Using precision farming to improve animal welfare

Elaine van Erp-van der Kooij[1,2] and S.M. Rutter[1,2*]

Address: [1]HAS University of Applied Sciences, Onderwijsboulevard 221, 's-Hertogenbosch, 5223 DE, The Netherlands.
[2]Harper Adams University, Newport, TF10 8NB, UK.

ORCID information: Elaine van Erp-van der Kooij (orcid: 0000-0002-9960-0107); S.M. Rutter (also known as Mark Rutter) (orcid: 0000-0002-9259-6061)

*__Correspondence:__ S.M. Rutter. Email: smrutter@harper-adams.ac.uk

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Abstract

Animal welfare is a multidimensional phenomenon and currently its on-farm assessment requires complex, multidimensional frameworks involving farm audits which are time-consuming, infrequent and expensive. The core principle of precision agriculture is to use sensor technologies to improve the efficiency of resource use by targeting resources to where they give a benefit. Precision livestock farming (PLF) enables farm animal management to move away from the group level to monitoring and managing individual animals. A range of precision livestock monitoring and control technologies have been developed, primarily to improve livestock production efficiency. Examples include using camera systems monitoring the movement of housed broiler chickens to detect problems with feeding systems or disease and leg-mounted accelerometers enabling the detection of the early stages of lameness in dairy cows. These systems are already improving farm animal welfare by, for example, improving the detection of health issues enabling more rapid treatment, or the detection of problems with feeding systems helping to reduce the risk of hunger. Environmental monitoring and control in buildings can improve animal comfort, and automatic milking systems facilitate animal choice and improve human-animal interactions. Although these precision livestock technologies monitor some parameters relevant to farm animal welfare (e.g. feeding, health), none of the systems yet provide the broad, multidimensional integration that is required to give a complete assessment of an animal's welfare. However, data from PLF sensors could potentially be integrated into automated animal welfare assessment systems, although further research is needed to define and validate this approach.

Keywords: animal welfare, precision livestock farming, welfare assessment

Review Methodology: The relevant literature was searched based on keywords including precision livestock farming, precision farming, smart farming, automatic monitoring and sensors in combination with the words welfare, behaviour, eating, drinking, locomotion, health, stress and dairy farming, pigs, poultry, broilers and laying hens. Literature was also identified using a forward search from the citations and a backward search using the references of the papers found through the keyword search. We searched the following databases: AGRIS, BioMed Central, CAB Direct, DOAJ, PubMed, ScienceDirect, Springer Link and Web of Science and used the search engine Google Scholar. We also spoke to colleagues and followed up on articles recommended by the Mendeley reference program.

Defining and assessing animal welfare

Several authors have proposed relatively simple *definitions* of animal welfare, for example Broom's based on the animal's 'attempts to cope with the environment' [1], Duncan's focus on 'how the animal feels' [2], Webster's 'fit and happy' [3] and Dawkins' 'are the animals healthy; do they have what they want?' [4]. However, these simple definitions do not translate into simple frameworks to assess animal welfare, as many factors contribute to health, feeling happy or coping, and there is a general consensus that animal welfare is a multidimensional phenomenon [5, 6]. This means that animal welfare *assessment* needs to include a broad range of assessment criteria or factors. The 'Five Freedoms' [1] framework has achieved worldwide recognition [7] and become the most widely recognised approach to assessing animal welfare in 41 years since it was originally proposed by the United Kingdom's Farm Animal Welfare Council [8]. The Five Freedoms originally covered 11 factors [6], but in the latest revision [7], it covers 9 (see column 1 in Table 1). The Five Freedoms are effectively outcome measures, and the associated provisions (see column 1 in Table 1) outline the husbandry procedures required to facilitate these outcomes [9]. One of the criticisms of the Five Freedoms is that animal welfare is more than the absence of cruelty and the provision of basic needs, but that we should also take into account the animal's positive experiences [5]. To address this, in 2009, FAWC proposed that an animal's quality of life could be classified as a life not worth living, a life worth living and a good life based on the balance between good and poor welfare [7]. Criticism of the Five Freedoms have also led to other welfare assessment frameworks being proposed.

The Welfare Quality framework [10] is based on animal as well as environmental factors, structured into four 'principles' and 12 criteria; three more factors than the current Five Freedoms. The Welfare quality framework is translated into assessment protocols for cows, pigs and poultry, but the combination of animal and farm factor assessment, to be scored by trained assessors, is rather time-consuming [11]. Attempts have been made to reduce the time taken for the Welfare Quality assessment protocols, with reductions ranging from 25% to 67% for broilers [12] and from 7–8 hours to 2 hours for dairy cows [13].

