstimmungsgesellschaft" [Acceptance: legitimacy in the „voting society"].* Wiesbaden: VS Verlag für Sozialwissenschaften.

Lusk, J.L., T.C. Schroeder, and G.T. Tonsor. 2014. Distinguishing beliefs from preferences in food choice. *European Review of Agricultural Economics* 41: 627–655.

Luy, J., W. Sonntag, M. von Meyer-Höfer, N. Brümmer, N. Purwins, A. Spiller, I. Christoph-Schulz, and J. Simons. 2019. Der Umgang mit Zielkonflikten: Eine Herausforderung. In SocialLab—Nutztierhaltung im Spiegel der Gesellschaft [Dealing with conflicting goals: A challenge. In SocialLab—animal husbandry in the mirror of society]. *Agra Europe* 13/19: 7–10.

María, G.A. 2006. Public perception of farm animal welfare in Spain. *Livestock Science* 103 (3): 250–256.

Miele, M., I. Veissier, A. Evans, and R. Botreau. 2011. Animal welfare: Establishing a dialogue between science and society. *Animal Welfare* 20 (1): 103–117.

Millar, K.M., S.M. Tomkins, R.P. White, and T.B. Mepham. 2002. Consumer attitudes to the use of two dairy technologies. *British Food Journal* 104 (1): 31–44.

Moore, D.A., and P.J. Healy. 2008. The trouble with overconfidence. *Psychological Review* 115 (2): 502–517.

Mowrer, O.H. 1960. *Learning theory and behavior*. New York: Wiley.

Onur Bodur, H., D. Brinberg, and E. Coupey. 2000. Belief, affect, and attitude: Alternative models of the determinants of attitude. *Journal of Consumer Psychology* 9 (1): 17–28.

Pfeiffer, J., A. Gabriel, and M. Gandorfer. 2019. Social acceptance of digital livestock farming technologies: the dairy sector. Papers presented at the 9th European Conference on Precision Livestock Farming, Cork, ed. B. O'Brien, D. Hennessy, and. L. Shalloo, 364–369.

Reichardt, M., and C. Jürgens. 2009. Adoption and future perspective of precision farming in Germany: Results of several surveys

among different agricultural target groups. *Precision Agriculture* 10 (1): 73–94.
Richard, V.M., and M.K. Lahman. 2015. Photo-elicitation: Reflexivity on method, analysis, and graphic portraits. *International Journal of Research & Method in Education* 38 (1): 3–22.
Ronteltap, A., J.C.M. Van Trijp, R.J. Renes, and L.J. Frewer. 2007. Consumer acceptance of technology-based food innovations: Lessons for the future of nutrigenomics. *Appetite* 49 (1): 1–17.
Roosen, J., A. Bieberstein, S. Blanchemanche, E. Goddard, S. Marette, and F. Vandermoere. 2015. Trust and willingness to pay for nanotechnology food. *Food Policy* 52: 75–83.
Rose, D.C., and J. Chilvers. 2018. Agriculture 4.0: Broadening responsible innovation in an era of smart farming. *Frontiers in Sustainable Food Systems* 2: 87.
Schäfer, M., and D. Keppler. 2013. *Modelle der technikorientierten Akzeptanzforschung. Überblick und Reflexion am Beispiel eines Forschungsprojekts zur Implementierung innovativer technischer Energieeffizienz-Maßnahmen [Models of technology-oriented acceptance research. Overview and reflection using the example of a research project on the implementation of innovative technical energy efficiency measures].* Discussion paper. Technical University of Berlin.
Scholderer, J., and L.J. Frewer. 2003. The biotechnology communication paradox: Experimental evidence and the need for a new strategy. *Journal of Consumer Policy* 26: 125–157.
Shafir, E., I. Simonson, and A. Tversky. 1993. Reason-based choice. *Cognition* 49: 11–36.
Shamshiri, R.R., C. Weltzien, I.A. Hameed, I.J. Yule, T.E. Grift, S.K. Balasundram, L. Pitonakova, D. Ahmad, and G. Chowdhary. 2018. Research and development in agricultural robotics: A perspective of digital farming. *International Journal of Agriculture and Biology* 11 (4): 1–14.
Sharp, J.S., and M. Tucker. 2005. Awareness and concern about large-scale livestock and poultry: Results from a statewide survey of Ohioans. *Rural Sociology* 70 (2): 208–228.
Shaw, A. 2002. 'It just goes against the grain'. Public understandings of genetically modified (GM) food in the UK. *Public Understanding of Science* 11: 273–291.
Shouse, E. 2005. Feeling, emotion, affect. *M/C Journal* 8 (6): 1–5.
Siegrist, M. 2008. Factors influencing public acceptance of innovative food technologies and products. *Trends in Food Science and Technology.* 19 (11): 603–608.
Siegrist, M., G. Cvetkovich, and C. Roth. 2000. Salient value similarity, social trust, and risk/benefit perception. *Risk Analysis* 20 (3): 353–362.
Simons, J., J. Luy, I. Birkle, J. Klink-Lehmann, A. Rovers, M. von Meyer-Höfer, C. Vierboom, I. Härlen, N. Brümmer, W. Sonntag, S. Saggau, M. Hartmann, A. Spiller, and I. Christoph-Schule. 2019. Wahrnehmung und Akzeptanz. In SocialLab—Nutztierhaltung im Spiegel der Gesellschaft [Perception and acceptance. In SocialLab—animal husbandry in the mirror of society]. *Agra Europe* 13/19: 1–7.
Sjöberg, L. 2007. Emotions and risk perception. *Risk Management* 9 (4): 223–237.
Slovic, P. 1993. Perceived risk, trust, and democracy. *Risk Analysis* 13: 675–682.
Slovic, P.M.L., E. Peters Finucane, and D.G. MacGregor. 2007. The affect heuristic. *European Journal of Operational Research* 177 (3): 1333–1352.
Sparks, P., R. Shepherd, and L.J. Frewer. 1994. Gene technology, food production, and public opinion: A UK study. *Agriculture and Human Values* 11: 19–28.
Specht, K., R. Siebert, and S. Thomaier. 2016. Perception and acceptance of agricultural production in and on urban buildings (ZFarming): A qualitative study from Berlin, Germany. *Agriculture and Human Values* 33 (4): 753–769.
Spence, A., and E. Townsend. 2008. Examining consumer behavior toward genetically modified (GM) food in Britain. *Risk Analysis* 26: 657–670.
Srite, M., and E. Karahanna. 2006. The role of espoused national cultural values in technology acceptance. *MIS Quarterly* 30: 679–704.
Stanton, J.M. 1998. An empirical assessment of data collection using the Internet. *Personnel Psychology* 51 (3): 709–725.
Stiehler, W. 2015. *Akzeptanz von Biogas in Bayern [Public acceptance of biomass cogeneration heat in Bavaria]*. PhD dissertation, Technical University of Munich.
Stilgoe, J., R. Owen, and P. Macnaghten. 2013. Developing a framework for responsible innovation. *Research Policy* 42: 1568–1580.
Suchar, C.S. 1989. The sociological imagination and documentary still photography: the interrogatory stance. In *Eyes across the water: The Amsterdam conference on visual anthropology and sociology*, ed. R.B. Flaes. Amsterdam: Het Spinhuis.
Te Velde, H., N. Aarts, and C. van Woerkum. 2002. Dealing with ambivalence: Farmers' and consumers' perceptions of animal welfare in livestock breeding. *Journal of Agricultural and Environmental Ethics* 15: 203–219.
TNS Emnid, 2012. Das Image der deutschen Landwirtschaft. https://www.ima-agrar.de/fileadmin/redaktion/download/image-studie/2012/ima-imagestudie-landwirtschaft_bericht-2012.pdf. Accessed 10 March 2020.
Ventura, B.A., M.A. Von Keyserlingk, H. Wittman, and D.M. Weary. 2016. What difference does a visit make? Changes in animal welfare perceptions after interested citizens tour a dairy farm. *PLoS ONE* 11 (5): e0154733.
Verbeke, W., L.J. Frewer, J. Scholderer, and H.F. De Brabander. 2007. Why consumers behave as they do with respect to food safety and risk information. *Analytica Chimica Acta* 586: 2–7.
Van Liere, K.D., and R.E. Dunlap. 1980. The social bases of environmental concern: A review of hypotheses, explanations and empirical evidence. *Public Opinion Quarterly* 44: 181–197.
Wathes, C.M., H.H. Kristensen, J.M. Aerts, and D. Berckmans. 2008. Is precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall? *Computers and Electronics in Agriculture* 64 (1): 2–10.
Weary, D.M., and M.A.G. Von Keyserlingk. 2017. Public concerns about dairy-cow welfare: How should the industry respond? *Animal Production Science* 57 (7): 1201–1209.
Weber, G.M., T.J. Hoban, P.A. Kendall, and L.S. Bull. 1995. Consumer concerns about modern technology in agriculture: Considerations for undergraduate and graduate teaching. *Journal of Animal Science* 73 (9): 2727–2732.
Weersink, A., E. Fraser, D. Pannell, E. Duncan, and S. Rotz. 2018. Opportunities and challenges for Big Data in agricultural and environmental analysis. *Annual Review of Resource Economics* 10: 19–37.
Weinrich, R., S. Kühl, A. Zühlsdorf, and A. Spiller. 2014. Consumer attitudes in Germany towards different dairy housing systems and their implications for the marketing of pasture raised milk. *International Food and Agribusiness Management Review* 17: 205–222.
Wenzel, C., S. Schönreiter-Fischer, and J. Unshelm. 2003. Studies on step–kick behavior and stress of cows during milking in an automatic milking system. *Livestock Production Science* 83 (2–3): 237–246.
Wildraut, C., and M. Mergenthaler. 2019. Sichtweise der Landwirtschaft. In SocialLab—Nutztierhaltung im Spiegel der Gesellschaft [The view of agriculture. In SocialLab—animal husbandry in the mirror of society]. *Agra Europe* 13/19: 10–12.

Wildraut, C., M. V. Meyer-Höfer, A. Rovers, M. Mergenthaler, W. Sonntag, A. Spiller, and I. Christoph-Schulz. 2019. Landwirte und Verbraucher im Dialog. In SocialLab—Nutztierhaltung im Spiegel der Gesellschaft [Farmers and consumers in dialogue. In SocialLab—animal husbandry in the mirror of society]. *Agra Europe* 13/19: 12–16.
Winter, M., C. Fry, and S.P. Carruthers. 1998. European Agricultural Policy and Farm Animal Welfare. *Food Policy* 23: 305–323.
Wolfram, J., N. Brümmer, M. Mergenthaler, and I. Christoph-Schulz. 2019. Landwirtschaftliche Tierhaltung in den Medien. In SocialLab—Nutztierhaltung im Spiegel der Gesellschaft [Animal husbandry in the media. In SocialLab—animal husbandry in the mirror of society]. *Agra Europe* 13/19: 16–18.
Wuepper, D., P. Wree, and G. Ardali. 2019. Does information change German consumers' attitudes about genetically modified food? *European Review of Agricultural Economics* 46 (1): 53–78.
Wüstenhagen, R., M. Wolsink, and M.J. Bürer. 2007. Social acceptance of renewable energy innovation: An introduction to the concept. *Energy Policy* 35 (5): 2683–2691.
Zajonc, R.B. 1980. Feeling and thinking: Preferences need no inferences. *American Psychologist* 35 (2): 151–175.

Johanna Pfeiffer is a researcher at the Institute for Agricultural Engineering and Animal Husbandry, Bavarian State Research Center for Agriculture. Johanna is working on the socio-economic aspects of digital agriculture technologies.

Andreas Gabriel is a researcher at the Institute for Agricultural Engineering and Animal Husbandry, Bavarian State Research Center for Agriculture, and at the Chair of Economics of Horticulture and Landscaping, Technical University of Munich. His focus is on empirical social research in the fields of agriculture, nutrition and horticulture.

Markus Gandorfer is head of the Digital Farming Group at the Institute for Agricultural Engineering and Animal Husbandry, Bavarian State Research Center for Agriculture. His focus is on the comprehensive assessment of digital agriculture technologies.

Pfeiffer, J., Spykman, O., Gandorfer, M. (2021). Sensor and video: two complementary approaches for evaluation of dairy cow behavior after calving sensor attachment. Animals, 11(7), 1917.
[https://www.mdpi.com/2076-2615/11/7/1917]
[Publisher: MDPI]

animals

Article

Sensor and Video: Two Complementary Approaches for Evaluation of Dairy Cow Behavior after Calving Sensor Attachment

Johanna Pfeiffer [1,2,*], Olivia Spykman [1,2] and Markus Gandorfer [1]

1 Bavarian State Research Center for Agriculture, Institute for Agricultural Engineering and Animal Husbandry, 94099 Ruhstorf an der Rott, Germany; olivia.spykman@lfl.bayern.de (O.S.); markus.gandorfer@lfl.bayern.de (M.G.)
2 TUM School of Life Sciences, Technical University of Munich, 85354 Freising, Germany
* Correspondence: johanna.pfeiffer@lfl.bayern.de

Simple Summary: We analyzed whether attaching sensors to the tail of cows for the early detection of calving leads to behavioral changes. In this study, we combined conventional video analysis with data from digital sensor technologies. To detect the potential agitation of cows after calving sensor attachment, we analyzed cow activity behavior. Based on the combined results of video and sensor analysis, there was no clear evidence that attaching sensors to the tail generally altered the ethological pattern of all cows analyzed. However, the investigation of individual cows showed an increase in the frequency of tail raising and rubbing the tail after calving sensor attachment. These changes would be worth analyzing in more detail on a larger scale.

Abstract: Studies evaluating calving sensors provided evidence that attaching the sensor to the tail may lead to changes in the cows' behavior. Two different calving sensors were attached to 18 cows, all of which were equipped with a rumen bolus to record their activity. Two methodological approaches were applied to detect potential behavioral changes: analysis of homogeneity of variance in cow activity (5 days pre-sensor and 24 h post-sensor) and analysis of video-recorded behavior (12 h pre- and post-sensor, respectively) in a subgroup. The average results across the sample showed no significant changes in the variability of activity and no statistically significant mean differences in most visually analyzed behaviors, namely walking, eating, drinking, social interaction, tail raising, rubbing the tail, and the number of standing and lying bouts after calving sensor attachment. In addition to considering mean values across all cows, individual cow investigations revealed an increased number of time slots showing a significant increase in the variability of activity and an increased frequency of tail raising and rubbing the tail on objects after calving sensor attachment in some cows, which should be investigated in more detail on a larger scale.

Keywords: activity; Brown–Forsythe test; digital; variance; video

check for updates

Citation: Pfeiffer, J.; Spykman, O.; Gandorfer, M. Sensor and Video: Two Complementary Approaches for Evaluation of Dairy Cow Behavior after Calving Sensor Attachment. *Animals* **2021**, *11*, 1917. https://doi.org/10.3390/ani11071917

Academic Editor: Sébastien Buczinski

Received: 21 April 2021
Accepted: 18 June 2021
Published: 28 June 2021

1. Introduction

1.1. Sensor Systems to Improve Calving Management

Calving monitoring and assistance can reduce the incidence of stillbirths and the proportion of cows with post-partum endometritis and uterine infections while also having a positive effect on reproductive performance [1,2]. To improve calving management, sensors for early calving detection are discussed as a technological solution. These sensors can detect parameters such as behavior or body temperature, which change a few hours before calving [3]. Saint-Dizier and Chastant-Maillard [3] described four different types of commercially available calving detection devices: accelerometers and inclinometers that are attached to the tail and measure activity, abdominal belts to monitor uterine contractions, vaginal probes to monitor vaginal temperature, and devices in the vagina or on the labia that detect expulsion of the calf. Predicting the onset of calving through the continuous monitoring of tail movement is possible due to changes in the behavior of a cow before calving, such as a significant increase in the frequency and duration of tail raising [4,5]. There are currently three different market available sensors for attachment to the tail, which differ in the way they are attached: with a ratchet (Moocall, Moocall Ltd., Dublin, Ireland), with an adhesive and tape (CalveSense, Allflex Group Germany GmbH, Bad Bentheim, Germany), and with a clamp and tape (Calving Alert Set, Patura KG, Laudenbach, Germany). In addition, many sensor systems that were originally used exclusively for estrus detection have been further developed in recent years to include the function of calving monitoring. Parameters such as activity, temperature, or rumination are used for this purpose. The available literature shows that some sensors on the market have the potential to achieve satisfying results in the early detection of calving [5–9]. Studies on tail-attached sensors have reported sensitivities of up to 95% [5].

Although the literature suggests that sensors can help to improve calving management and, therefore, specific animal welfare aspects (e.g., calf mortality), there is also evidence that sensors attached to the cow's tail in particular can cause behavioral changes or even injuries. Studies evaluating tail-attached calving sensors have so far focused on the Moocall sensor. Investigations on the behavior of dairy cows after attaching a calving sensor to the tail are, however, rare. In this context, Lind and Lindahl [10] reported on practical experience with the Moocall calving sensor. Their study on cow behavior after the attachment of the sensor system had to be discontinued due to frequent tail injuries. They subsequently conducted telephone interviews with 15 farmers and confirmed these initial experiences: 80% of the farmers stated that the behavior of the cow worsened after the Moocall sensor system had been attached, which they inferred from increased tail raising and fidgeting. Additionally, 87% noticed injuries to the tail of the animals. However, the interviewed farmers' assessment that the cows' behavior changed in a way that was judged to be negative after attaching a Moocall sensor [10] was a visual and subjective one, as it was not recorded according to a uniform classification scheme. Recently, Giaretta et al. [5] investigated precision of calving prediction with the Moocall sensor and dairy cow behavior after its attachment. They visually analyzed walking, eating, lying down, standing, and tail movement one day before and on the day of calving sensor attachment, concluding that the Moocall sensor was well tolerated by the cows, as only eating behavior showed an increase after its attachment to the tail. Voss et al. [8] conducted a study on the Moocall sensor, focusing on its fit on the tail and skin integrity after attachment. In their experiment, the Moocall sensor did not continuously remain on the tail in 86.1% of the animals, with reason being mainly categorized as 'fell off tail' or 'tail swollen or painful'.

1.2. How Can Behavioral Changes in Dairy Cows Equipped with Tail-Attached Calving Sensors Be Assessed?

To assess behavioral changes or even stress in cows, various parameters have been analyzed and different approaches have been applied in literature. The extent to which animals respond to stress depends not only on the duration and intensity of exposure to a stressor, but also on environmental conditions, physiological status, and previous experience with the stressor [2]. So far, the analyzed stressors for cows include isolation from the herd [11–14], confrontation with novelty such as a milking system [15–17], exposure to stray voltage [18–21], or heat [22–31], among others. The previous studies showed that cows responded to stress by increased activity [12,14,16,18,20].

To describe changes in the behavior of an animal, the mean and median of activity data from different time periods are often used [20,29,32]. In addition, analyzing variability of activity and movement behavior is a common methodological approach to characterize and predict, among others, diseases in cows [33–38]. For instance, Edwards and Tozer [33] showed a reduced average walking activity, recorded with pedometers, in cows with metabolic or digestive disorders compared to healthy cows. Their study also indicated that the variability of activity was higher in sick cows compared to healthy ones, regardless of lactation number and calving season. Thus, multiple studies indicate that not only the activity level per se is relevant for describing cow behavior, but rather it appears that the scattering of activity values around a mean value can provide further valuable information.

Digital sensor technologies for dairy farming are currently being used with the argument of improving animal welfare as they contribute to calving and health management. At the same time, there are concerns as to whether the attachment of sensors has negative effects on cows. In the worst case, there could be a contradiction: Does a digital technology with the intention to improve animal welfare by monitoring calving actually disturb cows? This study therefore addresses the question of whether the attachment of two different calving sensors leads to behavioral changes indicating that cows are being disturbed by these monitoring devices.

2. Materials and Methods

2.1. Data Collection

2.1.1. Animals and Housing

The data (mid-July to early December 2018) originate from a dairy research and demonstration farm located in Bavaria, southern Germany. On the dairy farm, cows were kept in a free-stall barn year-round. Six to eight weeks before the expected calving date, the animals were dried off and moved to the dry cow area. Approximately eight days before the expected calving date, the cows were separated into one of four maternity pens littered with straw. The animals were paired in the maternity pens solely dependent on their expected date of calving and thus independent of age, lactation, breed, and type of calving sensor attached. In the maternity pen, the total mixed ration was provided daily at the same time (09:15 to 09:30 a.m.) and water was available ad libitum. Two video cameras were placed above the four maternity pens and recorded continuously. Mobotix D15 cameras were used, which ensured good night vision by means of an integrated infrared lens. The video recordings were stored in a network-attached storage. The analysis included 15 cows and 3 heifers (mean age $\pm$ SD = 5.5 $\pm$ 2.6 years; mean parity $\pm$ SD = 4.1 $\pm$ 2.5), of which eleven were Simmentals, four were Brown Swiss, and three were Holstein breed (see Table A1 in Appendix A).

