INTEGRATION OF ETHICAL AND SOCIAL ASPECTS INTO PRECISION LIVESTOCK FARMING – ACHIEVING REAL-WORLD IMPACT RESPONSIBLY

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EDITORIAL
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Editorial: Integration of Ethical and Social Aspects Into Precision Livestock Farming—Achieving Real-World Impact Responsibly

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Editorial on the Research Topic

Integration of Ethical and Social Aspects Into Precision Livestock Farming—Achieving Real-World Impact Responsibly

Precision Livestock Farming (PLF) uses technology to monitor and manage animals—often in real-time and at the individual animal level (Berckmans, 2014). Such technology can range from wearable sensors providing data related to animal activity and/or location to computer vision solutions using cameras that can provide relevant animal data in a less intrusive way.

The challenges of developing PLF solutions capable of monitoring individual animals who often live in large groups with other animals of nearly identical appearance and in a tough farm environment, where equipment and data transmission are often affected by dirt, moisture and by the animals themselves, are considerable (to say the least). However, solving technical problems alone is not enough. The developed PLF solutions will be implemented in real-world scenarios, in farming systems where humans and animals interact, and in societies where there may be ethical or cultural ramifications to replacing human labor and decision-making with machines and artificial intelligence.

Research underlying the development of the PLF solutions is often presented as benefiting both humans and animals (Guarino et al., 2017; Werkheiser, 2020). For humans, using PLF is proposed as a way to use limited human resources to better effect by giving farmers tools to keep track of more animals and to intervene earlier when problems arise. For animals, it is touted as a way to give them more individualized care, tailored to their unique needs, which should improve their quality of life. Yet, as with all technology, there can be unintended consequences or alternative uses that should be considered, before the technology is developed too far or widely adopted (Russell et al., 2015; Werkheiser, 2020). For example, will use of technology to directly monitor and manage animals result in objectification of the animal and destroy the human-animal relationships farmers care so much about (Bos et al., 2018; Werkheiser, 2018).

Schillings et al. examined the likely impacts of PLF on animal welfare through the lens of the Five Domains Model. They concluded that while current PLF technologies broadly have abilities to reduce obvious negative welfare issues, such as injuries or illness, they are not yet able to promote positive welfare. However, such limitations may not be entirely the fault of technology, as there is an active scientific inquiry into what parameters are reliable indicators of positive welfare states, regardless of what approach is used to detect such indicators in an animal.

Dawkins posits that whether PLF will improve the welfare of livestock on commercial farms will depend on exactly how welfare is defined and agreed upon by the various human actors developing

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and using the technology as well as the wider public. Only by having a common definition, and one that truly considers quality of life from the perspective of the animal, Dawkins argues, can the impact of PLF on animal welfare truly be assessed. Where animal welfare was once a term to be avoided by mainstream animal scientists, it has now become adopted so widely that it is often used or defined incorrectly, whether deliberately or not, by those that hope to benefit from including the term in their papers and presentations. Thus, the importance of a common, robust and meaningful definition remains as critical for animal welfare as we strive to monitor it with technology as it did at the inception of the scientific study of the subject. Dawkins also argues that high standards of animal welfare must be an explicit priority when developing PLF so that systems are trained to recognize and promote welfare to the satisfaction of animal caretakers and also the public (which circles back to the importance of that common definition).

Analysis of manuscript topics and text using both Natural Language Processing and manual examination of articles by Guzhva et al., reveals that relatively few technical papers related to development of PLF technologies make even a general mention of social or ethical implications of their work. When outcomes with social or ethical implications are stated, they are often presented as sweeping generalizations of "improving welfare" or "helping farmers." Few concrete or explicit links are made between the data generated by the technology and how this information will translate into a tangible benefit for either the human user or the animal recipient. In the few papers found to acknowledge downsides to the adoption of PLF, the most common pitfalls described were farmer frustration with technology failures or limitations, need for farmers to learn new skills and the potential for PLF to increase intensification and size of farms.

In addition, there may be unintended societal or ethical consequences to the widespread use of technology and algorithms that the technical experts have not yet considered. For example, computer scientists working on designing algorithms that can recognize sick or diseased animals should explicitly consider that this technology could be used to automate decisions related to veterinary treatment or euthanasia. Developers should be trained to look beyond the immediate technical challenge they are solving to anticipating practical applications of their work and the ethical consequences. How might farmer personality and interaction with technology affect whether humans care more or less for their animals (Kling-Eveillard et al., 2020). Finally, what is the potential for a particular technology or algorithm to have crossover applications related to monitoring humans or automating important decisions about human health or life (Werkheiser, 2020).

Solving a technical problem in a vacuum ignores the fact that the technology will be used in the real world and may lead far down a path unacceptable to society before this disconnect is acknowledged. The articles in this special topic are intended to encourage thoughtful development of PLF and to create awareness in PLF developers of the social and ethical ramifications that they may not have considered previously. While it is not reasonable to expect all PLF developers to be philosophers or social scientists, it is possible to consult with colleagues who are or to work on interdisciplinary teams when developing PLF.

AUTHOR CONTRIBUTIONS

JS: conceptualization. JS and OG: writing and editing original draft. All authors contributed to the article and approved the submitted version.

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REFERENCES

Berckmans, D. (2014). Precision livestock farming technologies for welfare management in intensive livestock systems. *Rev. Sci. Tech. Off. Int. Epiz.* 33, 189–196. doi: 10.20506/rst.33.1.2273

Bos, J. M., Bovenkerk, B., Feindt, P. H., and van Dam, Y. K. (2018). The quantified animal: precision livestock farming and the ethical implications of objectification. *Food Ethics* 2, 77–92. doi: 10.1007/s41055-018-00029-x

Guarino, M., Norton, T., Berckmans, D., Vranken, E., and Berckmans, D. (2017). A blueprint for developing and applying precision livestock farming tools: a key output of the EU-PLF project. *Anim. Front.* 7, 12–17. doi: 10.2527/af.2017.0103

Kling-Eveillard, F., Allain, C., Boivin, X., Courboulay, V., Creach, P., Philibert, A., et al. (2020). Farmers' representations of the effects of precision livestock farming on human-animal relationships. *Livest. Sci.* 2020:104057. doi: 10.1016/j.livsci.2020.104057

Russell, S., Dewey, D., and Tegmark, M. (2015). Research priorities for robust and beneficial artificial intelligence. *AI Mag.* 36, 105–114. doi: 10.1609/aimag.v36i4.2577

Werkheiser, I. (2018). Precision livestock farming and farmers' duties to live- stock. *J. Agr. Environ. Ethic.* 31, 181–195.

Werkheiser, I. (2020). Technology and responsibility: a discussion of underexamined risks and concerns in precision livestock farming. *Anim. Front.* 10, 51–57. doi: 10.1093/af/vfz056

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REVIEW
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Exploring the Potential of Precision Livestock Farming Technologies to Help Address Farm Animal Welfare

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The rise in the demand for animal products due to demographic and dietary changes has exacerbated difficulties in addressing societal concerns related to the environment, human health, and animal welfare. As a response to this challenge, Precision Livestock Farming (PLF) technologies are being developed to monitor animal health and welfare parameters in a continuous and automated way, offering the opportunity to improve productivity and detect health issues at an early stage. However, ethical concerns have been raised regarding their potential to facilitate the management of production systems that are potentially harmful to animal welfare, or to impact the human-animal relationship and farmers' duty of care. Using the Five Domains Model (FDM) as a framework, the aim is to explore the potential of PLF to help address animal welfare and to discuss potential welfare benefits and risks of using such technology. A variety of technologies are identified and classified according to their type [sensors, bolus, image or sound based, Radio Frequency Identification (RFID)], their development stage, the species they apply to, and their potential impact on welfare. While PLF technologies have promising potential to reduce the occurrence of diseases and injuries in livestock farming systems, their current ability to help promote positive welfare states remains limited, as technologies with such potential generally remain at earlier development stages. This is likely due to the lack of evidence related to the validity of positive welfare indicators as well as challenges in technology adoption and development. Finally, the extent to which welfare can be improved will also strongly depend on whether management practices will be adapted to minimize negative consequences and maximize benefits to welfare.

Keywords: affective states, human-animal relationship, livestock production, sensors, smart farming, precision livestock farming, animal welfare

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INTRODUCTION

One of the biggest challenges our society is facing is the ability to feed a growing population, which is expected to reach around 9.7 billion people by 2050, while minimizing environmental impacts, ensuring human health (FAO, 2018), and addressing the public's rising concern over animal welfare (European Commission, 2016). In the UK, animal welfare standards have been a key subject of public concern, particularly with proposed changes to trade and agricultural policies in light of Brexit (Main and Mullan, 2017). In addition, there have been government commitments to achieving net zero and other environmental improvements in the Agriculture Act, Environment Bill and 25-years Environment Plan. The National Farmers' Union, e.g., has set a 2040 target for net zero emissions in the agriculture sector, and the Agriculture Act and associated plan to improve farm productivity indicates that English farmers can receive financial support to produce "public goods" such as environmental or animal welfare improvements (DEFRA, 2021).

However, meeting these commitments is challenging, not least because global meat production is expected to double by 2050[1]. This increase in production may be achieved by a combination of expansion in animal numbers and increased productivity, which will be particularly important in the poultry and pig sector (Gilbert et al., 2015). While it is not possible to predict precisely what agriculture will look like in 2050 (factors such as income distribution, dietary choices and technological innovations will have an important influence), the FAO suggests that in a "business-as-usual" scenario, animal herds are likely to increase by 46% globally compared to 2012, with poultry numbers increasing over five-fold, three-fold for pigs, and two-fold for small and large ruminants (FAO, 2018). This increase in animal numbers could make their management more challenging, especially if, as was observed in the EU, the number of farmers continues to decrease (Eurostat, 2020). In the UK, while livestock numbers remained stable between 2018 and 2019, the labor force on commercial holdings decreased by 0.3% (DEFRA, 2019). Having fewer farmers to look after larger numbers of animals may make it more difficult to address animal health and welfare challenges.

As a response to these challenges, the development of new technologies has gained momentum. Among these developments are Precision Livestock Farming (PLF) technologies, which are designed to support farmers in livestock management by monitoring and controlling animal productivity, environmental impacts, as well as health and welfare parameters in a continuous, real-time and automated manner (Berckmans, 2014). A variety of systems using technologies such as sensors, cameras or microphones can directly alert farmers via connected devices (e.g., phones, computers, or tablets) about detected anomalies, thus allowing farmers to intervene at an early stage. Research is pointing toward the great potential for these "smart technologies" to help livestock farmers in monitoring the welfare of their animals and several countries are already investing in their development, reflecting their potential to be part of strategies to move toward sustainable agriculture (Rose and Chilvers, 2018; Norton et al., 2019).

While their potential is promising, the use of these new technologies also raises ethical concerns, such as their potential impact on the human-animal relationship, the objectification of animals, the notion of care and farmers' identity as animal keepers (Bos et al., 2018; Werkheiser, 2018, 2020). The human-animal relationship is an important aspect which can influence both animal welfare and productivity. The behavior of stock people, which is influenced by their attitudes toward farm animals, has an influence on animals' fearfulness toward humans, with positive behaviors leading to decreased levels of avoidance and negative handling increasing fearfulness toward humans (Hemsworth and Barnett, 1991; Waiblinger et al., 2002; Probst et al., 2012). In addition, it also influences productivity. For example, reduced milk yields were found on dairy farms where farmers had more negative attitudes toward interactions with cows during milking (Waiblinger et al., 2002). Aversive handling was also shown to impact the growth performance of pigs and negative relationships were found between level of fearfulness toward humans and egg production (Hemsworth and Barnett, 1991; Cransberg et al., 2000). On the other hand, habituation, early positive contact and genetic dispositions can be important factors to influence the quality of the HAR (Mota-Rojas et al., 2020). For example, studies found that young broiler chickens exposed to positive human contact had greater growth rates, and that positive attitudes were associated with more use of positive behaviors (Gross and Siegel, 1979; Lensink et al., 2000). If PLF technologies are used to facilitate and/or replace certain tasks involving human-animal interactions and to reduce time spent on observing individual animals by 'replacing farmers eyes and ears' (Berckmans, 2014), it could be questioned whether PLF could impact the HAR by reducing the frequency of human-animal interactions and impacting farmers' attitudes toward their animals and hence their behavior. Animals may have less opportunity to become habituated to people and farmers if the frequency of neutral or positive interactions is reduced (this may be particularly true on larger farms where opportunities for human-animal contacts are usually reduced) (Rushen et al., 1999; Cornou, 2009; Mota-Rojas et al., 2020). Similarly, concerns were also raised in regards to the extent to which PLF could redefine the notion of care, and whether farmers attitudes may shift further toward reducing animals to "tracking devices" and focus primarily on productivity (e.g., disease prevalence or costs of medical treatments) while overlooking the animal's qualitative experiences (Bos et al., 2018).

Taking these benefits and ethical challenges into consideration, it seems important to evaluate the extent to which these technologies can actually address the issue of animal welfare. The notion of animal welfare is complex to define and, while the focus has long revolved around minimizing negative experiences such as pain and suffering, studies in animal behavior and neuroscience have led scientists to highlight the importance of positive affects in animal welfare (Boissy et al., 2007; Yeates and Main, 2008). Affective states relate to feelings or emotions which can vary in intensity, duration, level of arousal and how pleasant or unpleasant they are. While survival-related affects reflect the animal's internal physiological state (e.g., thirst or hunger), situation-related affects reflect the animal's perception of its external circumstances (e.g., comfort, playfulness, depression, loneliness) (Mellor, 2015a). Positive animal welfare cannot be achieved with a sole emphasis on minimizing negative experiences; opportunities to experience positive affects (e.g., by allowing animals to engage in rewarding goal-directed behaviors such as through affiliative interactions, exploring, or play) must also be provided (Mellor and Beausoleil, 2015). Taking these aspects into account, the "Five Domains Model" (FDM) has been developed to facilitate the assessment of animal welfare and considers both negative and positive affective

[1]Food and Agriculture Organization. (2019). Meat & Meat Products. Available online at: http://www.fao.org/ag/againfo/themes/en/meat/home.html (accessed December 7, 2020).

states (Mellor and Beausoleil, 2015). The first three domains (labeled "nutrition," "physical environment," and "health") include survival-related factors, while the fourth (labeled "behavioral interactions") includes situation-related factors. Based on these four domains it is then possible to evaluate the associated affective consequences within a fifth domain, "mental state" (Mellor et al., 2020). The method can be updated using the latest scientific evidence in animal welfare and can be used in different animal-related sectors (Mellor, 2017).

Using the FDM as a framework, this study thus aims to understand better the potential of PLF technologies to help address the notion of animal welfare by looking at a non-exhaustive, yet wide range of technologies. To this end, PLF developments in a variety of farmed species were identified along with their development stages to distinguish better between commercially available technologies and technologies that are further away from being fully developed. Secondly, the potential welfare benefits and risks of PLF are explored along with their potential ability to promote/address affective states.

METHODS

Identification of PLF Technologies

A combination of methods was used to identify PLF technologies. These include searches on scientific papers databases, visiting technology exhibitions, input from colleagues as well as during a workshop organized by the author. These methods are further described below.

Research Papers

Search Criteria

The databases *Scopus* (Elsevier) and *Web of Science* were used to search for papers relevant to this study. The search was conducted between February and April 2020. Only research articles were selected, with no limits on date of publication. Each search included: a keyword related to Precision Livestock Farming, a species, and either the words "welfare," "health," or "behavior" (see **Table 1**). Considering the variety of methods that could relate to PLF technologies, the selection of PLF-related keywords was based on categories that were commonly being referred to in related literature reviews (Benjamin and Yik, 2019; Halachmi et al., 2019; Li et al., 2019; Norton et al., 2019; Astill et al., 2020). These include the use of image-based technology (e.g., using 2D or 3D cameras, computer vision, optical flow, thermal cameras), sound (e.g., using microphones or sonars), sensors [e.g., using accelerometers, pressure or infrared sensors (IR)], Radio-Frequency Identification (RFID) and wireless technologies. It is acknowledged that by using these specific keywords and databases, other types of technologies may have been omitted. It was not the goal of this paper to review all possible PLF technologies for all species, but rather to obtain a general view of current developments and discuss how these apply to animal health and welfare monitoring. The species were selected on the basis of being the main species farmed in the UK. To complete our search, relevant papers referenced in review articles and not present in the databases were also considered.

TABLE 1 | List of the keywords used in the search.

Technology	Species	Parameter
Precision livestock farming	Cattle, cow, beef, calf	Welfare
PLF	Pig, swine, sow	Health
Smart farming	Poultry, laying hen, chick*, broiler	Behavi*r
Automat* AND sound	Fish, salmon, trout	
Automat* AND image	Goat, turkey, sheep	
Automat* AND sensor		
Automat* AND vision		
Automat* AND wireless		
Automat* AND RFID		
Precision fish farming		

Each search consisted of one **"***technology***"***, one* **"***species***,"** *and one* **"***parameter***,"** *except for* **"***Precision Fish Farming***"** *which was only associated with fish, salmon and trout. An example of search in Web of Science was:* **"***TS =* **[***'Precision Livestock Farming' AND (cattle OR cow OR beef OR calf) AND (welfare OR health OR behav*r)***]"***. The asterisk (*) is a wildcard: it represents any group of characters, including no character.*

Selection of Papers

Only accessible papers written in English were considered. From the author's understanding based on the literature and the workshop organized by the author (of which more details can be found in Section Workshop), the definition of PLF technologies can be understood differently by different people. In this study, PLF refers to technologies that are, or have the potential to be, automated, and allowing to monitor animal health, welfare, and environmental parameters continuously and in real-time. Technologies such as virtual fencing or milking robots were, e.g., not considered in our study. Papers were selected when the aim of the study was to present a method to automatically monitor farm animal health, welfare, or behavior parameters. These included, e.g., monitoring lameness, respiratory diseases, heat, body temperature, or environmental conditions. Methods at various stages of development were considered, from proof-of-concepts to validated, fully automated systems. Papers were not selected when the purpose was mainly to refine existing models or algorithms such as to improve image resolution or the detection of certain parts of the body (as they were not about PLF systems in themselves). Papers were also not selected when they addressed transport or post-slaughter issues, when they applied to other contexts than farming (e.g., monitoring of wild animals or applications for laboratory studies), or when authors concluded that the proposed methods did not present satisfying enough results for the purpose of their study.

Commercialized Technologies

Commercially available PLF technologies were found in several ways, including visiting technology exhibitions, finding mentions in research or news articles, getting recommendations from colleagues, as well as during a workshop organized by the author of this paper (see next section). When mentions of particular technologies were found, the websites of the relevant companies were visited, and technologies were selected when they allowed to automatically monitor health and welfare parameters of farm animals.

Workshop

The workshop, called "*Current developments in Precision Livestock Farming (PLF) technologies: What can we measure and what are the welfare benefits and challenges*' was funded by the Animal Welfare Research Network (AWRN) and organized by the first author. Over 150 international participants registered to the online workshop, however, places were limited to 100 participants due to the video conferencing software used (Zoom 5.4). Participants were selected on a "first come, first served" basis with the condition of participants having to be members of the AWRN (or currently applying to become a member). Approximately 90 participants logged in at the start of the workshop, which included researchers and students (59 and 15%, respectively), industry workers (8%), NGOs (4%), vets (4%), civil servants (4%), assurance schemes workers (4%), and farmers (2%). Most attended the workshop activities, and ∼70 participants remained until the end. Four 30 min keynote presentations (including questions and answers) and two, 1-h activities (including presentations of the outcomes by the participants) allowed the participants to discuss current developments in PLF for several species (from proof-of-concepts to commercially available technologies), their benefits, potential challenges (to animal welfare and beyond) and solutions. An outline of the workshop is presented in Annex 1. Participants were split into eight different groups during the activities, each focusing on one or two livestock sectors. During the first activity, participants were asked to discuss up to five commercially available and up to five "promising" PLF technologies that have the most potential to improve animal welfare for their selected species, and to qualitatively discuss the chosen technologies' potential benefits to welfare. Volunteers in each group presented the outcomes of their discussion to the rest of the participants in 3 min each, sometimes using visual support showing notes taken during the discussions (e.g., whiteboard from the Zoom software or via a Microsoft PowerPoint slide). In a second activity, participants (divided into the same groups) were asked to qualitatively discuss the risks and challenges of using PLF technologies (to their species and beyond), and how these could be minimized. Results were presented in the same way as for the first activity. The first author took notes during these presentations and collected copies of the whiteboards or PowerPoint slides where available. The outputs of these discussions, as well as technologies and welfare benefits and risks mentioned during the keynote presentations, were used to complement the findings of this study (e.g., if the author had omitted specific technologies or benefits and risks that were not initially identified). As the outcomes of the workshop related to animal welfare, but also to aspects beyond the scope of this study (since they are closely related with other aspects such as impacts on farmers, consumers and other stakeholders), only the outcomes directly related to animal welfare (PLF technologies, benefits and risks to welfare) were used to complement the findings of this review.

Classification

The different technologies found using the above methods were classified by the first author of this paper with the help of the co-authors and a colleague (expert in the fields of agricultural technologies and animal welfare) in tables according to their type (e.g., image, sensors, sound, RFID, bolus), their application (e.g., detection of lameness or estrus) and their development stage categories. Each table was associated to a Physical/Functional Domain of the Five Domains Model ("nutrition," "physical environment," "health," or "behavioral interactions"). The technologies' potential welfare benefits and risks and their potential to address affective experiences based on the fifth domain ("mental state") were also discussed.

Technology Types and Applications

To simplify the tables, the "technology type" category was kept broad. For example, although technically different, accelerometers and infrared sensors were both classified into a broader "sensor" category. Similarly, some applications were grouped within categories. For example, the applications related to "feed intake," "grazing," "jaw movements," "rumination," or "bites" were all grouped into the "feeding behavior" category. Similarly, "ammonia concentrations" or "particle matter concentrations" were classified into the "air/water quality" category. The category "disease/parasites monitoring" includes technologies aiming to detect ill animals with diseases/parasites such as Bovine Respiratory Disease (BRD) or sea lice in salmon. "Activity" included behavior monitoring such as walking, standing, lying or swimming. The technologies were classified according to the specific aims of the papers. For example, when the aim was to determine whether a technology could accurately detect walking and lying patterns, the technology was placed into the "activity" category within the "behavioral interactions" domain. Similarly, when the specific aim was to accurately detect estrus in cattle, the technology was placed into the "estrus" category within the "health" domain, even if the technology was based on activity data.

Development Stages

The development stage categories were inspired by the Technology Readiness Levels (TRLs) developed by the National Aeronautics and Space Administration (NASA). The technologies were assigned within three categories which are broadly comparable with TRLs: "proof-of-concept phase" (P1), "validation phase" (P2) and "commercialization phase" (P3). Technologies were assigned into the P3 category when the systems were commercially available. Papers which included steps to validate specific technologies or where further papers were published to validate the method were assigned into the P2 category, while those which did not were classified into the P1 category. When several papers addressed a similar application with a similar type of technology, only the highest category was shown. It is acknowledged that the grouping into wider categories may not allow to precisely reflect the state of development of each different type of technologies, especially as developments and further validation may have occurred between the initial search and the writing of the paper or may have been omitted due to the restricted number of keywords. Instead, it allows to obtain an overview of current developments and to discuss their potential to address animal welfare.

Welfare Implications

The classification into the different domains was based on the updated Five Domains Model (FDM) table developed by Mellor et al. (2020). Classification under the first four physical domains was based on the parameters monitored by the technologies (e.g., technologies monitoring feeding behaviors were classified into the "nutrition" domain, while technologies monitoring lameness were classified under the "health" domain). Discussions on affective states were based on the FDM table which provides examples of positive and negative factors with their associated inferred negative or positive affective experiences from the fifth domain. For example, under the "*physical environmental conditions*" section of the table, "*air pollutants:* NH_3*,* CO_2*, dust, smoke*" is associated with the negative affects "*respiratory discomfort*" (e.g., breathlessness, air passage irritation/pain). For this reason, if a technology was designed to help farmers monitor air pollutants such as NH_3, the author suggested that the use of such technology could have an impact on respiratory discomfort. Similarly, a technology monitoring water intake would have been suggested to have a possible impact on the associated negative affect "*thirst*." Where there were many affects associated with specific factors, only a few examples were suggested to avoid lengthy paragraphs. For example, the FDM indicates that the presence of injuries or diseases may be associated to the following negative affects: pain (many types), breathlessness, debility, weakness, sickness, malaise, nausea, and dizziness. To avoid listing all possible affects, the authors selected either those related to a specific condition (such as breathlessness related to respiratory diseases) or those that were most likely to be understood by a wider audience (such as feelings of sickness resulting from diseases). Finally, welfare benefits and risks were discussed both in relation to the specific domains and across domains in a separate section (Section Welfare Benefits and Risks Across Domains). These were identified in the research papers found in this study, technology company websites, within the wider PLF literature and during the workshop.

RESULTS

Research Paper Selection

The search revealed 793 research articles in total. After manual selection of papers which we considered relevant to our study, we retained 247 papers. Excluded papers included those that did not focus on specific PLF technologies, papers related to technologies other than PLF, papers that were not accessible or that were in a language other than English. Excluded papers also included duplicates, papers that did not relate to farming or to the species of interest (such as wild or laboratory animals) or that addressed stages of production which we did not consider in this review (e.g., slaughter). A number of excluded papers also included those that were not related to animals (e.g., human medicine). Selected papers included 101 papers related to cattle, 68 to pigs, 37 to poultry, 15 to fish, and 26 to other species (including turkeys, goats, and sheep).

In the following sections, technologies relating to the physical/functional domains of the Five Domains Model are described along with a discussion on their domain-specific welfare implications based on the fifth domain. These are followed by a section (Welfare Benefits and Risks Across Domains) on welfare benefits and risks across domains.

Nutrition

The monitoring of drinking and feeding behaviors (which includes grazing, ruminating, jaw movements, chewing, or feed intake), and gastrointestinal health were the main applications related to the "nutrition" domain (**Table 2**). The cattle sector appears to benefit from a wider variety of PLF technologies at later development stages in comparison to other species, although commercially available technologies can also be found for pigs, poultry and fish. For small ruminants, technologies mainly range from the proof-of-concept phase "P1" to the validation phase "P2."

Commercially Available Technologies

In cattle, smart camera systems using computer vision combined with deep learning can monitor eating time and feed availability at group level, while neck collars equipped with 3D accelerometers continuously monitor rumination and eating time in individual animals. Gastrointestinal health can also be monitored using boluses sitting in cattle reticulum which measure pH and temperature. In pigs, RFID ear tags are used as part of electronic feeding systems, while in the aquaculture sector, hydroacoustic-based technologies and cameras combined with machine learning allow to monitor fish pellet consumption and appetite. Finally, water consumption can be monitored with commercially available boluses in cattle and with sensors in cattle, pigs, and poultry.