2.1.2. Sensors and Calving Management

On this dairy farm, cows were equipped with a calving sensor and received a rumen bolus (smaXtec animal care GmbH, Graz, Austria) several weeks before the expected calving date. We used Moocall (Moocall Ltd., Dublin, Ireland; weight: 329 g including pad) and CalveSense (Allflex Group Germany GmbH, Bad Bentheim, Germany; weight: 172 g) as sensors for an early detection of calving. Both calving sensors analyze tail movement and issue a message to the farmer a few hours before calving. Therefore, they are attached to the cow's tail only a few days before the estimated calving date. As tail-attached calving sensors are only applied for a short period before calving, the behavioral analysis focused on a short-term adaptation period (see also [5]). The user has no insight into the recorded raw data from the calving sensors, but only receives messages in the case of an imminent calving. As it was not the purpose of this study to analyze the calving alarms of the sensor systems themselves, this was not a limitation. The second type of sensor, a rumen bolus, is a commercial product administered orally into the reticulorumen using an oral applicator. In the reticulorumen, it continuously records animals' activity in ten-minute intervals on a scale between 1 and 100 as a dimensionless index using a 3D acceleration sensor. It additionally measures core body temperature with an accuracy of $\pm$0.05 °C [39]. The data is then sent to a base station, from where it may be exported for analysis. The activity measurement is not influenced by rumen motility since disturbance factors that cannot be attributed to the movement of the animal itself (e.g., movement of the rumen) are filtered out [40]. The smaXtec bolus has already been applied in scientific studies to clarify a range of research questions (see [41–43]). Studies on the performance of the activity-based estrus detection of the smaXtec bolus showed a sensitivity of 92% (blood progesterone as reference) and a precision (positive predictive value) of 89% [44]. Based on a review of estrus detection rates in other sensor systems [45], this accuracy can be classified as good.

In the maternity pen, either a Moocall or CalveSense sensor was attached to the tail five days in advance of the estimated calving date. The attachment of the calving sensors was carried out by only two staff members, who received instructions and training on the correct handling of the two sensor systems with cows outside the study cohort before the start of documentation. As such, a learning process of attaching the sensors, which could potentially influence the animals' behavior could be excluded. Sensor attachment was performed according to the respective manufacturer's guideline: the Moocall sensor was fastened with a ratchet whereas the CalveSense sensor was secured to the tail with an adhesive and tape. After the calving sensor attachment, the farm staff checked its fit on the cow's tail and for potential pressure marks or swellings on the tail. The calving sensor check was performed one to two hours after its attachment and then twice daily during the routine inspection of animals to calve. In this process, any abnormalities such as swelling of the tail, conspicuous behavior such as rubbing the tail on objects, or sensor dropping after attachment were documented. As recommended by the manufacturer, Moocall sensors were removed for three to four hours if they had already been attached to the tail for four days (and the cow had not yet calved) before being reattached.

On the dairy research and demonstration farm, CalveSense sensors were attached to a total of 36 animals and Moocall sensors were attached to a total of 37 animals. Due to the defined period of analysis and not all the calving sensors attached remaining on the tail (e.g., due to falling off), 18 animals could be included in methodological approach 1, and nine of them also in methodological approach 2. The analysis included only animals on which a calving sensor remained attached to the tail for at least 24 h (exception: cow 15 with sensor being removed after 23 h and 15 min).

Because a cow's behavior may be influenced by its overall state of health [46,47], we also considered health data for the analysis. As the dairy farm is participating in ProGesund, an information service for veterinarians and farmers, documentation on all diseases diagnosed by a veterinarian was available. Prior to calving sensor attachment, a health assessment of the animals was performed, which included a visual assessment of the animal as well as continuous data on core body temperature and number of drinking cycles collected via the rumen bolus.

2.2. Methodological Approach 1: Analysis of the Activity Index Recorded by Sensors (Rumen Bolus)

The first methodological approach was an analysis of the variability of activity [33–38]. All statistical calculations were performed using the software R [48] (packages: "tseries" [49], "car" [50], "DescTools" [51]). The aim of the statistical analysis was to determine whether the variability of the activity index recorded by the rumen bolus changed after attaching a calving sensor to the cow's tail. In this process, the cows served as their own control [34,37]. By choosing a reference period of four days (see Figure 1), our study resembled the approach of Thorup et al. [34] who considered a reference period of two to eight days for analyzing variability of activity. To be representative of the actual activity, its variability was measured over a period of multiple days. At the same time, the exclusion of potential influences of cow drying off, being moved to the dry cow area, and being separated into a maternity pen was taken into consideration, resulting in a four-day reference period. Given the timeframe of five days prior to sensor attachment required for data analysis (see Figure 1) and at least 36 h between sensor attachment and calving, it was possible to include 18 cows in the analysis (five cows with Moocall sensors, 13 cows with CalveSense sensors). A period of 36 h was required between sensor attachment and calving to allow for a 24-h post-sensor study period while also accounting for natural pre-calving changes in behavior [4,52,53].

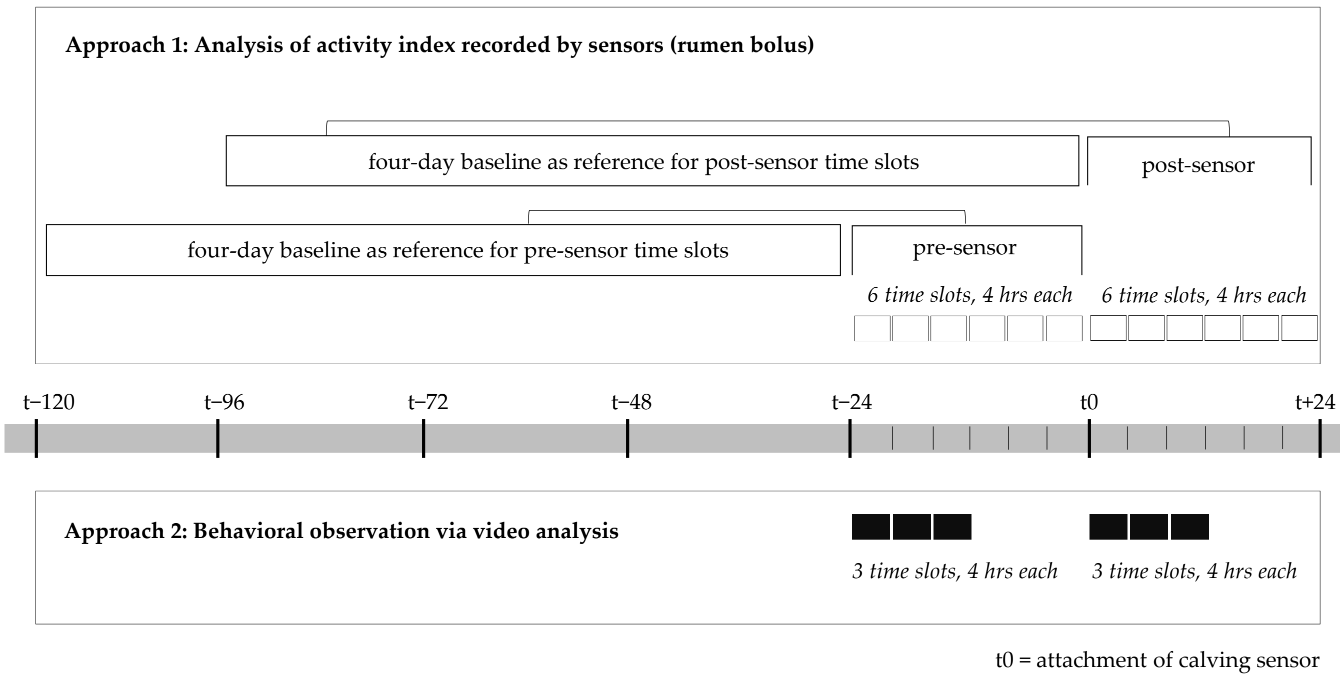

Figure 1. Schematic representation of the periods considered for analysis of behavior.

An analysis of the variability of activity was performed on the average activity index data across all 18 cows. We measured activity in six four-hour time slots, i.e., a total of 24 h consecutive to sensor attachment (t0 to t + 24; post-sensor) and compared it to the four-day baseline (t − 96 to t0) immediately prior to sensor attachment. To avoid any influences of the sensor attachment on the activity data of the first timeslot, we removed the data point(s) closest to the manually recorded time of attachment, thus generating a buffer of 10 to 15 min before the first data point was included in the analysis. To eliminate any bias from possible long-term trends, the activity data were detrended. The calculation of the first differences was sufficient to achieve stationarity for the time series before and after sensor attachment, as confirmed by the augmented Dickey–Fuller test ($p < 0.01$ for all tested cows and time series). All subsequent analyses were carried out on the detrended data. Since activity behavior may vary greatly from cow to cow [23,37], analyses of the detrended variability of the activity index were also performed separately for all cows. To assess whether activity behavior changed after attaching the calving sensor, we tested for homogeneity of variances between the four-day baseline and each of the post-sensor four-hour time slots, respectively (see Figure 1). Given the non-normal distribution of the data, we substituted the mean with the median, i.e., used the Brown–Forsythe test [54]. The term "variance" as such is technically not correct but is commonly used for reasons of comprehensibility [55,56]. Levene's test and its modification, the Brown–Forsythe test, are frequently applied for testing the homogeneity of variances in different contexts [57–64].

The time at which the sensor is attached to the cow's tail is defined as t0 and corresponds to a different time of day for each animal. To account for any possible influence of the diurnal activity pattern, we also conducted the Brown–Forsythe test for each of the six four-hour time slots on the day before the sensor was attached (pre-sensor). To remain consistent, the four days (t − 120 to t − 24) preceding this day were again used as a baseline (see Figure 1), resulting in a second baseline. This explains the required timeframe of five days prior to sensor attachment. In the process, the respective time slots, both pre- and post-sensor, refer to the same time of day for each animal (i.e., both first, second, . . . , and sixth time slots, respectively). The evaluation of 24-h pre- and post-sensor data enabled us to interpret changes in the variability of the activity index. More specifically, it allowed us to classify whether changes in the post-sensor activity behavior occurred more often than in the usual activity behavior of the cows (pre-sensor) and may thus be attributed to the calving sensor. To account for multiple testing, we applied the Bonferroni correction to maintain the significance level over all tests at 0.05 so that only those time slots for which $p < 0.0083$ were considered significant.

The analysis of significances focused on the absolute number of significant time slots. If a sensor attached to the tail is perceived as disturbing and agitates the cow, she may try removing the sensor while suffering from restlessness. We therefore continued with the premise that time slots showing an increase in variability of activity with regard to the attachment of calving sensors were the relevant indicator. As cows exhibited periods of lower or higher variability of activity more frequently, for example, due to diurnal patterns of activity, we focused on changes in the number of time slots showing a significant increase in variability of activity in the post-sensor compared to the pre-sensor period.

2.3. Methodological Approach 2: Behavioral Observation via Video Analysis

The second methodological approach was a conventional visual observation of the cows' behavior recorded on video. The video recordings were available for nine of the 18 cows included in methodological approach 1 (cow ID 1 to 9 in Table A1). The subsample for video analysis included three cows with Moocall and six cows with CalveSense sensors. The assignment of animal behavior was performed on all nine cows by the same observer using the software Interact (Mangold International GmbH, Germany). All behavior patterns were observed for the first twelve hours consecutive to calving sensor attachment (t0 to t + 12) and for twelve hours at the same time of day the day before calving sensor attachment (t − 24 to t − 12) as the reference period. The twelve-hour periods were divided into three time slots of four hours each (see Figure 1). Again, the respective time slots, both pre- and post-sensor, referred to the same time of day for each cow (i.e., both first, second, and third time slots, respectively). In congruence with methodological approach 1, the cows thus served as their own control.

For the behavioral observation, an ethogram appropriate for the research question and based on published literature was developed. The ethogram included eight behavior patterns (see Table 1).

Table 1. Ethogram including the respective descriptions of the behaviors.

Unit	Behavior	Description
Duration of	Walking	The cow is moving all four legs (walking or running) [13]
	Standing	The cow is standing without moving [13,25]
	Lying	The cow is lying in different natural lying positions [65]
	Eating	The cow places its head above the feeding table and searches, masticates or sorts the feed (silage) [66]
	Drinking	The cow places its head over the water trough [24]
Frequency of	Tail raising [1]	Lateral > 90°
Duration of	Rubbing the tail on objects [1]	Rubbing the tail on objects (other cow in maternity pen, penning, or water trough)
	Social interaction [1]	social licking: licking another cow's head, neck, and/or shoulder areas sniffing head: head or muzzle stretched towards/maybe touching another cow's head sniffing body: head or muzzle stretched towards/maybe touching another cow's body gentle pushing: hard push of body against body head butting: blow with the forehead directed at another cow fighting: head-to-head pushing, sometimes followed by head to neck pushing and manoeuvring for position ([67], based on work from [68])

[1] Observed parallel to the behaviors walking, standing, lying, eating, and drinking.

Walking [13,25,65], standing [17,24,25,65], lying [17,24–26], and the number of standing and lying bouts [26,65,69,70] per time slot were captured visually. Furthermore, eating [17,18,24,25,66] and drinking [18,24,25] were included in the ethogram. Eating and drinking took place exclusively while standing, but both behaviors were analyzed and presented separately. To take this into account, eating and drinking were counted as "standing" when determining the number of lying and standing bouts.

Since a potential perception of calving sensors as disturbing depends on sensor position on the tail, we observed two further behaviors, tail raising [5] and rubbing the tail on objects, which may indicate that the cow was trying to change the position of the sensor on the tail. To differentiate between slight tail movements, tail raising was defined as lateral >90°. Tail-rubbing was performed on another cow in the maternity pen, on the penning, or on the water trough. In addition to the observation of individual animal behavior, social interaction [65,67,68] was recorded.

Central tendencies were compared to evaluate whether changes in the analyzed behaviors occurred after attachment of calving sensors. Due to the non-normal distribution of the data, the Wilcoxon test for paired samples was applied. For each behavior, the medians of paired time slots were compared (i.e., first time slot pre- and post-sensor, second time slot pre- and post-sensor, and third time slot pre- and post-sensor, respectively). The sample of each time slot consisted of nine cows. Due to the sample size, a continuity correction was included in all Wilcoxon tests.

3. Results and Discussion

To interpret the results of our analyses, a brief overview of cows with relevant health documentation or showing abnormalities (Section 3.1) commences this section. Subsequently, the results on variability of activity and on behavioral observation (Sections 3.2 and 3.3) are interpreted and discussed.

3.1. Documentation Concerning Calving Sensor Attachment, Abnormalities after Calving Sensor Attachment, and Health

On the dairy research and demonstration farm, a total of 36 CalveSense devices were attached to the tail of cows, of which four devices (11.1%) fell off. Neither pressure marks nor swellings on the tail were documented after attachment of CalveSense devices. Of the total of 37 Moocall devices attached, 23 (62.2%) did not remain on the tail because they either fell off (and were then reattached) or were removed by the barn staff due to pressure marks, swellings, or technical problems (e.g., battery often empty although sensor charged). In eight of these 23 animals, pressure marks or swellings were documented during the twice daily routine inspection, whereupon the Moocall sensor was immediately removed. Due to the large number of Moocall sensors that did not remain on the tail, there were comparatively more cows with a CalveSense device in the analyzed sample of 18 animals.

Regarding the health documentation of the cows in the study, we focused on two weeks before and two weeks after attachment of the calving sensor. During this period, metaphylaxis against hypocalcemia was performed in eight of the 18 cows. However, it was carried out more than 24 h after the calving sensor was attached. Four cows (7, 12, 14, and 17) suffered from hypocalcemia after calving (diagnosed four, eight, two, and two days after attachment of the calving sensor, respectively). Also, after calving, one cow suffered from mastitis (cow 16; diagnosed four days after attachment of the calving sensor), one from metritis (cow 4; diagnosed ten days after attachment of the calving sensor), and one from retentio secundinarum (cow 3; diagnosed three days after attachment of the calving sensor).

Based on the farm staff's protocol, three of the 18 animals included in the analysis were identified to show abnormalities after attaching a calving sensor to their tail:

- In cow 2, conspicuous activity behavior was observed immediately after attaching the sensor (CalveSense) to the tail. She rubbed her tail heavily on the water trough for the first 15 min, although this decreased afterwards (also observed in video).

- About an hour after the calving sensor (Moocall) was attached to cow 7, the fit of the sensor on the tail had to be readjusted. The cow was fixed in the feed fence for a short time and the sensor was reattached (attachment: 08:24 a.m.; reattachment: 09:35 a.m.).
- Cow 15 showed discomfort in her activity behavior 23 h and 15 min after attachment of the calving sensor (Moocall). As pressure points and slight swelling were visible on the tail, the sensor was removed immediately (no video available).

3.2. Methodological Approach 1: Changes in the Variability of the Activity Index

On average across all 18 cows analyzed, the mean absolute deviation around the median (MAD) values as well as the medians were in a similar range for both of the four-day baselines (see Table 2). We could therefore assume that the selected baselines offered a stable representation of the usual activity behavior. This allowed for a comparison of each time slot with its respective baseline and subsequently the classification of deviations in activity behavior. The Brown–Forsythe test, applied to analyze variability of activity of all 18 cows, revealed that three of the pre-sensor and none of the post-sensor time slots showed a significant increase in the variability of activity. In addition, a significant decrease in the variability of activity was detected in one time slot pre-sensor, which was, however, outside of the focus of our investigation. In summary, the number of time slots showing a significant increase in the variability of the activity index in the post-sensor time slots was not increased compared to the pre-sensor time slots. On average across all 18 cows, an increase in the variability of the activity index after calving sensor attachment indicating severe agitation as a stress response as documented in other studies (e.g., [12,14,16,18,20]) was not observed.

Table 2. Median and mean absolute deviation around the median (MAD) of the activity index, and results of the Brown–Forsythe test for the pre-sensor and post-sensor time slots using the respective four-day baseline as reference (n = 18).

	Baseline [a] (Pre-Sensor)	Baseline [b] (Post-Sensor)	t − 24 to t − 20	t − 20 to t − 16	t − 16 to t − 12	t − 12 to t − 8	t − 8 to t − 4	t − 4 to t0	t0 to t + 4	t + 4 to t + 8	t + 8 to t + 12	t + 12 to t + 16	t + 16 to t + 20	t + 20 to t + 24
MAD	0.16	0.17	0.23	0.25	0.19	0.16	0.09	0.30	0.24	0.15	0.12	0.11	0.13	0.23
median	−0.02	−0.02	−0.05	−0.06	−0.06	0.09	0.01	0.01	0.01	−0.05	0.01	0.01	−0.04	0.05
Brown–Forsythe test			sig.[I]	sig.[I]			sig.[D]	sig.[I]						

[a] Four-day baseline (t − 120 to t − 24) as reference for pre-sensor time slots. [b] Four-day baseline (t − 96 to t0) as reference for post-sensor time slots. sig.[I] significant increase in variability of activity, $p < 0.05$, Bonferroni-corrected $p < 0.0083$. sig.[D] significant decrease in variability of activity, $p < 0.05$, Bonferroni-corrected $p < 0.0083$. t0 = attachment of calving sensor.

In addition to the overall evaluation of all 18 cows shown in the section above, individual animal investigations elicited further information. Again, the analysis of individual cows revealed that, for both four-day baselines of any given cow, the MAD values as well as the medians were in a similar range (see Table A2). Figure 2 visualizes the absolute number of pre-sensor and post-sensor time slots showing a significant increase in the variability of activity relative to the respective four-day baseline (Brown–Forsythe test: $p < 0.05$). After the calving sensor was attached, none of the 18 cows exhibited a constant significant increase in the variability of activity in all six post-sensor time slots, while for twelve out of 18 cows no significant increase in the variability of activity could be detected in any of the post-sensor time slots. Four cows revealed a significant increase in the variability of activity in only one of the six post-sensor time slots and only two cows showed a significant increase in the variability of activity in two of the six post-sensor time slots. Considering the six cows that showed a significant increase in the variability of activity in one or two post-sensor time slots, a similar significance pattern in the pre-sensor time slots emerged for four of them. Cows 11 and 15, however, did not reveal a significant increase in the variability of activity in any of the pre-sensor time slots.

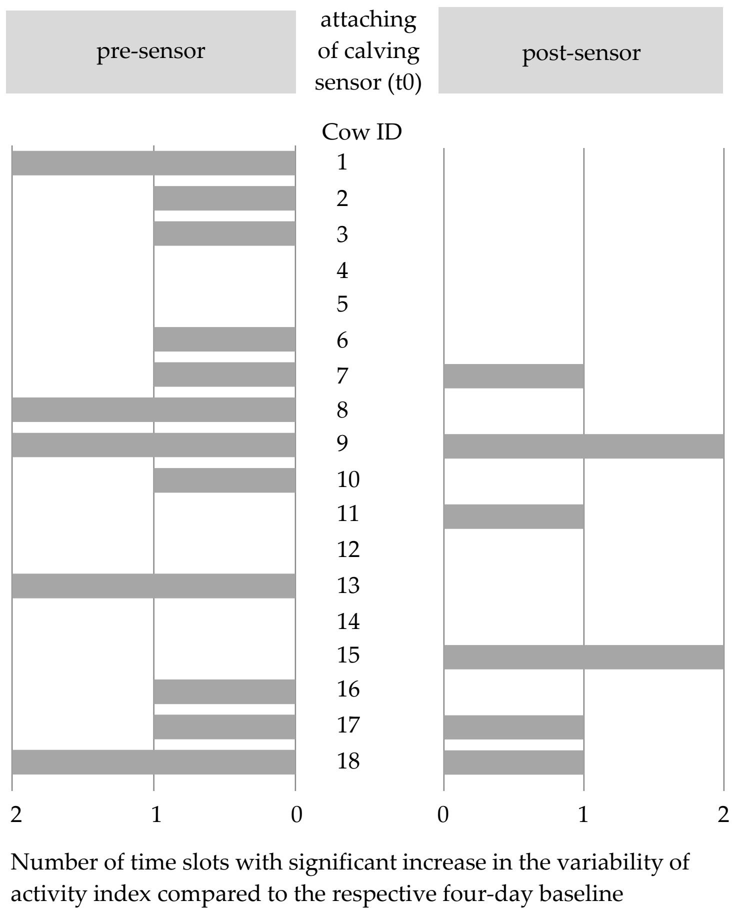

Figure 2. Depiction of the number of time slots pre-sensor (t − 24 to t0) and post-sensor (t0 to t + 24), showing a significant increase in the variability of the activity index using the respective four-day baseline as a reference (Brown–Forsythe test: $p < 0.05$, Bonferroni-corrected $p < 0.0083$).

Cows 7 and 15, for which abnormalities were visually detected by the farm staff within 24 h of attaching the calving sensor, showed a significant increase in the variability of activity in the first time slot following the attachment of the calving sensor (t0 to t + 4), thus making them the only cows to show such immediate reactions (see Table A2). In cow 7 (readjustment of the sensor in time slot t0 to t + 4), the Brown–Forsythe test did not reveal statistically significant increases in the variability of activity occurring in the subsequent time slots (t + 4 to t + 24). Cow 15, however, showed a significant increase in the variability of activity also in the time slot t + 21 to t + 24 h post-sensor (see Table A2). In this period, tail swelling was detected, and the calving sensor was removed by the farm staff.

Findings on cow behavior should be interpreted in a differentiated manner because reasons for changes in cow behavior may be rooted in a variety of causes. Changes in the activity of a cow can be attributed to individual animal behavior, diurnal patterns of activity, parity, stage of lactation, disease, estrus, and external effects [32–34,71,72], among other aspects. Behavioral changes may also be explained by a rebound effect, which has been demonstrated, for example, around the time of calving, with different surface types, or lying deprivation in dairy cattle [52,73,74]. As individual cow analyses revealed that some of the post-sensor time slots showing a significant increase in the variability of activity also showed statistical significance for the same time of day on the previous day, diurnal patterns of activity [32] became apparent.

Since a maximum of two of the six post-sensor time slots for each cow revealed a significant increase in the variability of activity, behavioral changes potentially caused by calving sensor attachment seem to have subsided after a short time. If the attachment of a calving sensor led to agitation in a cow, it can be assumed that this was only temporary. Several studies found that cows are able to acclimate to changes [13,18,75]. Concerns about the negative effects on animal welfare should therefore be greater in the presence of evidence of significant long-term changes in activity behavior. However, none of the 18 animals analyzed revealed significant changes in the variability of activity over the entire period of 24 h post-sensor attachment. In the two cows that did show a significant increase in the variability of activity in the first time slot post-sensor (cows 7 and 15), the significant result was not reproduced in the ensuing time slots. Farmers interviewed by Lind and Lindahl [10] reported that negative animal behavior lasted up to one hour after attaching a Moocall. Consequently, their observations are consistent with our results.

We applied the Brown–Forsythe test for comparing the variability of activity between the four-day baselines and four-hour time slots, i.e., between samples of different sizes. However, since observation of a sole 24-h time slot post-sensor would have been too imprecise, a subdivision into time slots was deemed appropriate. In the literature, it was reported that the Brown–Forsythe test is robust to unequal sample sizes [55,56].

The Bonferroni correction applied to account for Type I error accumulation in multiple testing is known to be conservative compared to alternative correction methods [76,77]. There is controversy about its use because reduction of the Type I error is accompanied by an increase in the risk of Type II error, leading to actual differences not being detected. However, as a low number of multiple tests was conducted in our evaluation, the Bonferroni-corrected significance level was not minimized to such an extent that the analysis would no longer have yielded any significant outcomes. A previous analysis of the significant time slots without Bonferroni correction revealed that the overall conclusion of methodological approach 1 remained the same, since Type I error accumulation affected both pre- and post-sensor time slots equally. This is a crucial point of our study, as our focus was on the change in the number of significant time slots between pre- and post-sensor periods rather than their absolute numbers.

The activity index used for methodological approach 1 is based on a proprietary algorithm that is not open source. Therefore, the detailed calculation of the activity index is not known. Although this is a limitation of our study, it does not weaken the proposed methodological approach of analyzing the variability of the activity index rather than activity itself to monitor dairy cows' behavior. Furthermore, since all analyzed data from all animals and all time slots are based on the same algorithm, all steps in our analysis are subject to the same limitations so that the results of the comparisons are not biased. The lack of details on the calculation of the proprietary algorithm therefore does not impact the basic conclusions of our study.

3.3. Methodological Approach 2: Behavioral Observation via Video Analysis

3.3.1. Standing, Walking, Lying, Eating, Drinking

The video analysis revealed that the behaviors standing, walking, lying, eating, and drinking were performed by all nine cows during the analyzed time. Behaviors being performed by a cow in the pre-sensor time slots were also observed in the post-sensor time slots (see Figure A1). Although different activity levels could be observed between the cows, the majority of post-sensor time slots revealed only slight changes in time spent being active compared to the previous day (see Figure A1). An exception was cow 8, which spent comparatively more time lying on the day of sensor attachment in the first time slot (t0 to t + 4), but comparatively less in the second time slot (t + 8 to t + 12). Considering all nine cows and their respective time slots, on average 45% (8 to 96%) were spent lying, 34% (4% to 69%) standing, 3% (0% to 8%) walking, 2% (0% to 12%) drinking, and 15% (0% to 40%) eating (see Figure A1).

The comparison of the behavior observed by means of video analysis in the pre- and post-sensor period is shown in Figure 3. Only the first time slots (t − 24 to t − 20; t0 to t + 4) of the behaviors standing and lying (n = 9) differed significantly in their means. Considering these time slots, the cows spent comparatively less time standing and more time lying on average after calving sensor attachment. However, these mean differences were mainly due to activity changes of cow 8 (see Figure A1). When excluding cow 8 from the Wilcoxon test, the sample of the remaining eight animals did not show any significant differences in the mean values of the behaviors standing and lying ($p > 0.05$).

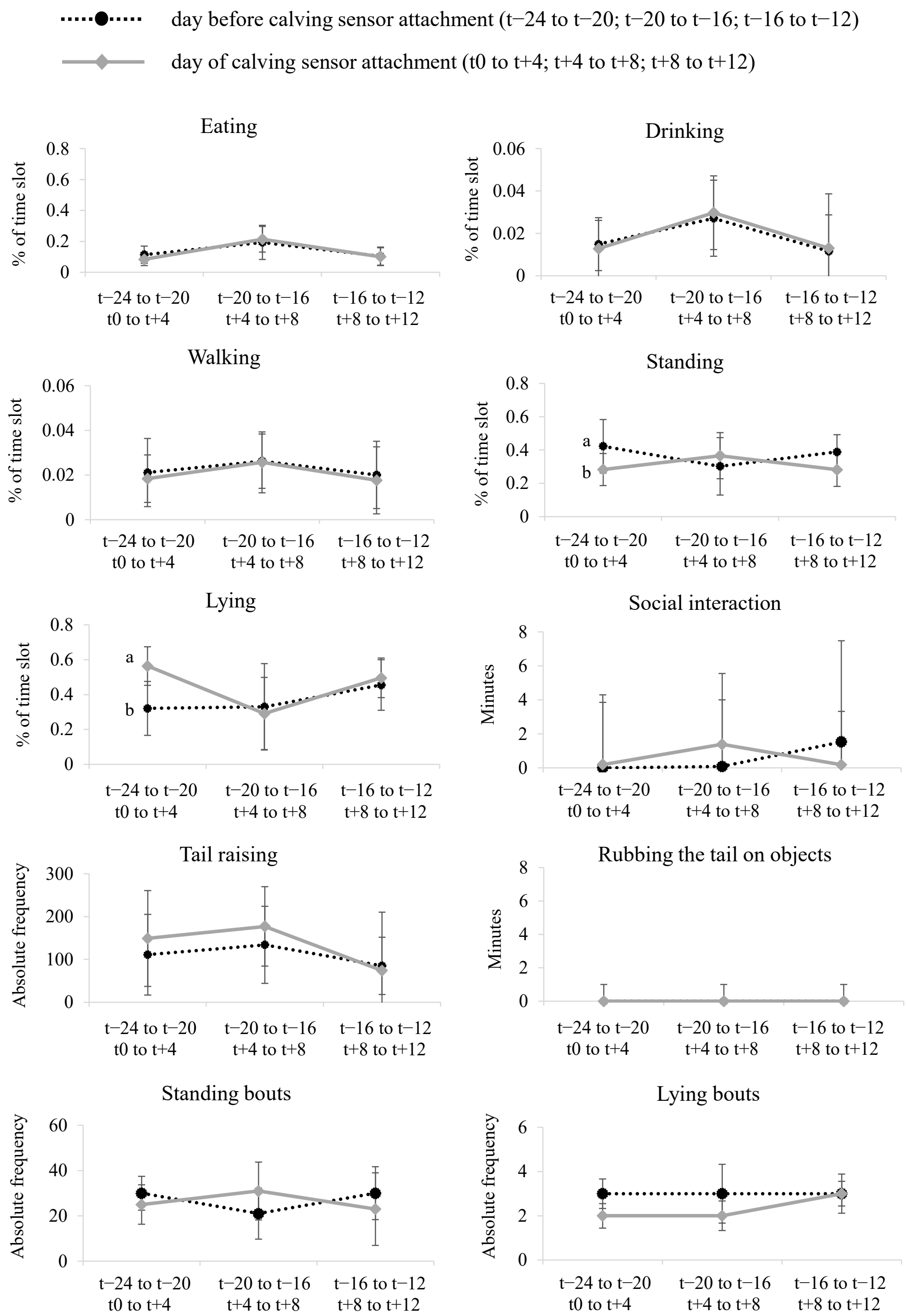

Figure 3. Medians of the behaviors observed by video analysis in the respective three time slots before (black dashed line) and after (gray solid line) calving sensor attachment ($n = 9$) (For each behavior, the black dashed lines represent the three pre-sensor time slots and the gray solid lines the three post-sensor time slots. Significant mean differences ($p < 0.05$) identified by the Wilcoxon test between the respective first, second, and third time slots pre- and post-sensor are marked with different superscripts (a, b). Mean absolute deviation around the median (MAD) is added).

As lying and standing behavior are used as a sign of well-being in cattle, they have been assessed in cow behavior studies to answer a variety of research questions. These studies investigated changes in standing and lying subject to a variety of influences such as management factors, stall size and configuration, stocking density, heat stress, social ranking, overall health status, and pen layout and flooring [31,69]. The type of flooring may have a substantial impact on standing and lying, as cows reduce their number of standing and lying bouts on floorings considered uncomfortable, indicating an avoidance of frequent changes of position from lying to standing [70]. However, an increased number of standing and lying bouts as well as higher stepping rates, more frequent step and kicking behavior, and higher activity levels were recorded as signs of restlessness and stress responses in cows [12,16–18,20]. As we did not find any restrictions in the basic activity behaviors standing, walking, lying, eating, and drinking in eight of the nine cows observed in methodological approach 2, we cannot assume a general discontent of the cows. Only cow 8 changed especially its lying and standing behavior, as she spent more time lying and less time standing in the first time slot post-sensor compared to pre-sensor. However, this may be interpreted as a mere shift of lying and standing time between the first two pre- and post-sensor time slots, respectively (e.g., rebound effect).

3.3.2. Tail Raising and Rubbing the Tail on Objects

Considering tail raising and rubbing the tail on objects, the Wilcoxon test did not show any significant mean differences between the respective pre- and post-sensor time slots (see Figure 3). However, an individual analysis of the cows provided further insights: Cows 2, 7, and 8 responded to the calving sensor attachment with an increased frequency of tail raising. In the post-sensor time slots, they performed the behavior of tail raising on average 2.0, 2.8, and 5.2 times as often (first, second, and third time slot) as in the pre-sensor time slots. While the analysis of activity index variability (methodological approach 1) did not show any significant results for the post-sensor period for cows 2 and 8, it revealed a significant increase in the variability of the activity index for the first post-sensor time slot (t0 to t + 4) for cow 7. Thus, the required readjustment of the sensor on the tail by farm staff during this time slot resulted in both an increased frequency of tail raising and an increase in the variability of the activity index in cow 7.

Whereas tail raising was performed by all nine cows, rubbing the tail on objects was observed only in cows 2 and 8. Both did not rub their tails on objects in the pre-sensor time slots, but in the post-sensor time slots for 3.1 (cow 2) and 0.8 (cow 8) minutes on average per time slot. For cow 2, rubbing of the tail on objects was predominantly observed in the first post-sensor time slot and for cow 8 in the first and second post-sensor time slots. Presumably, a certain degree of adaption can also be interpreted for the behavior of rubbing the tail on objects, reinforcing the findings of the Lind and Lindahl study [10], in which negative animal behavior reported by farmers persisted for up to one hour after calving sensor attachment, and of the Giaretta et al. [5] study, in which increased eating behavior after sensor attachment was characterized as temporary. Individual animal behavioral investigations via video observation leads to the assumption that especially tail raising (see [5]) and rubbing the tail on objects were appropriate, sensitive parameters to recognize that individual cows found the calving sensor uncomfortable and tried to remove it. However, this is not a reaction that occurred in all cows. The extent to which an increase in tail raising and rubbing the tail on objects can be considered stress in the cow is still an open question and would require more data for validation.

3.3.3. Social Interaction

Social interaction was observed in all nine cows analyzed. The observed behaviors predominantly included sniffing head, sniffing body, and social licking, and are therefore described as non-agonistic social interaction [67]. Sniffing head or body was observed in all nine cows. Only one gentle pushing (cow 8; time slot $t - 16$ to $t - 12$) and one head butting (cow 5; time slot $t + 8$ to $t + 12$) were observed as agonistic social interactions. Compared to the pre-sensor time slots, less social interaction was observed in the post-sensor time slots in five cows (1, 4, 6, 7, 9) and more social interaction was observed in four cows (2, 3, 5, 8). However, Wilcoxon testing did not indicate any significant mean differences between the respective compared pre- and post-sensor time slots (see Figure 3).

Social behavior [65,67,68] is an important welfare issue as stable social relationships in a dairy herd can help to reduce the effects of stressful conditions on animals. However, herding cows may also lead to aggression or social disturbance. For example, inappropriate housing conditions can cause social stress and aggressive behavior [68]. Since there were only two cows in the maternity pen simultaneously in our research facility, the results of social interaction should be interpreted carefully, as social interaction is usually recorded in loosely housed, larger dairy herds (e.g., [67]). Winckler et al. [78] already noted that the validity of analyzing social interaction over a short period of time may be limited due to high inter-day variation. It is known that the social interaction of licking specifically is perceived as comforting by animals [79]. For example, Galindo and Broom [79] compared social interaction of lame and non-lame cows. In lame cows, more non-agonistic social interaction, including licking, was observed on average. It was concluded that licking has a role in alleviating discomfort by looking for comfort from other cows. Although no statistically significant mean differences in social interaction were found in our study, it is striking to note that cow 8—which also exhibited an increased frequency of tail raising and rubbing the tail on objects in the post-sensor time slots—showed the greatest post-sensor increase in social interaction, thus possibly coping with discomfort.

3.4. General Discussion

Similar to what was described by Giaretta et al. [5], attaching a sensor to the tail did not generally alter the ethological pattern of the animals we analyzed. In Giaretta et al. [5] as well as in our study, no difference in tail movement after calving sensor attachment was detected across animals. Nevertheless, compared to Giaretta et al. [5], we analyzed tail raising continuously and over a longer period of time, finding an increase in the frequency of tail raising in three of nine animals, which was mainly observed in phases, indicating that tail raising should be recorded without gaps.

As also reported in Lind and Lindahl [10] and Voss [8], we point out that attaching a sensor with a ratchet (as is the case with the Moocall sensor) to an animal's tail is challenging, even after long-time practice. The two studies reported swellings to the tail in 17% [8] and 87% [10] of animals to which a Moocall sensor was attached, and frequent dropping off the tail. Both these problems were also experienced on the dairy research and demonstration farm. In contrast, the fixation of the CalveSense device with an adhesive and tape did not cause any swellings to the animals' tails. We thus reinforce that swelling of the tail due to calving sensor fixation is unacceptable (see [8,10]).

Applying two methodological approaches allowed for a multi-sided evaluation of the effect of attaching calving sensors on the behavior of cows. An analysis of the variability of the activity index provides additional insights to conventional visual observation of the active time of a cow (e.g., walking, eating). It was evident in many of the time slots that the variability of activity significantly increased while the median simultaneously decreased. This confirmed that an increase in the absolute activity level does not necessarily lead to an increase in the variability around this activity level (and vice versa). As analyzing the variability of general activity or specific movements is also a common methodological approach to predict diseases in cows [34–36], it may provide valuable information for describing the behavior of cows in further research and should receive more attention in animal behavioral research.

Both objective and subjective methods make an essential contribution to knowledge generation in animal behavior research [80]. While validity can be questioned for both subjective and objective methods, subjective methods are more prone to yielding different results when repeating an analysis of the same data set [80]. The reliability of animal observations can vary between several different observers (inter-observer reliability) as well as between observations repeated by one person (intra-observer reliability) [80,81]. The analysis of sensor-recorded activity data with regard to the variability of activity represents an objective and time-efficient solution that provides valuable information for the evaluation of animal behavior.

Stress situations usually trigger a reaction that is a combination of both physiological and behavioral parameters [2,11,28]. In addition to behavioral indicators, physiological parameters such as hormone measurements, heart rate, or respiration (e.g., [15,16,29]) would have provided a further gain in information, and potentially would have reacted more quickly or more sensitively to the attachment of sensors to the cows' tails. Additionally, some of the behaviors investigated in our study are described as maintenance behavior (e.g., lying, walking, intake of food and water [5]). Since animals are highly motivated to perform them, these behaviors are characterized by high resilience and therefore may not always be sensitive indicators for capturing animal responses [80]. Related to this, cows sometimes remain calm for very long periods of time despite discomfort or even pain [80,82], which makes the early detection of animal welfare problems challenging. Our results thus contribute to initial steps for identifying appropriate, sensitive behaviors and thereby answering the research question of whether the attachment of calving sensors leads to behavioral changes that could indicate disturbance by the sensors.

4. Conclusions

Based on the two methodological approaches, analysis of activity index and behavioral observation via video analysis, it can be concluded that there is little evidence that the attachment of calving sensors to the tails of dairy cows generally led to significant changes in behavior. No significant behavioral changes were found on average for the variability of the activity index and most visually analyzed behaviors, namely walking, eating, drinking, social interaction, tail raising, rubbing the tail, and the number of standing and lying bouts. On average across all cows analyzed, an increased lying time and reduced standing time was found in the first hours after calving sensor attachment, which, however, was sourced to one single cow and may be interpreted as a shift of lying and standing time. However, both methodological approaches revealed some abnormalities in individual cows. Individual cow investigations showed an increased number of time slots showing a significant increase in the variability of the activity index in two of 18 animals analyzed. Additionally, the two indicators, rubbing the tail on objects and tail raising, showed a temporarily increased occurrence after sensor attachment in two and three of nine cows analyzed, respectively. Since these two indicators may be interpreted as cow discomfort, further analysis is required to support the evidence. When calving sensors are attached to cows' tails, short adaptation periods may occur in the animals, which, however, should be weighed against positive effects of calving prediction in terms of calf and cow welfare. However, the application of calving sensors must be limited to those devices that do not cause swelling or even injury to the tail.

Author Contributions: Conceptualization, J.P. and M.G.; methodology, J.P., O.S. and M.G.; formal analysis, J.P. and O.S., investigation, J.P.; writing—original draft preparation, J.P.; writing—review and editing, J.P., O.S. and M.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Bavarian State Ministry of Food, Agriculture and Forestry (D/17/01). The funders did not play a role in study design, data collection and analysis, the decision to publish, or in preparing the manuscript.

Institutional Review Board Statement: Ethical review and approval were waived for this study due to data being obtained from the application of commercially available technologies (also used on commercial dairy farms) on a dairy research and demonstration farm which is certified according to Section 1 para. 1 no. 1 "Tierschutzgesetz" (animal protection law).