Technologies in Development

Other systems which are currently in the development stages (categories P1 to P2) can monitor ingestive behaviors in free-ranging cattle, goats and sheep using acoustic monitoring (Navon et al., 2013; Chelotti et al., 2016). In poultry, Aydin (2016) developed a sound-based monitoring system to detect short-term feeding behaviors of broiler chickens by recording pecking sounds. RFID systems have been used to monitor feeding patterns in pigs (Maselyne et al., 2016b; Adrion et al., 2018), turkeys (Tu et al., 2011) and laying hens (Li et al., 2017). Image analysis and binocular vision techniques have been developed to monitor feeding in pigs (Yang et al., 2020) and poultry (Xiao et al., 2019), while sensor-based systems can monitor feed intake in goats (Campos et al., 2019) and turkeys (Chagneau et al., 2006). Technologies at phase P2 also introduced the possibility to use 3D-vision to automatically assess reticulo-ruminal motility in cattle (Song et al., 2019). Finally, drinking behavior can be monitored using RFID in pigs (Maselyne et al., 2016a) and a combination of sensors and RFID have been used in cattle (Williams et al., 2020). Accelerometers have been used to monitor drinking in calves (Roland et al., 2018), while camera-based systems have been developed to monitor drinking behavior in pigs (Kashiha et al., 2013a) and chickens (Xiao et al., 2019).

TABLE 2 | Development stages of PLF technologies related to the "nutrition" domain of the Five Domains Model for different species (expressed in phases—P1, proof-of concept stages; P2, validation stages; P3, commercialization phases).

Application	Species	Technology developments				
		Bolus	Image	RFID	Sensors	Sound
Drinking behavior	Cattle	P3	-	P2	P3	-
	Pigs	-	P1	P2	P3	-
	Poultry	-	P1	-	P3	-
	Turkeys	-	-	-	P3	
Feeding behavior	Cattle	-	P3	-	P3	P2
	Fish	-	P3	-	-	P3
	Goats	-	-	-	P2	P1
	Pigs	-	P2	P3	-	-
	Poultry	-	P1	P2	-	P2
	Sheep	-	-	-	P2	P1
	Turkeys	-	-	P1	P1	-
Gastrointestinal health	Cattle	P3	P2	-	-	-

Welfare Implications

Using PLF to monitor drinking and feeding behaviors and gastrointestinal health could help provide additional support to minimize the experience of survival-related negative affects such as thirst, hunger or gastrointestinal pain. As changes in drinking or feeding patterns can be indicative of health compromises such as diseases (Nicol, 2011), we suggest that feelings of sickness could be minimized provided that farmers are taking adequate management decisions based on the data (e.g., providing animals with appropriate resources or treatment). In parallel, positive affects such as comfort of good health, gastrointestinal comfort and pleasures associated with drinking and eating could be promoted. However, studies suggest that positive affective states relating to most survival-related factors are usually short-lived (Mellor and Beausoleil, 2015), hence these technologies may mainly have an impact on the negative-to-neutral valence range.

Physical Environment

Table 3 shows that air or water quality, animal crowding and distribution and heating/ventilation are the main applications related to the "physical environment" domain. The monitoring of environmental factors is generally based on image and sensor technologies in the fish, poultry and pig sectors, most of them being commercially available.

Technology Developments

The monitoring of air/water quality includes the detection of a variety of parameters such as toxic molecules concentrations, pH, CO_2, temperature, or oxygen levels which can have important impacts on animal health and welfare. Sensors are commercially available to measure these environmental variables in the aquaculture, poultry and pig sectors. They are also available to monitor heating and ventilation in pig and poultry barns, while image-based systems using animal postures or distribution are still in early development stages (P1 to P2) (Shao et al., 1997; Xin, 1999; Kashiha et al., 2013b). Finally, animal distribution can be detected with commercially available cameras in the aquaculture and poultry sector.

Welfare Implications

Monitoring environmental parameters could help address negative affective experiences by minimizing thermal, physical, respiratory and olfactory discomfort due to inappropriate temperatures or, e.g., inappropriate levels of ammonia. Ensuring optimal environmental conditions could benefit welfare by minimizing risks of infectious and respiratory diseases and heat stress, as well as promoting feelings of comfort. In addition, monitoring animal distribution can also indicate welfare compromises or equipment malfunctions (e.g., heating or ventilation systems) (Kashiha et al., 2013b). The potential impacts on survival-related affective experiences remain within the negative-to-neutral valence range.

Health

A variety of technologies at different development stages monitor parameters related to the "health" domain, from specific diseases to foot health and stress, as well as physiological parameters such as heart rate or temperature. Most commercially available technologies appear to apply to cattle, but they can also be found for pigs, poultry, as well as for sheep and fish (**Table 4**).

Commercially Available Technologies

In cattle, body-mounted accelerometers can be used to detect calving, estrus and lameness based on activity data, while cameras combined with machine learning can help determine standing heat, body condition scores (BCS), assess lameness, and estimate weight. Boluses placed in the reticulum can also be used to monitor estrus, calving and physiological factors such as body temperature or pH, and ear sensors can monitor temperature. In the pig sector, camera-based systems can determine BCS, estrus and weight, while microphones placed in barns can detect coughing sounds and monitor respiratory health. In aquaculture, image-based systems can allow the detection of sea lice, and

TABLE 3 | Development stages of PLF technologies related to the "physical environment" domain of the Five Domains Model for different species (expressed in phases—P1, proof-of concept stages; P2, validation stages; P3, commercialization phases).

Application	Species	Technology developments				
		Bolus	Image	RFID	Sensors	Sound
Air/Water quality	Fish	-	-	-	P3	-
	Pigs	-	-	-	P3	-
	Poultry	-	-	-	P3	-
Crowding/Distribution	Fish	-	P3	-	-	-
	Poultry	-	P3	-	-	-
Heating/Ventilation	Pigs	-	P1	-	P3	-
	Poultry	-	P2	-	P3	-

TABLE 4 | Development stages of PLF technologies related to the "health" domain of the Five Domains Model for different species (expressed in phases—P1, proof-of concept stages; P2, validation stages; P3, commercialization phases).

Application	Species	Technology developments				
		Bolus	Image	RFID	Sensors	Sound
Birth (farrowing, calving)	Cattle	P3	-	-	P3	-
	Pigs	-	-	-	P2	-
Body condition	Cattle	-	P3	-	-	-
	Pigs	-	P3	-	-	-
Disease/parasites monitoring	Cattle	-	P1	-	P2	P1
	Fish	-	P3	-	-	-
	Poultry	-	P2	-	P2	P1
Estrus	Cattle	P3	P3	P1	P3	P2
	Pig	-	P3	-	P1	-
	Sheep	-	-	P2	-	-
Feather damage	Poultry	-	P1	-	-	-
Foot health	Cattle	-	P3	-	P3	P1
	Pigs	-	P2	-	P1	-
	Poultry	-	P2	-	P1	-
	Sheep	-	-	-	P2	P2
Physiology	Cattle	P3	P1	-	P3	-
	Fish	-	-	-	P1	-
	Pig	-	-	P1	-	-
	Poultry	-	P1	-	P1	-
	Sheep	-	-	-	P2	-
Sneezing/Coughing	Cattle	-	-	-	-	P1
	Pigs	-	-	-	-	P3
	Poultry	-	-	-	-	P1
Stress/Pain	Fish	-	P1	-	-	-
	Pigs	-	P1	-	-	P1
	Poultry	-	-	-	-	P1
	Sheep	-	P1	-	-	-
Weight	Cattle	-	P3	-	-	-
	Fish	-	P3	-	P3	-
	Pigs	-	P3	-	P3	-
	Poultry	-	P1	-	P3	P1

sensors and cameras can estimate fish growth. Finally, automatic weighing systems are available to detect the average weight of poultry flocks.

Technologies in Development

Growth rate can be measured in broiler chickens using technologies at development stages ranging from P1 to P2, using sound analysis (Fontana et al., 2015, 2017) or 3D cameras (Mortensen et al., 2016).

Estrus in cattle can be monitored based on individual vocalizations and caller identification (Röttgen et al., 2020) or with proximity loggers (Corbet et al., 2018). This can also be monitored using RFID technology in sheep (Alhamada et al., 2016), while sensor-based systems can detect pig farrowing (Manteuffel et al., 2015; Pastell et al., 2016; Liu et al., 2018).

Diseases such as mastitis in cattle or campylobacter infection in chickens can be monitored using sensor, sound and image-based technologies at phases P1 and P2 both in poultry (Okada et al., 2014; Banakar et al., 2016; Colles et al., 2016; Grilli et al., 2018) and cattle (Steensels et al., 2016; Vandermeulen et al., 2016; Yazdanbakhsh et al., 2017; Zaninelli et al., 2018; Watz et al., 2019).

Physiological parameters such as respiration rate, temperature or heart rate can be monitored in cattle using image or sensor-based technologies at development stages P1 to P2 (Nogami et al., 2013; Stewart et al., 2017; Strutzke et al., 2019) as well as in poultry (Hyun et al., 2007; Xiong et al., 2019), fish (Martos-Sitcha et al., 2019), and sheep (Dos et al., 2018; Fuchs et al., 2019).

Lameness can be detected in pigs using images and sensors (Pluym et al., 2013; Stavrakakis et al., 2015), while gait scores can be evaluated in poultry using optical flow and sensors (De Alencar Nääs et al., 2010; Dawkins et al., 2017; Van Hertem et al., 2018). Sensors can be used to detect lameness in sheep (Shrestha et al., 2018; Kaler et al., 2020) and sound-based systems to monitor lameness and foot lesions in cattle (Volkmann et al., 2019).

Technologies in the P1 and P2 phases can monitor coughs in cattle (Carpentier et al., 2018) and sneezing in poultry using sound-based technologies (Carpentier et al., 2019). Similarly, stress or signs of pain can be monitored in pigs (Schön et al., 2004) and poultry (Lee et al., 2015), as well as by using camera-based technologies in fish (Israeli, 1996), pigs (da Fonseca et al., 2020) or sheep using facial recognition (McLennan and Mahmoud, 2019). Finally, image processing can be used to detect asphyxia in sows during parturition (Okinda et al., 2018) or to predict feather damage in poultry (Lee et al., 2011).

Welfare Implications

The identified technologies could help address animal affective experiences such as pain, weakness or sickness emanating from diseases or physical injuries. For example, the early detection of coughing can indicate the onset of respiratory diseases which, if treated adequately, have the potential to prevent the experience of breathlessness which can cause significant threats to welfare (Beausoleil and Mellor, 2015). Similarly, monitoring foot health or predicting feather pecking outbreaks in poultry could help minimize painful experiences provided that appropriate management decisions are taken. This in turn could promote feelings of comfort linked to good health and functional capacity. In some cases, the automatic detection of estrus, whilst mostly beneficial for productivity, could reduce the need for stressful handling (e.g., in pigs), hence potentially addressing negative affective states such as anxiety or fearfulness. As for the "nutrition" and "physical environment" domains, the impacts on affective experiences remain within the negative-to-neutral valence range. As highlighted during the workshop, the early detection of diseases could help reduce their spread and support management decisions such as early interventions, better colostrum management, reducing the use of antibiotics, reducing stressful handling or preventing injurious events such as feather pecking.

Behavioral Interactions

Many PLF technologies are based on animal activity patterns, such as lying, walking/swimming or standing. As shown in **Table 5**, commercially available systems to monitor activity have been developed for most farmed species, particularly using image- and sensor-based technologies. Other technologies have been developed to detect agonistic behaviors, as well as social interactions and maternal behaviors in pigs, cattle and poultry. However, those generally remain at earlier development stages (P1 to P2).

Commercially Available Technologies

Accelerometers are mostly available for ruminants and are usually attached to the animals' bodies and allow to monitor behavior, location, or postures of individual animals such as lying, standing or walking. Image-based systems can be found in the aquaculture, pig and poultry sectors, whilst hydroacoustic-based systems allow to monitor fish movements. In sheep, pedigree match makers using RFID tags can be used to identify the maternal pedigree of lambs and to monitor behavior traits of lambs and ewes in extensive systems, which could provide information on potential changes in relationships (Brown et al., 2011; Morris et al., 2012).

Technologies in Development

Other technologies at earlier development stages can help monitor activity, such as drones in goats (Vayssade et al., 2019), RFID in poultry (Zhang et al., 2016) and sensors in fish (Martos-Sitcha et al., 2019), pigs (Mainau et al., 2009; Thompson et al., 2016), and poultry (Quwaider et al., 2010; Van Der Sluis et al., 2019). In pigs, tail biting or fighting can be monitored using depth sensors (Lee et al., 2016; Chen et al., 2019), 3D cameras and computer vision (Viazzi et al., 2014; D'eath et al., 2018). Excessive mounting can be detected using image analysis (Nasirahmadi et al., 2016), while nest building can be detected using accelerometer data (Oczak et al., 2015). Nursing behavior can also be monitored using video analysis (Yang et al., 2019). In cattle, systems have been developed to monitor agonistic behaviors based on sensors (Foris et al., 2019), while image-based technologies can monitor mounting behaviors (Chung et al., 2015; Guo et al., 2019) and social interactions (Guzhva et al., 2016), and accelerometers can estimate locomotor play in calves (Luu et al., 2013). Proximity interactions of individual dairy cows within large herds can also be monitored using local positioning sensor network (Chopra et al., 2020). Image- and RFID-based technologies in the poultry sector allow to monitor human-animal interactions (HAI) (Lian et al., 2019), nesting (Li et al., 2017), and perching behaviors

TABLE 5 | Development stages of PLF technologies related to the "behavioral interactions" domain of the Five Domains Model for different species (expressed in phases—P1, proof-of concept stages; P2, validation stages; P3, commercialization phases).

Application	Species	Technology developments				
		Bolus	Image	RFID	Sensors	Sound
Activity	Cattle	-	P2	-	P3	-
	Fish	-	P3	-	P1	P3
	Goat	-	P1	-	P3	-
	Pigs	-	P3	-	P2	-
	Poultry	-	P3	P2	P2	-
	Sheep	-	-	-	P3	-
Agonistic behavior	Cattle	-	-	-	P2	-
	Pigs	-	P1	-	P2	-
HAI	Poultry	-	P1	-	-	-
Excessive mounting	Pigs	-	P2	-	-	-
Nest building	Pigs	-	-	-	P1	-
Nesting	Poultry	-	-	P2	-	-
Nursing	Pigs	-	P1	-	-	-
Social interactions/	Cattle	-	P1	P2	P1	-
relationship	Sheep	-	-	P3	-	-
Perching	Poultry	-	-	P2	-	-

(Nakarmi et al., 2014; Wang et al., 2019). Finally, RFID can used to explore social behavior in cattle such as cow-calf affiliations (Swain and Bishop-Hurley, 2007; Boyland et al., 2013).

Welfare Implications

The monitoring of specific behaviors and situation-related factors could help to obtain a better understanding of levels of welfare and help evaluate animals' responses to their environment as well as supporting management decisions that may promote the experience of positive affects and minimize negative ones, hence having an impact on the negative-to-positive valence range. Ensuring that animals can engage in natural and rewarding behaviors which are important for their welfare such as nest building or nursing in pigs, social interactions in cows and sheep or nesting and perching in poultry, could indeed help minimize feelings of frustration and promote affects such as feeling maternally rewarded, protected or socially engaged. In pigs e.g., monitoring nest building behaviors can help decrease the time sows are kept in farrowing crates without increasing piglet mortality, while monitoring nesting or perching behaviors in poultry can help in housing system design and management. In addition, being able to monitor agonistic behaviors can provide a better understanding of how social relationships (e.g., dominance) are influenced by the animals' environment and to encourage measures that will help minimize fearfulness or anxiety by reducing risks of aggression and injuries, while promoting feelings of security. Finally, monitoring the HAR could have important impacts on animal welfare if adequate measures are put in place to reduce the occurrence of negative interactions and promote positive ones (e.g., gentle as opposed to rough handling, or talking softly as opposed to shouting).

Welfare Benefits and Risks Across Domains

In addition to the domain-specific welfare impacts suggested above, more general welfare benefits of the identified technologies include the potential to help support management decisions such as early intervention to ensure good health, reduce the use of antibiotics and prevent disease outbreaks, sometimes in systems where monitoring can be difficult (e.g., in extensive systems or where large numbers of animals are kept together). In addition, monitoring animals at individual level (e.g., using body-mounted devices or boluses) could help better understand the animals' specific needs.

During the workshop, questions were raised as to whether the use of wearable sensors (or those placed inside the animals) could cause discomfort or potential injuries to the animals. Ear tags e.g., which are often required for identification and traceability purposes can be a potential source of damage to the animals' ears, with severity depending on the type of tag (Edwards and Johnston, 1999). Although sensors in the form of neck collars do not require the same type of interventions, their potential impacts on animal behavior and welfare should be further studied. In addition, some of the technologies do not yet allow the monitoring of individuals, but do so at group level (in particular on farms with high number of animals e.g., poultry or fish). While these technologies could be beneficial for the detection of welfare compromises, the interpretation of the data must be done carefully, as management decisions made at group level could be detrimental for the welfare of those individuals whose needs differ from others (e.g., different nutrition or treatment requirements). For example, group monitoring of feed or water intake may not reflect social competition, which may hence be overlooked. Although studies have looked at possibilities to identify competitive interactions at the feedbunk, those were considered not practical due to high costs and labor (Huzzey et al., 2014).

Other concerns relate to the potential to reduce the frequency of visual or physical examination which could impact stockpeople's attitudes and behavior toward their animals, hence having a potential effect on the human-animal relationship (HAR) and animal welfare. This could be particularly problematic on systems with larger numbers of animals (e.g., poultry or aquaculture), where opportunities to become habituated to people are already limited. Finally, over-reliance on PLF technologies, which was also a concern raised during the workshop, could increase risks of harm if system failures were to occur, in particular where systems are fully automated.

DISCUSSION

The results from this study indicate that while PLF technologies can have a variety of benefits and may have a good potential to help minimize negative experiences, their current ability to contribute to promoting positive welfare remains limited. In addition, there are welfare risks associated with their use which must be considered, such as their potential impact on the human-animal relationship or to animal management. As Buller et al. (2020, p. 5) argue, "*If it is to make a substantive contribution to addressing genuine animal welfare concerns, PLF technology must therefore address [. . .] the effective monitoring and identification of systemic welfare failures and the active enhancement of opportunities for positive welfare experiences.*"

A wide range of commercially available technologies aim to reduce the occurrence and impact of health issues, such as sensors detecting lameness in cattle, microphones monitoring respiratory health in pigs, or cameras monitoring the presence of parasites in fish. They are also widely available to monitor and improve productivity such as growth in poultry or estrus in dairy cattle to increase pregnancy rate and optimize insemination. Most technologies monitoring parameters related to the "nutrition," "physical environment," and "behavioral interactions" domains such as feeding or drinking behavior, air/water quality or activity are also designed with the aim to optimize productivity and to minimize the impacts of diseases. Indeed, changes in feeding or drinking behaviors can indicate signs of illnesses (Nicol, 2011), while inappropriate environmental conditions can be detrimental to animal health and lead to increased mortality (Zhang et al., 2011; Segner et al., 2012). Finally, a variety of technologies that are still in early development stages have focused on preventing the occurrence of undesired behaviors which can cause significant injuries such as tail biting in pigs or feather pecking in poultry (Bilcik and Keeling, 1999; Di Giminiani et al., 2017).

The use of these technologies could have important benefits for welfare if the data are used to support farmers in making effective management decisions. Indeed, PLF could allow the early detection of health issues and reduce the occurrence of negative affective experiences, such as pain resulting from lameness or breathlessness caused by respiratory diseases. In their study e.g., Taneja et al. (2020) developed a system which allowed to detect lameness 3 days before it was visually captured by farmers, with an accuracy of 87%. Berckmans et al. (2015) showed that respiratory problems in pigs were detected up to 2 weeks earlier compared to farmers' and veterinarians' routine observations, thanks to a sound based PLF system. In addition, Kashiha et al. (2013b) developed a system which allowed to detect issues in broiler houses based on animal distribution index, which enables early intervention to minimize impacts on bird welfare. Timely detection of diseases could help reduce the need for antibiotics hence responding to the major global issue which is antimicrobial resistance resulting from the excessive use of antibiotics affecting both animals and humans (Trevisi et al., 2014; McEwen and Collignon, 2018). In addition, PLF could also allow monitoring larger numbers of animals more easily (e.g., using wearable sensors to monitor health status or smart cameras to monitor larger groups), including on extensive systems where the detection of sick or injured animals is often difficult (Rutter, 2014), as well as reducing potential stress resulting from repeated handling and moving of animals (e.g., manual weight detection in pigs) (Kashiha et al., 2014). Furthermore, the use of PLF technologies could also help other actors (e.g., veterinarians or farm advisors) support more efficient and farm-specific management decisions based on the data collected, although this may require improvements in relation to the sharing of data (Rojo-Gimeno et al., 2019).

While health is undeniably an integral part of animal welfare, it does not in itself guarantee "good" welfare. Studies in neuroscience indicate that negative affective states relating to most survival-related factors, such as thirst or hunger, can at best be neutralized and do not necessarily lead to anything more than short-lived positive welfare states (Mellor and Beausoleil, 2015). Minimizing these negative experiences can therefore shift a negative welfare state toward a more neutral one. However, moving toward a positive welfare state requires opportunities to live positive experiences. These include, e.g., affiliative interactions, play, or autogrooming, which are believed to have rewarding properties, and have the potential to indicate positive affective states (Boissy et al., 2007). Mellor (2015b, p.21) hence suggested that "*welfare reference standards should now be chosen to more strongly reflect a need for such [welfare-enhancing exploratory, foraging and affiliative behaviors] opportunities to be provided.*" Some of the technologies identified in this study monitor these types of behaviors (e.g., play and social interactions in cattle, nest building behaviors in pigs or perching in poultry), however, at present, they appear to be mostly at early development stages.

The use of such technologies could help getting a better understanding of aspects of welfare that have often received less attention and help support management decisions that could improve animal welfare by promoting positive affects such as feeling engaged, confident or being maternally rewarded, and by minimizing negative ones such as fearfulness or frustration from not being able to express natural behaviors. In pig production e.g., sows are often kept in farrowing crates during parturition to restrain their movements and avoid piglets from being crushed. In those conditions, pre-partum sows are not able to perform nest-building behaviors, which they are highly motivated to perform to provide shelter and comfort to their young (Wischner et al., 2009). Predicting the onset of farrowing using automated monitoring systems could therefore help in management decisions such as restricting the time sows are kept in farrowing crates only to the critical period where piglets are most vulnerable, hence providing the sows with opportunities to perform those highly motivated behaviors (Oczak et al., 2015), and potentially having an effect on the negative-to-positive valence range.

It could be argued that, while positive animal welfare has gained increased attention in animal welfare science, further research is still required regarding the feasibility, validity and reliability of positive welfare indicators, making their current applicability within welfare assessment protocols difficult. For example, while play behavior appears to be a valid indicator of positive welfare as it only occurs when all other needs are met (Held and Špinka, 2011), the low incidence of this behavior in farming conditions makes it difficult to use as part of current welfare assessments (Jensen and Kyhn, 2000; Napolitano et al., 2016). Similarly, while social licking can have positive effects on individual cows, the behavior might also reflect social tension within a herd (Napolitano et al., 2016). As raised by participants of the workshop, one particular challenge to technology development and implementation in the aquaculture sector may also be related to the existing debate around whether fish can feel pain or experience particular emotions despite growing evidence suggesting that they do (Sneddon, 2019). This limitation in terms of validity and feasibility could explain why technologies with a potential to monitor and promote positive welfare are still in early development stages. Progress is however made in this area: a recent study reviewed promising valid and reliable positive welfare indicators that could be used in welfare assessments of ruminants (Mattiello et al., 2019). These indicators were mostly related to the physical environment, behavioral interactions and mental state domains of the FDM and included, e.g., ear or tail posture, half-closed eyes, low-frequency calls or ruminating. From a technical point of view, it would appear that developing technologies monitoring these types of indicators is possible, as a variety of systems identified in the present study have been developed to monitor specific postures, vocalizations or behaviors such as rumination.

Another important aspect to consider in addition to technical feasibility is whether these particular types of technologies would likely be adopted by farmers since the widespread uptake of precision technologies thus far has been rather slow, including in dairy farming as a result of "innovation uncertainty" (Eastwood and Renwick, 2020). In their study, Vigors and Lawrence (2019) interviewed farmers on their perception of positive animal welfare and found that as a whole, farmers prioritized the reduction of negative experiences, and mostly considered that by doing so, positive welfare would arise as a result. Most of the interviewed farmers considered that different positive welfare indicators such as social interaction or play did not require farmers' direct input or management (except from preventing negative interactions to occur, for example) but that those would happen as a result of other management-based inputs. For this reason, the adoption potential of technologies aimed at monitoring such indicators could be challenging, as they may not be perceived as being a priority. Highlighting the benefits of promoting positive welfare such as the effect on productivity and also on farmers' well-being [see Vigors and Lawrence (2019)], could help enhance the acceptability of those indicators and therefore the technology adoption potential. Indeed, Lima et al. (2018) found that farmers' beliefs (including usefulness and practicality) played an important role in the adoption of Electronic Identification (EID) technology. They suggested that communicating the positive effects of such tools, including on performance, was likely to help enhance technology adoption.

More generally and as raised during the workshop, another potential limitation to PLF technologies adoption may relate to a lack of validation of some technologies which could result in a lack of trust by farmers but also the possibility for welfare-compromising issues to be missed by the technologies. The validation of technologies is usually required to predict how a system would perform under realistic operating conditions, and in the case of PLF, developments must take into account the complexity of living organisms, which are "*individually different, time-varying and dynamic*" (Norton and Berckmans, 2017). This complexity may explain why a wide range of PLF technologies still require further validation. In their study, Larsen et al. (2021) found that only 23% of publications related to PLF in pigs were properly validated, and a recent review indicated that only 14% of commercially available sensors in dairy cattle were externally validated (Stygar et al., 2021).

Technology adoption does not, however, guarantee that the technologies will be used in an optimal way in relation to welfare. Firstly, covering the many different ways welfare can be affected would require farmers to invest in multiple systems, as most technologies can only monitor a few parameters at a time and systems are often not connected to each other, adding a difficulty to data interpretation (Knight, 2020). Indeed, there is still a lack of integration of PLF technologies making it more challenging to determine effective mechanisms for intervention (Buller et al., 2020). It is also important to stress that most PLF technologies are monitoring systems, meaning that while they can alert farmers to detected issues, the decision to act on the data provided ultimately lies in the farmers' hands. The extent to which welfare can be improved therefore depends on how the technologies and resulting data are used, and especially whether management decisions are restricted to "curing" symptoms once they have appeared or whether those decisions would be adapted to prevent issues arising in the first place. Indeed, participants at the workshop believed that there could be a risk that management would be adapted to fit the use of technologies rather than focusing on welfare improvements, such as adapting light hours and levels to fit cameras or having more barren environments to minimize background noises.

In addition, there could be a risk that a greater recognition of issues among livestock keepers would result in greater acceptance of those issues rather than act as a call to action. In the case of lameness in dairy herds e.g., which is considered one of the most important welfare issue in dairy farming, a study found that a majority of farmers (90%) did not perceive lameness as being a major issue on their farm, even though the average lameness prevalence was high (36%) (Leach et al., 2010). According to Horseman et al. (2014), this may not necessarily be exclusively attributed to farmers not being able to detect lame cows, but could rather be linked to how farmers perceive lameness, as well as their understanding of the benefits of promptly treating lame cows. Indeed, it appears that farmers are more likely to treat severely lame cows more rapidly, leaving simply impaired cows untreated for longer, even though research suggests that it may be more beneficial to treat cows that are less severely lame early (Leach et al., 2010 as cited in Horseman et al., 2014). The extent to which welfare can be improved using PLF thus depends on whether the day-to-day management of animal health and welfare will be adapted with the implementation of those technologies.