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. Restrictions apply to the availability of video data that show farm staff.

Acknowledgments: We would like to thank the staff of 'Staatsgut Achselschwang' with special thanks to Georg Hammerl, Thomas Angermeier, Doreen Schwarz, and Robert Duschl.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Breed, age, parity, and type of calving sensor attached of the 18 animals included in the analysis.

Cow ID	Breed	Age [years]	Parity	Type of Sensor	Included in Methodological Approach
1	Simmental	4.1	3	Moocall	1 [a] and 2 [b]
2	Simmental	2.3	1	CalveSense	1 and 2
3	Brown-Swiss	2.1	1	CalveSense	1 and 2
4	Simmental	2.4	1	CalveSense	1 and 2
5	Simmental	10.4	8	CalveSense	1 and 2
6	Holstein	9.3	8	CalveSense	1 and 2
7	Simmental	8.6	7	Moocall	1 and 2
8	Simmental	4.3	3	Moocall	1 and 2
9	Brown-Swiss	5.5	4	CalveSense	1 and 2
10	Brown-Swiss	4.2	3	CalveSense	1
11	Simmental	4.3	3	CalveSense	1
12	Simmental	10.1	9	CalveSense	1
13	Holstein	6.6	5	Moocall	1
14	Simmental	6.8	5	CalveSense	1
15	Simmental	5.1	4	Moocall	1
16	Simmental	4.6	3	CalveSense	1
17	Holstein	4.2	3	CalveSense	1
18	Brown-Swiss	4.6	3	CalveSense	1

[a] Analysis of the activity index recorded by rumen bolus. [b] Behavioral observation via video analysis.

Table A2. Mean absolute deviation around the median (MAD), median, and results of the Brown–Forsythe test for the pre-sensor and post-sensor time slots (four hours each) using the respective four-day baseline as reference.

Cow ID	Breed	Time Sensor Was Attached	Type of Sensor	Item	Baseline [b] (Pre-Sensor)	Baseline [c] (Post-Sensor)	t − 24 to t − 20	t − 20 to t − 16	t − 16 to t − 12	t − 12 to t − 8	t − 8 to t − 4	t − 4 to t0	t0 to t + 4	t + 4 to t + 8	t + 8 to t + 12	t + 12 to t + 16	t + 16 to t + 20	t + 20 to t + 24
1	S	09:15	M	MAD	0.66	0.73	1.10	0.69	0.43	0.98	0.62	0.55	0.44	0.60	0.53	0.26	0.76	0.33
				median	−0.01	0.01	0.59	−0.09	−0.37	0.06	−0.05	0.25	0.12	−0.10	−0.05	0.04	−0.07	0.12
				BF [a]			sig.^{I}			sig.^{I}						sig.^{D}		sig.^{D}
2	S	19:20	C	MAD	0.66	0.65	1.00	0.50	0.52	0.60	0.73	0.59	0.86	0.50	0.67	0.55	0.48	0.29
				median	0.02	0.01	−0.37	−0.21	0.18	0.13	0.11	−0.09	−0.19	0.12	0.35	0.28	−0.04	−0.03
				BF			sig.^{I}											sig.^{D}
3	BS	09:50	C	MAD	0.79	0.77	0.97	1.28	0.51	0.55	0.42	0.58	0.97	0.90	0.70	0.63	0.55	0.60
				median	0.03	−0.03	−0.10	0.39	−0.27	−0.34	−0.04	0.06	0.03	0.15	−0.20	0.12	−0.21	0.23
				BF				sig.^{I}			sig.^{D}							
4	S	08:50	C	MAD	0.62	0.61	0.68	0.68	0.47	0.46	0.81	0.50	0.56	0.77	0.70	0.51	0.58	0.45
				median	0.03	−0.01	−0.10	0.30	−0.24	−0.20	0.30	−0.46	0.17	0.20	−0.38	0.12	−0.22	−0.02
				BF														
5	S	08:20	C	MAD	0.54	0.54	0.36	0.52	0.38	0.33	0.44	0.55	0.51	0.49	0.75	0.32	0.42	0.38
				median	−0.04	−0.02	0.01	−0.13	0.12	−0.04	−0.02	−0.01	−0.11	0.06	0.24	−0.05	0.10	−0.05
				BF														
6	H	08:50	C	MAD	0.36	0.35	0.28	0.54	0.27	0.45	0.12	0.35	0.21	0.37	0.29	0.27	0.34	0.19
				median	−0.03	−0.03	0.24	−0.16	−0.06	0.09	−0.07	0.09	0.09	0.09	−0.20	−0.19	−0.03	−0.04
				BF				sig.^{I}			sig.^{D}							sig.^{D}
7	S	08:24	M	MAD	0.53	0.55	0.39	0.31	0.32	0.41	0.55	0.94	0.87	0.66	0.36	0.48	0.69	0.50
				median	0.00	0.01	0.11	−0.24	0.13	−0.03	−0.02	0.05	−0.11	0.02	0.15	0.20	−0.20	0.10
				BF								sig.^{I}	sig.^{I}					
8	S	17:55	M	MAD	0.82	0.82	1.44	0.65	0.79	1.03	0.70	1.28	0.71	0.90	0.54	0.82	0.96	0.77
				median	−0.01	−0.01	−0.21	−0.02	−0.01	0.02	−0.38	−0.33	−0.31	−0.25	−0.23	0.09	0.03	−0.19
				BF			sig.^{I}					sig.^{I}						
9	BS	08:25	C	MAD	0.97	1.06	0.34	0.50	1.10	0.66	2.11	1.92	0.78	0.27	0.50	1.70	0.61	2.05
				median	0.01	0.03	0.17	−0.145	0.25	−0.09	0.56	−0.87	−0.20	0.04	−0.02	−0.29	−0.11	−0.69
				BF			sig.^{D}				sig.^{I}	sig.^{I}		sig.^{D}		sig.^{I}		sig.^{I}
10	BS	09:00	C	MAD	0.84	0.86	0.67	0.73	2.05	0.73	0.93	0.68	0.97	0.85	0.46	0.67	0.52	0.65
				median	0.01	−0.07	−0.08	−0.32	−0.46	−0.43	−0.30	0.05	−0.06	0.05	−0.24	0.00	0.45	−0.31
				BF					sig.^{I}						sig.^{D}			
11	S	18:45	C	MAD	0.52	0.49	0.34	0.38	0.31	0.50	0.71	0.59	0.39	0.46	0.46	0.48	0.63	0.73
				median	−0.04	−0.02	−0.18	0.06	0.20	−0.10	−0.16	−0.22	−0.05	0.11	−0.10	−0.10	0.28	−0.47
				BF														sig.^{I}
12	S	18:30	C	MAD	0.41	0.41	0.49	0.25	0.30	0.36	0.21	0.48	0.33	0.45	0.24	0.47	0.28	0.34
				median	−0.01	0.00	−0.18	0.18	−0.16	0.16	0.01	−0.05	−0.13	−0.06	0.20	−0.12	0.31	−0.10
				BF							sig.^{D}				sig.^{D}			
13	H	17:45	M	MAD	0.35	0.37	0.59	0.55	0.29	0.33	0.31	0.42	0.41	0.26	0.50	0.29	0.33	0.29
				median	0.02	0.01	0.11	−0.14	0.04	−0.03	−0.09	0.15	−0.08	−0.07	−0.11	−0.04	−0.13	0.04
				BF			sig.^{I}	sig.^{I}										
14	S	10:00	C	MAD	0.38	0.38	0.21	0.46	0.41	0.27	0.30	0.23	0.34	0.28	0.27	0.50	0.32	0.34
				median	0.01	0.01	0.20	−0.01	0.11	−0.22	0.04	−0.10	0.01	0.12	−0.12	−0.18	0.03	0.12
				BF														

Table A2. *Cont.*

Cow ID	Breed	Time Sensor Was Attached	Type of Sensor	Item	Baseline [b] (Pre-Sensor)	Baseline [c] (Post-Sensor)	t − 24 to t − 20	t − 20 to t − 16	t − 16 to t − 12	t − 12 to t − 8	t − 8 to t − 4	t − 4 to t0	t0 to t + 4	t + 4 to t + 8	t + 8 to t + 12	t + 12 to t + 16	t + 16 to t + 20	t + 20 to t + 24
15	S	08:50	M	MAD	0.48	0.46	0.45	0.55	0.32	0.53	0.24	0.37	0.86	0.57	0.45	0.40	0.34	0.75
				median	0.01	0.01	0.00	−0.03	0.04	0.15	0.01	0.07	−0.27	0.17	0.14	−0.30	−0.09	0.09
				BF							sig.[D]		sig.[I]					sig.[I]
16	S	19:20	C	MAD	0.56	0.54	1.09	0.35	0.25	0.41	0.53	0.41	0.37	0.32	0.41	0.47	0.39	0.43
				median	0.00	0.00	−0.32	−0.11	0.08	0.10	−0.02	0.06	−0.03	−0.01	0.06	0.04	0.07	0.01
				BF			sig.[I]		sig.[D]									
17	H	10:15	C	MAD	0.56	0.60	0.38	0.69	0.86	0.68	0.75	0.51	0.49	0.39	1.07	0.55	0.43	0.70
				median	0.02	0.06	0.25	0.19	0.27	0.18	−0.28	0.39	0.07	−0.17	0.25	−0.31	0.07	0.20
				BF					sig.[I]						sig.[I]			
18	BS	17:45	C	MAD	0.81	0.87	1.63	0.47	0.82	1.02	1.04	1.28	0.86	0.51	0.73	1.08	1.19	1.77
				median	−0.04	−0.07	−0.5	0.25	0.12	0.01	−0.28	0.35	−0.39	−0.14	0.22	0.43	−0.69	−0.26
				BF			sig.[I]					sig.[I]						sig.[I]

S = Simmental; BS = Brown Swiss; H = Holstein; C = CalveSense; M = Moocall. [a] Brown–Forsythe test. [b] Four-day baseline (t − 120 to t − 24) as reference for pre-sensor time slots. [c] Four-day baseline (t − 96 to t0) as reference for post-sensor time slots. sig.[I] significant increase in variability of activity, $p < 0.05$, Bonferroni-corrected $p < 0.0083$. sig.[D] significant decrease in variability of activity, $p < 0.05$, Bonferroni-corrected $p < 0.0083$. t0 = attaching of calving sensor.

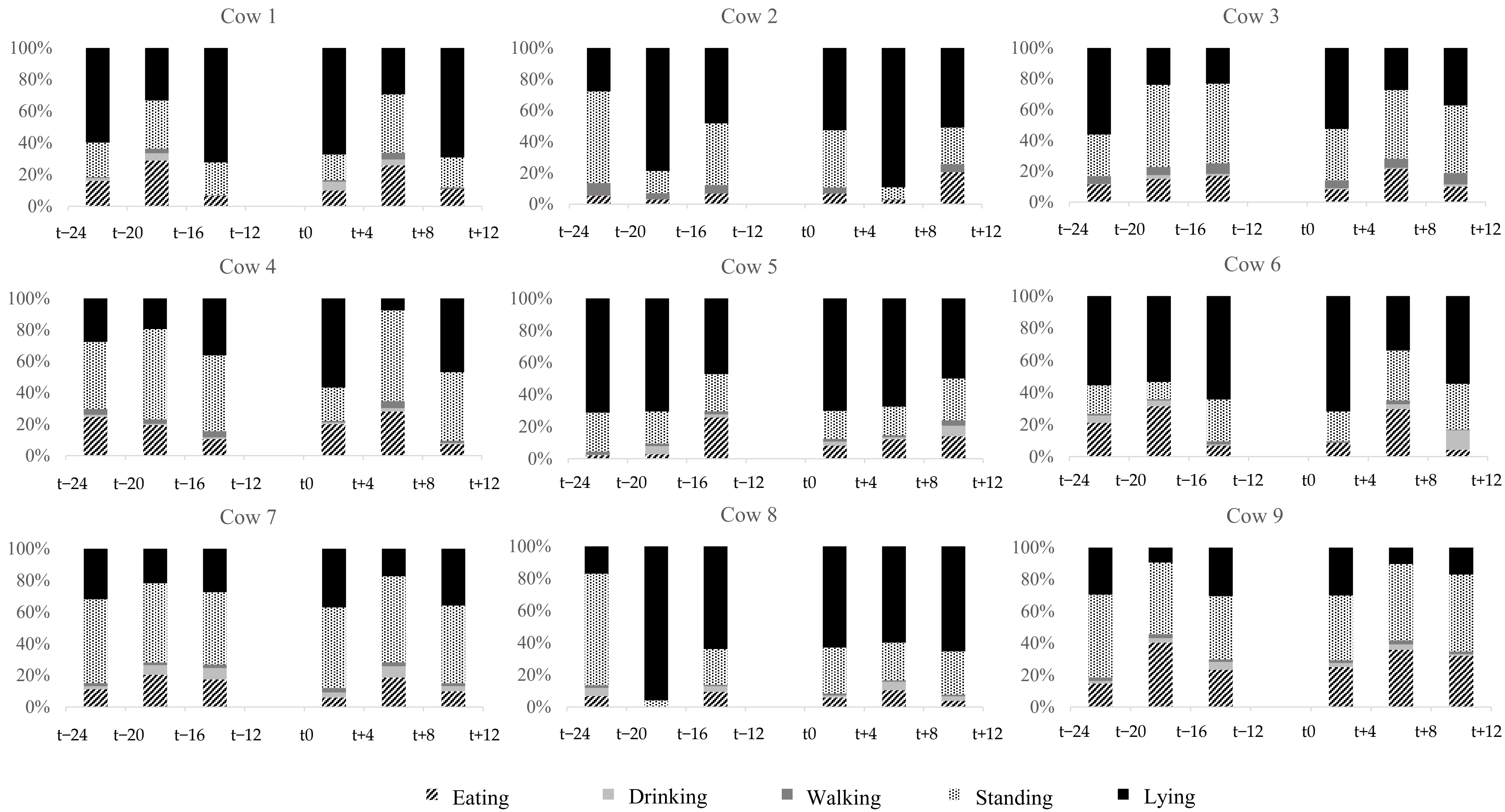

Figure A1. Relative share [%] of the behaviors eating, drinking, walking, standing, and lying of time slots analyzed.

References

1. Maroto Molina, F.; Pérez Marín, C.C.; Molina Moreno, L.; Agüera Buendía, E.I.; Pérez Marín, D.C. Welfare Quality® for dairy cows: Towards a sensor-based assessment. *J. Dairy Res.* **2020**, *87*, 28–33. [CrossRef] [PubMed]
2. Ratnakaran, A.P.; Sejian, V.; Jose, V.S.; Vaswani, S.; Bagath, M.; Krishnan, G.; Beena, V.; Indira Devi, P.; Varma, G.; Bhatta, R. Behavioral responses to livestock adaptation to heat stress challenges. *Asian J. Anim. Sci.* **2017**, *11*, 1–13. [CrossRef]
3. Saint-Dizier, M.; Chastant-Maillard, S. Methods and on-farm devices to predict calving time in cattle. *Vet. J.* **2015**, *205*, 349–356. [CrossRef] [PubMed]
4. Miedema, H.M.; Cockram, M.S.; Dwyer, C.M.; Macrae, A.I. Changes in the behaviour of dairy cows during the 24 h before normal calving compared with behaviour during late pregnancy. *Appl. Anim. Behav. Sci.* **2011**, *131*, 8–14. [CrossRef]
5. Giaretta, E.; Marliani, G.; Postiglione, G.; Magazzù, G.; Pantò, F.; Mari, G.; Formigoni, A.; Accorsi, P.A.; Mordenti, A. Calving time identified by the automatic detection of tail movements and rumination time, and observation of cow behavioural changes. *Animal* **2021**, *15*, 100071. [CrossRef]
6. Paolucci, M.; Di Giambattista, A.; Sylla, L.; Menichelli, M.; Banchio, A.; Monaci, M. Predicting time of parturition in Holstein Friesian cows by using C6 Birth Control. *Reprod. Domest. Anim.* **2008**, *43*, 57–58. [CrossRef]
7. Marchesi, G.; Leonardi, S.; Tangorra, F.M.; Calcante, A.; Beretta, E.; Pofcher, E.; Lazzari, M. Evaluation of an electronic system for automatic calving detection on a dairy farm. *Anim. Prod. Sci.* **2013**, *53*, 1112–1114. [CrossRef]
8. Voss, A.L.; Fischer-Tenhagen, C.; Bartel, A.; Heuwieser, W. Sensitivity and specificity of a tail-activity measuring device for calving prediction in dairy cattle. *J. Dairy Sci.* **2021**, *104*, 3353–3363. [CrossRef]
9. Horváth, A.; Lénárt, L.; Csepreghy, A.; Madar, M.; Pálffy, M.; Szenci, O. A field study using different technologies to detect calving at a large-scale hungarian dairy farm. *Reprod. Domest. Anim.* **2021**, *56*, 673–679. [CrossRef]
10. Lind, A.K.; Lindahl, C. Calving alert system—A helping technique or a welfare problem? In Proceedings of the 9th European Conference on Precision Livestock Farming, Cork, Ireland, 26–29 August 2019; pp. 385–388.
11. Rushen, J.; Boissy, A.; Terlouw, E.M.C.; De Passillé, A.M.B. Opioid peptides and behavioral and physiological responses of dairy cows to social isolation in unfamiliar surroundings. *J. Anim. Sci.* **1999**, *77*, 2918–2924. [CrossRef]
12. Rushen, J.; Munksgaard, L.; Marnet, P.G.; DePassillé, A.M. Human contact and the effects of acute stress on cows at milking. *Appl. Anim. Behav. Sci.* **2001**, *73*, 1–14. [CrossRef]
13. Müller, R.; Schrader, L. Behavioural consistency during social separation and personality in dairy cows. *Behaviour* **2005**, *142*, 1289–1306. [CrossRef]
14. Boissy, A.; Le Neindre, P. Behavioral, cardiac and cortisol responses to brief peer separation and reunion in cattle. *Physiol. Behav.* **1997**, *61*, 693–699. [CrossRef]
15. Kovács, L.; Kézér, F.L.; Póti, P.; Jurkovich, V.; Szenci, O.; Nagy, K. Heart rate variability, step, and rumination behavior of dairy cows milked in a rotary milking system. *J. Dairy Sci.* **2019**, *102*, 5525–5529. [CrossRef] [PubMed]
16. Wenzel, C.; Schönreiter-Fischer, S.; Unshelm, J. Studies on step–kick behavior and stress of cows during milking in an automatic milking system. *Livest. Prod. Sci.* **2003**, *83*, 237–246. [CrossRef]
17. Winter, A.; Hillerton, J.E. Behaviour associated with feeding and milking of early lactation cows housed in an experimental automatic milking system. *Appl. Anim. Behav. Sci.* **1995**, *46*, 1–15. [CrossRef]
18. Gorewit, R.C.; Scott, N.R.; Czarniecki, C.S. Responses of dairy cows to alternating electrical current administered semirandomly in a nonavoidance environment. *J. Dairy Sci.* **1985**, *68*, 718–725. [CrossRef]
19. Reinemann, D.J.; Stetson, L.E.; LeMire, S.D. Comparison of dairy cow aversion to continuous and intermittent current. *Trans. ASAE* **2004**, *47*, 1257. [CrossRef]
20. Rigalma, K.; Duvaux-Ponter, C.; Barrier, A.; Charles, C.; Ponter, A.A.; Deschamps, F.; Roussel, S. Medium-term effects of repeated exposure to stray voltage on activity, stress physiology, and milk production and composition in dairy cows. *J. Dairy Sci.* **2010**, *93*, 3542–3552. [CrossRef]
21. Lefcourt, A.M.; Kahl, S.; Akers, R.M. Correlation of indices of stress with intensity of electrical shock for cows. *J. Dairy Sci.* **1986**, *69*, 833–842. [CrossRef]
22. Ominski, K.H.; Kennedy, A.D.; Wittenberg, K.M.; Nia, S.M. Physiological and production responses to feeding schedule in lactating dairy cows exposed to short-term, moderate heat stress. *J. Dairy Sci.* **2002**, *85*, 730–737. [CrossRef]
23. Abeni, F.; Galli, A. Monitoring cow activity and rumination time for an early detection of heat stress in dairy cow. *Int. J. Biometeorol.* **2017**, *61*, 417–425. [CrossRef] [PubMed]
24. Cook, N.B.; Mentink, R.L.; Bennett, T.B.; Burgi, K. The effect of heat stress and lameness on time budgets of lactating dairy cows. *J. Dairy Sci.* **2007**, *90*, 1674–1682. [CrossRef] [PubMed]
25. Pilatti, J.A.; Vieira, F.M.C.; Rankrape, F.; Vismara, E.S. Diurnal behaviors and herd characteristics of dairy cows housed in a compost-bedded pack barn system under hot and humid conditions. *Animal* **2019**, *13*, 399–406. [CrossRef]
26. Heinicke, J.; Ibscher, S.; Belik, V.; Amon, T. Cow individual activity response to the accumulation of heat load duration. *J. Therm. Biol.* **2019**, *82*, 23–32. [CrossRef]
27. Wise, M.E.; Armstrong, D.V.; Huber, J.T.; Hunter, R.; Wiersma, F. Hormonal alterations in the lactating dairy cow in response to thermal stress. *J. Dairy Sci.* **1988**, *71*, 2480–2485. [CrossRef]