It is also noted that most technologies monitoring at the individual level appear to be available for dairy cattle, while technologies monitoring smaller animals often kept in highly populated units such as poultry or fish mostly do so at group level (e.g., using cameras) hence ensuring that the "average" animal receives adequate food, water and environmental conditions (Smaldon, 2020). This is explained by higher numbers of animals with lower financial value per farm, making individual body-mounted devices costly and difficult to implement. On farms where welfare would be assessed automatically at group level, there is a risk that the individual nature of animal welfare might not be sufficiently taken into account if the interpretation of the data is not done carefully. Indeed, assessing welfare parameters at group level does not allow evaluation of whether the measure applies equally to the whole group or to some individuals only, potentially neglecting animals in much lower welfare states (Winckler, 2019). In addition, concerns raised at the workshop related to the design of the technologies which could have an impact on welfare if it is not "wearer-driven" (e.g., such as taking into account genetic variability or rearing environment). It was also questioned whether facilitating management of larger groups could lead to further intensification.

Another important welfare risk, which was also mentioned at the workshop, relate to the potential impact on the human-animal relationship (HAR). Indeed, most of the technologies identified in this study can be used to replace the need for visual but also physical examination, such as monitoring lameness, environmental conditions or feeding behaviors. Depending on how the time saved in performing these tasks is used by farmers, the potential decrease in human presence and human-animal interactions could have an effect on the HAR. Research indeed suggests that the frequency, intensity and intimacy of human-animal interactions influence the level of attachment or detachment of farmers toward their animals (Bock et al., 2007). This loss of interactions and therefore further detached relationship with animals (which may be more and more perceived as production tools) could result in a decrease in empathy and reduced concerns toward animal suffering. In addition, while some potentially stressful tasks could be avoided using PLF, others which have the potential to strengthen the HAR and that allow animals to be habituated to the presence of humans to some extent may also be decreased. This could reduce human-animal interactions to tasks which cannot be replaced by PLF such as mutilations, hence impacting the HAR negatively (Boivin et al., 1994; Hemsworth and Boivin, 2011). Indeed, Tallet et al. (2019) showed that piglets which were tail docked with a cautery iron interacted with unfamiliar humans later than piglets that were not tail docked, and Lürzel et al. (2015) observed that calves avoidance distances were higher after disbudding. In their study, Kling-Eveillard et al. (2020) found that following the implementation of PLF, some farmers perceived the HAR as having improved, while others believed it deteriorated. They also mentioned concerns that having to manage an increased amount of data may reduce the time farmers spend with animals and impact farmers' observational skills. Concerns relating to the de-skilling of farm staff were also raised during the workshop. While the social impacts of PLF on farmer's work are not detailed here, it is ultimately closely linked to animal welfare, since knowledge and husbandry skills and the ability to identify deviations in behaviors and health compromises are key characteristics of animal care (Hemsworth et al., 2009). Farm management supported by the use of PLF should therefore take these potential impacts into consideration, as a negative HAR can be detrimental to animal welfare, but also to farm productivity and job satisfaction (Waiblinger et al., 2006).

While the study aimed at exploring the potential of PLF to help improve animal welfare and the potential risks associated with their use, there are limitations in this study which must be taken into account. As mentioned in the methods section, the identification of PLF technologies was limited to a restricted number of keywords, making it possible to have omitted a variety of technologies. In addition, the different technologies and applications were classified into wider categories with only the latest development stages of all technologies within those categories shown. For this reason, the classification may not reflect the stage of development of all the different types of technologies (although as emphasized in the methods, it was not the goal of the study to determine each existing technology). Finally, it must be re-emphasized that animal welfare is complex, with many variables having a potential impact, whether positive or negative. Using the FDM as a framework helped to capture both positive and negative aspects of welfare, however it remains challenging to predict how the use of technologies will impact on welfare. In addition, the affective states and welfare benefits and risks mentioned in this paper were based on qualitative discussions and evaluation by the authors. Thus, further research aimed at evaluating those positive and negative impacts using quantitative and qualitative methods would be useful to help in technology design, both to maximize potential welfare benefits and minimize the risks. As mentioned by participants of the workshop, further validation of PLF technologies and research on positive welfare indicators as well as a better collaboration between industry, researchers and farmers should also be encouraged, as well as increasing awareness and training of all relevant stakeholders (including training to improve attitudes and behavior of stock people toward animals).

CONCLUSION

The potential of PLF to help reduce the duration and/or severity of diseases and injuries in livestock farming systems is promising: technologies can detect health issues at an early stage and help ensure optimal environmental conditions. However, the extent to which current PLF systems can help improve welfare appears to be limited to reducing the occurrence of negative affective states. Some technology developments related to the "behavioral interactions" domain of the FDM have the potential to help in promoting positive affective states, however, these generally remain at early development stages. This is potentially explained by a lack of evidence regarding the validity of potential positive welfare indicators and the difficulties in measuring them, as well as doubts regarding the adoption potential of such technologies. In addition, the extent to which welfare could be improved depends on whether the data obtained using PLF would be used to adapt management practices while minimizing negative consequences (such as the impact on the HAR), and whether actions would be taken to address the root cause of the issues rather than solely focusing on treating the symptoms.

AUTHOR CONTRIBUTIONS

Conceptual work: JS led with support from DR and RB. JS: review work. Manuscript drafting: JS led with support from DR and RB. All authors contributed to the article and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fanim.2021.639678/full#supplementary-material

REFERENCES

Adrion, F., Kapun, A., Eckert, F., Holland, E. M., Staiger, M., Götz, S., et al. (2018). Monitoring trough visits of growing-finishing pigs with UHF-RFID. *Comput. Electron. Agricult.* 144, 144–153. doi: 10.1016/j.compag.2017.11.036

Alhamada, M., Debus, N., Lurette, A., and Bocquier, F. (2016). Validation of automated electronic oestrus detection in sheep as an alternative to visual observation. *Small Rum. Res.* 134, 97–104. doi: 10.1016/j.smallrumres.2015.12.032

Astill, J., Dara, R. A., Fraser, E. D. G., Roberts, B., and Sharif, S. (2020). Smart poultry management: smart sensors, big data, and the internet of things. *Comp. Electr. Agricult.* 170:105291. doi: 10.1016/j.compag.2020.105291

Aydin, A. (2016). Precision feeding in laying hens by sound technology. *J. Tekird. Agricult. Facult.* 13:3.

Banakar, A., Sadeghi, M., and Shushtari, A. (2016). An intelligent device for diagnosing avian diseases: newcastle, infectious bronchitis, avian influenza. *Comp. Electr. Agricult.* 127, 744–753. doi: 10.1016/j.compag.2016.08.006

Beausoleil, N., and Mellor, D. (2015). Introducing breathlessness as a significant animal welfare issue. *N Zeal Vet J.* 63, 44–51. doi: 10.1080/00480169.2014.940410

Benjamin, M., and Yik, S. (2019). Precision livestock farming in swinewelfare: a review for swine practitioners. *Animals* 9:133. doi: 10.3390/ani9040133

Berckmans, D. (2014). Precision livestock farming technologies for welfare management in intensive livestock systems. *Rev. Sci. Tech. Off. Int. Epiz.* 33, 189–196. doi: 10.20506/rst.33.1.2273

Berckmans, D., Hemeryck, M., and Berckmans, D. (2015). Animal sound … talks ! In: *Real-time Sound Analysis for Health Monitoring in Livestock.* International Symposium on Animal Environment and Welfare, 1–8.

Bilcik, B., and Keeling, L. J. (1999). Changes in feather condition in relation to feather pecking and aggressive behaviour in laying hens. *Br. Poult. Sci.* 40, 444–451. doi: 10.1080/00071669987188

Bock, B. B., Van Huik, M. M., Prutzer, M., Kling, F., and Dockes, E. A. (2007). Farmers' relationship with different animals: the importance of getting close to the animals. Case studies of French, Swedish and Dutch cattle, pig and poultry farmers. *Int. J. Sociol. Food Agricult.* 15. doi: 10.48416/ijsaf.v15i3.290

Boissy, A., Manteuffel, G., Jensen, M. B., Moe, R. O., Spruijt, B., Keeling, L. J., et al. (2007). Assessment of positive emotions in animals to improve their welfare. *Physiol. Behav.* 92, 375–397. doi: 10.1016/j.physbeh.2007.02.003

Boivin, X., Le Neindre, P., Garel, J. P., and Chupin, J. M. (1994). Influence of breed and rearing management on cattle reactions during human handling. *Appl. Anim. Behav. Sci.* 39, 115–122. doi: 10.1016/0168-1591(94)90131-7

Bos, J. M., Bovenkerk, B., Feindt, P. H., and van Dam, Y. K. (2018). The quantified animal: precision livestock farming and the ethical implications of objectification. *Food Ethics. Food Ethics.* 2, 77–92. doi: 10.1007/s41055-018-00029-x

Boyland, N. K., James, R., Mlynski, D. T., Madden, J. R., and Croft, D. P. (2013). Spatial proximity loggers for recording animal social networks: consequences of inter-logger variation in performance. *Behav. Ecol. Sociobiol.* 67, 1877–1890. doi: 10.1007/s00265-013-1622-6

Brown, D. J., Swan, A. A., and Mortimer, M. L. (2011). "Pedigree matchmaker: can it tell us more than just pedigree?" in *Proceedings of the 19th Conference of the Association for the Advancement of Animal Breeding and Genetics* (Perth, WA), 231–234.

Buller, H., Blokhuis, H., Lokhorst, K., Silberberg, M., and Veissier, I. (2020). Animal welfare management in a digital world. *Animals* 10, 1–12. doi: 10.3390/ani10101779

Campos, D. P., Abatti, P. J., Bertotti, F. L., De Paula Vieira, A., Hill, J. A. G., and da Silveira, A. L. F. (2019). Short-term fibre intake estimation in goats using surface electromyography of the masseter muscle. *Biosyst. Eng.* 183, 209–220. doi: 10.1016/j.biosystemseng.2019.04.021

Carpentier, L., Berckmans, D., Youssef, A., Berckmans, D., van Waterschoot, T., Johnston, D., et al. (2018). Automatic cough detection for bovine respiratory disease in a calf house. *Biosyst. Eng.* 173, 45–56. doi: 10.1016/j.biosystemseng.2018.06.018

Carpentier, L., Vranken, E., Berckmans, D., Paeshuyse, J., and Norton, T. (2019). Development of sound-based poultry health monitoring tool for automated sneeze detection. *Comp. Electr. Agricult.* 162, 573–581. doi: 10.1016/j.compag.2019.05.013

Chagneau, A. M., Laviron, F., Lamy, S., Bouvarel, I., Picard, M., Lessire, M., et al. (2006). Short-term number of pecks and feed intake levels: a link with the physical characteristics of feed in four-week-old Turkeys. *Poultry Sci.* 85, 923–931. doi: 10.1093/PS/85.5.923

Chelotti, J. O., Vanrell, S. R., Milone, D. H., Utsumi, S. A., Galli, J. R., Rufiner, H. L., et al. (2016). A real-time algorithm for acoustic monitoring of ingestive behavior of grazing cattle. *Comp. Electr. Agricult.* 127, 64–75. doi: 10.1016/j.compag.2016.05.015

Chen, C., Zhu, W., Liu, D., Steibel, J., Siegford, J., Wurtz, K., et al. (2019). Detection of aggressive behaviours in pigs using a RealSence depth sensor. *Comp. Electr. Agricult.* 166:105003. doi: 10.1016/j.compag.2019.105003

Chopra, K., Hodges, H. R., Barker, Z. E., and Diosdado, J. A. V. (2020). Proximity Interactions in a Permanently Housed Dairy Herd : Network Structure, Consistency, and Individual Differences. *Front. Vet. Sci.* 7:583715. doi: 10.3389/fvets.2020.583715

Chung, Y., Choi, D., Choi, H., Park, D., Chang, H.-H., and Kim, S. (2015). Automated detection of cattle mounting using side-view camera. *KSII Trans. Internet Inform. Syst.* 9:24. doi: 10.3837/tiis.2015.08.024

Colles, F. M., Cain, R. J., Nickson, T., Smith, A. L., Roberts, S. J., Maiden, M. C. J., et al. (2016). Monitoring chicken flock behavior provides early warning of infection by human pathogen Campylobacter. *Proc. Royal Soc. B Biol. Sci.* 283, 1–6. doi: 10.1098/rspb.2015.2323

Corbet, N. J., Patison, K. P., Menzies, D. J., and Swain, D. L. (2018). Using temporal associations to determine postpartum oestrus in tropical beef cows. *Anim. Product. Sci.* 58, 1465–1469. doi: 10.1071/AN17781

Cornou, C. (2009). Automation systems for farm animals: potential impacts on the human-animal relationship and on animal welfare. *Anthrozoos* 22, 213–220. doi: 10.2752/175303709X457568

Cransberg, P. H., Hemsworth, P. H., and Goleman, G. J. (2000). Human factors affecting the behaviour and productivity of commercial broiler chickens. *Br. Poultry Sci.* 41, 272–279. doi: 10.1080/713654939

da Fonseca, F. N., Abe, J. M., de Alencar Nääs, I., da Silva Cordeiro, A. F., do Amaral, F. V., and Ungaro, H. C. (2020). Automatic prediction of stress in piglets (Sus Scrofa) using infrared skin temperature. *Comp. Electr. Agricult.* 168:105148. doi: 10.1016/j.compag.2019.105148

Dawkins, M. S., Roberts, S. J., Cain, R. J., Nickson, T., and Donnelly, C. A. (2017). Early warning of footpad dermatitis and hockburn in broiler chicken flocks using optical flow, bodyweight and water consumption. *Vet. Record*. 180:499. doi: 10.1136/vr.104066

De Alencar Nääs, I., Correia De Lima, I., Paz, A., Marta,;, Baracho, S., Gomes De Menezes, A., et al. (2010). Assessing locomotion deficiency in broiler chicken. *Sci. Agric.* 67, 129–135. doi: 10.1590/S0103-90162010000200001

D'eath, R. B., Jack, M., Futro, A., Talbot, D., Zhu, Q., Barclay, D., et al. (2018). Automatic early warning of tail biting in pigs: 3D cameras can detect lowered tail posture before an outbreak. *PLoS ONE* 13:194524. doi: 10.1371/journal.pone.0194524

DEFRA (2019). *Agriculture in the United Kingdom, National Statistics.* London: DEFRA.

DEFRA (2021). *The Path to Sustainable Farming : An Agricultural Transition Plan 2021 to 2024*. London: DEFRA.

Di Giminiani, P., Edwards, S. A., Malcolm, E. M., Leach, M. C., Herskin, M. S., and Sandercock, D. A. (2017). Characterization of short- and long-term mechanical sensitisation following surgical tail amputation in pigs. *Scient. Rep.* 7, 1–9. doi: 10.1038/s41598-017-05404-y

Dos, D., Costa, S., Turco, S. H. N., Ramos, R. P., Silva, F. M. F. M., and Freire, M. S. (2018). Electronic monitoring system for measuring heart rate and skin temperature in small ruminants. *Engenh. Agrícola*. 38, 166–172. doi: 10.1590/1809-4430-Eng.Agric.v38n2p

Eastwood, C. R., and Renwick, A. (2020). Innovation uncertainty impacts the adoption of smarter farming approaches. *Front. Sust. Food Syst*. 4:24. doi: 10.3389/fsufs.2020.00024

Edwards, D. S., and Johnston, A. M. (1999). Welfare implications of sheep ear tags. *Vet. Rec*. 144, 603–606.

European Commission (2016). *Special Eurobarometer 442: Attitudes of Europeans Towards Animal Welfare. Animal Welfare*. doi: 10.2875/884639

Eurostat (2020). *Agriculture, Forestry, and Fishery Statistics: 2020 edition*. Luxembourg: Publications Office of the European Union.

FAO (2018). *The Future of Food and Agriculture—Alternative Pathways to 2050*. Rome.

Fontana, I., Tullo, E., Butterworth, A., and Guarino, M. (2015). An innovative approach to predict the growth in intensive poultry farming. *Comp. Electr. Agricult.* 119, 178–183. doi: 10.1016/j.compag.2015.10.001

Fontana, I., Tullo, E., Carpentier, L., Berckmans, D., Butterworth, A., Vranken, E., et al. (2017). Sound analysis to model weight of broiler chickens. *Poultry Sci.* 96, 1–6. doi: 10.3382/ps/pex215

Foris, B., Thompson, A., von Keyserlingk, M., Melzer, N., and Weary, D. (2019). Automatic detection of feeding- and drinking-related agonistic behavior and dominance in dairy cows. *J. Diary Sci.* 102, 9176–86. doi: 10.3168/jds.2019-16697

Fuchs, B., Sørheim, K. M., Chincarini, M., Brunberg, E., Stubsjøen, S. M., Bratbergsengen, K., et al. (2019). Heart rate sensor validation and seasonal and diurnal variation of body temperature and heart rate in domestic sheep. *Vet. Anim. Sci.* 8:100075. doi: 10.1016/j.vas.2019.100075

Gilbert, M., Conchedda, G., Van Boeckel, T. P., Cinardi, G., Linard, C., Nicolas, G., et al. (2015). Income disparities and the global distribution of intensively farmed chicken and pigs. *PLoS ONE*. 10:e013338. doi: 10.1371/journal.pone.0133381

Grilli, G., Borgonovo, F., Tullo, E., Fontana, I., Guarino, M., and Ferrante, V. (2018). A pilot study to detect coccidiosis in poultry farms at early stage from air analysis. *Biosyst. Eng.* 173, 64–70. doi: 10.1016/j.biosystemseng.2018.02.004

Gross, W. B., and Siegel, P. B. (1979). Adaptation of chickens to their handler, and experimental results. *Avian Dis*. 23, 708–714. doi: 10.2307/1589747

Guo, Y., Zhang, Z., He, D., Niu, J., and Tan, Y. (2019). Detection of cow mounting behavior using region geometry and optical flow characteristics. *Comp. Electr. Agricult.* 163:104828. doi: 10.1016/j.compag.2019.05.037

Guzhva, O., Ard,ö, H., Herlin, A., Nilsson, M., Åström, K., and Bergsten, C. (2016). Feasibility study for the implementation of an automatic system for the detection of social interactions in the waiting area of automatic milking stations by using a video surveillance system. *Comp. Electr. Agricult.* 127, 506–509. doi: 10.1016/j.compag.2016.07.010

Halachmi, I., Guarino, M., Bewley, J., and Pastell, M. (2019). Smart animal agriculture: application of real-time sensors to improve animal well-being and production. *Ann. Rev. Anim. Biosci*. 7, 403–425. doi: 10.1146/annurev-animal-020518-114851

Held, S. D. E., and Špinka, M. (2011). Animal play and animal welfare. *Anim. Behav*. 81, 891–899. doi: 10.1016/j.anbehav.2011.01.007

Hemsworth, P. H., and Barnett, J. L. (1991). The effects of aversively handling pigs, either individually or in groups, on their behaviour, growth and corticosteroids. *Appl. Anim. Behav. Sci.* 30, 61–72. doi: 10.1016/0168-1591(91)90085-C

Hemsworth, P. H., Barnett, J. L., and Coleman, G. J. (2009). The integration of human-animal relations into animal welfare monitoring schemes. *Anim. Welfare*. 18, 335–345.

Hemsworth, P. H., and Boivin, X. (2011). *Human Contact*. Animal Welfare, 2nd Edn. CAB International.

Horseman, S. V., Roe, E. J., Huxley, J. N., Bell, N. J., Mason, C. S., and Whay, H. R. (2014). The use of in-depth interviews to understand the process of treating lame dairy cows from the farmers' perspective. *Anim. Welfare* 23, 157–165. doi: 10.7120/09627286.23.2.157

Huzzey, J. M., Weary, D. M., Tiau, B. Y. F., and Von Keyserlingk, M. A. G. (2014). Short communication: automatic detection of social competition using an electronic feeding system. *J. Dairy Sci*. 97, 2953–2958. doi: 10.3168/jds.2013-7434

Hyun, H. Y., Yeong, H. B., and Wongi, M. (2007). "Implantable wireless sensor network to monitor the deep body temperature of broilers," in *Proceedings - SERA 2007: Fifth ACIS International Conference on Software Engineering Research, Management, and Applications* (Busan), 513–517. doi: 10.1109/SERA.2007.91

Israeli, D. (1996). Monitoring the behavior of hypoxia-stressed Carassius auratus using computer vision. *Aquacult. Eng.* 15, 423–440. doi: 10.1016/S0144-8609(96)01009-6

Jensen, M. B., and Kyhn, R. (2000). Play behaviour in group-housed dairy calves, the effect of space allowance. *Appl. Anim. Behav. Sci.* 67, 35–46. doi: 10.1016/S0168-1591(99)00113-6

Kaler, J., Mitsch, J., Vázquez-Diosdado, J. A., Bollard, N., Dottorini, T., and Ellis, K. A. (2020). Automated detection of lameness in sheep using machine learning approaches: novel insights into behavioural differences among lame and non-lame sheep. *Roy. Soc. Open Sci.* 7:190824. doi: 10.1098/rsos.190824

Kashiha, M., Bahr, C., Haredasht, S. A., Ott, S., Moons, C. P. H., Niewold, T. A., et al. (2013a). The automatic monitoring of pigs water use by cameras. *Comp. Electr. Agricult* 90, 164–169. doi: 10.1016/j.compag.2012.09.015

Kashiha, M., Bahr, C., Ott, S., Moons, C. P. H., and Niewold, T. A., Ödberg, F. O., et al. (2014). Automatic weight estimation of individual pigs using image analysis. *Comp. Electr. Agricult.* 107, 38–44. doi: 10.1016/j.compag.2014.06.003

Kashiha, M., Pluk, A., Bahr, C., Vranken, E., and Berckmans, D. (2013b). Development of an early warning system for a broiler house using computer vision. *Biosyst. Eng.* 116, 36–45. doi: 10.1016/j.biosystemseng.2013.06.004

Kling-Eveillard, F., Allain, C., Boivin, X., Courboulay, V., Créach, P., Philibert, A., et al. (2020). Farmers' representations of the effects of precision livestock farming on human-animal relationships. *Livestock Sci.* 238:104057. doi: 10.1016/j.livsci.2020.104057

Knight, C. H. (2020) Review: Sensor techniques in ruminants: more than fitness trackers. *Animal* 14, s187–s195. doi: 10.1017/S1751731119003276

Larsen, M. L. V., Wang, M., and Norton, T. (2021). Information technologies for welfare monitoring in pigs and their relation to welfare quality ®. *Sustainability*. 13:692. doi: 10.3390/su13020692

Leach, K. A., Whay, H. R., Maggs, C. M., Barker, Z. E., Paul, E. S., Bell, A. K., et al. (2010). Working towards a reduction in cattle lameness: 1. Understanding barriers to lameness control on dairy farms. *Res. Vet. Sci.* 89, 311–317. doi: 10.1016/j.rvsc.2010.02.014

Lee, H.-J., Roberts, S. J., Drake, K. A., and Dawkins, M. S. (2011). Prediction of feather damage in laying hens using optical flows and Markov models. *J. Roy. Soc. Interface*. 8, 489–499. doi: 10.1098/rsif.2010.0268

Lee, J., Jin, L., Park, D., and Chung, Y. (2016). Automatic recognition of aggressive behavior in pigs using a kinect depth sensor. *Sensors* 16:631. doi: 10.3390/s16050631

Lee, J., Noh, B., Jang, S., Park, D., Chung, Y., and Chang, H. H. (2015). Stress detection and classification of laying hens by sound analysis. *Asian-Austral. J. Anim. Sci*. 28, 592–598. doi: 10.5713/ajas.14.0654

Lensink, J., Boissy, A., and Veissier, I. (2000). The relationship between farmers' attitude and behaviour towards calves, and productivity of veal units. *Anim. Res.* 49, 313–327. doi: 10.1051/animres:2000122

Li, L., Zhao, Y., Oliveira, J., Verhoijsen, W., Liu, K., and Xin, H. (2017). A UHF RFID system for studying individual feeding and nesting behaviors of group-housed laying hens. *Trans. ASABE*. 60, 1337–1347. doi: 10.13031/trans.12202

Li, N., Ren, Z., Li, D., and Zeng, L. (2019). Review: automated techniques for monitoring the behaviour and welfare of broilers and laying hens: towards the goal of precision livestock farming. *Animal* 14, 617–625. doi: 10.1017/S1751731119002155

Lian, J., Zheng, Y., Jia, W., Zhao, Y., Fan, M., Wang, D., et al. (2019). Automated recognition and discrimination of human–animal interactions using Fisher vector and hidden Markov model. *Signal Image Video Process*. 13, 993–1000. doi: 10.1007/s11760-019-01437-0

Lima, E., Hopkins, T., Gurney, E., Shortall, O., Lovatt, F., Davies, P., et al. (2018). Drivers for precision livestock technology adoption: a study of factors associated with adoption of electronic identification technology by commercial sheep farmers in England and Wales. *PLoS ONE*. 13:e0190489. doi: 10.1371/journal.pone.0190489

Liu, L. S., Ni, J. Q., Zhao, R. Q., Shen, M. X., He, C. L., and Lu, M. Z. (2018). Design and test of a low-power acceleration sensor with Bluetooth Low Energy on ear tags for sow behaviour monitoring. *Biosystems Engineering. Academic Press*. 176, 162–171. doi: 10.1016/j.biosystemseng.2018.10.011

Lürzel, S., Münsch, C., Windschnurer, I., Futschik, A., Palme, R., and Waiblinger, S. (2015). The influence of gentle interactions on avoidance distance towards humans, weight gain and physiological parameters in group-housed dairy calves. *Appl. Anim. Behav. Sci.* 172, 9–16. doi: 10.1016/j.applanim.2015.09.004

Luu, J., Johnsen, J. F., Passill,é, A. M., de and Rushen, J. (2013). Which measures of acceleration best estimate the duration of locomotor play by dairy calves? *Appl. Anim. Behav. Sci.* 148, 21–27. doi: 10.1016/j.applanim.2013.07.004

Main, D., and Mullan, S. (2017). A new era of UK leadership in farm animal welfare. *Vet. Rec*. 181, 49–50. doi: 10.1136/vr.j3273

Mainau, E., Dalmau, A., Ruiz-de-la-Torre, J. L., and Manteca, X. (2009). Validation of an automatic system to detect position changes in puerperal sows. *Applied Animal Behaviour Science*. 121, 96–102. doi: 10.1016/j.applanim.2009.09.005

Manteuffel, C., Hartung, E., Schmidt, M., Hoffmann, G., and Schön, P. C. (2015). Towards qualitative and quantitative prediction and detection of parturition onset in sows using light barriers. *Comp. Electr. Agricult.* 116, 201–210. doi: 10.1016/j.compag.2015.06.017

Martos-Sitcha, J. A., Sosa, J., Ramos-Valido, D., Bravo, F. J., Carmona-Duarte, C., Gomes, H. L., et al. (2019). Ultra-low power sensor devices for monitoring physical activity and respiratory frequency in farmed fish. *Front. Physiol.* 10, 1–14. doi: 10.3389/fphys.2019.00667

Maselyne, J., Adriaens, I., Huybrechts, T., De Ketelaere, B., Millet, S., Vangeyte, J., et al. (2016a). Measuring the drinking behaviour of individual pigs housed in group using radio frequency identification (RFID). *Animal*. 10, 1557–1566. doi: 10.1017/S1751731115000774

Maselyne, J., Saeys, W., Briene, P., Mertens, K., Vangeyte, J., De Ketelaere, B., et al. (2016b). Methods to construct feeding visits from RFID registrations of growing-finishing pigs at the feed trough. *Comp. Electr. Agricult.* 128, 9–19. doi: 10.1016/j.compag.2016.08.010

Mattiello, S., Battini, M., De Rosa, G., Napolitano, F., and Dwyer, C. (2019). How can we assess positive welfare in ruminants? *Animals* 9, 1–27. doi: 10.3390/ani9100758

McEwen, S. A., and Collignon, P. J. (2018). Antimicrobial resistance: a one health perspective. *Microbiol. Spectr.* 6:2017. doi: 10.1128/microbiolspec.arba-0009-2017

McLennan, K., and Mahmoud, M. (2019). Development of an automated pain facial expression detection system for sheep (Ovis aries). *Animals* 9, 1–7. doi: 10.3390/ani9040196

Mellor, D. J. (2015a). Enhancing animal welfare by creating opportunities for positive affective engagement. *N. Zeal. Vet. J.* 63, 3–8. doi: 10.1080/00480169.2014.926799

Mellor, D. J. (2015b). Positive animal welfare states and reference standards for welfare assessment. *N. Zeal. Vet. J.* 63, 17–23. doi: 10.1080/00480169.2014.926802

Mellor, D. J. (2017). Operational details of the five domains model and its key applications to the assessment and management of animal welfare. *Animals* 7:60. doi: 10.3390/ani7080060

Mellor, D. J., and Beausoleil, N. J. (2015). Extending the "Five Domains" model for animal welfare assessment to incorporate positive welfare states. *Anim. Welfare*. 24, 241–253. doi: 10.7120/09627286.24.3.241

Mellor, D. J., Beausoleil, N. J., Littlewood, K. E., Mclean, A. N., Mcgreevy, P. D., Jones, B., et al. (2020). The 2020 five domains model: including human-animal interactions in assessments of animal welfare. *Animals* 10:1870. doi: 10.3390/ani10101870

Morris, J. E., Cronin, G. M., and Bush, R. D. (2012). Improving sheep production and welfare in extensive systems through precision sheep management. *Anim. Prod. Sci*. 52, 665–670. doi: 10.1071/AN11097

Mortensen, A. K., Lisouski, P., and Ahrendt, P. (2016). Weight prediction of broiler chickens using 3D computer vision. *Comp. Electr. Agricult.* 123, 319–326. doi: 10.1016/j.compag.2016.03.011

Mota-Rojas, D., Broom, D. M., Orihuela, A., Velarde, A., Napolitano, F., and Alonso-Spilsbury, M. (2020). Effects of human-animal relationship on animal productivity and welfare. *J. Anim. Behav*. 8, 196–205. doi: 10.31893/JABB.20026

Nakarmi, A. D., Tang, L., and Xin, H. (2014). Automated tracking and behavior quantification of laying hens using 3D computer vision and radio frequency identification technologies. *Transact. ASABE*. 57, 1455–1472. doi: 10.13031/trans.57.10505

Napolitano, F., Knierim, U., Grass, F., and De Rosa, G. (2016). Positive indicators of cattle welfare and their applicability to on-farm protocols. *Ital. J. Anim. Sci.* 8, 355–365. doi: 10.4081/ijas.2009.s1.355

Nasirahmadi, A., Hensel, O., Edwards, S., and Sturm, B. (2016). Automatic detection of mounting behaviours among pigs using image analysis. *Comp. Electr. Agricult.* 124, 295–302. doi: 10.1016/j.compag.2016.04.022

Navon, S., Mizrach, A., Hetzroni, A., and Ungar, E. D. (2013). Automatic recognition of jaw movements in free-ranging cattle, goats and sheep, using acoustic monitoring. *Biosyst. Eng.* 114, 474–483. doi: 10.1016/j.biosystemseng.2012.08.005

Nicol, C. (2011). "Behaviour as an indicator of animal welfare" in *2011, Management and Welfare of Farm Animals: The UFAW Farm Handbook*, ed J. Webster (Hoboken, NJ: John Wiley & Sons, Incorporated).