28. Schütz, K.E.; Rogers, A.R.; Poulouin, Y.A.; Cox, N.R.; Tucker, C.B. The amount of shade influences the behavior and physiology of dairy cattle. *J. Dairy Sci.* **2010**, *93*, 125–133. [CrossRef]
29. Schütz, K.E.; Cox, N.R.; Tucker, C.B. A field study of the behavioral and physiological effects of varying amounts of shade for lactating cows at pasture. *J. Dairy Sci.* **2014**, *97*, 3599–3605. [CrossRef]
30. Hillman, P.E.; Lee, C.N.; Willard, S.T. Thermoregulatory responses associated with lying and standing in heat stressed dairy cows. *Trans. ASAE* **2005**, *48*, 795–801. [CrossRef]
31. Kadzere, C.T.; Murphy, M.R.; Silanikove, N.; Maltz, E. Heat stress in lactating dairy cows: A review. *Livest. Prod. Sci.* **2002**, *77*, 59–91. [CrossRef]
32. Ouellet, V.; Vasseur, E.; Heuwieser, W.; Burfeind, O.; Maldague, X.; Charbonneau, É. Evaluation of calving indicators measured by automated monitoring devices to predict the onset of calving in Holstein dairy cows. *J. Dairy Sci.* **2016**, *99*, 1539–1548. [CrossRef]
33. Edwards, J.L.; Tozer, P.R. Using activity and milk yield as predictors of fresh cow disorders. *J. Dairy Sci.* **2004**, *87*, 524–531. [CrossRef]
34. Thorup, V.M.; Munksgaard, L.; Robert, P.E.; Erhard, H.W.; Thomsen, P.T.; Friggens, N.C. Lameness detection via leg-mounted accelerometers on dairy cows on four commercial farms. *Animal* **2015**, *9*, 1704–1712. [CrossRef] [PubMed]
35. Chapinal, N.; De Passille, A.M.; Rushen, J.; Wagner, S. Automated methods for detecting lameness and measuring analgesia in dairy cattle. *J. Dairy Sci.* **2010**, *93*, 2007–2013. [CrossRef] [PubMed]
36. Rushen, J.; Pombourcq, E.; de Passillé, A.M. Validation of two measures of lameness in dairy cows. *Appl. Anim. Behav. Sci.* **2007**, *106*, 173–177. [CrossRef]
37. Alsaaod, M.; Römer, C.; Kleinmanns, J.; Hendriksen, K.; Rose-Meierhöfer, S.; Plümer, L.; Büscher, W. Electronic detection of lameness in dairy cows through measuring pedometric activity and lying behavior. *Appl. Anim. Behav. Sci.* **2012**, *142*, 134–141. [CrossRef]
38. Van Nuffel, A.; Vangeyte, J.; Mertens, K.C.; Pluym, L.; De Campeneere, S.; Saeys, W.; Opsomer, G.; Van Weyenberg, S. Exploration of measurement variation of gait variables for early lameness detection in cattle using the GAITWISE. *Livest. Sci.* **2013**, *156*, 88–95. [CrossRef]
39. Smaxtec 2017. Smaxtec Basic Bolus. Available online: https://smaxtec.com/en/smaxtec-system-in-detail/#boli (accessed on 1 July 2019).
40. Oberegger, A. (Smaxtec Animal Care GmbH, Graz, Austria). Personal communication, 2019.
41. Ammer, S.; Lambertz, C.; Gauly, M. Comparison of different measuring methods for body temperature in lactating cows under different climatic conditions. *J. Dairy Res.* **2016**, *83*, 165–172. [CrossRef]
42. Antanaitis, R.; Juozaitienė, V.; Rutkauskas, A.; Televičius, M.; Stasiulevičiūtė, I. Reticulorumen temperature and pH as indicators of the likelihood of reproductive success. *J. Dairy Res.* **2018**, *85*, 23–26. [CrossRef]
43. Sharpe, K.T.; Heins, B.J.; Buchanan, E.S.; Reese, M.H. Evaluation of solar photovoltaic systems to shade cows in a pasture-based dairy herd. *J. Dairy Sci.* **2020**, *104*, 2794–2806. [CrossRef]
44. Stein, S. Activity-based heat detection with the smaXtec intraruminal bolus system. In Proceedings of the Conference on Precision Dairy Farming, Lexington, KY, USA, 30 May–1 June 2017; pp. 63–66.
45. Pfeiffer, J.; Gandorfer, M.; Ettema, J.F. Evaluation of activity meters for estrus detection: A stochastic bioeconomic modeling approach. *J. Dairy Sci.* **2020**, *103*, 492–506. [CrossRef]
46. Fregonesi, J.A.; Leaver, J.D. Behaviour, performance and health indicators of welfare for dairy cows housed in strawyard or cubicle systems. *Livest. Prod. Sci.* **2001**, *68*, 205–216. [CrossRef]
47. Walker, S.L.; Smith, R.F.; Routly, J.E.; Jones, D.N.; Morris, M.J.; Dobson, H. Lameness, activity time-budgets, and estrus expression in dairy cattle. *J. Dairy Sci.* **2008**, *91*, 4552–4559. [CrossRef]
48. R Core Team. *R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2020. Available online: https://www.R-project.org (accessed on 28 April 2020).
49. Trapletti, A.; Hornik, K. Tseries: Time Series Analysis and Computational Finance. R package version 0.10-48. 2020. Available online: https://CRAN.R-project.org/package=tseries (accessed on 28 October 2019).
50. Fox, J.; Weisberg, S. *An R Companion to Applied Regression*, 3rd ed.; Sage: Thousand Oaks, CA, USA, 2019. Available online: https://socialsciences.mcmaster.ca/jfox/Books/Companion/ (accessed on 28 October 2019).
51. Signorell, A.; Aho, L.; Alfons, A.; Anderegg, A.; Aragon, T.; Arachchige, C.; Arppe, A.; Baddeley, A.; Barton, K.; Bolker, B.; et al. DescTools: Tools for descriptive statistics. R package version 0.99.39. 2020. Available online: https://CRAN.R-project.org/package=DescTools (accessed on 28 October 2019).
52. Jensen, M.B. Behaviour around the time of calving in dairy cows. *Appl. Anim. Behav. Sci.* **2012**, *139*, 195–202. [CrossRef]
53. Rutten, C.J.; Kamphuis, C.; Hogeveen, H.; Huijps, K.; Nielen, M.; Steeneveld, W. Sensor data on cow activity, rumination, and ear temperature improve prediction of the start of calving in dairy cows. *Comput. Electron. Agric.* **2017**, *132*, 108–118. [CrossRef]
54. Brown, M.B.; Forsythe, A.B. Robust tests for the equality of variances. *J. Am. Stat. Assoc.* **1974**, *69*, 364–367. [CrossRef]
55. Olejnik, S.F.; Algina, J. Tests of variance equality when distributions differ in form and location. *Educ. Psychol. Meas.* **1988**, *48*, 317–329. [CrossRef]
56. Conover, W.J.; Johnson, M.E.; Johnson, M.M. A comparative study of tests for homogeneity of variances, with applications to the outer continental shelf bidding data. *Technometrics* **1981**, *23*, 351–361. [CrossRef]

57. Plourde, A.; Watkins, G.C. Crude oil prices between 1985 and 1994: How volatile in relation to other commodities? *Resour. Energy Econ.* **1998**, *20*, 245–262. [CrossRef]
58. Artavia, M.; Deppermann, A.; Filler, G.; Grethe, H.; Häger, A.; Kirschke, D.; Odening, M. Ertrags-und Preisinstabilität auf Agrarmärkten in Deutschland und der EU [Yield and price instability in agricultural markets in the Germany and the EU]. *Proc. Schr. Ges. Wirtsch. Soz. Landbaues eV* **2011**, *46*, 259–274. [CrossRef]
59. Gandorfer, M.; Porsch, A.; Bitsch, V. Producer price volatility in the German fruit and vegetable industry. *Eur. J. Hortic. Sci.* **2017**, *82*, 149–154. [CrossRef]
60. Gastwirth, J.L. Screening and selection. In *International Encyclopedia of Social Sciences*; Smelser, N.J., Bates, P.B., Eds.; Elsevier: Oxford, UK, 2001; pp. 13755–13767.
61. Pepe, M. *The Statistical Evaluation of Medical Tests for Classification and Prediction*; Wiley: Chichester, UK, 2003.
62. Kvamme, K.L.; Stark, M.T.; Longacre, M.A. Alternative procedures for assessing standardization in ceramic assemblages. *Am. Antiq.* **1996**, *61*, 116–126. [CrossRef]
63. Gastwirth, J.L.; Gel, Y.R.; Miao, W. The impact of Levene's test of equality of variances on statistical theory and practice. *Stat. Sci.* **2009**, 343–360. [CrossRef]
64. Boudadi-Maligne, M.; Escarguel, G. A biometric re-evaluation of recent claims for Early Upper Palaeolithic wolf domestication in Eurasia. *J. Archaeol. Sci.* **2014**, *45*, 80–89. [CrossRef]
65. Endres, M.I.; Barberg, A.E. Behavior of dairy cows in an alternative bedded-pack housing system. *J. Dairy Sci.* **2007**, *90*, 4192–4200. [CrossRef]
66. Martiskainen, P.; Järvinen, M.; Skön, J.P.; Tiirikainen, J.; Kolehmainen, M.; Mononen, J. Cow behaviour pattern recognition using a three-dimensional accelerometer and support vector machines. *Appl. Anim. Behav. Sci.* **2009**, *119*, 32–38. [CrossRef]
67. Rousing, T.; Wemelsfelder, F. Qualitative assessment of social behaviour of dairy cows housed in loose housing systems. *Appl. Anim. Behav. Sci.* **2006**, *101*, 40–53. [CrossRef]
68. Bouissou, M.F.; Boissy, A.; Le Neindre, P.; Veissier, I. The social behaviour of cattle. In *Social Behaviour in Farm Animals*; Keeling, L.J., Gonyou, H.W., Eds.; CAB International: Wallingford, Oxon, UK, 2001; pp. 113–145.
69. Nordlund, K.V.; Strassburg, P.; Bennett, T.B.; Oetzel, G.R.; Cook, N.B. Thermodynamics of standing and lying behavior in lactating dairy cows in freestall and parlor holding pens during conditions of heat stress. *J. Dairy Sci.* **2019**, *102*, 6495–6507. [CrossRef] [PubMed]
70. Haley, D.B.; Rushen, J.; Passillé, A.D. Behavioural indicators of cow comfort: Activity and resting behaviour of dairy cows in two types of housing. *Can. J. Anim. Sci.* **2000**, *80*, 257–263. [CrossRef]
71. Bewley, J.M.; Boyce, R.E.; Hockin, J.; Munksgaard, L.; Eicher, S.D.; Einstein, M.E.; Schutz, M.M. Influence of milk yield, stage of lactation, and body condition on dairy cattle lying behaviour measured using an automated activity monitoring sensor. *J. Dairy Res.* **2010**, *77*, 1–6. [CrossRef] [PubMed]
72. Brzozowska, A.; Lukaszewicz, M.; Sender, G.; Kolasinska, D.; Oprzadek, J. Locomotor activities in dairy cows in relation to season and lactation. *Appl. Anim. Behav. Sci.* **2014**, *156*, 6–11. [CrossRef]
73. Cooper, M.D.; Arney, D.R.; Phillips, C.J.C. Two-or four-hour lying deprivation on the behavior of lactating dairy cows. *J. Dairy Sci.* **2007**, *90*, 1149–1158. [CrossRef]
74. Schütz, K.E.; Cave, V.M.; Cox, N.R.; Huddart, F.J.; Tucker, C.B. Effects of 3 surface types on dairy cattle behavior, preference, and hygiene. *J. Dairy Sci.* **2019**, *102*, 1530–1541. [CrossRef]
75. Drenkard, D.H.; Gorewit, R.C.; Scott, N.R.; Sagi, R. Milk production, health, behavior, and endocrine responses of cows exposed to electrical current during milking. *J. Dairy Sci.* **1985**, *68*, 2694–2702. [CrossRef]
76. Noble, W.S. How does multiple testing correction work? *Nat. Biotechnol.* **2009**, *27*, 1135–1137. [CrossRef]
77. Armstrong, R.A. When to use the Bonferroni correction. *Ophthalmic Physiol. Opt.* **2014**, *34*, 502–508. [CrossRef]
78. Winckler, C.; Buehnemann, A.; Seidel, K. Social behaviour of commercial dairy herds as a parameter for on-farm welfare assessment. In Proceedings of the 36th International Congress of the ISAE, Wageningen, The Netherlands, 6–10 August 2002; p. 86.
79. Galindo, F.; Broom, D.M. The effects of lameness on social and individual behavior of dairy cows. *J. Appl. Anim. Welf. Sci.* **2002**, *5*, 193–201. [CrossRef]
80. Weary, D.M.; Niel, L.; Flower, F.C.; Fraser, D. Identifying and preventing pain in animals. *Appl. Anim. Behav. Sci.* **2006**, *100*, 64–76. [CrossRef]
81. O'Callaghan, K.A.O.; Cripps, P.J.; Downham, D.Y.; Murray, R.D. Subjective and objective assessment of pain and discomfort due to lameness in dairy cattle. *Anim. Welf.* **2003**, *12*, 605–610.
82. Gleerup, K.B.; Andersen, P.H.; Munksgaard, L.; Forkman, B. Pain evaluation in dairy cattle. *Appl. Anim. Behav. Sci.* **2015**, *171*, 25–32. [CrossRef]

Pfeiffer, J., Gandorfer, M., Ettema, J. F. (2020). Evaluation of activity meters for estrus detection: A stochastic bioeconomic modeling approach. Journal of Dairy Science, 103(1), 492-506.
[https://www.journalofdairyscience.org/article/S0022-0302(19)30998-1/fulltext#relatedArticles]
[Publisher: Elsevier]

J. Dairy Sci. 103:492–506
https://doi.org/10.3168/jds.2019-17063

Evaluation of activity meters for estrus detection: A stochastic bioeconomic modeling approach

J. Pfeiffer,[1*] M. Gandorfer,[1] and J. F. Ettema[2]
[1]Institute for Agricultural Engineering and Animal Husbandry, Bavarian State Research Center for Agriculture, Freising 85354, Germany
[2]SimHerd A/S, 8830 Tjele, Denmark

ABSTRACT

Although estrus detection makes a relevant contribution to the reproductive performance of dairy cattle, studies on the economic evaluation of automatic estrus detection systems are rare. The objective of the present study is to provide an economic evaluation of activity meters used for estrus detection. The effect of different estrus detection rates on gross margins was modeled with SimHerd (SimHerd A/S, Viborg, Denmark). The analysis considers all costs associated with the investment in activity meters. The economic evaluation was carried out through simulation of Simmental herds with yearly milk yields of 7,000 or 9,000 kg and Holstein Friesian herds with yearly milk yields of 9,000 or 11,000 kg, each with herd sizes of 70 or 210 cows. Furthermore, we distinguished between 2 investment scenarios. In scenario 1, only cows are equipped with activity meters for estrus detection, whereas scenario 2 assumes that cows and heifers are equipped with activity meters. Because existing empirical information for some variables shows significant variability (estrus detection rates, time for estrus detection), they were modeled with distributions using the Monte Carlo method in @RISK (Palisade Corporation, Ithaca, NY), allowing us to model a probability distribution of net returns (NR) of investment in activity meters for estrus detection. The simulation results show that the average NR of investment in activity meters for estrus detection over all scenarios ranges from +€7 to +€40 per cow per year for the Simmental breed, and from +€19 to +€46 per cow per year for the Holstein Friesian breed. Generally, the NR depends on the milk production level assumed. For the Simmental breed, depending on the scenario, the simulation results show a 54 to 200% larger average NR of investment in activity meters for estrus detection with a milk yield of 9,000 kg/yr compared with 7,000 kg/yr. For the Holstein Friesian breed, the effect of the modeled milk yield on the NR is much less pronounced. Average NR of investment in activity meters are greater for larger herd sizes because of cost degression effects. An additional equipping of heifers has, on average, a positive effect on the economics of activity meters for estrus detection because of the resulting reduction in the age at first calving. Considering all scenarios, the probability of a positive NR of investment in activity meters ranges between 74 and 98% for the Simmental breed and between 85 and 99% for the Holstein Friesian breed.

Key words: activity meter, estrus detection, Monte Carlo simulation, SimHerd

INTRODUCTION

Good health and reproductive performance are prerequisites for sustainable dairy farming. A literature review revealed that it is well known that good reproductive performance is crucial for the economic success of a farm (Groenendaal et al., 2004; Giordano et al., 2012; Galvão et al., 2013). Studies document that poor fertility is one of the main causes of culling in dairy cattle (Rozzi et al., 2007; Ahlman et al., 2011). Therefore, early and precise detection of estrus is essential. According to the literature, there is potential to optimize the visual estrus detection rate on dairy farms (Diskin and Sreenan, 2000; Roelofs and Van Erp-van der Koij, 2015). Visual estrus detection rates are often low due to decreasing durations and weaker signs of estrus (Mee, 2004), partly because of high milk production levels (Westwood et al., 2002; López-Gatius et al., 2005; Dobson et al., 2008). Accordingly, studies show that signs of estrus are often more intense in the evening and at night (Hurnik et al., 1975; Van Vliet and Van Eerdenburg, 1996; Wangler et al., 2005). Increasing farm sizes and workloads limit the time available for observation of individual animals. Activity meters for estrus detection have been discussed as

Received June 4, 2019.
Accepted September 27, 2019.
*Corresponding author: johanna.pfeiffer@lfl.bayern.de

a technical solution to tackle the described challenges. The development of automatic estrus detection systems began in the 1980s (Mottram, 2016). Available studies on the economics of activity meters for estrus detection indicated profitability but usually only considered individual farm-specific situations. For example, Van Asseldonk et al. (1999) showed an increase in gross margin (**GM**) by Dfl. 1.02 (9,000 kg of milk; Dfl. 1 = €0.45) or 1.28 (7,500 kg of milk) per 100 kg of milk per year under Dutch production conditions, assuming that the estrus detection rate increases from 50 to 90%. Rutten et al. (2014) calculated the economic benefit of investing in activity meters for automated estrus detection. Their estimate of an average marginal financial effect of €2,827 for a herd of 130 cows was based on the assumption of an increase in estrus detection rate from 50% (visual) to 80% (activity meter). Inchaisri et al. (2010) calculated the economic consequences of "poor," "average," and "good" reproductive performance. In the "average" scenario, changing the single input parameter of estrus detection rate from 30 to 50% and from 50 to 70% resulted in a reduction of the annual net economic loss by €53 and €11 per cow, respectively.

Depending on the study, different herd sizes, labor and labor costs, and milk yields were considered, and even stochastic simulation models were used for the calculations. The focus of some studies, however, was on reproductive performance, which is why costs for sensor-assisted estrus detection were not considered. Furthermore, herd dynamics and diseases were sometimes not modeled. All listed studies analyzed and compared several scenarios. For estrus detection rates, however, they assumed only one value per scenario, when Rutten et al. (2014) have already indicated that quite a variation exists in the estrus detection rate (visual and sensor-assisted).

The objective of our study was to present a comprehensive economic evaluation of activity meters for estrus detection. We demonstrated the potential of activity meters and their influence on farm profitability. To this end, we conducted an evaluation for farms with different reproductive performance. Similar to other studies, we worked with a stochastic simulation model and compared different scenarios for milk yield, herd size, labor costs, and equipment options. The simulation model for dairy herds we used considered herd dynamics as well as nonreproductive diseases. Differing from previous studies, we modeled estrus detection rates and time spent for estrus detection with probability functions to account for different farm-specific situations. Thus, we calculated the profitability of an investment in activity meters for estrus detection under various farm conditions.

MATERIALS AND METHODS

Stochastic Net Return Model

The net return (**NR**) of investment of activity meters for estrus detection was calculated through GM for both sensor-assisted and visual estrus detection, each expressed as a function of estrus detection rate. Additionally, all costs associated with the investment in activity meters for estrus detection were considered. Some costs (e.g., base station, antennas, necessary software) have a fixed character and are, therefore, widely independent of herd size. However, costs for the activity meters increase with herd size. Because sensor-assisted estrus detection affects the time necessary for estrus detection, labor costs in the cases of visual and sensor-assisted estrus detection were included in the calculation of NR:

$$NR(SED) = [GM_{SED}f(EDR) - (LC \times TED_{SED}) - (VC_{SED} + FC_{SED})] - [GM_{visual}f(EDR) - (LC \times TED_{visual})],$$

where NR = net return, GM = gross margin, f = as a function of, SED = sensor-assisted estrus detection, EDR = estrus detection rate, TED = time spent for estrus detection, VC = variable costs, FC = fixed costs, and LC = labor costs.