Nogami, H., Okada, H., Miyamoto, T., Maeda, R., and Itoh, T. (2013). Wearable and compact wireless sensor nodes for measuring the temperature of the base of a calf's tail. *Sensors Mater.* 25, 577–582. doi: 10.18494/sam.2013.907

Norton, T., and Berckmans, D. (2017). The Dairy Industry and Precision Livestock Farming Developing precision livestock farming tools for precision dairy farming. *Anim. Front.* 7:18. doi: 10.2527/af.2017.0104

Norton, T., Chen, C., Larsen, M. L. V., and Berckmans, D. (2019). Review: precision livestock farming: building "digital representations" to bring the animals closer to the farmer. *Animal* 3, 3009–3017. doi: 10.1017/S175173111900199X

Oczak, M., Maschat, K., Berckmans, D., Vranken, E., and Baumgartner, J. (2015). Classification of nest-building behaviour in non-crated farrowing sows on the basis of accelerometer data. *Biosyst. Eng.* 140, 48–58. doi: 10.1016/j.biosystemseng.2015.09.007

Okada, H., Suzuki, K., Kenji, T., and Itoh, T. (2014). Applicability of wireless activity sensor network to avian influenza monitoring system in poultry farms. *J. Sens. Technol.* 4, 18–23. doi: 10.4236/jst.2014.41003

Okinda, C., Lu, M., Nyalala, I., Li, J., and Shen, M. (2018). Asphyxia occurrence detection in sows during the farrowing phase by inter-birth interval evaluation. *Comp. Electr. Agricult.* 152, 221–232. doi: 10.1016/j.compag.2018.07.007

Pastell, M., Hietaoja, J., Yun, J., Tiusanen, J., and Valros, A. (2016). Predicting farrowing of sows housed in crates and pens using accelerometers and CUSUM charts. *Comp. Electr. Agricult.* 127, 197–203. doi: 10.1016/j.compag.2016.06.009

Pluym, L. M., Maes, D., Vangeyte, J., Mertens, K., Baert, J., Van Weyenberg, S., et al. (2013). Development of a system for automatic measurements of force and visual stance variables for objective lameness detection in sows: SowSIS. *Biosystems Eng.* 116, 64–74. doi: 10.1016/j.biosystemseng.2013.06.009

Probst, J. K., Spengler Neff, A., Leiber, F., Kreuzer, M., and Hillmann, E. (2012). Gentle touching in early life reduces avoidance distance and slaughter stress in beef cattle. *Appl. Anim. Behav. Sci.* 139, 42–49. doi: 10.1016/j.applanim.2012.03.002

Quwaider, M., Daigle, C. L., Biswas, S. K., Siegford, J. M., and Swanson, J. C. (2010). Development of a wireless body-mounted sensor to monitor location and activity of laying hens in a non-cage housing system. *Trans. ASABE.* 53, 1705–1713. doi: 10.13031/2013.34890

Rojo-Gimeno, C., van der Voort, M., Niemi, J. K., Lauwers, L., Kristensen, A. R., and Wauters, E. (2019). Assessment of the value of information of precision livestock farming: a conceptual framework. *NJAS Wageningen J. Life Sci.* 90:100311. doi: 10.1016/j.njas.2019.100311

Roland, L., Lidauer, L., Sattlecker, G., Kickinger, F., Auer, W., Sturm, V., et al. (2018). Monitoring drinking behavior in bucket-fed dairy calves using an ear-attached tri-axial accelerometer: a pilot study. *Comp. Electr. Agricult.* 145, 298–301. doi: 10.1016/j.compag.2018.01.008

Rose, D. C., and Chilvers, J. (2018). Agriculture 4.0: Broadening Responsible Innovation in an Era of Smart Farming. *Front. Sust. Food Syst.* 2:87. doi: 10.3389/fsufs.2018.00087

Röttgen, V., Schön, P. C., Becker, F., Tuchscherer, A., Wrenzycki, C., Düpjan, S., et al. (2020). Automatic recording of individual oestrus vocalisation in group-housed dairy cattle: development of a cattle call monitor. *Animal* 14, 198–205. doi: 10.1017/S1751731119001733

Rushen, J., Taylor, A. A., and De Passillé, A. M. (1999). Domestic animals' fear of humans and its effect on their welfare. *Appl. Anim. Behav. Sci.* 65, 285–303. doi: 10.1016/S0168-1591(99)00089-1

Rutter, S. M. (2014). Smart technologies for detecting animal welfare status and delivering health remedies for rangeland systems. *OIE Revue Scientifique et Technique.* 33, 181–187. doi: 10.20506/rst.33.1.2274

Schön, P. C., Puppe, B., and Manteuffel, G. (2004). Automated recording of stress vocalisations as a tool to document impaired welfare in pigs. *Anim. Welfare* 13, 105–110.

Segner, H., Sundh, H., Buchmann, K., Douxfils, J., Sundell, K. S., Mathieu, C., et al. (2012). Health of farmed fish: its relation to fish welfare and its utility as welfare indicator. *Fish Physiol. Biochem.* 38, 85–105. doi: 10.1007/s10695-011-9517-9

Shao, J., Xin, H., and Harmon, J. D. (1997). Neural network analysis of postural behavior of young swine to determine the IR thermal comfort state. *Trans. Am. Soc. Agricult. Eng.* 40, 755–760. doi: 10.13031/2013.21306

Shrestha, A., Loukas, C., Le Kernec, J., Fioranelli, F., Busin, V., Jonsson, N., et al. (2018). Animal lameness detection with radar sensing. *IEEE Geosci. Remote Sensing Lett.* 15, 1189–1193. doi: 10.1109/LGRS.2018.2832650

Smaldon, J. (2020). *Managing Poultry Welfare in a Transitioning World of Technology.* Taunton, MA: Nuffield Farming Scholarships *Trust.* doi: 10.2307/j.ctvr7f6m7.10

Sneddon, L. U. (2019). Evolution of nociception and pain: evidence from fish models. *Philosoph. Trans. Roy. Soc. B Biol. Sci.* 374:1785. doi: 10.1098/rstb.2019.0290

Song, X., van der Tol, P., Groot Koerkamp, P., and Bokkers, E. (2019). Hot topic: automated assessment of reticulo-ruminal motility in dairy cows using 3-dimensional vision. *J. Dairy Sci.* 102, 9076–9081. doi: 10.3168/jds.2019-16550

Stavrakakis, S., Wei, L., Guy, J. H., Morgan, G., Ushaw, G., Johnson, G. R., et al. (2015). Validity of the Microsoft Kinect sensor for assessment of normal walking patterns in pigs. *Comp. Electr. Agricult.* 117, 1–7. doi: 10.1016/j.compag.2015.07.003

Steensels, M., Antler, A., Bahr, C., Berckmans, D., Maltz, E., and Halachmi, I. (2016). A decision-tree model to detect post-calving diseases based on rumination, activity, milk yield, BW and voluntary visits to the milking robot'. *Animal* 10, 1493–1500. doi: 10.1017/S1751731116000744

Stewart, M., Wilson, M., Schaefer, A., Huddart, F., and Sutherland, M. (2017). The use of infrared thermography and accelerometers for remote monitoring of dairy cow health and welfare. *J. Dairy Sci.* 100, 3893–3901. doi: 10.3168/jds.2016-12055

Strutzke, S., Fiske, D., Hoffmann, G., Ammon, C., Heuwieser, W., and Amon, T. (2019). Technical note: development of a noninvasive respiration rate sensor for cattle. *J. Dairy Sci.* 102, 690–695. doi: 10.3168/jds.2018-14999

Stygar, A. H., Gómez, Y., Berteselli, G. V., Dalla Costa, E., Canali, E., Niemi, J. K., et al. (2021). A systematic review on commercially available and validated sensor technologies for welfare assessment of dairy cattle. *Front. Vet. Sci.* 8:634338. doi: 10.3389/fvets.2021.634338

Swain, D. L., and Bishop-Hurley, G. J. (2007). Using contact logging devices to explore animal affiliations: quantifying cow-calf interactions. *Appl. Anim. Behav. Sci.* 102, 1–11. doi: 10.1016/j.applanim.2006.03.008

Tallet, C., Rakotomahandry, M., Herlemont, S., and Prunier, A. (2019). Evidence of pain, stress, and fear of humans during tail docking and the next four weeks in piglets (Sus scrofa domesticus). *Front. Vet. Sci.* 6:462. doi: 10.3389/fvets.2019.00462

Taneja, M., Byabazaire, J., Jalodia, N., Davy, A., Olariu, C., and Malone, P. (2020). Machine learning based fog computing assisted data-driven approach for early lameness detection in dairy cattle. *Comp. Electr. Agricult.* 171:105286. doi: 10.1016/j.compag.2020.105286

Thompson, R., Matheson, S. M., Plötz, T., Edwards, S. A., and Kyriazakis, I. (2016). Porcine lie detectors: automatic quantification of posture state and transitions in sows using inertial sensors. *Comp. Electr. Agricult.* 127, 521–530. doi: 10.1016/j.compag.2016.07.017

Trevisi, E., Zecconi, A., Cogrossi, S., Razzuoli, E., Grossi, P., and Amadori, M. (2014). Strategies for reduced antibiotic usage in dairy cattle farms. *Res. Vet. Sci.* 96, 229–233. doi: 10.1016/j.rvsc.2014.01.001

Tu, X., Du, S., Tang, L., Xin, H., and Wood, B. (2011). A real-time automated system for monitoring individual feed intake and body weight of group housed turkeys. *Comp. Electr. Agricult.* 75, 313–320. doi: 10.1016/j.compag.2010.12.007

Van Der Sluis, M., De Klerk, B., Ellen, E. D., De Haas, Y., Hijink, T., and Rodenburg, T. B. (2019). Validation of an ultra-wideband tracking system for recording individual levels of activity in broilers. *Animals* 9:580. doi: 10.3390/ani9080580

Van Hertem, T., Norton, T., Berckmans, D., and Vranken, E. (2018). Predicting broiler gait scores from activity monitoring and flock data. *Biosystems Eng.* 173, 93–102. doi: 10.1016/j.biosystemseng.2018.07.002

Vandermeulen, J., Bahr, C., Johnston, D., Earley, B., Tullo, E., Fontana, I., et al. (2016). Early recognition of bovine respiratory disease in calves using automated continuous monitoring of cough sounds. *Comp. Electr. Agricult.* 129, 15–26. doi: 10.1016/j.compag.2016.07.014

Vayssade, J. A., Arquet, R., and Bonneau, M. (2019). Automatic activity tracking of goats using drone camera. *Comp. Electr. Agricult.* 162, 767–772. doi: 10.1016/j.compag.2019.05.021

Viazzi, S., Ismayilova, G., Oczak, M., Sonoda, L. T., Fels, M., Guarino, M., et al. (2014). Image feature extraction for classification of aggressive interactions among pigs. *Comp. Electr. Agricult.* 104, 57–62. doi: 10.1016/j.compag.2014.03.010

Vigors, B., and Lawrence, A. (2019). What are the positives? Exploring positive welfare indicators in a qualitative interview study with livestock farmers. *Animals* 9:694. doi: 10.3390/ani9090694

Volkmann, N., Kulig, B., and Kemper, N. (2019). Using the footfall sound of dairy cows for detecting claw lesions. *Animals* 9:78. doi: 10.3390/ani9030078

Waiblinger, S., Boivin, X., Pedersen, V., Tosi, M. V., Janczak, A. M., Visser, E. K., et al. (2006). Assessing the human-animal relationship in farmed species: a critical review. *Appl. Anim. Behav. Sci.* 101, 185–242. doi: 10.1016/j.applanim.2006.02.001

Waiblinger, S., Menke, C., and Coleman, G. (2002). The relationship between attitudes, personal characteristics and behaviour of stockpeople and subsequent behaviour and production of dairy cows. *Appl. Anim. Behav. Sci*. 79, 195–219. doi: 10.1016/S0168-1591(02)00155-7

Wang, K., Liu, K., Xin, H., Chai, L., and Wang, Y. (2019). An RFID-based automated individual perching monitoring system for group-housed poultry. *Agricult. Biosyst. Eng*. 62, 695–704. doi: 10.13031/trans.13105

Watz, S., Petzl, W., Zerbe, H., Rieger, A., Glas, A., Schröter, W., et al. (2019). Technical note: automatic evaluation of infrared thermal images by computerized active shape modeling of bovine udders challenged with Escherichia coli. *J. Dairy Sci*. 102:5. doi: 10.3168/jds.2018-15761

Werkheiser, I. (2018). Precision Livestock Farming and Farmers' Duties to Livestock. *J. Agricult. Environ. Ethics* 31, 181–195. doi: 10.1007/s10806-018-9720-0

Werkheiser, I. (2020). Technology and responsibility: a discussion of underexamined risks and concerns in precision livestock farming. *Anim. Front*. 10, 51–57. doi: 10.1093/af/vfz056

Williams, L. R., Moore, S. T., Bishop-Hurley, G. J., and Swain, D. L. (2020). A sensor-based solution to monitor grazing cattle drinking behaviour and water intake. *Comp. Electr. Agricult.* 168:105141. doi: 10.1016/j.compag.2019.105141

Winckler, C. (2019). Assessing animal welfare at the farm level: do we care sufficiently about the individual?. *Anim. Welfare.* 28, 77–82. doi: 10.7120/09627286.28.1.077

Wischner, D., Kemper, N., and Krieter, J. (2009). Nest-building behaviour in sows and consequences for pig husbandry. *Livestock Sci*. 124, 1–8. doi: 10.1016/j.livsci.2009.01.015

Xiao, L., Ding, K., Gao, Y., and Rao, X. (2019). Behavior-induced health condition monitoring of caged chickens using binocular vision. *Comp. Electr. Agricult.* 156, 254–262. doi: 10.1016/j.compag.2018.11.022

Xin, H. (1999). Environment and behavior 1: recent advances in assessment and management of heat stress in domestic animals assessing swine thermal comfort by image. *J. Anim. Sci.* 77, 1–9. doi: 10.2527/1999.77suppl_21x

Xiong, X., Lu, M., Yang, W., Duan, G., Yuan, Q., Shen, M., et al. (2019). An automatic head surface temperature extraction method for top-view thermal image with individual broiler. *Sensors* 19:5286. doi: 10.3390/s19235286

Yang, A., Huang, H., Yang, X., Li, S., Chen, C., Gan, H., et al. (2019). Automated video analysis of sow nursing behavior based on fully convolutional network and oriented optical flow. *Comp. Electr. Agricult.* 167:105048. doi: 10.1016/j.compag.2019.105048

Yang, A., Huang, H., Zheng, B., Li, S., Gan, H., Chen, C., et al. (2020). An automatic recognition framework for sow daily behaviours based on motion and image analyses. *Biosyst. Eng.* 192, 56–71. doi: 10.1016/j.biosystemseng.2020.01.016

Yazdanbakhsh, O., Zhou, Y., and Dick, S. (2017). An intelligent system for livestock disease surveillance. *Inform. Sci.* 378, 26–47. doi: 10.1016/j.ins.2016.10.026

Yeates, J. W., and Main, D. C. J. (2008). Assessment of positive welfare: A review. *Vet. J.* 293–300. doi: 10.1016/j.tvjl.2007.05.009

Zaninelli, M., Redaelli, V., Luzi, F., Bronzo, V., Mitchell, M., Dell'Orto, V., et al. (2018). First evaluation of infrared thermography as a tool for the monitoring of udder health status in farms of dairy cows. *Sensors* 18:862. doi: 10.3390/s18030862

Zhang, F. Y., Hu, Y. M., Chen, L. C., Guo, L. H., Duan, W. J., and Wang, L. (2016). Monitoring behavior of poultry based on RFID radio frequency network. *Int. J. Agricult. Biol. Eng.* 9, 139–147. doi: 10.3965/j.ijabe.20160906.1568

Zhang, G., Zhang, Y., Kim, Y., Kim, J., Liu, L., Yu, X., et al. (2011). Field study on the impact of indoor air quality on broiler production. *Indoor Built Environ.* 20, 449–455. doi: 10.1177/1420326X11409468

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The Hitchhiker's Guide to Integration of Social and Ethical Awareness in Precision Livestock Farming Research

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While fully automated livestock production may be considered the ultimate goal for optimising productivity at the farm level, the benefits and costs of such a development at the scale at which it needs to be implemented must also be considered from social and ethical perspectives. Automation resulting from Precision Livestock Farming (PLF) could alter fundamental views of human-animal interactions on farm and, even further, potentially compromise human and animal welfare and health if PLF development does not include a flexible, holistic strategy for integration. To investigate topic segregation, inclusion of socio-ethical aspects, and consideration of human-animal interactions within the PLF research field, the abstracts from 644 peer-reviewed publications were analysed using the recent advances in the Natural Language Processing (NLP). Two Latent Dirichlet Allocation (LDA) probabilistic models with varying number of topics (13 and 3 for Model 1 and Model 2, respectively) were implemented to create a generalised research topic overview. The visual representation of topics produced by LDA Model 1 and Model 2 revealed prominent similarities in the terms contributing to each topic, with only weight for each term being different. The majority of terms for both models were process-oriented, obscuring the inclusion of social and ethical angles in PLF publications. A subset of articles (5%, $n = 32$) was randomly selected for manual examination of the full text to evaluate whether abstract text and focus reflected that of the article as a whole. Few of these articles (12.5%, $n = 4$) focused specifically on broader ethical or societal considerations of PLF or (9.4%, $n = 3$) discussed PLF with respect to human-animal interactions. While there was consideration of the impact of PLF on animal welfare and farmers in nearly half of the full texts examined (46.9%, $n = 15$), this was often limited to a few statements in passing. Further, these statements were typically general rather than specific and presented PLF as beneficial to human users and animal recipients. To develop PLF that is in keeping with the ethical values and societal concerns of the public and consumers, projects, and publications that deliberately combine social context with technological processes and results are needed.

Keywords: human-animal interactions, natural language processing, ethics, social impact, responsible innovation

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INTRODUCTION

Precision Livestock Farming (PLF) technologies are being proposed as solutions that allow farmers to balance producing animal products to meet growing human demands while creating conditions for good animal welfare, health, and environmental sustainability (Guarino et al., 2017; Tullo et al., 2019). The use of PLF is intended to help farmers better understand their animals as individuals, allowing them to monitor and manage animals in real time based on data from the animals themselves (Smith et al., 2015; Guarino et al., 2017). The use of PLF may also lead to fewer humans working on the farm, which may be beneficial in terms of risks related to physical, chemical, and biological injury and exposure. Limiting exposure to zoonotic diseases that may have pandemic implications could be another relevant reason to reduce numbers of human workers on farms (Dawood et al., 2011).

Historically, jobs in the livestock sector were physically demanding, repetitive, and conducted in harsh and adverse environments (Kolstrup and Jakob, 2016; Kumaraveloo and Lunner Kolstrup, 2018). Though there has been increased use of machinery on farms, particularly since the 1950s, manual labour is still extensively used in livestock production, providing jobs for workers across different generations, countries, and socio-economic conditions (Kolstrup, 2008, 2012; Lunner-Kolstrup and Ssali, 2016; Martin, 2016). However, farmers are increasingly using different sensors and digital decision-supporting tools to improve their daily workflow and maximise the economic output of their production systems while optimising labour-intensive tasks and management related to them (Karttunen et al., 2016; Hartung et al., 2017; Lunner-Kolstrup et al., 2018; Klerkx et al., 2019). A shift to relying on automation for monitoring animals as well as for performing physically demanding and repetitive work related to caregiving could lead to a radical paradigm shift in livestock sector priorities, drifting away human-animal interactions as a dominant feature at the core of farming. Using fully-automated technology to complete more husbandry tasks on livestock and poultry farms will change the nature of work on farms and could have impacts on how and how often farmers interact with their animals (Hartung et al., 2017; Kling-Eveillard et al., 2020). Research will be needed to more completely understand the questions that will arise in response to such changes in human-animal interactions, including:

1. Does reliance on technology change farmer satisfaction with their jobs?
2. Will the need for technology force some farmers out of work due to the monetary cost or need for re-learning how to farm with the technology?
3. Will automation lead to an improved ability to monitor and manage animals as individuals on farms of increasing size?
4. Will animals on fully-automated farms live lives worth living? Particularly if increased technology drives further intensification and increases in farm size?
5. Will automation lead to ethical conundrums related to farming if animals are cared for solely by technology and not humans?

For PLF to really address these questions, there must be explicit consideration of the ethical issues surrounding the use of technology with sentient beings, as mammals, birds, and even fish are widely considered to be capable of feeling by the public and demonstrated to be so by science (Duncan, 2006; Proctor et al., 2013; Russell et al., 2015; Rossi and Mattei, 2019; Rotz et al., 2019). To maintain farmers' and consumers' trust and ensure that processes that potentially could become automated and adapted for "minimised human involvement" remain ethically and socially acceptable, research addressing such consequences and challenges of digitalisation and AI in livestock production is needed before such technologies are fully integrated in animal agriculture (Stilgoe et al., 2013; Torresen, 2018).

Compared to the plant agriculture section, the animal agriculture sector has been relatively slow to adopt smart farming technologies (Kamphuis et al., 2015). Possible reasons include lack of clear financial benefit relative to existing practises, outputs that do not provide clear management advice, privacy concerns, and reluctance to use technology perceived as complex or not long lived (Daberkow and McBride, 2003; Kamphuis et al., 2015; Shepherd et al., 2018; Eastwood and Renwick, 2020). Increased automation of specific tasks in livestock production is postulated to contribute to more reliable and efficient outcomes in terms of consistently meeting standards of performance and product quality (Kamphuis et al., 2015; Bekara et al., 2017). However, the extensive use of automated solutions will significantly affect the daily work routine for farmers (Hansen, 2015; Marinoudi et al., 2019; Kling-Eveillard et al., 2020) and, potentially, shift the focus away from the animals (Rowe et al., 2019). Therefore, while there is a significant opportunity for improved logistics and automation as a result of using PLF solutions and AI, there are also barriers from a human adoption perspective that must be considered (Busse et al., 2015; Hartung et al., 2017).

The complexity of the cultural and legal frameworks around modern livestock production means that incorporating PLF, AI, and digitalisation into animal agriculture will also affect multiple aspects of the food sector and society at large (Millar and Mepham, 2001), such as:

1. Impact on the job market resulting from a shift from manual to automated labour;
2. The image of automated livestock production and its effects on individual animal welfare and health in the eyes of consumers;
3. Changes in the required competencies for working in the livestock sector;
4. Acceptance of PLF, AI and digitalisation by farmers and other end users;
5. Integration of PLF, AI, and digitalisation in different ethical, legal, and regulatory frameworks surrounding livestock production.

At present, PLF has been most well developed in the dairy industry, particularly the monitoring technologies that are linked to detecting oestrus and to robotic milking systems and their accompanying feeders (Mottram, 2016). However, for other species such as pigs and poultry, most of the solutions in PLF field are still in the research and development stage (Bailey et al., 2018; Benjamin and Yik, 2019; Li et al., 2020). At present, ethical frameworks, and consideration of societal consequences of automation in PLF do not appear to have developed in ways that constrain unintended or undesirable uses of such systems. To address this gap, we need to better integrate socio-ethical aspects into the assessment of innovative PLF solutions (Brey, 2012; Klerkx and Rose, 2020). However, such an assessment requires a deep understanding of the PLF research field's topics in a standardised, consistent way where initial experience-based bias is minimised.

This research aims to use recent advances in the Natural Language Processing (NLP) sub-branch of AI to examine abstracts from peer-reviewed publications to create and visualise a generalised topic overview of literature in the PLF research field and investigate the extent to which broader socio-ethical aspects are included in this work. This was followed by a manual examination of the full text of a randomly selected subset of articles to evaluate whether the topical representation from abstracts aligned with complete article content.