We used SimHerd (SimHerd A/S, Viborg, Denmark) to calculate scenario-specific GM as a function of estrus detection rate. In SimHerd, estrus detection rates varied in 5% steps. Thus, the relationship between estrus detection rate and GM was known for each scenario.

Model Structure of SimHerd

The SimHerd model simulates the production and state changes of a dairy herd, including young stock, and has been used to study various herd-management tasks (Østergaard et al., 2005a; Kristensen et al., 2008; Ettema et al., 2017) as well as implications of genetic trends for their effects on reproduction management (Ettema et al., 2011) and the derivation of economic value of production and functional traits (Nielsen, 2004). In SimHerd, the reproductive state of an animal is defined by age, parity, lactation stage, actual milk yield, body weight, culling status, reproductive status (i.e., estrus and pregnancy), somatic cell count, disease status, and a fixed component of milk yield potential. The current state is predicted week-by-week for each cow and heifer in the herd. Drawing random numbers from relevant probability distributions triggers individual inherent and lactational milk yield potential and simulates discrete events, such as conception, abortion, sex, and viability of the calf, diseases, involuntary culling, and death. The state of the individual animal is updated, and the production and input consumption of the entire herd are calculated. Production and development within the herd are thus determined indirectly by simulation of production and changes in state of each individual cow and heifer. This makes SimHerd a mechanistic model.

Model behavior is controlled by a set of decision variables that define particular production systems and management strategies. Modeled culling and reproduction rates are the key components responsible for the effects on herd structure of various simulated scenarios. A cow that does not conceive during the AI period is replaced if it is the lowest-yielding candidate for voluntary culling, and a heifer is ready to calve and, thus, to enter the herd. The proportion of cows showing estrus after calving was set to 0.95. The replacement rate is determined as a result of individual cows' reproductive performance, disease occurrence, involuntary culling, and mortality, and the availability of replacement heifers. Involuntary culling is determined given a base-risk of 0.9% in wk 1, which declines linearly to a risk of 0.079% in wk 29. Thereafter, the weekly risk remains constant at 0.079% for the remainder of the lactation period. Mortality is based on a constant weekly base-risk of 0.034%. In addition to the base risks of involuntary culling and mortality, production diseases such as mastitis (Østergaard et al., 2005b), metabolic diseases (Østergaard et al., 2000), and diseases resulting in lameness (Ettema et al., 2010), as simulated in SimHerd, may increase a cow's individual risk of involuntary culling and mortality. All parameters describing the lactation curve model in SimHerd are identical to those described by Kristensen et al. (2008). The conception rate of heifers is set to 0.55, and the default value for the visual estrus detection rate is also 0.55. An additional risk of fetal death, including early fetal death, is set to 0.13 for both cows and heifers. These assumptions result in conception among 90% of all heifers during the AI period. Heifers that do not conceive during this period are sold to slaughter. Heifers are sold as livestock if no cows are selected for culling and the maximum number of cows in the herd is reached. Additional heifers are purchased if the herd size falls below a given minimum number.

Many studies have been performed on the influence of milk yield on the occurrence of diseases. However, these studies do not provide a clear answer to the question, but often only very vague or even contradictory results. Fleischer et al. (2001) reviewed several studies on this issue and concluded that it is not generalizable that increased milk production is associated with higher risk of disease. Rather, he found many studies that refuted this relation. In SimHerd, herds with different milk production levels have the same base risk for disease. However, within a given herd, cows with greater milk yield have a higher risk of disease compared with those with an average milk yield. Herd demography also influences disease incidence, as older animals become more susceptible to diseases (Gröhn et al., 1995). Therefore, in SimHerd, the values for incidence of diseases per cow and per year are not fixed but are adjusted according to the scenario.

The economic evaluation was carried out both for the milk-oriented Holstein Friesian breed and for the dual-purpose Simmental breed. In SimHerd, we parameterized Simmental herds with milk yields of 7,000 or 9,000 kg/yr and Holstein Friesian herds with milk yields of 9,000 or 11,000 kg/yr. The standard herds were of good health and average reproductive performance. SimHerd is parameterized by default for Holstein Friesian. However, prices were changed according to the current market situation. For the Simmental breed, we made some adaptations based on the literature (Table 1). The mature weight of a Simmental cow was set to 725 kg (average Bavarian herdbook cows in 2015). The Simmental breed shows generally good health, also, compared with other breeds (Schichtl, 2007; LKV, 2018). Therefore, the default values for incidence of disease per cow-year were reduced by 10% for the Simmental breed. With reference to the average SCC for Simmental cattle in 2017 in Bavaria, Germany (LKV, 2018), SCC was set to 200,000 cells per mL. According to the literature, the probability of stillbirth in Simmental cattle is below the default value (Grupp, 2003; LKV, 2018), which was therefore reduced by 10% to 5.0%. Mean producer prices (e.g., for milk, slaughter cows, heifers for sale) of the last 3 years in Bavaria were used to determine the GM (period: January 2016 to January 2019). Likewise, the cost of feed was calculated using the current 3-yr average (January 2016 to January 2019). All other default values represent the status of SimHerd in January 2019.

Time Spent for Estrus Detection

Because values for some variables (estrus detection rates and time spent for estrus detection) significantly differ from farm to farm, they were modeled using the Monte Carlo method in @RISK (Palisade Corporation, Ithaca, NY) to account for the heterogeneity observed in practice. To take into account the time requirements for visual and sensor-assisted estrus detection, triangle distributions were incorporated into the model. Because scant literature is available on the time savings related to sensor-assisted estrus detection, assumptions regarding time spent for estrus detection were made according to empirical data, expert assessments, and practice reports (Michaelis et al., 2013; Greil, 2017). For a herd size of 70 cows, we assumed a minimum of 0.9, a mode of 2.4, and a maximum of 5.2 h per cow per year for visual estrus detection, and a minimum of 0.4, a mode of 1.2, and a maximum of 3.5 h per cow per year for sensor-assisted estrus detection. For a herd size of 210 cows, we assumed a minimum of 0.9, a mode of 2.3, and a maximum of 2.8 h per cow per year for visual estrus detection, and a minimum of 0.4, a mode of 1.0, and a maximum of 1.7 h per cow per year for sensor-assisted estrus detection. Therefore, based on the underlying distributions, farmers may benefit significantly in terms of time savings from applying activity meters for estrus detection.

Estrus Detection Rates

Rates of visual and sensor-assisted estrus detection were determined from the literature, as shown in Table 2. For this purpose, we considered studies in which the estrus detection rates of activity meters were determined. Rates ranged between 35 (Peter and Bosu, 1986) and 91% (Dela Rue et al., 2012) for visual estrus detection and between 59 (Holman et al., 2011) and 92% (Firk et al., 2003) for the activity meters. The empirical distribution of visual and sensor-assisted estrus detection rates based on the literature (see Table 2) was used to simulate random estrus detection rates based on the empirical cumulative probability function using the RiskCumul function in @RISK. Cumulative probabilities for visual and sensor-assisted estrus detection rates are illustrated in Figure 1. The curves show that the estrus detection rates determined in the studies tended to be higher for activity meters than for visual assessment. The minimum values found in the literature were smaller for visual estrus detection than for sensor-assisted estrus detection. Nevertheless, both methods allowed achievement of estrus detection rates of over 90%. With visual estrus detection, however, more time tends to be required to do so.

Although farmers, on average, save time from investing in activity meters for estrus detection, we further assumed that farmers who spend more time on visual estrus detection tend to also do so when using activity meters. Thus, we considered a correlation of 0.9 between the time spent on visual and time spent on sensor-assisted estrus detection, using the Define Correlation option in @RISK. We made this assumption so as not to exclude completely the possibility that, for some dairy farmers, investing in activity meters for estrus detection may not lead to any time savings. To test the sensitivity of this assumption, we analyzed correlations between r = 0.8 and r = 1. The sensitivity analysis showed no significant effect on the results.

We determined a correlation of r = 0.94 between the time spent for estrus detection and the estrus detection rate, based on the work of Van Vliet and Van Eerden-

Table 1. Assumptions for the calibration of SimHerd

Parameter[1]	Holstein Friesian	Simmental
Mature weight,[2] kg	680	725
Stillbirth risk,[3] %	5.5	5.0
SCC,[4] cells per mL (× 1,000)	230	200
Price,[5] €		
ECM, /kg	0.34	0.34
Cull cow, per kg of live weight	1.00	1.40
Dead cow	−134.23	−134.23
Springing heifer	1,367.90	1,431.80
Nonpregnant heifer	822.57	1,108.93
Bull calf, sold at 14 d	97.00	264.50
Heifer calf, sold at 14 d	56.50	144.00
First-parity cow, sold for life	1,509.90	1,641.40
Milk replacer, per kg of powder	1.62	1.62
Price per feeding unit for concentrates, heifers	0.26	0.26
Price per feeding unit for roughage, heifers	0.11	0.11
Breeding, unsexed proven bull semen	22.00	22.00

[1]Yearly milk yield classes were set at 9,000 or 11,000 kg/yr for Holstein Friesian cattle and at 7,000 or 9,000 kg/yr for Simmental. Prices for feeding unit of TMR for cows of each of these classes were calculated as €0.15 or 0.16, and €0.14 or 0.15, respectively.

[2]Default values for Holstein Friesian. For Simmental, average Bavarian herdbook cows in 2015.

[3]Default values for Holstein Friesian. For Simmental, Grupp (2003), LKV (2018).

[4]Default values for Holstein Friesian. For Simmental, LKV (2018).

[5]Net prices (average of the last 3 yr in Bavaria, period: January 2016 to January 2019) according to LfL (2019), GM (gross margin) calculator.

burg (1996), who described achieved estrus detection rates as a function of time spent. We considered this correlation in the case of both visual and sensor-assisted estrus detection. Based on the results of Michaelis et al. (2013), we assumed in the model that estrus detection rates of dairy farms do not deteriorate after the installation of activity meters for estrus detection.

Annual Cost of Investing in Activity Meters for Estrus Detection

The annual cost of the investment in activity meters for estrus detection comprises expenses for the acquisition of sensors and basic additional equipment (e.g., antenna, transformer, wire, software) as well as implementation and repair costs. The implementation costs account for the time spent on initial information (we estimated 5 h), learning, and installation (estimated 10 h). The time requirement was included in the calculation with labor costs of €10 and €20/h. An interest rate of 4% and cost for repair of 8% per year were assumed. The annual cost of investment was calculated from the mean of 3 activity meters commonly used in Germany: Heatime Pro by SCR (Madison, WI), Smarttag by Nedap (Groenlo, the Netherlands), and Track a Cow by ENGS Systems (Rosh Pina, Israel). Systems are attached to the foot or neck and detect estrus through changes in behavior. The useful life of the activity meters was set to 7 years. The average annual cost of investment for the 3 systems are shown in Figure 2. Increasing herd sizes lead to a cost degression caused by the distribution of costs, especially for basic equipment over a larger number of animals. Depending on the simulated scenario, the annual cost of investment amounts to €22 to 36 per cow per year.

Table 2. Estrus detection rates (%) reported in the literature for visual estrus detection and detection via activity meters[1]

Source	Estrus detection rate, %
Visual	
Peter and Bosu, 1986	35
Heersche and Nebel, 1994	38
Peralta et al., 2005	49
Stevenson and Britt, 1977	51
Fulkerson et al., 1983	54[2]
Kempf, 2016	55[2]
At-Taras and Spahr, 2001	55[2]
Kossaibati and Esslemont, 1995	55
Williamson et al., 1972	56
Rougoor et al., 1997	56
Liu and Spahr, 1993	58
Fulkerson et al., 1983	61
Maatje et al., 1997	67
Williams et al., 1981	68
Mayne et al., 2002	71
LeBlanc et al., 1998	79[2]
Dela Rue et al., 2012	91
Activity meter	
Holman et al., 2011[3]	59
Chanvallon et al., 2014[3]	62
Dela Rue et al., 2012[3]	62
Holman et al., 2011	63
Dela Rue et al., 2012	70
Chanvallon et al., 2014	71
Aungier et al., 2012	72
Peter and Bosu, 1986	76
Dela Rue et al., 2012	77
Klindtworth et al., 2002[3]	78
Talukder et al., 2015	80
Cavalieri et al., 2003	81
At-Taras and Spahr, 2001	85[2]
De Mol et al., 1997	87[2]
Hockey et al., 2010	87[2]
Klindtworth et al., 2002	88
Jónsson et al., 2011	89
Dela Rue et al., 2012	89
Kempf, 2016	89[2]
Cohen et al., 1990	91
Klindtworth et al., 2002	91
Firk et al., 2003	92

[1]Studies sorted in ascending order of estrus detection rates.

[2]Average of several experiments.

[3]Authors tested several activity meters.

Modeled Scenarios

The economic evaluation was carried out for different scenarios (see Table 3). For Simmental we assumed yearly milk production levels of 7,000 or 9,000 kg, and 9,000 or 11,000 kg for Holstein Friesian, using herd sizes of 70 or 210 cows for each milk production level. Furthermore, we distinguished between 2 investment scenarios: in scenario 1, only cows were equipped with activity meters, whereas scenario 2 assumed monitoring of both cows and heifers of breeding age. Labor costs for estrus detection were included at rates of €10 and €20/h. For each scenario, 10,000 iterations were performed in @RISK.

RESULTS AND DISCUSSION

Gross Margin Depending on Estrus Detection Rate

The GM modeled in SimHerd, depending on estrus detection rate of only cows and cows plus heifers in Simmental (milk production levels 7,000 or 9,000 kg/yr) and Holstein Friesian (milk production levels 9,000 or 11,000 kg/yr) herds is shown in Figure 3. In the NR model, the GM was calculated as a function of the estrus detection rate from the respective estimated second-degree polynomial equation (see Figure 3). Van Asseldonk et al. (1999) also determined GM as a function of estrus detection rate for similar milk yields (7,500 and 9,000 kg) and demonstrated that the relationship was not linear. In our model, an increase in GM with an improved estrus detection rate was largely attributable to increased revenues from calves and heifers for both breeds, resulting from shorter calving intervals and, thus, a larger number of births per year in the herd (lower replacement costs). Moreover, the age at first calving could be decreased with the additional equipping of heifers, enhancing the GM effect. The age at first calving (for scenarios with addition of heifers) and the calving interval decreased to similar extents for both breeds over all considered milk production levels. Thus, the revenues from calves increased in all scenarios analyzed. Changes in milk yield were dependent on the balance between positive and negative effects. On the one hand, improved estrus detection rates led to a shorter duration of the late lactation period, more calves being born, and a greater share of lactating cows at peak yield per year. On the other hand, this also led to a greater share of dry cows, because cows reach the dry period faster when reproducing, having a negative effect on the average milk yield of the herd. In all scenarios, a larger proportion of cows at the herd level was dry and a smaller share lactated (but at larger peak yields). In sum, these effects produced no positive change in the milk yield per cow-year for milk yield level of 7,000 kg, and only a small positive change for milk yield levels of 9,000 and 11,000 kg. Considering only the milking days, however, improved estrus detection rates resulted in a greater increase in milk yield per cow-year for both breeds and for the respective milk production levels.

In the model, heifers are sold whenever there are no cows on the culling list (for example, due to very long calving-to-conception intervals) and the maximum number of cows is reached. Particularly for animals showing weaker signs of estrus, using activity meters improves estrus detection and insemination success. The activity meters enable the detection of even slight changes in activity both during the day and at night, and often provide a recommendation for the optimal insemination time. Thus, using activity meters results in improved estrus detection rates and shorter calving-to-conception intervals in many cases. As a result, fewer cows leave the herd due to poor fertility. This increases the number of productive years per cow in all scenarios analyzed, resulting in a increased lifetime production of milk per cow overall. Because fewer old cows leave the herd, more heifers are available for sale. The larger number of productive years per cow also leads to changes in the herd demography. Cows remain in the herd to older ages, which increases their susceptibility to diseases (Gröhn et al., 1995). As a result, it is simulated that better reproductive performance of the herd increases expenses for disease treatment

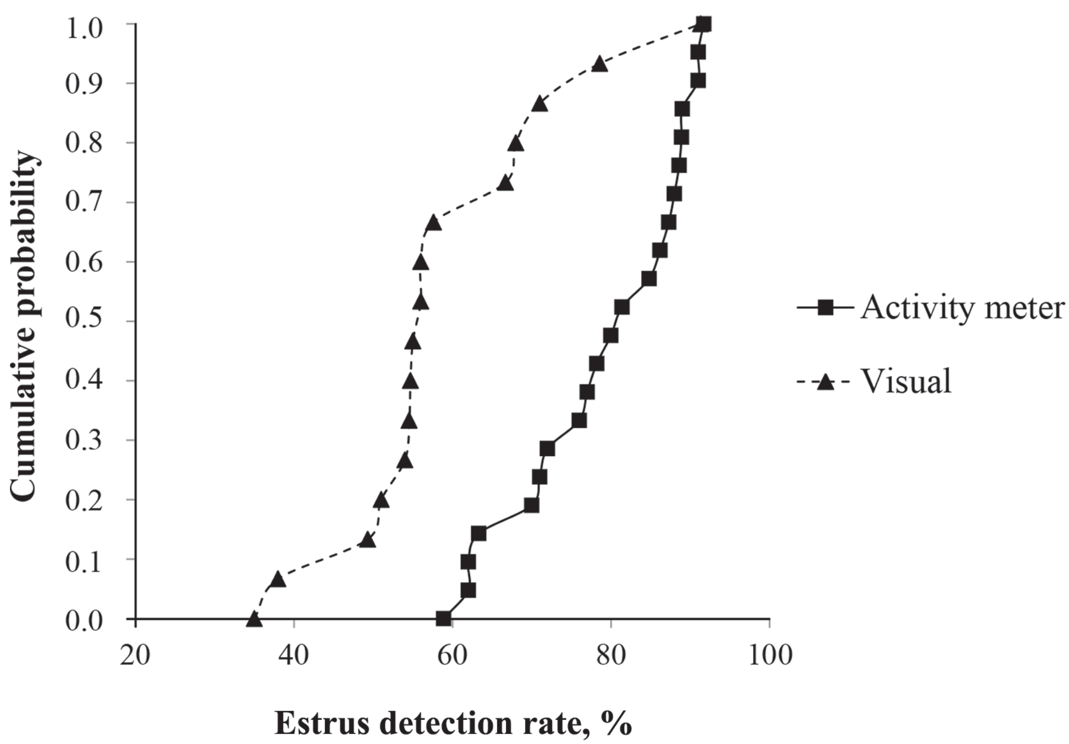

Figure 1. Cumulative probability for estrus detection rates (%) of activity meters and visual estrus detection.

Table 3. Scenarios simulated in the study

Milk yield, kg/yr	Herd size, no. of cows	Animals equipped	Labor costs, €/h	Breed
7,000	70	Cows	10	Simmental
			20	Simmental
		Cows + heifers	10	Simmental
			20	Simmental
	210	Cows	10	Simmental
			20	Simmental
		Cows + heifers	10	Simmental
			20	Simmental
9,000	70	Cows	10	Simmental
				Holstein Friesian
			20	Simmental
				Holstein Friesian
		Cows + heifers	10	Simmental
				Holstein Friesian
			20	Simmental
				Holstein Friesian
	210	Cows	10	Simmental
				Holstein Friesian
			20	Simmental
				Holstein Friesian
		Cows + heifers	10	Simmental
				Holstein Friesian
			20	Simmental
				Holstein Friesian
11,000	70	Cows	10	Holstein Friesian
			20	Holstein Friesian
		Cows + heifers	10	Holstein Friesian
			20	Holstein Friesian
	210	Cows	10	Holstein Friesian
			20	Holstein Friesian
		Cows + heifers	10	Holstein Friesian
			20	Holstein Friesian

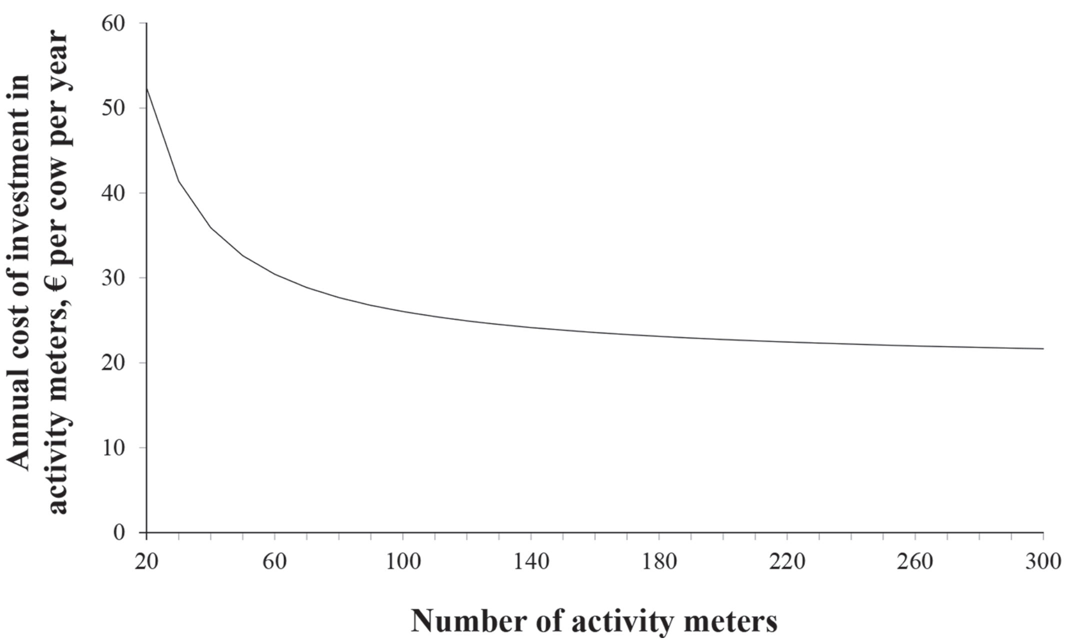

Figure 2. Annual cost of investment (€ per cow per year) in activity meters for estrus detection, considering prices of Heatime Pro by SCR (Madison, WI), Smarttag by Nedap (Groenlo, the Netherlands), and Track a Cow by ENGS Systems (Rosh Pina, Israel). Assumed labor costs: €20/h.

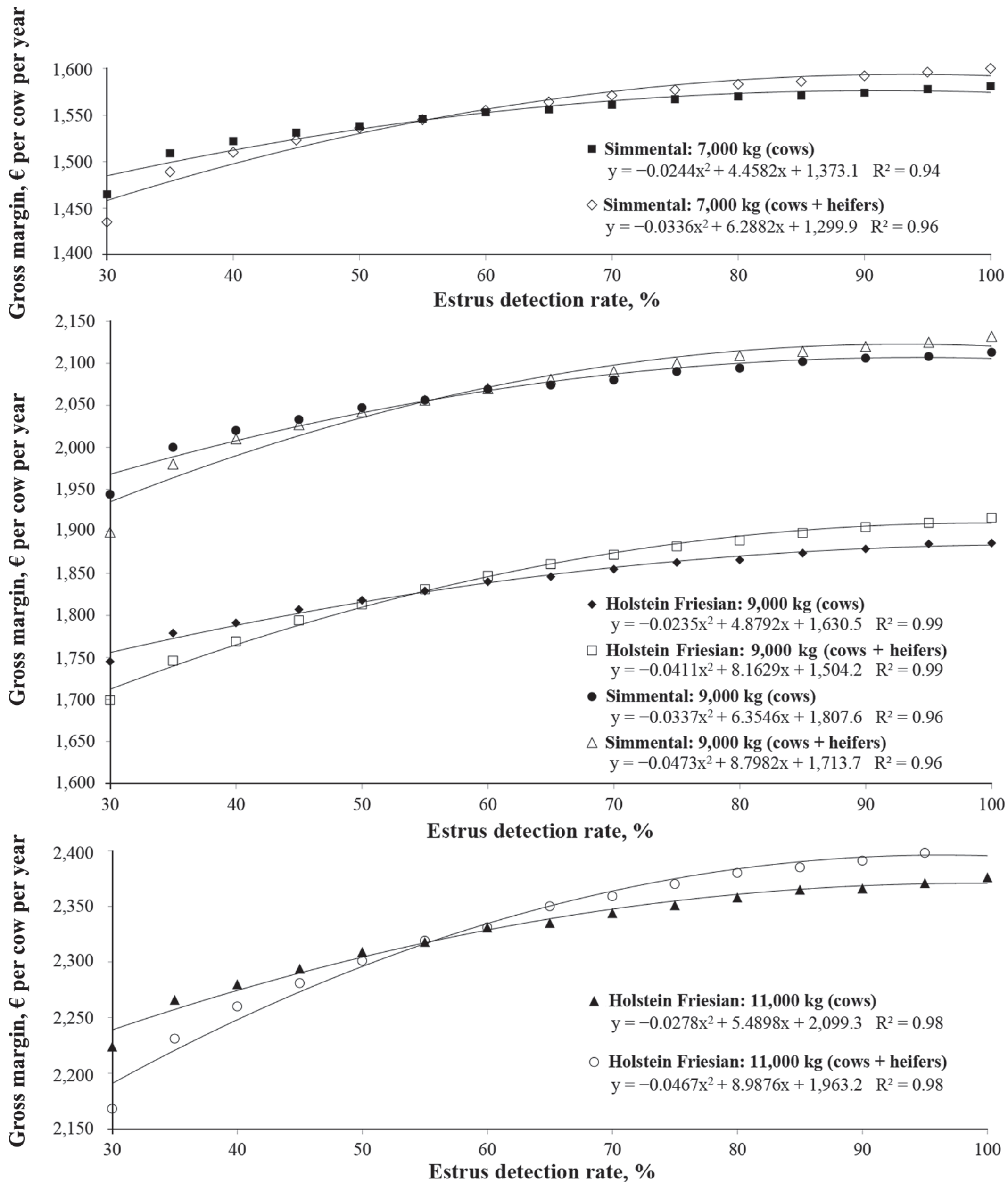

Figure 3. Gross margin (€ per cow per year) for the Simmental breed (yearly milk yield levels: 7,000 or 9,000 kg) and the Holstein Friesian breed (yearly milk yield levels: 9,000 or 11,000 kg) as a function of estrus detection rate (%) of cows only or of cows and heifers. Polynomial of degree 2 and coefficient of determination R^2 added in each case.

and the number of dead cows on the herd level in all scenarios. In sum, improved estrus detection rates and improved reproductive performance lead to increased revenues and, in most scenarios, to greater expenses. However, the revenues rise at a faster rate, resulting in an increase in the GM.

The effect of changes in reproductive performance on milk yield also depends on the shape of the lactation curve (Seegers, 2006). It is already known that the effect of long calving intervals on productivity depends on the persistency of the lactation curve (Louca and Legates, 1967; Olds et al., 1979). With deteriorating reproductive performance, reduction in milk yield is greater in cases of lactation curves with low persistency and strong peaks than in cases of flat curves with good persistency (Seegers, 2006). Therefore, at the herd level it is particularly beneficial to equip cows with characteristically low persistency with activity meters.

The change in GM due to improved estrus detection rates further depends on whether the same culling criteria are maintained. In SimHerd, a cow becomes a culling candidate as soon as she exceeds a maximum number of days open. If this maximum number is maintained after the estrus detection rate is improved, the number of culled cows will be greatly reduced. If, on the other hand, the maximum number of days open is reduced in combination with improved estrus detection rate, the culling rate will remain unchanged. The profitability of maintaining or changing the culling criteria depends, in part, on the slaughter value of cows. Different culling criteria were not included in this analysis and would have introduced yet another dimension to the research question.

Net Return of Investment in Activity Meters for Estrus Detection

The integration of uncertainty in selected variables using @RISK results in probability distributions for the NR of investment in activity meters for estrus detection in each of the scenarios analyzed. For each scenario, 10,000 iterations reveal possible combinations of estrus detection rates and time spent for estrus detection, including their probability of occurrence, based on the defined distributions and correlations. The simulation results show that the average NR on investing in activity meters for estrus detection ranges from +€7 to +€40 per cow per year for the Simmental breed and from +€19 to +€46 per cow per year for the Holstein Friesian breed (Table 4). The probability distributions of the NR are shown for selected scenarios in Figure 4.

A comparison of all scenarios shows higher NR for larger herd sizes on average, owing to cost degression effects for both breeds. The calculations by Rutten et al. (2014) and Bekara et al. (2017) also resulted in greater benefits from an investment in activity meters for estrus detection in larger herds.

Equipping not only cows but also heifers results in larger mean NR and also in larger values for the 90th percentiles, due to a possible reduction in the age at first calving. Due to additional costs for activity meters for heifers, the NR can decline if reproductive performance is not sufficiently improved. This applies equally to the Simmental and the Holstein Friesian breeds. However, it is recommended that most dairy farms equip both cows and heifers at breeding age with activity meters for estrus detection because of the importance of an optimal age at first calving, for which the economic benefits are already known (Ettema and Santos, 2004). It should also be considered that dairy farmers choose the age at first calving and calving intervals individually for their farms. Because a young age at first calving can increase the risk for dystocia and stillbirths (Wickersham and Schultz, 1963; Ettema and Santos, 2004),

Table 4. Net return of investment (€ per cow per year) for activity meters for estrus detection under simulated scenarios[1]

Item[2]	Herd size 70 Cows	Herd size 70 Cows + heifers	Herd size 210 Cows	Herd size 210 Cows + heifers	Herd size 70 Cows	Herd size 70 Cows + heifers	Herd size 210 Cows	Herd size 210 Cows + heifers
Simmental								
Milk yield, kg/yr	7,000				9,000			
10th percentile	−7	−10	−6	−11	−3	−8	−3	−8
	3	3	7	−11	11	8	9	4
Mean	7	13	12	17	21	26	25	30
	18	23	21	26	32	37	35	40
90th percentile	17	28	24	37	37	50	46	60
	32	39	32	61	47	57	53	66
Ratio (%) net return	76	74	79	77	86	82	88	84
> €0 per cow per year	92	93	98	93	97	95	98	93
Holstein Friesian								
Milk yield, kg/yr	9,000				11,000			
10th percentile	−1	−5	−1	−5	−2	−6	−2	−6
	13	12	11	8	13	11	10	−11
Mean	19	31	24	35	20	32	24	37
	30	41	33	44	30	43	33	46
90th percentile	33	57	43	68	35	60	44	70
	44	61	49	73	44	63	50	95
Ratio (%) net return	89	87	89	88	88	86	89	87
> €0 per cow per year	98	97	99	95	97	97	99	85

[1]10,000 iterations of each scenario.

[2]For each statistical item [10th percentile, mean, 90th percentile, and ratio (%) net return > €0 per cow per year], the first row of values indicates labor costs set to €10/h, and the second row of values indicates labor costs of €20/h.

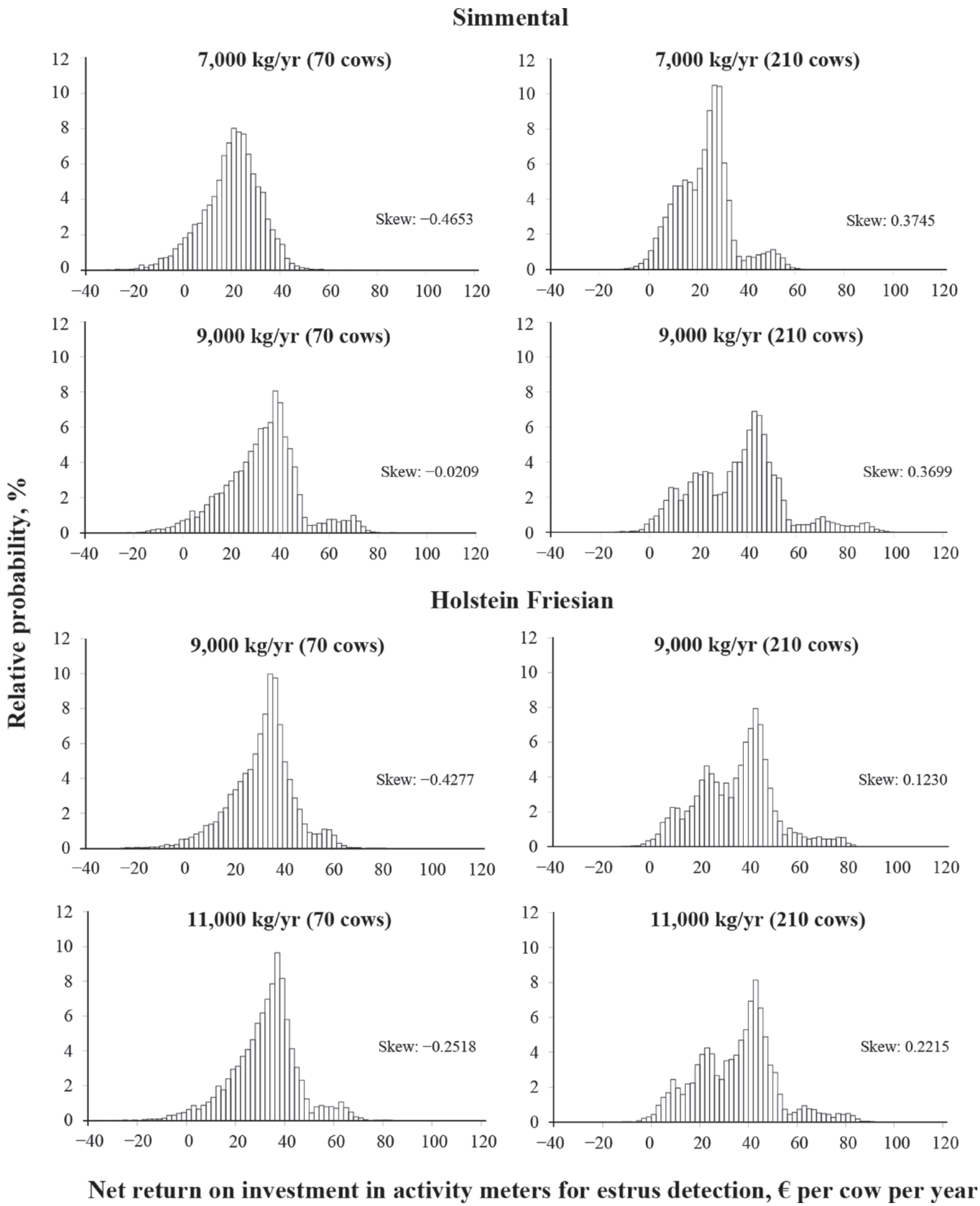

Figure 4. Probability distribution of net return of investment (€ per cow per year) in activity meters for estrus detection for each milk yield class (kilograms per year) of the Simmental and Holstein Friesian breeds, with herd sizes of 70 and 210 cows (equipping of cows only) and assumed labor costs of €20/h.

it should be reduced only to a certain limit. Because SimHerd is a dynamic model, it takes into account the effects of disease incidence as parameters, such as age at first calving and calving interval, change. However, the calving intervals realized in the model are within a reasonably practicable range in all scenarios and are consistent with those of farms in Germany (Bundesverband Rind und Schwein e.V., 2018). This applies equally to the simulated age at first calving.

Due to the different slopes of the GM functions (see Figure 3), the assumed milk yield affects the NR calculated in the scenarios. In the Simmental scenarios, the average NR is greater by 54 to 200% (depending on the scenario) for milk yield of 9,000 kg/yr compared with 7,000 kg/yr. Also the probability of a positive NR is generally higher at a milk yield of 9,000 kg/yr than at 7,000 kg/yr. In the case of the Holstein Friesian breed, the difference in effect of the 2 modeled milk yield levels on the NR of investment in activity meters for estrus detection is much less pronounced. Comparing the milk yield level of 9,000 kg/yr for both breeds, it becomes clear that the average NR are similar. However, the probability of a positive NR with a milk yield of 9,000 kg/yr is slightly higher in all Holstein Friesian scenarios.

In general, NR are greater for both Simmental and Holstein Friesian breeds when a higher cost of labor was assumed. Often, time savings, greater attractiveness of work, and a higher level of convenience resulting from sensor-assisted estrus detection are weighted more strongly than economic benefits. For example, during labor-intensive periods of the year, activity meters for estrus detection can provide helpful support for fertility management and present a relief to dairy farmers. The results show a certain sensitivity of the NR to the assumed remuneration of working time. Especially for farms with restricted working time available, an investment in activity meters for estrus detection can generate great value. To improve herd fertility performance, in many cases, it may be more appropriate to invest in sensors rather than a larger amount of time to achieve improved estrus detection rates. Similarly, Rutten et al. (2014) showed that investing in activity meters to improve estrus detection rates could be more profitable than increasing labor input for estrus detection.

Our simulation results reveal that investing in activity meters for estrus detection results in a positive NR for the majority of dairy farms. Considering all the scenarios shown in Table 4, the probability of a positive NR for investing in activity meters ranges between 74 and 98% for Simmental and between 85 and 99% for Holstein Friesian. The economic advantage or disadvantage of investing in the technology depends on the pre-existing fertility management of a dairy farm. Generally, dairy farms that initially have a high visual estrus detection rate or that spend little time for estrus detection, or both, tend to have small or even negative NR. In contrast, the NR will be large for farms with previously poor visual estrus detection rates or high expenditure of time for estrus detection, or both. Owing to the slopes of the GM functions (Figure 3), in both Simmental and Holstein Friesian herds, improvement in the estrus detection rate leads to a greater increase in GM for farms with initially poor visual estrus detection rates compared with farms with initially good visual estrus detection rates. This was also evident in other studies (Inchaisri et al., 2010). Nevertheless, it should be noted that it always takes a few years for the effects of improved reproductive performance to be realized. Because changes in the number of calvings and in the number of productive years per cow and, thus, in the demography of the herd are only noticeable after a certain time, economic effects and others do not become immediately evident.

Our results largely agree with the few available studies on the profitability of activity meters for estrus detection, confirming their economic potential. Rutten et al. (2014) analyzed the economic benefit of investing in activity meters for estrus detection. In their calculations, an investment in activity meters turned out to be profitable in most scenarios analyzed (e.g., different herd sizes, labor costs, and estrus detection rates), as is the case in our results, where, on average across all scenarios, 88% (Simmental) and 92% (Holstein Friesian) of the simulation runs show a positive NR. For example, an increase in the estrus detection rate from 50% (assumed for visual estrus detection) to 80% (assumed for sensor-assisted estrus detection) resulted in an average marginal financial effect of €2,827 for the baseline scenario, which assumed a herd of 130 cows and a default milk production level of 8,310 kg per cow per 305 d (Rutten et al., 2014). This corresponds to an average marginal financial effect of €22 per cow per year when investing in activity meters. Accordingly, the scale of the financial benefit of investing in activity meters for estrus detection is roughly in line with our simulated average NR, considering that Rutten et al. (2014) assumed labor costs of €18/h for the baseline scenario. However, nonreproductive diseases, such as lameness, were not considered in their study, although they affect fertility. Inchaisri et al. (2010) analyzed the economic implications of different reproductive performances using 3 scenarios: "poor," "average," and "good" reproductive performance. Compared with their "good" scenario, the scenarios with "average" and "poor" reproductive performance showed a mean net economic loss of €34 and €231 per cow per year, respectively. They also found a reduction in the annual net economic loss of €53 and €11 per cow with an increase in the estrus detection rate from 30 to 50% and from 50 to 70% in the "average" scenario, which roughly coincides with the average NR in our study. However, the focus of the study by Inchaisri et al. (2010) was on the reproductive performance per se and not on sensor technology, which is why no costs for the investment in sensors and no working time effects were accounted for.

In their scenarios with "average" and "poor" reproductive performance, Inchaisri et al. (2010) found that the cost of decreased milk production explains on average 100 and 52%, respectively, of the total net economic losses compared with the "good" scenario. For Rutten et al. (2014), increasing milk yield due to improvement in estrus detection had the largest effect on the financial benefits. In our simulations of improved estrus detection rates with SimHerd, however, the additional total revenues result to a greater extent from an increase in sales of calves and heifers than from an increase in milk production. For the Simmental breed, in comparison to the Holstein Friesian breed, these additional revenues from heifers account for a greater share of the additional total revenues. This is due to the fact that the assumed prices for calves and heifers are higher for the Simmental breed than for the Holstein Friesian breed. This difference arises because Simmental is a dual-purpose breed, whereas Holstein Friesian is a milk-oriented breed.

Bekara et al. (2017) simulated an investment in automatic estrus detection devices for 7 different dairy farms in France, for which an improvement of the estrus detection rate from 50% (visual) to 90% (sensor-assisted) was assumed. They found that investing in the technology was profitable for most (two-thirds) of the simulated scenarios, with a large herd size and high milk prices, among other things, having a positive effect. Their study showed that the annual GM per cow increased by €9 to €93 when estrus detection rate was increased with the use of automatic estrus detection devices. These results also correspond roughly to the simulation results of our study, although the heterogeneity of the farms simulated by Bekara et al. (2017) made it difficult to draw conclusions about individual influencing factors. Additionally, changes in labor time related to sensor-assisted estrus detection were not included by Bekara et al. (2017), whereas they were included in our calculations. The survey by Michaelis et al. (2013) confirmed the benefits of activity meters for estrus detection, as 95% of the participating dairy farmers who employed the estrus detection system Heatime (SCR) would install it again (n = 219). Although only 54% of the dairy farmers surveyed reported cost savings from using the system, only 18% stated that the technology achieved no cost savings. The remaining dairy farmers (25%) experienced neither a positive nor a negative financial effect (Michaelis et al., 2013). These practical experiences coincide with the results of the present study, because, on average across all scenarios analyzed, only 10% of simulation runs show negative NR.

Methodological Considerations

The multiplicity and complexity of influencing factors make it difficult to determine the economic effects of activity meters for automatic estrus detection, which is why a stochastic model is applied in this study as an appropriate approach to evaluating such effects.