MATERIALS AND METHODS

Method Description

There are several commonly used methods for text data analysis and visualisation of meaningful information patterns. Natural Language Processing (NLP) is one of the sub-branches of AI that deals with effective interpretation between computer systems and humans using natural language.

One of the popular techniques in NLP is Topic Modelling (Hoffman et al., 2010; Sievert and Shirley, 2014)—an unsupervised technique used for clustering the information found in text data and performing dimensionality reduction for better representation of semantic structures (trends) within the text. Simply put, topic models look for hidden patterns within the text such as specific word occurrence in terms of context and similarities between words as well as their overall contribution to the text structure. Topic modelling helps reduce vast amounts of textual information to their core attributes for more straightforward interpretation, further analysis, and visualisation.

There are several approaches that could be used for topic modelling, one of which is Latent Dirichlet Allocation (LDA), which was used in the present study. The LDA is a generative probabilistic model that assumes that each and every topic is a mixture (or a "bag") of words with their own "weights" contributing to the overall meaning/importance of the topic and that each text is a mixture of different topics tied together with their distribution probabilities.

At its core, the LDA is a Bayesian network, a statistical model representing the set of variables (topics) and their conditional dependencies (weights) *via* a directed acyclic graph. The plate notation of LDA model can be visualised as shown in **Figure 1**.

There are a number of topics (K), which consist of "bags" of words described by the Dirichlet distribution ϕ (phi) and controlled by the hyperparameter β (beta). Additionally, there are a number of documents (M), each containing words (N), contributing to the overall text complexity. The W is an example of a word whose weight contributes to topic Z's importance, with θ (theta) being the Dirichlet distribution of all topics across all documents, and this distribution is controlled by another hyperparameter α (alpha).

These two hyperparameters, alpha, and beta, affect the output of the LDA model and could be adjusted depending on text complexity and the number of documents in need of analysis:

- alpha is responsible for document-topic density (and the higher this parameter is, the broader the description of the document becomes);
- beta is responsible for topic-word density (and the higher this parameter is, the more words will be assumed to contribute to the overall topic importance);

While alpha and beta hyperparameters are mostly used for fine-tuning the LDA model, there is also a third hyperparameter potentially adding the bias to the LDA model's output. This parameter is the number of topics (n) that the model will produce when provided with a certain number of documents as input. Potentially, the larger the number of topics (n) is, the more nuanced the representation of text can be achieved. However, it could also lead to an obscured picture due to the LDA model producing topics that are nearly identical. Thus, the n number is often set manually since the model cannot decide upon this variable itself. The usual approach is to initially use default model values and then adjust the n value after the first model run to achieve a broader or denser output as desired.

However, since the aim of this research was to perform an overview of words and trends present in abstracts with minimal human bias potentially affecting model output, a decision to automate the selection and evaluation of the optimal value for the n parameter was made. The iterative script written in the Python programming language was used to estimate LDA model coherence scores based on a different number of topics being applied to the target dataset. The iterative script operated with the following parameters: num_passes (number of times the model trains on all the words present in the target dataset) set to 50 and 250 to investigate the tendency for the overfitting of the model and n (number of topics potentially produced by LDA model) ranged from 1 to 25. The results of the evaluation can be seen in **Figures 2**, **3** (LDA Model 1) and (LDA Model 2), and the n-values leading to the highest coherence score (here, 13 and 3 for LDA Model 1 and 2, respectively) were used in the implementation of two final models. The decision to keep two different models with 13 and 3 topics, respectively was also motivated by the explorative nature of this study as an additional hypothesis was to evaluate how the interpretability of the PLF research field changes with a different number of topics produced by the LDA model and how those topics blend.

Dataset Preparation

One way to obtain correctly formatted text files of sufficient lengths is to use an official application programming interface (API) from scientific search engines (e.g., Web of Knowledge, ScienceDirect, Scopus). For the present study, Scopus was chosen as the primary engine for dataset compilation as Scopus allows output to several standard file formats (text, CSV, XML), making

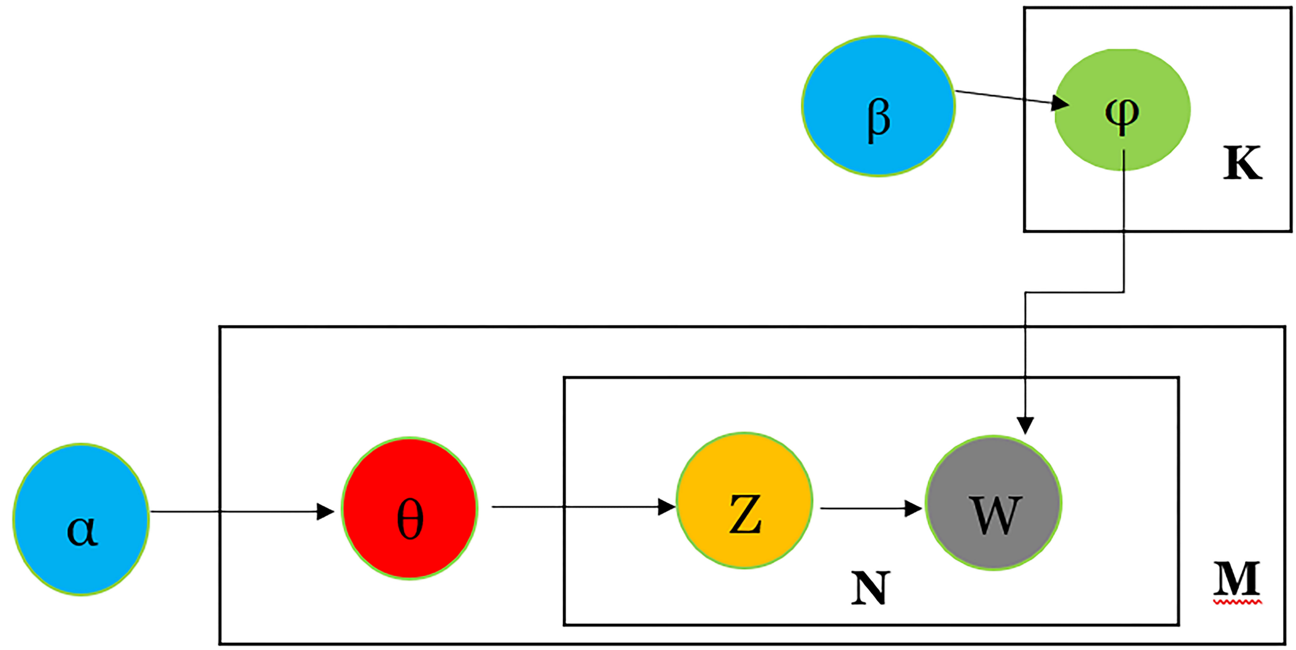

FIGURE 1 | Plane notation of the LDA Topic Model.

it easy to import data into the Python libraries used for pre-processing. Scopus also provides a specific structure to the output file, containing not only relevant text data but also links to full articles as well as indexed and author-defined keywords.

The following keywords were used (with and without word derivatives produced by the * operator) for building the search query in Scopus to identify articles for further analysis with LDA: precision livestock farming, PLF, ethic, social, value, impact, human-animal, relationship, technology, monitor, automation, welfare, farm, animal, and sensor. The decision of which search terms to initially use to identify articles for further analysis is the point at which the most human bias could be introduced. Terms were deliberately selected with the goal of discovering research articles focused on the development of technologies used within animal, not plant-based, agriculture for the automated monitoring and management of animals. Specific terms related to human-animal interactions as well as social and ethical aspects were also included to ensure that such research was identified rather than obscured by the plethora of technical studies that have been done.

To ensure that all the potentially relevant articles were found, several separate search queries with precision livestock farming/PLF keywords being the main ones and other keywords being added one at a time, and in different combinations, were conducted through the Scopus API. The search resulted in a joint Microsoft Excel file with 774 entries with separate columns containing each of the following variables: publication title, publication year, authors, abstract text, author keywords, indexed keywords, and publisher. These 774 entries were manually examined to remove articles not related (e.g., strictly animal/veterinary science with no mentioning of the PLF or technology, or with focus on plant production) to the search or with corrupted text data resulting in 644 articles falling within the defined search query. The abstract texts from each of the remaining 644 articles were then used for the NLP analysis to represent prominent trends within the PLF research domain.

The abstract text data were turned into a pandas (library for the Python programming language) dataframe to allow for higher computational efficiency during pre-processing and analysis stages.

Model Implementation

The LDA model was implemented in the Python programming language using the Gensim version of LDA. Gensim is a robust, resource-efficient library used for unsupervised semantic modelling from plain text.

To minimise subjectivity in the initial selection and interpretation of the terms present in the dataset, the following procedure was followed during pre-processing of data:

- all abstracts forming the target dataset were tokenised (split into smaller input units like words/terms for further processing *via* decapitalisation, removal of punctuation or other special characters);
- tokenised words/terms were lemmatised (reduction of the inflectional forms, e.g., prefix, suffix or infix, and sometimes derivationally related forms of a word to a common base form), using spacy and NLTK Python programming language packages for NLP;

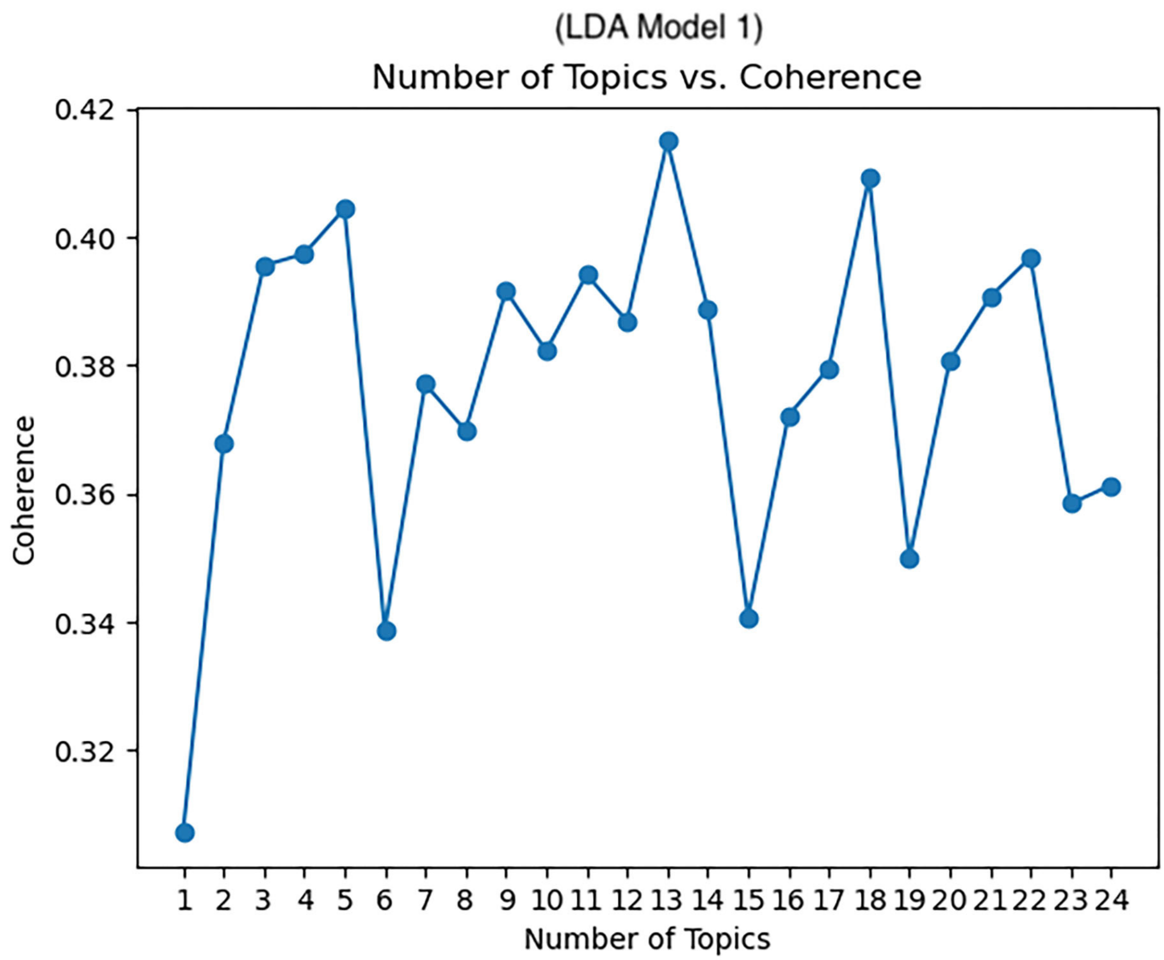

FIGURE 2 | The evaluation results showing the optimal number of topics for highest coherence score for the LDA Model after 50 passes.

- stopwords (common words/terms that do not contribute to the coherence of the text) were removed using NLTK package;

After selecting and evaluating the optimal model parameters, and the desired number of topics for output, the final LDA models yielded a coherence scores of 0.41 (LDA Model 1) and 0.43 (LDA Model 2). The coherence score (c_v) measures the relative distance between words within a topic. It is rare to see a coherence of 1 or 0.9 unless the words being measured are either identical words or bi-trigrams. The overall coherence score of a topic is the average of the semantic distances between words and could be used as a relative measure of "text interpretability." Each topic produced by the LDA model is a vector that contains the words and their weights contributing to the final topic weight within the processed text/document.

The visual output of LDA models, with pyLDAvis library as a backend (Sievert and Shirley, 2014), is an interactive plot in HTML (webpage) format. For each model, the interactive plot consists of two panels. The left panel depicts circles representing a topic (cluster) of information, grouped based on Jensen-Shannon divergence, and the right panel presents horizontal bars visualising terms appearing within the selected topic. Each circle in the left panel represents one topic/cluster of information from the dataset, with the size of the circle being directly related to topic significance within the dataset. The distance between the centre points of different circles indicates topic similarity/difference based on the occurrence of words forming the particular topic. The bar chart in the right panel displays the 30 most relevant terms for the selected topic, where the uniqueness of a displayed term within a topic can be adjusted using a slider at the top of the panel, given a relevance parameter, λ. The length of the red bars represents the frequency of a term within the selected topic, and the length of the blue bars represents a term's frequency across the entire dataset. Setting the relevance (λ-value) closer to 0 highlights potentially rare, exclusive terms within the topic, while larger λ values highlight more common terms in the selected topic. Due to the non-supervised nature of the LDA algorithm, low relevance or λ-values and high term specificity do not contribute to the explorative nature of the study. By having the relevance metric set

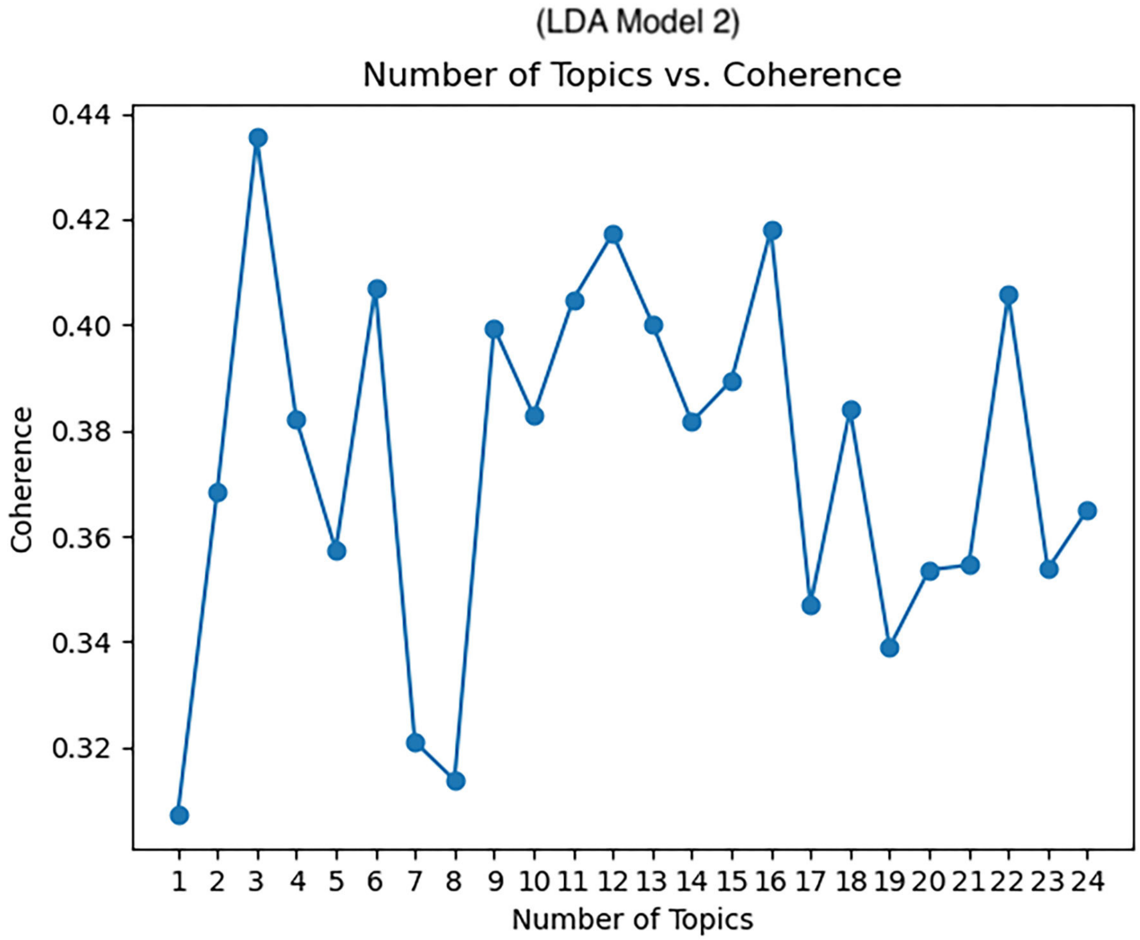

FIGURE 3 | The evaluation results showing the optimal number of topics for highest coherence score for the LDA Model after 250 passes.

to 0.6, a general overview of each topic is made possible (Sievert and Shirley, 2014).

Manual Analysis of Full Text of Subset of Articles

To more deeply examine the selected articles with respect to coverage of ethical and social issues, we performed a manual content analysis of the full text of a subset of the articles. We used a random number generator to select 5% of the 644 articles subjected to the LDA (n = 32). To determine whether these articles did explicitly address ethical, societal, and human-animal implications of PLF technology, the following keywords and their derivatives were used to search the full text, including figures and tables: ethics, social, society, human, relationships, interactions, farmer, producer, manager, stockperson/stockpeople/stockman/stockmen, person, public, consumer, customer, welfare, well being (also well-being, wellbeing), concern, moral, value, impact, risk, challenge, care/caring. The following rules were applied to exclude use of search terms when used in a mathematical or analytical sense (e.g., human observer/decoder), technical sense (e.g., challenge) in an economic sense (e.g., value), study approval sense (e.g., ethics), or in a descriptive sense [e.g., concern(ing)], which were not relevant to the analysis.

RESULTS

When comparing the initial terms produced by the two LDA models that were run with different parameters (13 vs. 3 topics and 50 vs. 250 passes for Model 1 and Model 2, respectively), the similarities of terms contributing to each model output are prominent, with only term order being different (**Table 1**).

The terms composing the initial output in both models are nearly identicaland require the broader context to support the initial hypothesis of the study: socio-ethical trends or those more focused on animal/farmer welfare are less dominant compared to more technical, process-oriented ones.

Figure 4 shows the visual output of LDA Model 1 (50 passes) with 13 topics identified and grouped based on their similarity and dominating trend.

Figure 5 shows the visual output of LDA Model 2 (250 passes) with 3 topics identified and grouped based on their similarity and dominating trend.

An overview of the terms from each topic produced by LDA Models 1 and 2 is presented in **Table 2**. For better segregation of

TABLE 1 | Terms from the initial output produced by LDA models generated with the different number of passes.

Model Terms	LDA Model 1 (13 topics, 50 passes)	LDA Model 2 (3 topics, 250 passes)
	"farm"	"farm"
	"technology"	"technology"
	"production"	"system"
	"welfare"	"production"
	"management"	"animal"
	"farmer"	"welfare"
	"animal"	"management"
	"system"	"livestock"
	"dairy"	"farmer"
	"livestock"	"sensor"

the terms contributing to each topic, only the 5 highest ranked and 5 lowest ranked terms were selected from the 30 most relevant terms shown by pyLDAvis tool. In case of the term being a highly niched abbreviation, country name or PLF (or a direct derivative), the next term was chosen instead for better topic interpretability. The relevance metric (λ) was also set to 0.6 to provide a generalistic overview used and to align with the visual outputs of **Figures 4** and **5**.

Manual analysis of a subset of 32 articles (5% of the total dataset) identified three general types of articles: (1) those that made no mention of ethics, societal context, human-animal interactions, or human or animal welfare implications of PLF; (2) those that linked PLF to improved welfare of animals or to changed work (usually beneficial) of farmers; and (3) those that addressed ethical or social context surrounding PLF. In the first category, 15 of the 32 articles (46.9%) focused on development of PLF technology or data analysis and did not explicitly mention ethical or social issues related to using their PLF on farms, refer to how their PLF would impact farmers' work or interactions with animals, or consider implications of PLF on animal welfare. In the final category, four of the articles (12.5%) spent considerable (e.g., detailed discussion on a subject matter through the whole text) attention on ethical or societal implications of using PLF on

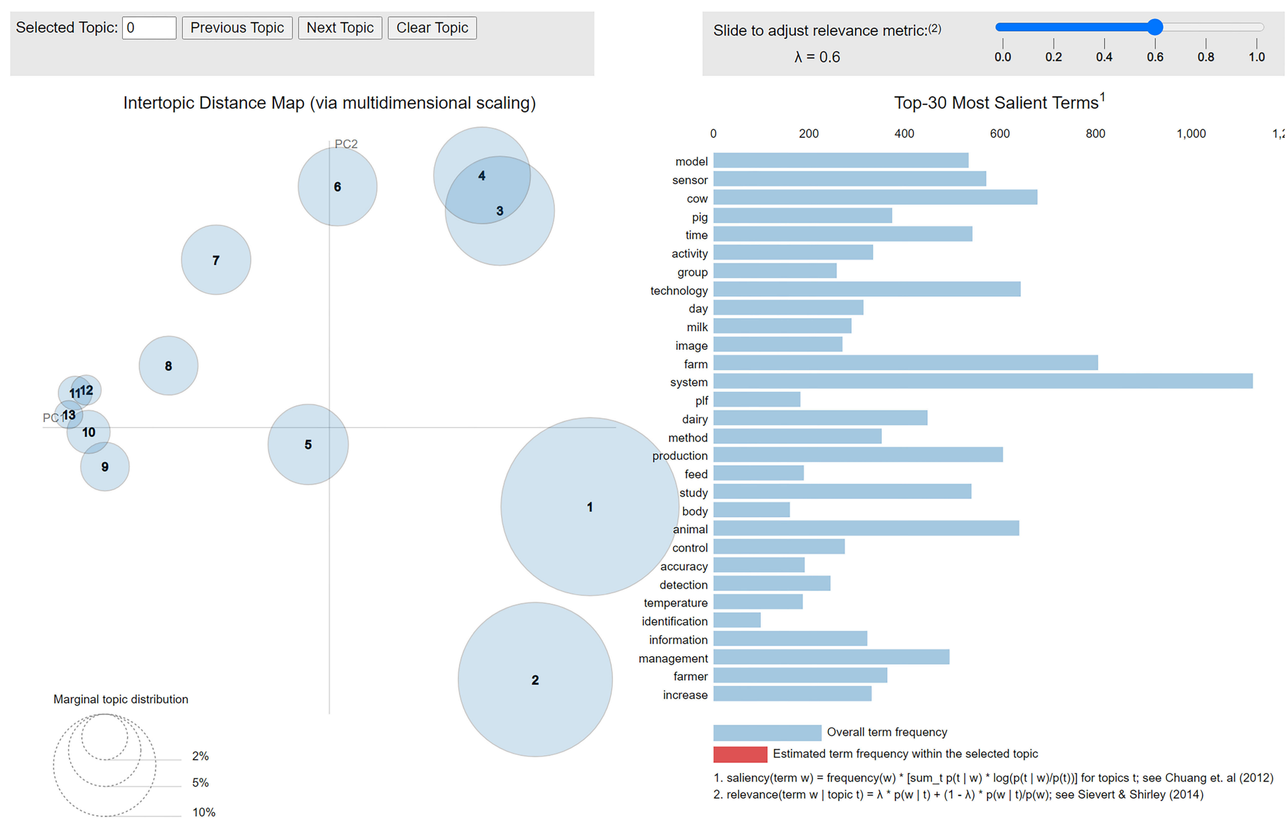

FIGURE 4 | Overview of the results produced by LDA Model 1 (50 passes, 13 topics) with the relevance metric (λ) set to 0.6 and no specific topic cluster selected. Topics 1 and 2 depict broader generalistic PLF clusters, Topics 3 and 4 are oriented mainly toward dairy cattle, and the remaining topics are more focused and represent pig and poultry production as well as highly specific areas such as feeding, emission control, and so forth.

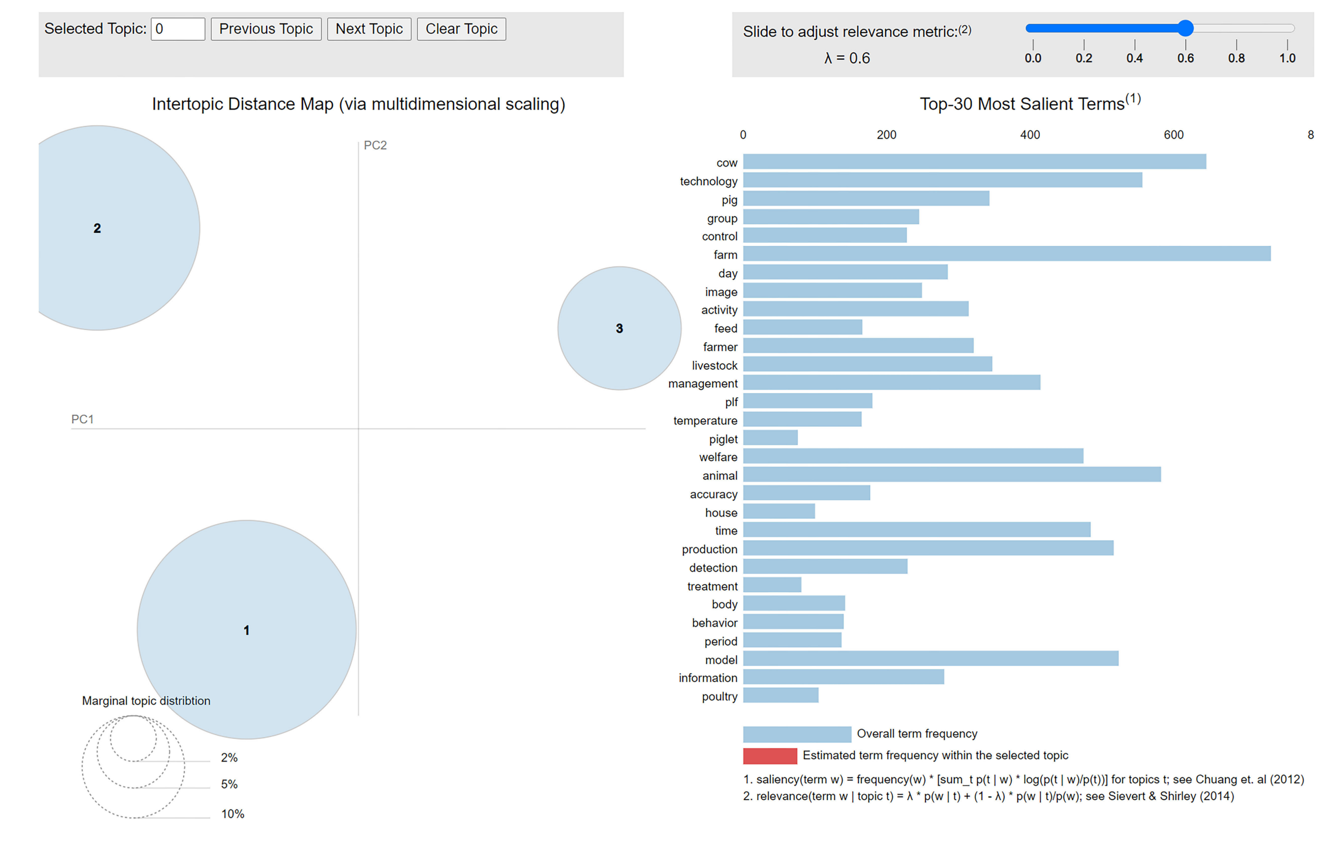

FIGURE 5 | Overview of the results produced by LDA Model 2 (250 passes, 3 topics) with the relevance metric (λ) set to 0.6 and no specific topic cluster selected. Topics 1 and 2 depict broader generalistic PLF clusters with a predominant focus on dairy cattle. Topic 3 is more specifically oriented toward pig and poultry production and aspects such as feeding, housing, and management.

farm. However, in one of these articles, PLF was only mentioned as a specific means of monitoring and assessing animal welfare to meet societal expectations rather than being the main focus of the paper (i.e., Hocquette and Chatellier, 2011).