In addition to changes in the time required for estrus detection, there may be changes in the total time required for further work per animal. The results modeled in SimHerd show that, with improvements in the rate of estrus detection, on the one hand, time required for milking decreases (more dry cows at herd level), but on the other hand, working time needed for disease treatment increases. In sum, however, only a marginal change in the working time requirement per cow per year results from these and other effects, which were therefore not taken into account in the calculation of NR. Regarding the increased workload associated with the treatment of animal diseases, it can be argued that many of the commercially available activity meters for estrus detection enable early detection of diseases. This benefit positively influences the cost-effectiveness of the technology. Health monitoring is possible because sensor systems can continuously record further parameters in addition to animal activity. Changes in activity and rumination, and variations in temperature and pH, may indicate possible diseases. Owing to abnormalities in these parameters, it is possible to detect diseases before the appearance of visually recognizable symptoms.

Our calculations account for the estrus detection rates (sensitivity) of the activity meters specified in the literature. However, in assessing the quality of these sensors, other metrics, such as specificity, play an important role. A good estrus detection rate, per se, does not give any indication of the correctness of all messages from the sensor system. Good sensitivity sometimes even comes at the expense of specificity (Mottram, 2016). For example, Rutten et al. (2014) compared different scenarios with different assumptions for sensitivities and specificities of activity meters. Assuming that a farmer inseminates his animals "blindly" upon every alert, an investment in activity meters turned out to be unprofitable. Activity meters for estrus detection with high sensitivity but low specificity can present a challenge to dairy farmers. In practice, there is often a combination of visual estrus detection and estrus detection by sensors, which is generally justified by greater efficiency compared with mere visual or automatic estrus detection (Peralta et al., 2005; Holman et al., 2011; Rutten et al., 2014), resulting in positive effects for the dairy farm.

CONCLUSIONS

The results of our study show that activity meters for estrus detection can increase the profitability of a dairy farm. Analyzed scenarios consider the Simmental (yearly milk yields 7,000 or 9,000 kg) and Holstein Friesian (yearly milk yields 9,000 or 11,000 kg) breeds, herd sizes of 70 or 210 cows, equipping only of cows or of both cows and heifers, and labor costs of €10 or €20/h. The results show positive annual NR for the majority of simulation runs (88% for the Simmental breed and 92% for the Holstein Friesian breed on average) when investing in activity meters for estrus detection. The financial advantage or disadvantage depends strongly on the previously dominant reproduction management method of the dairy farm. It becomes clear that milk yield, herd size, and assumptions on labor cost influence the economic effects of sensor-assisted estrus detection. In many cases, a positive economic effect could be achieved from the additional equipping of heifers, which results in a younger age at first calving. Moreover, activity meters for estrus detection often have additional functions for early detection of illnesses, resulting in additional cost savings.

ACKNOWLEDGMENTS

Johanna Pfeiffer and Markus Gandorfer thank the Bavarian State Ministry of Food, Agriculture and Forestry (Freising, Germany) for funding.

REFERENCES

Ahlman, T., B. Berglund, L. Rydhmer, and E. Strandberg. 2011. Culling reasons in organic and conventional dairy herds and genotype by environment interaction for longevity. J. Dairy Sci. 94:1568–1575. https://doi.org/10.3168/jds.2010-3483.

At-Taras, E. E., and S. L. Spahr. 2001. Detection and characterisation of oestrus in dairy cattle with an electronic heatmount detector and an electronic activity tag. J. Dairy Sci. 84:792–798. https://doi.org/10.3168/jds.S0022-0302(01)74535-3.

Aungier, S. P. M., J. F. Roche, M. Sheehy, and M. A. Crowe. 2012. Effects of management and health on the use of activity monitoring for estrus detection in dairy cows. J. Dairy Sci. 95:2452–2466. https://doi.org/10.3168/jds.2011-4653.

Bekara, M. A., N. Bareille, F. Bidan, C. Allain, and C. Disenhaus. 2017. An ex ante analysis of the economic profitability of automatic oestrus detection devices in different dairy farming systems in France. Pages 333–339 in Proc. 8th European Conference on Precision Livestock Farming (ECPLF), Nantes, France. D. Berckmans and A. Keita, ed.

Bundesverband Rind und Schwein e. V. 2018. Rinderproduktion in Deutschland 2017. Bundesverband Rind und Schwein e.V., ed. Druck Center, Meckenheim, Germany.

Cavalieri, J., V. E. Eagles, M. Ryan, and K. L. Macmillan. 2003. Comparison of four methods for detection of oestrus in dairy cows with resynchronised oestrus cycles. Aust. Vet. J. 81:422–425.

Chanvallon, A., S. Coyral-Castel, J. Gatien, J.-M. Lamy, D. Ribaud, C. Allain, P. Clément, and P. Salvetti. 2014. Comparison of three devices for the automated detection of estrus in dairy cows. Theriogenology 82:734–741. https://doi.org/10.1016/j.theriogenology.2014.06.010.

Cohen, T., M. Eisenberg, M. Amir, M. Etam, and E. Aizinbud. 1990. Estrus detection in dairy cows by a computerized system using pedometry and milk recording. Hassadeh Q. 1:21–23.

De Mol, R. M., G. H. Kroeze, J. M. F. H. Achten, K. Maatje, and W. Rossing. 1997. Results of a multivariate approach to automated oestrus and mastitis detection. Livest. Prod. Sci. 48:219–227. https://doi.org/10.1016/S0301-6226(97)00028-6.

Dela Rue, B. T., C. Kamphuis, C. R. Burke, and J. G. Jago. 2012. Field evaluation of automated estrus detection systems—Meeting farmers' expectations. Proc. 11th International Conference on Precision Agriculture (ICPA), Indianapolis, IN. J. Staffrord, J. Schepers, and P. Carter, ed. Springer, New York, NY.

Diskin, M. G., and J. M. Sreenan. 2000. Expression and detection of oestrus in cattle. Reprod. Nutr. Dev. 40:481–491. https://doi.org/10.1051/rnd:2000112.

Dobson, H., S. L. Walker, M. J. Morris, J. E. Routly, and R. F. Smith. 2008. Why is it getting more difficult to successfully artificially inseminate dairy cows? Animal 2:1104–1111. https://doi.org/10.1017/S175173110800236X.

Ettema, J. F., and J. E. Santos. 2004. Impact of age at first calving on lactation, reproduction, health, and income in first-parity holstein on commercial farms. J. Dairy Sci. 87:2730–2742. https://doi.org/10.3168/jds.S0022-0302(04)73400-1.

Ettema, J. F., S. Østergaard, and A. R. Kristensen. 2010. Modelling the economic impact of three lameness causing diseases using herd and cow level evidence. Prev. Vet. Med. 95:64–73. https://doi.org/10.1016/j.prevetmed.2010.03.001.

Ettema, J. F., S. Østergaard, and M. K. Sørensen. 2011. Effect of including milk yield on evaluating the use of sexed semen and other reproduction strategies in a dairy herd. Animal 5:1887–1897. https://doi.org/10.1017/S175173111100108X.

Ettema, J. F., J. R. Thomasen, L. Hjortø, M. Kargo, S. Østergaard, and A. C. Sørensen. 2017. Economic opportunities for using sexed semen and semen of beef bulls in dairy herds. J. Dairy Sci. 100:4161–4171. https://doi.org/10.3168/jds.2016-11333.

Firk, R., E. Stamer, W. Junge, and J. Krieter. 2003. Automation of oestrus detection in dairy cows: A review. Livest. Prod. Sci. 75:219–232. https://doi.org/10.1016/S0301-6226(01)00323-2.

Fleischer, P., M. Metzner, M. Beyerbach, M. Hoedemaker, and W. Klee. 2001. The relationship between milk yield and the incidence of some diseases in dairy cows. J. Dairy Sci. 84:2025–2035. https://doi.org/10.3168/jds.S0022-0302(01)74646-2.

Fulkerson, W. J., G. J. Sawyer, and I. Crothers. 1983. The accuracy of several aids in detecting oestrus in dairy cattle. Appl. Anim. Ethol. 10:199–208. https://doi.org/10.1016/0304-3762(83)90141-4.

Galvão, K. N., P. Federico, A. De Vries, and G. M. Schuenemann. 2013. Economic comparison of reproductive programs for dairy herds using estrus detection, timed artificial insemination, or a combination. J. Dairy Sci. 96:2681–2693. https://doi.org/10.3168/jds.2012-5982.

Giordano, J. O., A. S. Kalantari, P. M. Fricke, M. C. Wiltbank, and V. E. Cabrera. 2012. A daily herd Markov-chain model to study the reproductive and economic impact of reproductive programs combining timed artificial insemination and estrus detection. J. Dairy Sci. 95:5442–5460. https://doi.org/10.3168/jds.2011-4972.

Greil, Q. 2017. Bayern Watch—Hält das System was es verspricht? Fleckviehwelt 2:14–15.

Groenendaal, H., D. T. Galligan, and H. A. Mulder. 2004. An economic spreadsheet model to determine optimal breeding and replacement decisions for dairy cattle. J. Dairy Sci. 87:2146–2157. https://doi.org/10.3168/jds.S0022-0302(04)70034-X.

Gröhn, Y. T., S. W. Eicker, and J. A. Hertl. 1995. The association between previous 305-day milk yield and disease in New York State dairy cows. J. Dairy Sci. 78:1693–1702. https://doi.org/10.3168/jds.S0022-0302(95)76794-7.

Grupp, T. 2003. An economical revolution—Pure breeding with Fleckvieh and crossbreeding with Fleckvieh × Holstein Friesian. Retrieved April 20, 2019, from https://www.yumpu.com/en/document/read/20942559/pure-breeding-with-fleckvieh-and-crossbreeding-with-fleckvieh-x-.

Heersche, G., and R. L. Nebel. 1994. Measuring efficiency and accuracy of detection of estrus. J. Dairy Sci. 77:2754–2761. https://doi.org/10.3168/jds.S0022-0302(94)77218-0.

Hockey, C., J. Morton, S. Norman, and M. McGowan. 2010. Evaluation of a neck mounted 2-hourly activity meter system for detecting cows about to ovulate in two paddock-based Australian dairy herds. Reprod. Domest. Anim. 45:e107–e117. https://doi.org/10.1111/j.1439-0531.2009.01531.x.

Holman, A., J. Thompson, J. E. Routly, J. Cameron, D. N. Jones, D. Grove-White, R. F. Smith, and H. Dobson. 2011. Comparison of oestrus detection methods in dairy cattle. Vet. Rec. 169:47–52. https://doi.org/10.1136/vr.d2344.

Hurnik, J. F., G. J. King, and H. A. Robertson. 1975. Estrous and related behaviour in postpartum Holstein cows. Appl. Anim. Ethol. 2:55–68. https://doi.org/10.1016/0304-3762(75)90065-6.

Inchaisri, C., R. Jorritsma, P. Vos, G. C. van der Weijden, and H. Hogeveen. 2010. Economic consequences of reproductive performance in dairy cattle. Theriogenology 74:835–846. https://doi.org/10.1016/j.theriogenology.2010.04.008.

Jónsson, R., M. Blanke, N. K. Poulsen, F. Caponetti, and S. Hosjsgaard. 2011. Oestrus detection in dairy cows from activity and lying data using on-line individual models. Comput. Electron. Agric. 76:6–15. https://doi.org/10.1016/j.compag.2010.12.014.

Kempf, A. 2016. Visuelle und computergestützte (Heatime) Brunsterkennung. Eine klinische Vergleichsstudie in einem norddeutschen Milcherzeugungsbetrieb. PhD thesis. Clinic for Cattle, University of Veterinary Medicine, Hannover, Germany.

Klindtworth, K., S. Trinkl, and G. Wendl. 2002. Effizienz verschiedener Aktivitätssensoren zur Brunstüberwachung bei Milchkühen. Landtechnik 57:86–87.

Kossaibati, M. A., and R. J. Esslemont. 1995. Wastage in dairy cows. Report No 4. DAISY Dairy Information System, University of Reading.

Kristensen, E., S. Østergaard, M. A. Krogh, and C. Enevoldsen. 2008. Technical indicators of financial performance in the dairy herd. J. Dairy Sci. 91:620–631. https://doi.org/10.3168/jds.2007-0201.

LeBlanc, S. J., K. E. Leslie, H. J. Ceelen, D. F. Kelton, and G. P. Keefe. 1998. Measures of oestrus detection and pregnancy in dairy cows after administration of gonadotropin-releasing hormone within an oestrus synchronisation program based on prostaglandin F. J. Dairy Sci. 81:375–381. https://doi.org/10.3168/jds.S0022-0302(98)75587-0.

LfL (Bayerische Landesanstalt für Landwirtschaft). 2019. GM (gross margin) calculator. Accessed Jan. 5, 2019. https://www.stmelf.bayern.de/idb/default.html;jsessionid=8141F9DC898819F3916E20C062E991D9.

Liu, X., and S. L. Spahr. 1993. Automated electronic activity measure ment for detection of estrus in dairy cattle. J. Dairy Sci. 76:2906–2912. https://doi.org/10.3168/jds.S0022-0302(93)77630-4.

LKV (Landeskuratorium der Erzeugerringe für tierische Veredelung) Bayern e.V. 2018. Milchleistungsprüfung, Bayern 2017.

López-Gatius, F., P. Santolaria, I. Mundet, and J. L. Yaniz. 2005. Walking activity at estrus and subsequent fertility in dairy cows. Theriogenology 63:1419–1429. https://doi.org/10.1016/j.theriogenology.2004.07.007.

Louca, A., and J. E. Legates. 1967. Production losses in dairy cattle due to open days. J. Dairy Sci. 51:573–584. https://doi.org/10.3168/jds.S0022-0302(68)87031-6.

Maatje, K., S. H. Loeffler, and B. Engel. 1997. Predicting optimal time of insemination in cows that show visual signs of estrus by estimating onset of estrus with pedometers. J. Dairy Sci. 80:1098–1105. https://doi.org/10.3168/jds.S0022-0302(97)76035-1.

Mayne, C. S., D. R. Mackey, M. Verner, W. J. Mccaughey, F. J. Gordon, M. A. Mccoy, S. D. Lennox, D. C. Catney, A. R. G. Wylie, and B. W. Kennedy. 2002. Fertility of dairy cows in Northern Ireland. Vet. Rec. 150:707–713. https://doi.org/10.1136/vr.150.23.707.

Mee, J. F. 2004. Temporal trends in reproductive performance in Irish dairy herds and associated risk factors. Ir. Vet. J. 57:158–166. https://doi.org/10.1186/2046-0481-57-3-158.

Michaelis, I., E. Hasenpusch, and W. Heuwieser. 2013. Estrus detection in dairy cattle: Changes after the introduction of an automated activity monitoring system? Tierarztl Prax Ausg G Grosstiere Nutztiere41:159–165.

Mottram, T. 2016. Animal board invited review: Precision livestock farming for dairy cows with a focus on oestrus detection. Animal 10:1575–1584. https://doi.org/10.1017/S1751731115002517.

Nielsen, H. M. 2004. Economic values for production and functional traits in dairy cattle breeding goals derived by stochastic simulation. PhD thesis. Department of Animal Science and Animal Health, Royal Veterinary and Agricultural University, Copenhagen, Denmark.

Olds, D., T. Cooper, and A. Thrift. 1979. Effects of days open on economic aspects of current lactation. J. Dairy Sci. 62:1167–1170. https://doi.org/10.3168/jds.S0022-0302(79)83391-3.

Østergaard, S., M. G. G. Chagunda, N. C. Friggens, T. W. Bennedsgaard, and I. C. Klaas. 2005a. A stochastic model simulating pathogen-specific mastitis control in a dairy herd. J. Dairy Sci. 88:4243–4257. https://doi.org/10.3168/jds.S0022-0302(05)73111-8.

Østergaard, S., N. C. Friggens, and M. G. G. Chagunda. 2005b. Technical and economic effects of an inline progesterone indicator in a dairy herd estimated by stochastic simulation. Theriogenology 64:819–843. https://doi.org/10.1016/j.theriogenology.2004.10.022.

Østergaard, S., J. T. Sørensen, and A. R. Kristensen. 2000. A stochastic model simulating the feeding-health-production complex in a dairy herd. J. Dairy Sci. 83:721–733. https://doi.org/10.3168/jds.S0022-0302(00)74934-4.

Peralta, O. A., R. E. Pearson, and R. L. Nebel. 2005. Comparison of three estrus detection systems during summer in a large commercial dairy herd. Anim. Reprod. Sci. 87:59–72. https://doi.org/10.1016/j.anireprosci.2004.10.003.

Peter, A. T., and W. T. K. Bosu. 1986. Postpartum ovarium activity in dairy cows: Correlation between behavioral estrus, pedometer measurements and ovulations. Theriogenology 26:111–115. https://doi.org/10.1016/0093-691x(86)90117-2.

Roelofs, J. B., and E. Van Erp-van der Kooij. 2015. Estrus detection tools and their applicability in cattle: Recent and perspectival situation. Anim. Reprod. Sci. 12:498–504.

Rougoor, C. W., A. A. Dijkhuizen, R. B. M. Huirne, F. Mandersloot, and W. J. A. Hanekamp. 1997. Relationships between technical, economic and environmental results on dairy farms: An explanatory study. Livest. Prod. Sci. 47:235–244. https://doi.org/10.1016/S0167-5877(99)00007-0.

Rozzi, P., F. Miglior, and K. J. Hand. 2007. A total merit selection index for Ontario organic dairy farmers. J. Dairy Sci. 90:1584–1593. https://doi.org/10.3168/jds.S0022-0302(07)71644-2.

Rutten, C. J., W. Steeneveld, C. Inchaisri, and H. Hogeveen. 2014. An ex ante analysis on the use of activity meters for automated estrus detection: To invest or not to invest? J. Dairy Sci. 97:6869–6887. https://doi.org/10.3168/jds.2014-7948.

Schichtl, V. 2007. Einfluss der Kreuzung von Deutschen Holsteins und Deutschem Fleckvieh auf Milchleistung, Milchqualität und allgemeine Gesundheitsmerkmale in einem automatischen Melksystem. PhD thesis. Institute for Animal Breeding, Ludwig Maximilian University, Munich, Germany.

Seegers, H. 2006. Economics of the reproductive performance of dairy herds. Pages 292–302 in proc. 24th World Buiatrics Congress, Nice, France. Accessed Mar. 1, 2019. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.507.3857&rep=rep1&type=pdf.

Stevenson, J. S., and J. H. Britt. 1977. Detection of estrus by three methods. J. Dairy Sci. 60:1994–1998. https://doi.org/10.3168/jds.S0022-0302(77)84135-0.

Talukder, S., P. C. Thomson, K. L. Kerrisk, C. E. F. Clark, and P. Celi. 2015. Evaluation of infrared thermography body temperature and collar-mounted accelerometer and acounstic technology for predicting time of ovulation of cows in a pasture-based system. Theriogenology 83:739–748. https://doi.org/10.1016/j.theriogenology.2014.11.005.

Van Asseldonk, M., A. W. Jalvingh, R. B. M. Huirne, and A. A. Dijkhuizen. 1999. Potential economic benefits from changes in management via information technology applications on Dutch dairy farms: A simulation study. Livest. Prod. Sci. 60:33–44. https://doi.org/10.1016/S0301-6226(99)00039-1.

Van Vliet, J. H., and F. J. C. M. Van Eerdenburg. 1996. Sexual activities and oestrus detection in lactating Holstein cows. Appl. Anim. Behav. Sci. 50:57–69. https://doi.org/10.1016/0168-1591(96)01068-4.

Wangler, A., A. Meyer, F. Rehbock, and P. Sanftleben. 2005. Wie effizient ist die Aktivitätsmessung als ein Hilfsmittel in der Brunsterkennung bei Milchrindern? Zuchtungskunde 77:110–127.

Westwood, C. T., I. J. Lean, and J. K. Garvin. 2002. Factors influencing fertility of Holstein dairy cows: A multivariate description. J. Dairy Sci. 85:3225–3237. https://doi.org/10.3168/jds.S0022-0302(02)74411-1.

Wickersham, E. W., and L. H. Schultz. 1963. Influence of age at first breeding on growth, reproduction, and production of well-fed Holstein heifers. J. Dairy Sci. 46:544–549. https://doi.org/10.3168/jds.S0022-0302(63)89092-X.

Williams, W. F., D. R. Yver, and T. S. Gross. 1981. Comparison of oestrus detection techniques in dairy heifers. J. Dairy Sci. 64:1738–1741. https://doi.org/10.3168/jds.S0022-0302(81)82757-9.

Williamson, N. B., R. S. Morris, D. C. Blood, and C. M. Cannon. 1972. A study of oestrus behaviour and oestrus detection methods in a large commercial dairy herd. The relative efficiency of methods of oestrus detection. Vet. Rec. 91:50–58. https://doi.org/10.1136/vr.91.3.50.

ORCIDS

J. Pfeiffer https://orcid.org/0000-0002-6045-4878
M. Gandorfer https://orcid.org/0000-0002-0624-153X
J. F. Ettema https://orcid.org/0000-0002-3255-3297