DISCUSSION

Due to the unsupervised nature of the method which potentially could remove the human bias from the review process, and capacity to process a large number of documents at a relatively low computational cost, the use of NLP and Topic Modelling is becoming more popular in academia for explorative literature studies (Valle et al., 2014; Liu et al., 2016; Asmussen and Møller, 2019; Muchene and Safari, 2021). The interpretation of the results produced by LDA models, however, might pose a challenge if the initial hypothesis is not supported by manual overview of the text material or if the number of topics produced by the model is not cross-fold validated against the initial dataset. There are several evaluation metrics (e.g., coherence, perplexity of the text material) that can be used for the assessment of the results produced by LDA models (Wallach et al., 2009; Mimno et al., 2011). However these metrics are highly contextual when applied for descriptive studies and not text classification, and also depend on the initial broadness of the analysed material. Higher coherence scores, achieved after the extensive hyperparameter tuning of the LDA model do not always guarantee human interpretability, thus producing diffuse word vectors that do not add to a comprehensible understanding of how the text data are clustered (Roberts et al., 2016).

The relatively low coherence scores produced during model evaluation and selection of the optimal number of topics (0.41 and 0.43 for LDA Model 1 and Model 2, respectively) for visual representation in pyLDAvis tool can potentially be explained by the broadness of PLF as a research field (Greene et al., 2014). Such broadness leads to interconnectability among the research trends and makes it difficult to locate and quantify specific areas of interest, in this case the ethical or societal aspects of innovative development within the livestock technology sector. The majority of terms produced by LDA Models 1 and 2, as seen in **Table 2**, are process-oriented with terms like "welfare," "farmer," "result" being used in exclusively descriptive context aiming at the direction of PLF development which was supported by the manual analysis of the full-text of selected articles.

As also indicated in **Table 2**, the ranking of terms contributing to each produced topic could lead to false assumptions of certain trends being over/underrepresented if the conclusion is based on

TABLE 2 | Per-topic term overview of LDA Model 1 and LDA Model 2 with only 5 highest and 5 lowest ranked terms from each topic displayed.

	LDA model 1, λ = 0.6		LDA model 2, λ = 0.6	
Topic #	**High-rank terms**	**Low-rank terms**	**High-rank terms**	**Low-rank terms**
1	System, sensor, precision, analysis, device	Control, parameter, measure, Management, software	Cow, time, model, activity, study	Performance, analysis, pig, show, video
2	Technology, farm, production, welfare, farmer	Benefit, issue, process, cost, help	Technology, farm, system, Production, Animal	Practise, productivity, approach, tool, challenge
3	Image, accuracy, detection, method, camera	Show, depth, dataset, specificity, estimation	Group, pig, piglet, control, feed	Feeding, right_reserve, vocalisation, respiratory, drug
4	Cow, time, milk, day, piglet	Accurate, activity, variability. estimate, compare		
5	Pig, body, tail. head, point	Distance, label, direction, side, husbandry		
6	Activity, sow, broiler, flock, tag	Vocalisation, link, age, level, week		
7	Feed, water, heat_stress, Volume, climate	Drinker, swine, occupation, correlate, water_point		
8	Model, simulation, equation, input, classify	Motion, intelligent, construct, growth, computer		
9	Calf, sensor, framework, grass, hen	Material, warning, supervision, distribute, farrowing		
10	Output, Air, identification, compute, recognition	Machinery, indication, network, history, template		
11	Determination, signal, feeder, ventilation, call	Identify, intelligence, format, distress_call, sample		
12	Drive, Drug, cover, space, improve_animal_welfare	Coverage, relapse, hierarchy, early_sign, something		
13	Eastrus_detection, estrus, smartbow, meat_pigeon, localisation	Economic_benefit, HAR, dairy_goat, radius, ovulation		

the term ranking within the dataset corpus only. Since the LDA approach is unsupervised and operates based on term counts and approximation of distances to other terms contributing to the text structure, an additional qualitative approach to increase the interpretability of the results from the human perspective is highly advised when used for generating the research field overview (Asmussen and Møller, 2019).

In the present case, manual analysis of the full text of a subset of articles similarly revealed that the process of PLF development was the central focus of most articles. However, over half of the articles examined manually made at least passing mention of how the technology would affect farmers or animals in their care. Many of the articles that mentioned the impact of PLF on farmers described it as beneficial in terms of reduced physical or repetitive work and increased ability to monitor or make timely decisions (e.g., Kwong et al., 2009). A few articles did mention the need for farmers to gain new skills relative to using technology or managing data (e.g., Bánkuti et al., 2020) and one (i.e., Benaissa et al., 2020) mentioned frustration of farmers when technology does not work well or fails to integrate with other systems. Often the information to be gained by monitoring or aspect to be improved for the animal was related to animal welfare (e.g., Nóbrega et al., 2020), though in some cases increased production or reduced workload was the focus (e.g., Bekara et al., 2017; Abeni et al., 2019).

Improving animal welfare was often mentioned as a general reason for using PLF, as automated, continuous monitoring of animals was proposed as a way to improve focus on individual animals, particularly on farms of increasingly large size or with fewer stockpersons per animal (e.g., Morris et al., 2012; Norton and Berckmans, 2017). However, there were not often concrete examples as to how exactly a farmer could use the information to intervene effectively in a way that would address or prevent the welfare problem. Thus, most articles we examined were focused on developing the ability to detect a particular feature of interest, not on how the technology could be integrated usefully into management (Lunner-Kolstrup et al., 2018). Similarly, though the term 'welfare' was often used with respect to benefits of PLF to animals, the entirety of the concept was not typically captured (Van Erp-van der Kooij, 2020). Animal welfare is a complex, multidimensional concept that embodies more than simply good health or physical functioning, approaching a wholistic notion of quality of life from physical, emotional, and evolutionary perspectives (Fraser et al., 1997). Thus, most PLF only typically detects one attribute, either health or behaviour, that could influence welfare, not actually welfare itself (Buller et al., 2020).

Three articles (9.4%) specifically mentioned human-animal interactions related to development or use of PLF. In one case the authors (i.e., Benaissa et al., 2020) stated that human-animal interactions were ignored when dairy cattle monitoring systems were being developed. In another article (i.e., Berckmans, 2014), PLF was proposed as a way of replacing farmers' eyes and ears, but rather than reducing human-animal interactions, this continuous monitoring by PLF was proposed to help compensate for the increasing disconnect between the modern farmer and their animals. The final article in this set (i.e., Mancini and Zamansky, 2014) focused on using technology of all types to improve animal welfare, including providing insight into human-animal interactions, and proposed developing a field of animal welfare informatics for this specific purpose. However, the psychological aspect of farmers losing daily and physical contact with their animals due to automation of tasks was not mentioned in the subset of articles that were manually analysed. Taking daily care of animals and knowing the animals as individuals have both been found to increase farmer job satisfaction and be strong motivating factors for choosing to work with animals, such as dairy cows, among farmers, employed workers, and students at agricultural schools (Kolstrup, 2012). Animal caretakers often have a strong sense of empathy for their animals, and may suffer when technology takes over the role of the caretaker and reduces their physical contact with the animals. In a study on possible associations between health of farm staff and dairy cows, it was found that farmers experienced more physical symptoms of health problems in dairy herds with lower cow disease incidence rates (Lunner K. C. Hultgren J., 2011). Conversely, the same study found that a high incidence rate of health problems in a herd was associated with more frequent or intense exposures to negative psychosocial environmental factors among the employed dairy workers. A possible explanation to this could be that keeping a dairy herd in good health requires a lot of physical manual work and enthusiasm, while when dairy cow health and well-being is poor it is mentally stressful. Thus, when introducing comprehensive AI into animal production, it is important to consider both impacts on animal welfare as well as on human health and welfare.

Some developers of PLF, as well as social scientists, economists and ethicists interested in agricultural technology or artificial intelligence have written specifically about the implications of PLF related to farmer satisfaction, job security, or privacy concerns; the welfare of animals living in systems where technology replaces humans; the value of PLF data in the food system; and to broader issues of agricultural sustainability (e.g., Adams-Progar et al., 2017; Wathes et al., 2008; Rojo-Gimeno et al., 2019; Tullo et al., 2019; Kling-Eveillard et al., 2020; Lovarelli et al., 2020; Werkheiser, 2020; Schillings et al., 2021). While there appear to be an increase in the number of these publications, as of yet, social and ethical questions do not appear to be fully integrated into the PLF research and development paradigm. This could be due to both the rapid speed at which PLF development is currently occurring, as well as prioritisation of solving technical problems over considering ethical ones.

However, though not every article presenting the use of computer vision or a body worn sensor can or should equally cover the ethical or social ramifications of such technology, more explicit consideration of consequences to both immediate and distant end users should be made (Werkheiser, 2020). Formation of stronger collaborative teams that include tech developers, scientist with animal knowledge, farmers with practical experience, and ethicists or social scientists would lead to more robust solutions. Such teams will become particularly important as we move beyond the steps of initially developing technology for detection types of tasks and move into automating this technology and develop commercial management applications. For example, ethical and legal boundaries that frame AI must be developed, and consequences to animals, farmers and rural communities fully considered before rather than after PLF is deployed (Stilgoe et al., 2013; Torresen, 2018). Data ownership issues and privacy concerns must be balanced with demands for traceability and transparency in the food system (Adams-Progar et al., 2017). Improvements from earlier detection of problems and targeted treatment of individual animals must be balanced with whether these animals will have lives worth living if PLF leads to further intensification and increases in farm size (Schillings et al., 2021).

CONCLUSIONS

Examination of peer-reviewed scientific literature related to PLF using an automated Natural-Language Processing approach indicates that most articles on PLF are process-oriented and do not address the social or ethical context in which this technological development occurs. Subsequent analysis of full text of a subset of the identified articles found that connexions between PLF technology and applications that could minimise human labour or improve animal welfare were the most common considerations of how PLF technology could impact humans and animals. Though articles devoted explicitly to ethical uses of PLF technology, economic implications of PLF or considerations of social consequences exist, and consideration of such societal topics does appear in some technology-oriented articles, the topics and terms associated with ethics and society were not well represented among the common topic themes or terms identified in this study. Research efforts and resulting articles that engage diverse perspectives to bridge the divide between technology developers and social scientists are needed to keep

PLF development grounded by the needs, uses and consideration of those it will effect, both human and animal, on and off the farm.

DATA AVAILABILITY STATEMENT

The datasets generated for this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://github.com/dr-moo/PLF_Topic_Modelling.

AUTHOR CONTRIBUTIONS

OG, JS, and CK: conceptualisation and writing—original draft preparation. OG and JS: methodology and data analysis. OG: validation and data curation. All authors contributed to the article and approved the submitted version.

REFERENCES

Abeni, F., Petrera, F., and Galli, A. (2019). A survey of Italian dairy farmers' propensity for precision livestock farming tools. *Animals* 9:202. doi: 10.3390/ani9050202

Adams-Progar, A., Fink, G., Walker, E., and Llewellyn, D. (2017). "Chapter 18: Security and privacy issues in the internet of cows," in *Security and Privacy in Cyber-Physical Systems: Foundations, Principles, and Applications*, eds H. Song, G. A. Fink, and S. Jeschke (Hoboken, NJ: John Wiley & Sons, Inc.), 375–398. doi: 10.1002/9781119226079.ch18

Asmussen, C. B., and Møller, C. (2019). Smart literature review: a practical topic modelling approach to exploratory literature review. *J. Big Data* 6, 1–18. doi: 10.1186/s40537-019-0255-7

Bailey, D. W., Trotter, M. G., Knight, C. W., and Thomas, M. G. (2018). Use of GPS tracking collars and accelerometers for rangeland livestock production research. *Trans. Anim. Sci.* 2, 81–88. doi: 10.1093/tas/txx006

Bánkuti, F. I., Prizon, R. C., Damasceno, J. C., De Brito, M. M., Pozza, M. S. S., and Lima, P. G. L. (2020). Farmers' actions toward sustainability: a typology of dairy farms according to sustainability indicators. *Animal* 14, s417–s423. doi: 10.1017/S1751731120000750

Bekara, M. E. A., Bareille, N., Bidan, F., Allain, C., and 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)* (p. np). Available online at: https://hal.archives-ouvertes.fr/hal-01591150

Benaissa, S., Tuyttens, F. A. M., Plets, D., Trogh, J., Martens, L., Vandaele, L., et al. (2020). Calving and estrus detection in dairy cattle using a combination of indoor localization and accelerometer sensors. *Comput. Electron. Agric.* 168:105153. doi: 10.1016/j.compag.2019.105153

Benjamin, M., and Yik, S. (2019). Precision livestock farming in swine welfare: a review for swine practitioners. *Animals* 9:133. doi: 10.3390/ani9040133

Berckmans, D. (2014). Precision livestock farming technologies for welfare management in intensive livestock systems. *Rev. Off. Int. Epizoot.* 33, 189–196. doi: 10.20506/rst.33.1.2273

Brey, P. A. E. (2012). Anticipatory ethics for emerging technologies. *Nanoethics* 6, 1–13. doi: 10.1007/s11569-012-0141-7

Buller, H., Blokhuis, H., Lokhorst, K., Silberberg, M. and Veissier, I. (2020). Animal welfare management in a digital world. *Animals* 10:1779. doi: 10.3390/ani10101779

Busse, M., Schwerdtner, W., Siebert, R., Doernberg, A., Kuntosch, A., König, B., and Bokelmann, W. (2015). Analysis of animal monitoring technologies in Germany from an innovation system perspective. *Agric. Syst.* 138, 55–65. doi: 10.1016/j.agsy.2015.05.009

Daberkow, S. G., and McBride, W. D. (2003). Farm and operator characteristics affecting the awareness and adoption of precision agricultural technologies in the US. *Precision Agric.* 4, 163–177. doi: 10.1023/A:1024557205871

Dawood, F. S., Dong, L., Liu, F., Blau, D. M., Peebles, P. J., Lu, X., et al. (2011). A pre-pandemic outbreak of triple-reassortant swine influenza virus infection among university students, South Dakota, 2008. *J. Infect. Dis.* 204, 1165–1171. doi: 10.1093/infdis/jir502

Duncan, I. J. H. (2006). The changing concept of animal sentience. *Appl. Anim. Behav. Sci.* 100, 11–19. doi: 10.1016/j.applanim.2006.04.011

Eastwood, C., and Renwick, A. (2020). Innovation uncertainty impacts the adoption of smarter farming approaches. *Front. Sustain. Food Syst.* 4:24. doi: 10.3389/fsufs.2020.00024

Fraser, D., Weary, D. M., Pajor, E. A., and Milligan, B. N. (1997). A scientific conception of animal welfare that reflects ethical concerns. *Anim. Welfare* 6, 187–205. Available online at: https://www.wellbeingintlstudiesrepository.org/cgi/viewcontent.cgi?article=1000&context=ethawel

Greene, D., O'Callaghan, D., and Cunningham, P. (2014). "How many topics? stability analysis for topic models," in *Joint European Conference on Machine Learning and Knowledge Discovery in Databases* (Berlin, Springer), 498–513. Available online at: https://arxiv.org/abs/1404.4606v3

Guarino, M., Norton, T., Berckmans, D., Vranken, E., and Berckmans, D. (2017). A blueprint for developing and applying precision livestock farming tools: a key output of the EU-PLF project. *Anim. Front.* 7, 12–17. doi: 10.2527/af.2017.0103

Hansen, B. G. (2015). Robotic milking-farmer experiences and adoption rate in Jæren, Norway. *J. Rural Stud.* 41, 109–117. doi: 10.1016/j.jrurstud.2015.08.004

Hartung, J., Banhazi, T., Vranken, E., and Guarino, M. (2017). European farmers' experiences with precision livestock farming systems. *Anim. Front.* 7, 38–44. doi: 10.2527/af.2017.0107

Hocquette, J. F., and Chatellier, V. (2011). Prospects for the European beef sector over the next 30 years. *Anim. Front.* 1, 20–28. doi: 10.2527/af.2011-0014

Hoffman, M., Bach, F. R., and Blei, D. M. (2010). "Online learning for latent dirichlet allocation," in *Advances in Neural Information Processing Systems* (Vancouver, BC: Curran Associates, Inc., Hyatt Regency), 856–864.

Kamphuis, C., Steeneveld, W., and Hogeveen, H. (2015). "Economic modelling to evaluate the benefits of precision livestock farming technologies," in *Precision livestock farming applications: Making sense of sensors to support farm management* (Wageningen: Wageningen Academic Publishers), 163–171.

Karttunen, J. P., Rautiainen, R. H., and Lunner-Kolstrup, C. (2016). Occupational health and safety of Finnish dairy farmers using automatic milking systems. *Front. public Heal.* 4:147. doi: 10.3389/fpubh.2016.00147

Klerkx, L., Jakku, E., and 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 J. Life Sci.* 90:100315. doi: 10.1016/j.njas.2019.100315

Klerkx, L., and Rose, D. (2020). Dealing with the game-changing technologies of Agriculture 4.0: How do we manage diversity and responsibility in food system transition pathways? *Glob. Food Sec.* 24:100347. doi: 10.1016/j.gfs.2019.100347

Kling-Eveillard, F., Allain, C., Boivin, X., Courboulay, V., Creach, P., Philibert, A., et al. (2020). Farmers' representations of the effects of precision livestock farming on human-animal relationships. *Livest. Sci.* 104057. doi: 10.1016/j.livsci.2020.104057

Kolstrup, C. L. (2012). What factors attract and motivate dairy farm employees in their daily work? *Work* 41, 5311–5316. doi: 10.3233/WOR-2012-0049-5311

Kolstrup, C. L., and Jakob, M. (2016). Epidemiology of musculoskeletal symptoms among milkers and dairy farm characteristics in Sweden and Germany. *J. Agromedicine* 21, 43–55. doi: 10.1080/1059924X.2015.1106373

Kolstrup, C. (2008). *Work Environment and Health among Swedish Livestock Workers*. Alnarp: Acta Universitatis Agriculturae Sueciae, 1652–6880.

Kumaraveloo, K. S., and Lunner Kolstrup, C. (2018). Agriculture and musculoskeletal disorders in low-and middle-income countries. *J. Agromedicine* 23, 227–248. doi: 10.1080/1059924X.2018.1458671

Kwong, K. H., Wu, T. T., Goh, H. G., Stephen, B., Gilroy, M., Michie, C., et al. (2009). Wireless sensor networks in agriculture: Cattle monitoring for farming industries. *Piers Online* 5, 31–35. doi: 10.2529/PIERS0810011 10156

Li, N., Ren, Z., Li, D., and Zeng, L. (2020). Automated techniques for monitoring the behaviour and welfare of broilers and laying hens:

toward the goal of precision livestock farming. *Animal* 14, 617–625. doi: 10.1017/S1751731119002155

Liu, L., Tang, L., Dong, W., et al. (2016). An overview of topic modeling and its current applications in bioinformatics. *SpringerPlus* 5:1608. doi: 10.1186/s40064-016-3252-8

Lovarelli, D., Bacenetti, J., and Guarino, M. (2020). A review on dairy cattle farming: is precision livestock farming the compromise for an environmental, economic and social sustainable production?. *J. Clean. Prod.* 262:121409. doi: 10.1016/j.jclepro.2020.121409

Lunner K. C. and Hultgren J. (2011). Perceived physical and psychosocial exposure and health symptoms of dairy farm staff and possible associations with dairy cow health. *J. Agric. Safety Health* 17,111–125. doi: 10.13031/2013.36496

Lunner-Kolstrup, C., Hörndahl, T., and Karttunen, J. P. (2018). Farm operators' experiences of advanced technology and automation in Swedish agriculture: a pilot study. *J. Agromedicine* 23, 215–226. doi: 10.1080/1059924X.2018.1458670

Lunner-Kolstrup, C., and Ssali, T. K. (2016). Awareness and need for knowledge of health and safety among dairy farmers interviewed in Uganda. *Front. Public heal.* 4:137. doi: 10.3389/fpubh.2016.00137

Mancini, C., and Zamansky, A. (2014). "Charting unconquered territories: intelligent systems for animal welfare," in *40th Annual Convention of the Society for the Study of Artificial Intelligence and the Simulation of Behaviour* (pp. 181–182).

Marinoudi, V., Sørensen, C. G., Pearson, S., and Bochtis, D. (2019). Robotics and labour in agriculture: a context consideration. *Biosyst. Eng.* 184, 111–121. doi: 10.1016/j.biosystemseng.2019.06.013

Martin, P. L. (2016). *Migrant Workers in Commercial Agriculture*. Available online at: http://www.ilo.org/wcmsp5/groups/public/ed_protect/protrav-migrant/documents/publication/wcms_538710.pdf.

Millar, K. M., and Mepham, T. B. (2001). Bioethical analysis of biotechnologies: lessons from automatic milking systems (AMS) and bovine somatotrophin (bST). *BSAP Occasional Public.* 28, 29–36. doi: 10.1017/S1463981500040954

Mimno, D., Wallach, H., Talley, E., Leenders, M., and McCallum, A. (2011). "Optimizing semantic coherence in topic models," in *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing*, 262–272.

Morris, J. E., Cronin, G. M., and Bush, R. D. (2012). Improving sheep production and welfare in extensive systems through precision sheep management. *Anim. Produc. Sci.* 52, 665–670. doi: 10.1071/AN11097

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

Muchene, L., and Safari, W. (2021). Two-stage topic modelling of scientific publications: a case study of University of Nairobi, Kenya. *PLoS ONE* 16:e0243208. doi: 10.1371/journal.pone.0243208

Nóbrega, L., Gonçalves, P., Antunes, M., and Corujo, D. (2020). Assessing sheep behavior through low-power microcontrollers in smart agriculture scenarios. *Comput. Electron. Agric.* 173:105444. doi: 10.1016/j.compag.2020.105444

Norton, T., and Berckmans, D. (2017). Developing precision livestock farming tools for precision dairy farming. *Anim. Front.* 7, 18–23. doi: 10.2527/af.2017.0104

Proctor, H. S., Carder, G., and Cornish, A. R. (2013). Searching for animal sentience: a systematic review of the scientific literature. *Animals* 3, 882–906. doi: 10.3390/ani3030882

Roberts, M. E., Stewart, B. M., and Tingley, D. (2016). Navigating the local modes of big data: the case of topic models. *Comput. Soc. Sci.* 4. doi: 10.1017/CBO9781316257340.004

Rojo-Gimeno, C., van der Voort, M., Niemi, J. K., Lauwers, L., Kristensen, A. R., and Wauters, E. (2019). Assessment of the value of information of precision livestock farming: A conceptual framework. *NJAS-Wageningen J. Life Sci.* 90:100311. doi: 10.1016/j.njas.2019.100311

Rossi, F., and Mattei, N. (2019). "Building ethically bounded AI," in *Proceedings of the AAAI Conference on Artificial Intelligence*, 9785–9789. Available online at: http://dx.doi.org/10.1609/aaai.v33i01.33019785

Rotz, S., Gravely, E., Mosby, I., Duncan, E., Finnis, E., Horgan, M., et al. (2019). Automated pastures and the digital divide: How agricultural technologies are shaping labour and rural communities. *J. Rural Stud.* 68, 112–122. doi: 10.1016/j.jrurstud.2019.01.023

Rowe, E., Dawkins, M. S., and Gebhardt-Henrich, S. G. (2019). A systematic review of precision livestock farming in the poultry sector: Is technology focussed on improving bird welfare? *Animals* 9:614. doi: 10.3390/ani9090614

Russell, S., Dewey, D., and Tegmark, M. (2015). Research priorities for robust and beneficial artificial intelligence. *Ai Mag.* 36, 105–114. doi: 10.1609/aimag.v36i4.2577

Schillings, J., Bennett, R., and Rose, D. C. (2021). Exploring the potential of precision livestock farming technologies to help address farm animal welfare. *Front. Anim. Sci.* 2:639678. doi: 10.3389/fanim.2021.639678

Shepherd, M., Turner, J. A., Small, B., and Wheeler, D. (2018). Priorities for science to overcome hurdles thwarting the full promise of the 'digital agriculture'revolution. *J. Sci. Food Agric.* 9346. doi: 10.1002/jsfa.9346

Sievert, C., and Shirley, K. (2014). "LDAvis: A method for visualising and interpreting topics," in *Proceedings of the Workshop on Interactive Language learning, Visualisation, and Interfaces*, 63–70. Available online at: http://dx.doi.org/10.3115/v1/W14-3110

Smith, D., Lyle, S., Berry, A., Manning, N., Zaki, M., and Neely, A. (2015). *Internet of Animal Health Things (IoAHT) Opportunities and Challenges*. Cambridge: University of Cambridge.

Stilgoe, J., Owen, R., and Macnaghten, P. (2013). Developing a framework for responsible innovation. *Res. Policy* 42, 1568–1580. doi: 10.1016/j.respol.2013.05.008

Torresen, J. (2018). A review of future and ethical perspectives of robotics and AI. *Front. Robot.* AI 4, 75. doi: 10.3389/frobt.2017.00075

Tullo, E., Finzi, A., and Guarino, M. (2019). Environmental impact of livestock farming and Precision Livestock Farming as a mitigation strategy. *Sci. Total Environ.* 650, 2751–2760. doi: 10.1016/j.scitotenv.2018.10.018

Valle, D., Baiser, B., Woodall, C. W., and Chazdon, R. (2014). Decomposing biodiversity data using the Latent Dirichlet Allocation model, a probabilistic multivariate statistical method. *Ecol. Lett.* 17, 1591–1601. doi: 10.1111/ele.12380

Van Erp-van der Kooij, E. and Rutter, S.M. (2020). "Using precision farming to improve animal welfare," in *CAB Reviews: perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources*, 15(051). Available online at: http://dx.doi.org/10.1079/PAVSNNR202015051

Wallach, H. M., Murray, I., Salakhutdinov, R., and Mimno, D. (2009). "Evaluation methods for topic models," in *Proceedings of the 26th annual international conference on machine learning*, 1105–1112.

Wathes, C.M., Kristensen, H.H., Aerts, J.M. and Berckmans, D. (2008). Is precision livestock farming an engineer's daydream or nightmare, an animal's friend and foe, and a farmer's panacea or pitfall?. *Comput. Electron Agric.* 64, 2–10. doi: 10.1016/j.compag.2008.05.005

Werkheiser, I. (2020). Technology and responsibility: a discussion of underexamined risks and concerns in precision livestock farming. *Anim. Front.* 10, 51–57. doi: 10.1093/af/vfz056

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Does Smart Farming Improve or Damage Animal Welfare? Technology and What Animals Want

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"Smart" or "precision" farming has revolutionized crop agriculture but its application to livestock farming has raised ethical concerns because of its possible adverse effects on animal welfare. With rising public concern for animal welfare across the world, some people see the efficiency gains offered by the new technology as a direct threat to the animals themselves, allowing producers to get "more for less" in the interests of profit. Others see major welfare advantages through life-long health monitoring, delivery of individual care and optimization of environmental conditions. The answer to the question of whether smart farming improves or damages animal welfare is likely to depend on three main factors. Firstly, much will depend on how welfare is defined and the extent to which politicians, scientists, farmers and members of the public can agree on what welfare means and so come to a common view on how to judge how it is impacted by technology. Defining welfare as a combination of good health and what the animals themselves want provides a unifying and animal-centered way forward. It can also be directly adapted for computer recognition of welfare. A second critical factor will be whether high welfare standards are made a priority within smart farming systems. To achieve this, it will be necessary both to develop computer algorithms that can recognize welfare to the satisfaction of both the public and farmers and also to build good welfare into the control and decision-making of smart systems. What will matter most in the end, however, is a third factor, which is whether smart farming can actually deliver its promised improvements in animal welfare when applied in the real world. An ethical evaluation will only be possible when the new technologies are more widely deployed on commercial farms and their full social, environmental, financial and welfare implications become apparent.

Keywords: welfare, computer recognition, smart farming, precision, welfare algorithm

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INTRODUCTION

Smart or precision farming involves the use of technology to monitor and manage the keeping of farm animals (Banhazi et al., 2012; Berckmans, 2017). It therefore includes sensors to measure a range of environmental and animal-based variables as well as the control mechanisms to make management decisions, either with or without human intervention. The ability to monitor animals continuously in real-time throughout their lives and to control their environments means that both productivity and welfare can potentially be improved through early detection of health problems

(Wathes et al., 2008; Banhazi et al., 2012; Berckmans, 2017; Veissier et al., 2019), leading to targeted (and therefore reduced) use of medication, lower mortality and improved health. These outcomes in turn have other social benefits such as less waste, greater efficiency and lower environmental impact (Clark and Tilman, 2017; Perakis et al., 2020).

Furthermore, the smart data that can be collected from thousands of farms can be interrogated to find solutions to management, disease, welfare, productivity and even environmental issues that have previously been based only on the experience of one company or small-scale research projects. Intelligent use of the large data sets that smart farming makes possible can be used to further improve the results of smart farming itself.

On the other hand, however, precision farming also raises ethical concerns primarily because of its possible adverse effects on animal welfare (Wathes et al., 2008; Werkheiser, 2020). The concern is that gains in production and efficiency will lead to a deterioration in animal welfare through promotion of more intensive farming (Stevenson, 2017), an emphasis on group rather than individual welfare (Winckler, 2019) and the replacement of trained stock people by anonymous algorithms.

Although improved animal welfare is often one of the stated aims of smart farming (Rowe et al., 2019), it is far from clear that this is achieved in practice. One reason for this uncertainty is that much of the technology is still being developed and has not yet been widely enough applied in practice for its full implications to be clear. Precision agriculture as applied to livestock is therefore at a crucial stage where its impact on animal welfare could become either positive or negative. In this article, I shall argue that there are three factors that will largely determine the ultimate ethical verdict on smart farming. These are (i) whether smart farming adopts a definition of "animal welfare" that is acceptable to the public and in particular whether that definition includes the animals' point of view (ii) whether computer recognition of animal welfare is successful enough and is given high enough priority to satisfy the ethical standards that people demand and to genuinely improve welfare (iii) whether smart farming can actually deliver its promised improvements in animal welfare when applied in practice.

AN AGREED DEFINITION OF ANIMAL WELFARE

The first factor that will determine whether smart farming is seen as improving or damaging animal welfare is whether it will be possible to arrive at a definition of "welfare" that everyone—including scientists, farmers, animal charities and members of the public—can all agree on. This may sound like a trivial problem but in fact it is a serious stumbling block to a consensus view on the ethics of smart farming because there is currently no agreed definition of "welfare" in any context (Green and Mellor, 2011; Thompson, 2017; Ede et al., 2019; Weary and Robbins, 2019). For some people, "good welfare" must include making the animal's environment as "natural" as possible (Nussbaum, 2004; Yeates, 2018), while for others a natural life does not guarantee good welfare (Bracke and Hopster, 2006) and what animals need can be better met in a controlled, if artificial, environment in which technology plays a significant part (Gygax and Hillmann, 2018). The list of proposed measures of welfare now includes longevity (Hurnik, 1993), reproductive success (Broom, 1991), behavioral diversity (Rabin, 2003; Cronin and Ross, 2019), heart rate variability (von Borell et al., 2007; Kovacs et al., 2015), eye temperature (Gomez et al., 2018), skin temperature (Herborn et al., 2015) and hormone levels (Ralph and Tilbrook, 2016; Palme, 2019), along with many others. Such a plethora of different welfare "measures" means that what is an ethical way of keeping animals for one person is unethical for another. Without a definition of animal welfare that everyone can subscribe to and that genuinely improves animal welfare, precision farming could run into considerable opposition on the grounds that it does not meet the standards of a particular definition and does not live up to its promise of improving the lives of animals. For all the potential that Machine Learning has for determining the conditions that give rise to the best welfare outcomes, we still need a specification of what a "good" or desirable welfare outcome is (Morota et al., 2018).

A possible unifying definition of good welfare is that an animal is (i) in a state of good physical health and (ii) has what it wants (Dawkins, 2008, 2012, 2021). This is a distillation of many other widely used approaches such as the Ten General principles (OIE, 2012; Fraser et al., 2013), Five Freedoms (FAWC, 2009), the Five Provisions or Domains (Mellor, 2016), the Four Principles put forward by the Welfare Quality® project (Welfare Quality®, 2018) and the Three Circles of Welfare (Fraser, 2008) and so captures what many people from different perspectives mean by welfare (Dawkins, 2021). All of these schemes stress the fundamental importance of physical health to good welfare and "what animals want" gives a prominent place to the animals' own view of their environments (Welfare Quality®, 2018; Franks, 2019). It is also in line with the recent trends to move away from defining welfare negatively as absence of suffering to defining it more positively so that animals have a Life Worth Living (LWL) or, even better, a positively Good Life (Broom, 2007; FAWC, 2009; Wathes, 2010; Green and Mellor, 2011; Webb et al., 2019). "What animals want" has been discussed in the scientific literature as animals having "positive emotions" (Boissy et al., 2007) or being in a "positive affective state" (Mendl et al., 2010; Gygax, 2017) but the simpler wording is more understandable to non-scientists and more directly indicative of the data that needs to be collected.

COMPUTER RECOGNITION OF ANIMAL WELFARE

Defining welfare explicitly in terms of health and what animals want has the further advantage that it lends itself directly to computer recognition of animal welfare. This is important because the ethical credentials of smart farming will depend to a very large extent on people being convinced that computers are capable of recognizing and assessing animal welfare and then that the computers are programmed to make sure that good welfare is a high priority. The definition of welfare used in smart farming must therefore be directly translatable into terms a computer can be programmed to recognize and apply in practice. The technology now available for smart farming includes "smart sensors" that collect real time information from animals and/or their environment (Neethirajan, 2017; Fogarty et al., 2018), the integration of different sorts of information into big data sets that can be used for Machine Learning to give the best production and welfare outcomes (Liakos et al., 2018; Bahlo et al., 2019) and systems that deliver fine control of an animal's environment and diet (Astill et al., 2020). Translating all of this data into practical improvements in welfare, however, depends crucially on how good computers are at interpreting the data they collect in welfare terms. How well are computers able to recognize the two elements of good welfare?

Computer Recognition of Health and Disease

Veterinary medicine has so far made much more limited use of computers to measure health than human medicine but there is now increasing use of automated methods for detecting signs of disease or injury in farm animals (Fournel et al., 2017; Awaysheh et al., 2019). This is most advanced in the dairy sector, where changes in the health status of each individual cow have an appreciable economic impact and so farmers find investment in the technology that gives detailed information on each animal to be important to their entire business (Lovarelli et al., 2020). For example, lameness in dairy cows can now be automatically detected in a variety of ways including visual images, accelerometer data from devices fitted to the cows' legs, pressure sensitive pads that record the way cows distribute their weight and even from the sound of their footfall (Alsaaod et al., 2019; Eckelkamp, 2019; Volkmann et al., 2019; Pilette et al., 2020). Changes in behavior such as longer bouts of lying, shorter bouts of feeding or ruminating can be automatically derived from visual images and accelerometers and serve as early warnings of both lameness and other health problems (Beer et al., 2016; Alsaaod et al., 2019; Eckelkamp, 2019; Grinter et al., 2019). In pigs, changes in tail position can be automatically detected by cameras and used as warnings for outbreaks of tail-biting, a serious source of injury (D'Eath et al., 2018). Digital imaging technology can also be used to analyze different postures indicating sick or injured birds (Zhuang et al., 2018) or to pick out lame broilers by abnormalities of their body oscillations, step frequency and step length (Aydin, 2017).

Large animals such as cows or sows can be individually monitored either by placing tags, trackers or measuring devices on or even inside each animal or by visually recognizing individual animals from camera data (Jorquera-Chavez et al., 2019; Sun et al., 2019; Baxter and O'Connell, 2020). Such devices can contribute to animal welfare by enabling each animal to have its own individualized diet and medical treatment (Caja et al., 2016). Computer vision and machine learning can now identify facial expressions of pain in sheep, giving early warning of diseases such as foot rot and mastitis and enabling an affected individual to be treated before the disease spreads to the rest of the flock (McLennan and Mahmoud, 2019).

However, where thousands of smaller animals are kept together, individual recognition is currently difficult and the entire group is assessed and treated as a whole. Commercially reared poultry, for example, do not have feed, vaccination, medication, drinker height, lighting and other factors adjusted for single individuals but, rather, set for the average needs of the entire flock. Welfare assessment is similarly based on group outcomes such as % of a flock with gait defects, % mortality, sounds or movements of whole flocks (Dawkins et al., 2012, 2017). This is one area where precision farming is currently limited but could in future make a real contribution to the welfare of group-housed animals. The "precision" in precision crop agriculture refers to the measurement of soil properties, moisture levels, weeds and diseases in specific parts of a field and the application of treatments such as fertilizers and herbicides precisely where these are really needed rather than to the field as a whole (Yufeng et al., 2011; Yost et al., 2017). The welfare of chickens could, similarly, benefit from technology that allowed farmers to identify injured birds and treat them individually or to be alerted to a particular areas of a house where a potential problem such smothering or over-crowding was beginning to occur. Houses containing many thousands of birds would no longer be treated as a single unit but as flocks of many individuals, experiencing different conditions and having different welfare outcomes. This would enable greater focus on the welfare of individual animals than either farmers or machines are able to do at the moment.

Even with current technology, however, valuable health information can be gained from monitoring the whole group without distinguishing individuals. For example, the sound of coughing has been used to automatically detect early signs of Bovine Respiratory Disease, despite the difficulties of distinguishing the sound of a cough from other background noises (Vandermeulen et al., 2016; Carpentier et al., 2018). The sounds of coughing in pigs (Silva et al., 2008) and sneezing in chickens (Carpentier et al., 2019) have also been used to detect respiratory diseases. Using visual images, broiler chicken flocks with high levels of leg damage and lameness can be automatically detected from anomalies in flock movement (Fernandez et al., 2018), even before these become apparent to the human eye (Dawkins et al., 2012, 2017, 2021; Zhuang et al., 2018).

It is thus clear that technology already has the ability to measure at least one element of good welfare—animal health—at both individual and group level. New automated ways of doing this are rapidly being developed and their use is likely to increase markedly in the near future as diagnostic tools become better able to focus on individual animals and to give early warning of incipient health problems (Eckelkamp, 2019; Wurtz et al., 2019; Li et al., 2020; Rios et al., 2020).

Computer Recognition of What Animals Want (the Animal's Point of View)

While signs of ill-health are comparatively easy for computers to recognize, there is more to good welfare than just absence of injury and disease and so a key question is whether computers are also capable of delivering on the second component of animal welfare—what animals want.

Specifying Welfare Algorithms

The success of an algorithm to detect when animals have what they want will depend on a computer being able to discriminate between the behavior or physiological state of animals that have what they want and the behavior or physiological state of animals that do not have what they want. Animal welfare scientists have already made great progress in drawing up these "body language" lists for different species and indeed they are often used as measures of either positive or negative welfare. Many can now be detected automatically with sensors, including hormone levels, activity levels, vocalizations, skin temperature, eye temperature, pupil size, heart rate variability and many more.

With such a large number of measures now available, there would appear to be a strong empirical base from which to develop welfare algorithms suitable for inclusion in smart farming systems. Unfortunately, it turns out that many of these measures are problematic because they fail to discriminate between animals having what they want and the complete opposite—animals not having what they want or being forced to remain in conditions they want to avoid or escape from. For example, cows showed a decrease in eye temperature when confined in a cattle crush to have their feet trimmed but also when given highly palatable food (Gomez et al., 2018). Large increases in glucocorticoid levels (often called "stress" hormones) are shown by animals that have what they want (such as food, voluntary exercise or a sexual partner) as well as by animals that want to escape or avoid something (Rushen, 1986; Koolhaas et al., 2011; Ralph and Tilbrook, 2016).

This ambiguity of many currently used measures of welfare—the fact that many can be interpreted as much as expressions of an excited animal having what it wants as an aroused animal attempting to avoid what is not wanted—means that an extra test needs to be applied before any should used in a welfare algorithm. That test is empirical evidence that the measure used is a genuine diagnostic of whether the animals themselves regard a given situation as something they want to continue/repeat (that is, they find it positive or rewarding) or as something they want to avoid (negative or punishing) (Dawkins, 1990, 2021; Guesgen and Bench, 2017; Gygax, 2017; Franks, 2019). This positive/negative classification is also called valence (Mendl et al., 2010).

Determining Valence

There are now a number of well-tried and tested ways of finding out what animals want including operant conditioning (Kilgour et al., 1991; Patterson-Kane et al., 2008), various sorts of choice tests, spatial distribution and other more indirect methods (Dawkins, 2021). The simplest of these include offering animals choices between various options and seeing which one they choose initially or where they go over a longer period. For example, when broiler chickens are offered a choice between traditional bar perches and platform perches, they spend considerably more time on the platforms than the bars, particularly as they get older, heavier and find it more difficult to balance on bars (Baxter et al., 2020). Their point of view is expressed in where they choose to spend their time.

Evidence of what animals want becomes even more convincing if animals can be shown to actually "work" to get what they want or pay a cost to obtain their reward. For example, dairy cows will learn to operate a switch to activate the motors of rotating brushes, which they then rub up against to groom themselves (Westerath et al., 2014). Furthermore, they will make great efforts to get to these brushes if it is made more difficult for them, for example if they have to push open a heavy gate (McConnachie et al., 2018). Cows clearly want the physical grooming provided by the brushes.

Traditionally, studies of animal choices and resource use are conducted by direct human observation or tedious analysis of video, which greatly limits their scope. Long-term computer analysis of where animals spend their time and how often and how much they will work for different resources provides much more quantitative data. It shows how choices change on a diurnal basis and as the animals age (Kashiha et al., 2014). It thus helps to overcome objections that have been raised to the use of choice tests in welfare assessment (Fraser and Nicol, 2011) such as animals not being familiar with the options available, the choices changing with experience or animals initially "wanting" something but then not "liking" it when they obtain it (Berridge et al., 2009).

The Expression of Valence

Although establishing *what* animals want is an essential first stage in the development of welfare algorithms, it is knowing *how animals express themselves* when they have (or do not have) what they want that enables the often ambiguous data from sensors to be correctly interpreted in welfare terms (Guesgen and Bench, 2017). Once it is known what animals want, then it is possible to observe them in the presence both of things or environments they have shown they want and in the presence of situations they have shown they want to avoid. If there are diagnostic differences between their behavior and physiology in these two situations—that is, reliable indicators of valence—then these are the ones that can be used with confidence as part of a welfare algorithm. These might be characteristic sounds, patterns of behavior or hormone profiles that enable a machine (or stockperson) to make a welfare assessment and any necessary management changes. For example, growing chicks give loud high high-pitched "distress" calls when they are cold, hungry, thirsty or isolated (i.e., do not have what they want) and soft, "twitter" calls when they are with the mother or other chicks, at the right temperature and otherwise have what they want (Collias and Joos, 1953; Wood-Gush, 1971). The calls are distinct and easy for both humans and computers to distinguish. The current welfare of chicks can therefore be assessed by monitoring these calls (Herborn et al., 2020), since their value as diagnostic valence indicators has already been established.

Computers, with their immense power to learn from large data sets could greatly increase the accuracy of welfare recognition algorithms and their ability to distinguish behavior of different valence. For example, the grunts emitted by pigs are different depending on whether the pigs are in situations they find rewarding or punishing (Leliveld et al., 2016), but there is a great deal overlap between the two categories of grunts, making them, at present, unreliable indicators of whether pigs have what they want (Friel et al., 2019). However, what we now see as unreliable signs of what the pigs want, could, with the power of machine learning to interpret them, become much more reliable, either because computers detect distinctions that escape us, or because they are able combine them with other behaviors and interpret them in context. Machine Learning, using very large data sets for training and testing deep learning models, will almost certainly detect as yet unknown correlations and insights into how to achieve better welfare outcomes than we currently have available (Liakos et al., 2018; Morota et al., 2018; Li et al., 2020).

There are, however, particular challenges posed by the automated analysis of behavior due to its variety. An animal that wants food will behave differently from the same animal when it wants a mate or wants warmth. Even wanting one thing such as food may sometimes take the form of searching a large area, at other times vocalizing and at yet other times sitting still to conserve energy. "Searching" in turn may consist of running, stalking, digging, turning over stones or any number of other behaviors that may themselves vary on different occasions even within the same individual. An added complication is that when the animal has found food, it will switch from "wanting" food to "liking" it (Berridge et al., 2009; Gygax, 2017) and show a whole new set of behavior associated with eating and post-prandial digestion. The body language list for recognizing when animals have what they want will therefore have to be extensive for each species and include this variety of different behaviors.

The list is likely to be even longer for how animals express themselves when they do not have what they want because there are so many different situations that animals may want to avoid or escape from, each giving rise to different behavior. An animal that does not have but can see what it wants (is "thwarted" or "frustrated") will behave differently from one in a barren environment (is "deprived" or "bored"). An animal that wants to avoid danger (is "fearful") will show a range of behaviors from vigilance to full-scale flight depending on the degree of danger. Aggression can take many forms and real fighting can actually look very similar to play fighting. The only thing that could unite these diverse behaviors and put them on the same negative list is that, from the animal's point of view, they are all indication of something that is not wanted nor liked.

Note that these animal-centered lists may not be the same as the lists that well-meaning humans, without the benefit of this background research, might come up with. For example, not all "natural" behaviors will make it to the positive list of what animals want. Some behaviors that occur naturally in the wild, such as being chased by a predator, may be the opposite of what an animal wants and be seen as indicative of poor welfare (Bracke and Hopster, 2006; Dawkins, 2021).

Once these lists have been compiled, however, they can be used to develop the validated welfare algorithms that smart farming needs if it is to be of practical use to farmers. Consumers can be assured that the welfare algorithms being used are based on what keeps animals healthy and also on the animals' own verdicts on what they do or do not want.

Computers Can Provide What Animals Want

More actively, computers can be used not just to measure what animals want but to actually give them what they want. Voluntary milking for cows (Munksgaard et al., 2011; Rodenberg, 2017) for example, or systems in which animals can control their own level of illumination (Taylor et al., 1996) show how smart farming could even lead to animal-centered environments in which animals adjust their environments to their own liking. The full welfare implications of this have yet to be understood.

Some Remaining Problems With Machine Analysis of Welfare

Having emphasized the role that computers could play in the recognition and assessment of animal welfare, it is important also to identify the problems that still remain. With sound, it may be difficult to distinguish vocalizations from background noise or there may be genuine overlap between vocalizations indicating positive or negative welfare.

With machine vision technology, there is an even greater range of technical problems still to be overcome (Dominiak and Kristensen, 2017; Liakos et al., 2018; Wurtz et al., 2019). The human brain is so good at recognizing people, subtle facial expressions, letters of the alphabet written in different scripts and objects that are only partially visible that it sometimes comes as a surprise that we still out-perform any computer on many of these visual tasks (Rolls, 2021). We excel at view-invariance—that is, at being able to recognize the same object even though its appearance may be very different depending on the angle, distance or orientation at which we see it. A pen looks long and thin when held one way but like a small round coin when looked at end-on but we still know it is a pen. A bus is still a bus to us even though half hidden by a wall so that it no longer has a typical bus shape. Such tasks are difficult for computers even with static objects presented in a uniform way (which is why tests of whether you are a robot on a website work). When confronted by active behavior sequences of moving animals seen from different angles, different distances from the camera, in different lighting conditions and often obscured by other animals, the task becomes even more difficult. If these problems are not solved satisfactorily, computer recognition will give false positive or false negative results, both of which detract from its usefulness in practice (Dominiak and Kristensen, 2017; Liakos et al., 2018).

Consequently, there is still a long way to go before welfare algorithms will do what is required of them as a reliable part of smart farming systems operating in commercial farm conditions (Wurtz et al., 2019). Progress is, however, being made all the time. The widespread use of video surveillance has driven the need for view-invariant computer recognition of different kinds of human activity that can operate independently of light level, camera angle background or other variables encountered in real life (Ramanathan et al., 2019; Singh et al., 2019). Such developments are of direct relevance to the problems of machine recognition of animal behavior in farm conditions (Li et al., 2021).

CAN SMART FARMING DELIVER ON ITS PROMISED BENEFITS TO ANIMAL WELFARE?

Smart or precision livestock farming promises both greater efficiency to farmers and higher welfare standards for animals, but to quote a landmark paper by Wathes et al. (2008) it is still not clear whether smart farming is the animals "friend or foe" or the farmers "panacea or pitfall". Despite the major progress that has been made since this paper was published, precision livestock farming still lags behind plant crop production in its application of precision technology in many sectors (dairy farming being an exception). Many of its most ambitious features—such as automated welfare assessment—are still in the development phase (Rowe et al., 2019) and have yet to prove their value when applied to real farming conditions. As a result, many farmers particularly those in the poultry sector, are yet to be convinced that smart farming techniques are right for them or that they give any better results than be achieved without the help of expensive technology. Only when there is widespread commercial application and evidence of the results of smart farming in practice will we be able to judge its true outcomes. These outcomes will need to include whether it results in a reduction of waste, whether it reduces the incidence of disease and consequently reduces or increases the use of medication, what effects it has on the environment and the people working with animals and on whether it allows farmers to make a living.

Economic factors will be crucial. Only if farmers can see commercial benefits will they make the necessary investment in smart farming equipment and it is this emphasis on profit and efficiency that causes the most concern for animal welfare. There is a common belief that animal welfare is in conflict with efficient farming because its benefits are intangible and derive from ethics and moral values or what the public see as a "good" (Christensen et al., 2012). However, animal welfare also has direct financial benefits too and once these are appreciated animal welfare is less likely to be seen as in conflict with efficient farming (Guy et al., 2012; Dawkins, 2016). It is therefore worth considering the possible effects of smart farming on the two components of animal welfare discussed in this article in the light of their financial implications.

The impact of precision farming on the first component of animal welfare—good health—is likely to be positive and also to be financially beneficial. By having the greater control over environmental conditions that smart farming offers, animals can be kept in conditions that are optimal for their health, which makes them less likely to die or need medication or to be a source of disease to each other or to humans. Keeping broiler chickens within recommended limits of temperature and humidity, particularly during the first week of life, reduces not only mortality but other key health indicators as well such as hockburn, foot pad dermatitis and lameness (Dawkins et al., 2004; Jones et al., 2005). A broiler farm with 10 houses could be producing as many as 3 million birds a year so that even a 1% saving in mortality could be financially crucial for poultry producers. If the controlled environment achievable with precision farming also reduced downgrades due to leg and foot lesions, breast blisters and other signs of ill-health this could be an additional financial gain. Making sure that birds all grow at an even rate is another consideration with economic implications since supermarkets often demand birds all of the same weight. This is also important for bird welfare since underweight birds may find difficulty in accessing food and water. If precision farming results a higher percentage of saleable, healthy birds of even weight, farmers will gain financially and bird welfare will be improved at the same time.

With the second component of good welfare—animals having what they want—precision farming also has the potential to deliver efficiency and profit alongside better welfare. There is growing evidence that links "stress" to an impaired immune system (Hoerr, 2010; Inbaraj et al., 2019; Pratelli et al., 2021). In humans, good immune function is closely related to peoples' subjective reports of being happy and satisfied with their lives (Nakata et al., 2010; Takao et al., 2018), which is a promising model for relating immunity to non-human animals having what they want (Dawkins, 2019). This is an area where research is urgently needed, specifically to test the hypothesis that keeping animals in high welfare conditions (where they are both healthy and have what they want) boosts their immune systems, makes them more resistance to disease and leads to healthier more contented animals. If precision farming can provide the conditions that animals show by their behavior they want and like and they are also healthier, then this will provide a direct and immediate commercial advantage. If monitoring the animals' behavior can be shown to be useful in indicating when conditions are less than optimal from the animal's point of view, then the extra technology will have its own financial justification.

In addition to the direct financial benefits of giving priority to animal welfare, there are also indirect benefits, such as the public viewing farmers favorably and choosing to buy the products of precision farming because they are seen as "welfare friendly." This is likely to become increasingly important as new trade deals lead to greater competition and animal welfare becomes a key selling point for producers who can achieve it. A retailer or food outlet that is able reassure its customers that there is constant welfare monitoring on the farms it buys from and is able to explain what this means and even how the welfare is measured will be at a (commercial) advantage.

We do not yet know whether these promises of smart livestock farming will be fulfilled in practice. That will only become clear as systems become more widely used and as the smart systems themselves become more fully developed. Large data sets that can be interrogated by deep learning techniques will be crucial both to evaluating the effects of smart farming and to improving what it can achieve. Of these effects, animal welfare will be key to the future of smart farming, both as a major factor in its financial success or failure but more importantly as its ethical judge. Smart farming may stand or fall by whether it really can improve the lives of animals.

CONCLUSIONS

Smart or precision farming is a collection of relatively new technologies whose effects on animal welfare have yet to become clear. The ethical verdict on smart farming is likely to depend on how the technology is developed over the next few years and how much priority is given to animal welfare. Three developments will be crucial to the ethical evaluation of smart farming in its treatment of animals: the definition of "welfare" it adopts, computer recognition of welfare and crucially, whether the welfare of farmed animals is actually improved by the application smart farming technology.

AUTHOR CONTRIBUTIONS

The author confirms being the sole contributor of this work and has approved it for publication.

REFERENCES

Alsaaod, M., Fadui, M., and Steiner, A. (2019). Automated lameness detection in cattle. *Vet. J.* 246, 35–44. doi: 10.1016/j.tvjl.2019.01.005

Astill, J., Dara, R. A., Fraser, E. D. G., Roberts, B., and Sharif, S. (2020). Smart poultry management: smart sensors, big data, and the internet of things. *Comput. Electron. Agr.* 170:105291. doi: 10.1016/j.compag.2020.105291

Awaysheh, A., Wilcke, J., Elvinger, F., Rees, L., Fan, W., and Zimmerman, K. L. (2019). Review of medical decision support and machine-learning methods. *Vet. Pathol.* 56, 512–525. doi: 10.1177/0300985819829524

Aydin, A. (2017). Development of an early-detection system for lameness in broilers using computer vision. *Comp. Electron. Agr.* 136, 140–145. doi: 10.1016/j.compag.2017.02.019

Bahlo, C., Dahlhaus, P., Thompson, H., and Trotter, N. (2019). The role of interoperative data standards in precision livestock farming in external livestock systems: a review. *Comput. Electron. Agr.* 156: 459–466. doi: 10.1016/j.compag.2018.12.007

Banhazi, T. M., Lehr, H., Black, J. L., Crabtree, H., Schofield, P., and Tscharke, M. (2012). Precision Livestock Farming: an international review of scientific and commercial aspects. *Int. J. Agr. Biol. Eng.* 5, 1–9. doi: 10.3965/j.ijabe.20120503.001

Baxter, M., and O'Connell, N. (2020). Testing ultra-wideband technology as a method of tracking growing broilers under commercial conditions. *Appl. Anim. Behav. Sci.* 233:105150. doi: 10.1016/j.applanim.2020.105150

Baxter, M., Richmond, A., Lavery, U., and O'Connell, N. E. (2020). Investigating optimal levels of perch provision for windowed broiler housing. *Appl. Anim. Behav. Sci.* 225:104967. doi: 10.1016/j.applanim.2020.104967

Beer, G., Alsaaod, M., Starke, A., Schuepbach-Regula, G., Müller, H., Kohler, P., and Steiner, A. (2016). Use of extended characteristics of locomotion and feeding behavior for automated identification of lame dairy cows. *PLoS ONE* 11:e0155796. doi: 10.1371/journal.pone.0155796

Berckmans, D. (2017). General introduction to precision livestock farming. *Anim. Front.* 7: 6–11. doi: 10.2527/af.2017.0102

Berridge,. K. C., Robinson, T. E., and Aldridge, J. W. (2009). Dissecting components of reward: "liking", "wanting" and learning. *Curr. Opin. Pharmacol.* 9, 65–73. doi: 10.1016/j.coph.2008.12.014

Boissy, A., Manteuffel, G., Jensen, M. B., Moe, R. O., Spruijt, B., Keeling, L. J., et al. (2007). Assessment of positive emotions to improve their welfare. *Physiol. Behav.* 92, 375–397. doi: 10.1016/j.physbeh.2007.02.003

Bracke, M. B. M., and Hopster, H. (2006). Assessing the importance of natural behaviour for animal welfare. *J. Agric. Environ. Ethic.* 19, 77–89. doi: 10.1007/s10806-005-4493-7

Broom, D. M. (1991). Animal welfare—concepts and measurement. *J. Anim. Sci.* 69: 4167–4175. doi: 10.2527/1991.69104167x

Broom, D. M. (2007). Quality of Life means welfare: how is it related to other concepts and assessed? *Anim. Welfare* 16, 43–53. doi: 10.1016/0376-6357(91)90014-Q

Caja, G., Castro-Costa, A., and Knight, C. H. (2016). Engineering to support wellbeing of dairy animals. *J. Dairy Res.* 83, 136–147. doi: 10.1017/S0022029916000261

Carpentier, L., Berckmans, D., Youssef, A., Berckmans, D., van Watertschoot, T., Johnston, D., et al. (2018). Automatic cough detection for bovin respiratory disease in a calf house. *Biosyst. Eng.* 173, S45–56. doi: 10.1016/j.biosystemseng.2018.06.018

Carpentier, L., Vranken, E., Berckmans, D., Paeshuyse, J., and Norton, T. (2019). Development of sound-based poultry health monitoring tool for automated sneeze detection. *Comput. Electron. Agr.* 162, 573–581. doi: 10.1016/j.compag.2019.05.013

Christensen, T., Lawrence, A., Lund, M., Stott, A., and Sandøe, P. (2012). How can economists help to improve animal welfare? *Anim.Welfare* 21, 1–10. doi: 10.7120/096272812X13345905673449

Clark, M., and Tilman, D. (2017). Comparative analysis of environmental impacts of agricultural, input efficiency and food choice. *Environ. Res. Lett.* 12:064016. doi: 10.1088/1748-9326/aa6cd5

Collias, N. E., and Joos, M. (1953). The spectrographic analysis of sound signals of the domestic fowl. *Behaviour* 5, 175–188. doi: 10.1163/156853953X00104

Cronin, K. A., and Ross, S. R. (2019). Technical contribution: a cautionary keynote on the use of behavioural diversity (H-index) in animal welfare science. *Anim. Welfare* 28, 157–164. doi: 10.7120/09627286.28.2.157

Dawkins, M. S. (1990). From an animal's point of view: motivation, fitness and animal welfare. *Behav. Brain Sci.* 13, 1–6. doi: 10.1017/S0140525X00077104

Dawkins, M. S. (2008). The science of animal suffering. *Ethology* 114, 937–945. doi: 10.1111/j.1439-0310.2008.01557.x

Dawkins, M. S. (2012). *Why Animals Matter: Animal Consciousness, Animal Welfare and Human Well-being*. Oxford: Oxford University Press.

Dawkins, M. S. (2016). Animal welfare and efficient farming: is conflict inevitable? *Anim Prod. Sci.* 57, 201–208. doi: 10.1071/AN15383

Dawkins, M. S. (2019). Animal welfare as preventative medicine. *Anim. Welfare* 28, 137–141. doi: 10.7120/09627286.28.2.137

Dawkins, M. S. (2021). *The Science of Animal Welfare: Understanding What Animals Want*. Oxford: Oxford University Press.

Dawkins, M. S., Cain, R., and Roberts, S. J. (2012). Optical flow, flock behaviour and chicken welfare. *Anim. Behav.* 84, 219–222. doi: 10.1016/j.anbehav.2012.04.036

Dawkins, M. S., Donnelly, C. A., and Jones, T. A. (2004). Chicken welfare is influenced more by housing conditions than by stocking density. *Nature* 427, 342–344. doi: 10.1038/nature02226

Dawkins, M. S., Roberts, S. J., Cain, R. J., Nickson, T., and Donnelly, C. A. (2017). Early warning of footpad dermatitis and hock burn in broiler chicken flocks using optical flow, body weight and water consumption. *Vet. Rec.*180, 448–452 doi: 10.1136/vr.104066

Dawkins, M. S., Wang, L., Ellwood, S. A., Roberts, S. J., and Gebhardt-Henrich, S. G. (2021). Optical flow, flock behaviour and broiler chicken welfare in the UK and Switzerland. *Appl. Anim. Behav. Sci.* 234:105180. doi: 10.1016/j.applanim.2020.105180

D'Eath, R. B., Jack, M., Futro, A., Talbot. D., Zhu, Q., Barclay, D., Baxter, E. M. (2018). Automatic early warning of tail biting in pigs: 3D cameras can detect lowered tail posture before an outbreak. *PLOS One* 13:e0194524. doi: 10.1371/journal.pone.0194524

Dominiak, K. N., and Kristensen, A. R. (2017). Prioritizing alarms from sensor-based detection models in livestock production: a review on model performance and alarm-reducing methods. *Comp. Electron. Agr.* 133, 46–67. doi: 10.1016/j.compag.2016.12.008

Eckelkamp, E. A. (2019). Invited review: current state of wearable precision dairy technologies in disease detection. *Appl. Anim. Sci.* 35, 209–220. doi: 10.15232/aas.2018-01801

Ede, T., Lecorps, B., von Keyserlingk, M. A. G., and Weary, D. M. (2019). Scientific assessment of affective states in dairy cattle. *J. Dairy Sci.* 102, 10677–10694. doi: 10.3168/jds.2019-16325

FAWC (Farm Animal Welfare Council) (2009). *Farm Animal Welfare in Great Britain: Past, Present and Future*. FAWC, London.

Fernandez, A. P., Norton, T., Tullo, E., van Hertem, T., Youssef, A., Exxadaktylos, V., et al. (2018). Real-time monitoring of broiler flock's welfare status using camera-based technology. *Biosyst. Eng.* 173, 103–114. doi: 10.1016/j.biosystemseng.2018.05.008

Fogarty, E. S., Swain, D. L., Cronin, G., and Trotter, M. (2018). Autonomous on-animal sensors in sheep research: a systematic review. *Comp. Electron. Agr.* 150, 245–256. doi: 10.1016/j.compag.2018.04.017

Fournel, S., Rousseau, A. N., and Laberge, B. (2017). Rethinking environmental control strategy of confined animal housing systems through precision livestock farming. *Biosyst. Eng.* 155, 96–123. doi: 10.1016/j.biosystemseng.2016.12.005

Franks, B. (2019). What animals want. *Anim. Welfare* 28, 1–10. doi: 10.7120/09627286.28.1.001

Fraser, D. (2008). *Understanding Animal Welfare: the Science in its Cultural Context*. Universities Federation for Animal Welfare, Wiley-Blackwell, Chichester, UK.

Fraser, D., Duncan, I. J. H., Edwards, S. A., Grandin, T., Gregory, N. G., et al. (2013). General Principles for the welfare of animals in production systems: the underlying science and its application. *Vet. J.* 198, 19–27. doi: 10.1016/j.tvjl.2013.06.028

Fraser, D., and Nicol, C. J. (2011). "Preference and motivation research," in *Animal Welfare*, 2nd ed, eds M. C. Appleby, J. A. Mench, I. A. Olsson and B. O. Hughes (Wallingford, Oxfordshire: CABI), 183–199. doi: 10.1079/9781845936594.0183

Friel, M., Kunc, H. P., Griffin, K., Asher, L., and Collins, L. M. (2019). Positive and negative contexts predict duration of pig vocalisations. *Sci. Rep.* 9:2062. doi: 10.1038/s41598-019-38514-w

Gomez, Y., Bieler, R., Hankele, R., Zähner, M., Savary, P., and Hillmann, E. (2018). Evaluation of visible eye white and maximum eye temperature as non-invasive indicators of stress in dairy cows. *Appl. Anim. Behav. Sci.* 198, 1–8. doi: 10.1016/j.applanim.2017.10.001

Green, T. C., and Mellor, D. J. (2011). Extending ideas about animal welfare assessment to include 'quality of life' and related concepts. *New Zeal. Vet. J.* 59, 263–271. doi: 10.1080/00480169.2011.610283

Grinter, L. N., Campler, M. R., and Costa, J. H. C. (2019). Technical note: validation of a behavior-monitoring collar's precision and accuracy to measure rumination, feeding, and resting time of lactating dairy cows. *J. Dairy Sci.* 102: 3487–3494. doi: 10.3168/jds.2018-15563

Guesgen, M. J., and Bench, C. J. (2017). What can kinematics tell us about the affective states of animals? *Anim. Welfare* 25, 383–387. doi: 10.7120/09627286.26.4.383

Guy, J. H., Cain, P. J., Seddon, Y. M., Baxter, E. M., and Edwards, S. A. (2012). Economic evaluation of high welfare indoor farrowing systems for pigs. *Anim. Welfare* 21, 19–24. doi: 10.7120/096272812X13345905673520

Gygax, L. (2017). Wanting, liking and welfare: the role of affective states in proximate control of behaviour in vertebrates. *Ethology* 123, 689–704. doi: 10.1111/eth.12655

Gygax, L., and Hillmann, E. (2018). "Naturalness" and its relation to animal welfare from an ethological perspective. *Agriculture* 8:136. doi: 10.3390/agriculture8090136

Herborn, K. A., McElligott, A. G., Mitchell, M. A., Sandilands, V., Bradshaw, B., and Asher, L. (2020). Spectral entropy of early-life distress calls as an iceberg indicator of chicken welfare. *J. R. Soc. Interface* 17:167. doi: 10.1098/rsif.2020.0086

Herborn, K. A., Graves, J. L., Jerem, P., Evans, N. P., Nager, R., McCafferty, D. J., et al. (2015). Skin temperature reveals the intensity of acute stress. *Physiol. Behav.* 15, 225–230. doi: 10.1016/j.physbeh.2015.09.032

Hoerr, F. J. (2010). Clinical signs of immunosuppression in poultry. *Avian Dis*. 54, 2–15. doi: 10.1637/8909-043009-Review.1

Hurnik, J. F. (1993). Ethics and animal agriculture. *J. Agric. Environ. Ethic.* 6, 21–35.

Inbaraj, S., Sejian, V., and Ramasamy, S. (2019). Role of environmental stressor-host immune system-pathogen interactions in development of infectious disease in farm animals. *Biol. Rhythm Res.* 2019, 1–18. doi: 10.1080/09291016.2019.1695084

Jones, T. A., Donnelly, C. A., and Dawkims, M. S. (2005). Environmental and management factors affecting the welfare of chickens on commercial farms in the United Kingdom and Denmark stocked at five densities. *Poult. Sci.* 84, 1155–1165. doi: 10.1093/ps/84.8.1155

Jorquera-Chavez, M., Fuentes, S., Dunshea, F. R., Warner, R. D., Poblete, T., and Jogman, E. C. (2019). Modelling and validation of computer vision techniques to assess heart0rate, eye temperature, ear-base temperature and respiration rate in cattle. *Animals* 9:1089. doi: 10.3390/ani9121089

Kashiha, M. A., Green, A. R., Sales, T. G., Bahr, C., Berckmans, D., and Gates, R. (2014). Performance of an image processing system for hen tracking in an environmental preference chamber. *Poult. Sci.* 93, 2439–2445. doi: 10.3382/ps.2014-04078

Kilgour, R., Foster, T. M., Temple, W., Matthews, L. R., and Bremner, K. J. (1991). Operant technology applied to solving farm animal problems. *An assessment. Appl. Anim. Behav. Sci.* 30, 141–166. doi: 10.1016/0168-1591(91)90092-C

Koolhaas, J. M., Bartomolomucci, A., Buwalda, B., de Boer, S. F., Flugge, G., Korte, S. M., et al. (2011). Stress revisited: a critical evaluation of the stress concept. *Neurosci. Biobehav. Rev.* 35, 1291–1301. doi: 10.1016/j.neubiorev.2011.02.003

Kovacs, L., Kezer, L., Kezer, F. L., Jurkovich, V., Kulcsar-Huszenicza, M., and Tozser, J. (2015). Heart rate varisability as an indicator of chronic stress caused by lameness in dairy cows. *PLoS ONE* 1:e0134792. doi: 10.1371/journal.pone.0134792

Leliveld, L. M. C., Dupjan, S., Tuchscherer, A., and Puppe, B. (2016). Behavioural and physiological measures indicate subtle variations in the emotional valence of young pigs. *Physiol. Behav.* 157, 116–124. doi: 10.1016/j.physbeh.2016.02.002

Li, G. M., Hueng, Y. B., Chen, Z. Q., Chesser, G., D., Purswell, J., et al.(2021). Practices and applications of convolutional neural network-based computer vision systems in animal farming: a review. *Sensors* 21:1492. doi: 10.3390/s21041492

Li, N., Ren, Z., Li, D., and Zeng, L. (2020). Review: automated techniques for monitoring the behaviour and welfare of broilers and laying hens: towards the goal of precision livestock farming. *Animal* 14, 617–625. doi: 10.1017/S1751731119002155

Liakos, K. G., Busato, P., Moshou, D., Pearson, S., and Bochtids, D. (2018). Machine learning in agriculture: a review. *Sensors* 18:2674. doi: 10.3390/s18082674

Lovarelli, D., Becenetti, J., and Guarino, M. (2020). A review of cattle farming: is precision livestock farming the compromise for an environmental, economic and social sustainable production. *J. Clean. Prod.* 262:121409. doi: 10.1016/j.jclepro.2020.121409

McConnachie, E., Smid, A. M. C., Thompson, A. J., Weary, D. M., Gaworski, M. A., and von Keyserlingk, M. A. G. (2018). Cows are highly motivated to access a grooming substrate. *Biol. Lett.* 14:20180303. doi: 10.1098/rsbl.2018.0303

McLennan, K., and Mahmoud, M. (2019). Development of an automated pain facial expression detection systems for sheep (*Ovis aries*). *Animals* 9:196. doi: 10.3390/ani9040196

Mellor, D. J. (2016). Updating animal welfare thinking: moving beyond the 'Five Freedoms' towards 'a life worth living'. *Animals* 6:21. doi: 10.3390/ani6030021

Mendl, M., Burman, O. H. P., and Paul, E. S. (2010). An integrative and functional framework for the study of animal emotions and mood. *Proc.R. Soc. B* 277, 2895–2904. doi: 10.1098/rspb.2010.0303

Morota, G., Ventura, R. V., Silva, F. F., Koyama, M., and Fernandez, S. C. (2018). Machine learning and data mining advance predictive big data analytics in precision animal agriculture. *J. Anim. Sci.* 96, 1540–1550. doi: 10.1093/jas/sky014

Munksgaard, L., Rushen, J., de Passillé, A. M., and Krohn, C. C. (2011). Forced versus free traffic in an automated milking system. *Livest. Sci.* 138, 244–250. doi: 10.1016/j.livsci.2010.12.023

Nakata, A., Takahashi, M., Irie, M., and Swanson, N. G. (2010). Job satisfaction is associated with elevated natural killer cell immunity among healthy white-collar employees. *Brain Behav. Immun.* 24, 1268–1275. doi: 10.1016/j.bbi.2010.05.004

Neethirajan, S. (2017). Recent advances in wearable sensors for animal health management. *Sensing Bio-sens. Res.* 12, 16–29. doi: 10.1016/j.sbsr.2016.11.004

Nussbaum, M. C. (2004). "Beyond compassion and humanity. Justice for nonhuman animals," in *Animal Rights: Current Debates and New Directions*, eds C. S. Sunstein and M. C. Nussbaum (Oxford: Oxford University Press), Chapter 14, 299–320. doi: 10.1093/acprof:oso/9780195305104.003.0015

OIE (World Organization for Animal Health) (2012). Global Animal Welfare Strategy. OIE, Paris, France. Available online at: http://www.oie.int/fileadmin/

Home/eng/Animal_Welfare/docs/pdf/Others/EN_OIE_AW_Strategy.pdf (accessed May 8, 2020)

Palme, R. (2019). Non-invasive measurement of glucocorticoids: advances and problems. *Physiol. Behav*. 199, 229–243. doi: 10.1016/j.physbeh.2018.11.021

Patterson-Kane, E. G., Pittman, M., and Pajor, E. A. (2008). Operant animal welfare: productive approaches and persistent difficulties. *Anim. Welfare.* 17, 139–148.

Perakis, K., Lampathaki, F., Fenareti, L., Nikas, K., Georgiou, Y., Marko, O., et al. (2020). CYBELE-Fostering precision agriculture and livestock farming through secure access to large-scale HPC-enabled virtual industrial experimentation environments fostering scaleable big data analytics. *Comput. Netw*. 168:107035. doi: 10.1016/j.comnet.2019.107035

Pilette, D., Norton, T., Exadaktylos, V., and Berckmans, D. (2020). Individualized automated lameness detection in dairy cows and he impact of historical window length on algorithm performance. *Animal* 1, 409–417. doi: 10.1017/S1751731119001642

Pratelli, A., Cirone, F., Capozza, P., Trotta, A., Corrente, M., Balestrieri, A., and Buonavoglia, C. (2021). Bovine respiratory disease in beef calves supported long transport stress: an epidemiological study and strategies for control and prevention. *Res. Vet. Sci.* 35, 450–455. doi: 10.1016/j.rvsc.2020.11.002

Rabin, L. A. (2003). Maintaining behavioural diversity in captivity for conservation: natural behaviour management. *Anim. Welfare* 12, 85–94.

Ralph, C. R., and Tilbrook, A. J. (2016). The usefulness of measuring glucocorticoids for assessing animal welfare. *J. Anim. Sci.* 34, 457–470. doi: 10.2527/jas.2015-9645

Ramanathan, M., Yau, W. Y., Thalmann, N. M., and Teoh, E. K. (2019). Mutually reinforcing notion-pose for invariant action recognition. *Int. J. Biomet.* 11, 113–147. doi: 10.1504/IJBM.2019.099014

Rios, H. V., Waquil, P. D., de Carvalho, P. S., and Norton, T. (2020). How are information technologies addressing broiler welfare? A systematic review based on the Welfare Quality (R) Assessment. *Sustainability* 12:1413. doi: 10.3390/su12041413

Rodenberg, J. (2017). Robotic milking: technology, farm design and effects on work flow. *J. Dairy Sci.* 100, 7729–38. doi: 10.3168/jds.2016-11715

Rolls, E. T. (2021). Learning invariant object and spatial view representations in the brain using slow unsupervised learning. *Front. Comput. Neurosci*. 15:686239. doi: 10.3389/fncom.2021.686239

Rowe, E., Dawkins, M. S., and Gebhardt-Henrich. (2019). A systematic review of precision livestock farming in the poultry sector: is technology focused on improving bird welfare? *Animals* 9:614. doi: 10.3390/ani9090614

Rushen, J. (1986). Some problems with the physiological concept of 'stress'. *Aust. Vet. J.* 63, 359–361. doi: 10.1111/j.1751-0813.1986.tb02896.x

Silva, M., Ferrari, S., Costa, A., Aerts, J. M., Guarino, M., and Berckmans, D. (2008). Cough localization for the detection of respiratory diseases in pig houses. *Comput. Electron. Agr*. 64, 286–292. doi: 10.1016/j.compag.2008.05.024

Singh, R., Kushwaha, A. K. S., and Srivastava, R. (2019). Multi-view recognition system for human activity based on multiple features for video surveillance system. *Multimed. Tools Appl.* 78, 17165–17198. doi: 10.1007/s11042-018-7108-9

Stevenson, P. (2017). *Precision Livestock Farming: Could it Drive the Livestock Sector in the Wrong Direction*. Available online at: https://www.ciwf.org/research/animal-welfare/precision-livestock-farming-could-it-drive-the-livestock-sector-in-the-wrong-direction/ (accessed August 18, 2020).

Sun, Y. K., Huo, P. J., Wang, Y. J., Cui, Z. Q., Li, Y., Dai, B. S., et al. (2019). Automatic monitoring system for individual dairy cows based on a deep learning framework that provides identificatiob via body parts and estimation of body condition score. *J. Dairy Sci*. 102, 10140–10151. doi: 10.3168/jds.2018-16164

Takao, Y., Okuno, Y., Mori, Y., Asada, M., Yamanishi, K., and Iso, H. (2018). Associations of perceived mental stress, sense of purpose in life, and negative life events with the risk of incidental Herpes zosta and post herpetic neuralgia. *Am. J. Epidemiol.* 187, 251–259. doi: 10.1093/aje/kwx249

Taylor, N., Prescott, N., Perry, G., Potter, M., Le Sueur, C., and Wathes, C. (1996). Preference of growing pigs for illuminance. *Appl. Anim. Behav. Sci.* 96, 19–31. doi: 10.1016/j.applanim.2005.04.016

Thompson, P. B. (2017). *From Field to Fork: Food Ethics for Everyone*, *2nd ed.* Oxford: Oxford University Press.

Vandermeulen, J., Bahr, C., Johnston, D., Earley, B., Tullo, E., et al. (2016). Early recognition of bovine respiratory disease in calves using continuous monitoring of cough sounds. *Comp. Electron. Agr.*129, 15–26. doi: 10.1016/j.compag.2016.07.014

Veissier, I., Kling-Eveillard, F., Mialon, M. M., Silberberg, M., De Boyer Des Roches, A., et al. (2019). Precision livestock farming and animal welfare: is the numerical revolution in agriculture able to take into account animals' and farmers' needs? *INRA Prod. Anim.* 32, 281–290. doi: 10.20870/productions-animales.2019.32.2.2478

Volkmann, N., Kulig, B., and Kemper, N. (2019). Using the footfall sound of dairy cows for detecting claw lesions. *Animals* 9:78. doi: 10.3390/ani9030078

von Borell, E., Langbein, J., Després, G., Hansen, S., Leterrier, C., Marchent-Forde, J., et al. (2007). Heart rate variability as a measure of autonomic regulation of cardiac activity for assessing stress and welfare in farm animals—a review. *Physiol. Behav.* 92, 293–316. doi: 10.1016/j.physbeh.2007.01.007

Wathes, C. M. (2010). Lives worth living? *Vet. Rec.* 166, 468–9. doi: 10.1136/vr.c849

Wathes, C. M., Kristensen, H. H., Aerts, J.-M., and 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? *Comp. Electron. Agr.* 64, 2–10. doi: 10.1016/j.compag.2008.05.005

Weary, D. M., and Robbins, J. A. (2019). Understanding the multiple conceptions of animal welfare. *Anim. Welfare* 28, 33–40. doi: 10.7120/09627286.28.1.033

Webb, L. E., Veenhoven, R., Harfield, J. L., and Jensen, M. B. (2019). What is animal happiness? *Ann. NY Acad. Sci.* 438, 62–76. doi: 10.1111/nyas.13983

Welfare Quality® (2018). Available online at: http://www.EUwelfarequality.net/en-us/home/ (accessed May 25, 2020).

Werkheiser, I. (2020). Technology and responsibility: a discussion of underexamined risks and concerns in Precision Livestock Farming. *Anim. Front*. 10, 51–56. doi: 10.1093/af/vfz056

Westerath, H. S., Gygax, L., and Hillmann, E. (2014). Are special feed and being brushed judged positive by calves*? Appl. Anim. Behav. Sci.* 156, 12–21. doi: 10.1016/j.applanim.2014.04.003

Winckler, C. (2019). Assessing animal welfare at the farm level: do we care sufficiently about the individual*? Anim. Welfare* 28, 77–82. doi: 10.7120/09627286.28.1.077

Wood-Gush, D. G. M. (1971). *The Behaviour of the Domestic Fowl*. London: Heinemann Educational Books.

Wurtz, K., Camerlink, I., D'Eath, R. B., Fernandez, A. P., Norton, T., Steibel, J., et al. (2019). Recording behaviour of indoor-housed farm animals automatically using machine vision technology: a systematic review. *PLoS ONE* 14:e0226669. doi: 10.1371/journal.pone.0226669

Yeates, J. W. (2018). Naturalness and animal welfare. *Animals* 8:53. doi: 10.3390/ani8040053

Yost, M. A., Kitchen, N. R., Sudduth, K. A., Sadler, E. J., Drummond, S. T., and Volkmann, M. R. (2017). Long-term impact of a precision agriculture system on grain crop production. *Precis Agric*. 18, 823–842. doi: 10.1007/s11119-016-9490-5

Yufeng, G. E., Thomasson, A., and Ruixiu, S. (2011). Remote sensing of soil properties in precision agriculture: a review. *Earth Sci.* 5,

Zhuang, X. L., Bi, M. N., Guo, J. L., Wu, S. Y., and Zhang, T. M. (2018). Development of an early warning algorithm to detect sick broilers. *Comp. Electron Agr*. 144, 102–113. doi: 10.1016/j.compag.2017.11.032

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