More recently, Mellor's Five Domains describe a highly structured approach to assessing animal welfare and is centred around the four internal domains of nutrition, environment, health, and behaviour, with the accumulation of these affects into the fifth domain, mental state [14]. These Five Domains have between them a total of 118 contributing factors, approximately 10 times more than the Welfare Quality framework.

Although varying considerably in detail, these three approaches to animal welfare assessment (i.e. Five Freedoms, Welfare Quality and the Five Domains) share a number of core characteristics and can be mapped onto each other (Table 1). They effectively present the same way to slice the welfare 'cake', albeit with different sized slices.

What is precision livestock farming?

The application of precision agriculture approaches in the livestock industry (known as precision livestock farming or PLF) uses advanced technologies aimed at automatic, real-time monitoring of animal behaviour, health, environmental impact and production [15]. The purpose is to detect deviations at an early stage and improve animal health, welfare and efficiency, expecting an improvement in production sustainability [16]. Although one of the aims of PLF is to improve animal welfare, most of the systems monitor just one or only a few factors. The results of these measurements are compared to a general standard or farm-specific threshold, and a conclusion or alert is communicated to the farmer, prompting them to check the animal and take action if necessary. This is useful in farm management but does not provide a complete welfare assessment. Attempts to establish simple 'iceberg' indicators of animal welfare (i.e. using only one or a few factors) so far have been unsuccessful [17].

Table 1. The relationships between the various components of three welfare assessment frameworks, that is FAWC 'Five Freedoms', 'Welfare Quality®' principles and criteria and Mellor's 'Five Domains' model.

<table>
<tr><th rowspan="2">FAWC 'Five Freedoms'
and the associated provisions</th><th colspan="2">'Welfare Quality®' Programme</th><th colspan="2" rowspan="2">Mellor's 'Five Domains' Model (118 factors)</th></tr>
<tr><th>4 Principles</th><th>12 Criteria</th></tr>
<tr><td rowspan="2">Freedom from hunger and thirst *by ready access to water and a diet to maintain health and vigour*</td><td rowspan="2">Good feeding</td><td>Absence of prolonged hunger</td><td rowspan="2">Nutrition (11 factors)</td><td rowspan="11">Mental State (58 factors)</td></tr>
<tr><td>Absence of prolonged thirst</td></tr>
<tr><td rowspan="3">Freedom from discomfort *by providing a suitable environment including shelter and a comfortable resting area*</td><td rowspan="3">Good environment</td><td>Comfort around resting</td><td rowspan="3">Environment (18 factors)</td></tr>
<tr><td>Thermal comfort</td></tr>
<tr><td>Ease of movement</td></tr>
<tr><td rowspan="3">Freedom from pain, injury or disease *by prevention or rapid diagnosis and treatment*</td><td rowspan="3">Good health</td><td>Absence of injuries</td><td rowspan="3">Health (12 factors)</td></tr>
<tr><td>Absence of disease</td></tr>
<tr><td>Absence of pain induced by management procedures</td></tr>
<tr><td rowspan="3">Freedom to express normal behaviour *by providing sufficient space, proper facilities and company of the animal's own kind*</td><td rowspan="4">Appropriate behaviour</td><td>Expression of social behaviours</td><td rowspan="3">Behaviour (19 factors)</td></tr>
<tr><td>Expression of other behaviours</td></tr>
<tr><td>Good human-animal relationship</td></tr>
<tr><td>Freedom from fear and distress *by ensuring conditions which avoid mental suffering*</td><td>Positive emotional state</td><td colspan="2"></td></tr>
</table>

The numbers in brackets denote the numbers of factors Mellor lists in each of his domains.

PLF systems

There are several levels of PLF, varying from collecting and analysing data at the group level down to monitoring individual animals, utilising sensors that can be static, moving or animal-mounted [18]. The technology ranges from monitoring production and fertility to health and behaviour; some systems monitor environmental factors to control climate conditions and there are robotic systems that automate human handling such as milking, feeding and cleaning [18]. Many PLF systems are already commercially available for on-farm use (Table 2), with further systems in development and likely to be commercialised in the future (Table 3).

PLF systems monitoring feeding and drinking

Eating and drinking data can be derived directly from automatic feeders [19] or water meters [20, 21], or indirectly from sensors that monitor behaviour, location or the sound created by animals. In dairy cows, feeding behaviour and grazing can be monitored automatically using activity meters, location sensors or sound sensors [22–25]. Rumination can be measured with a neck collar, based on accelerometer data or sound [26, 27]. Sound analysis can also be used to measure the time budget of the combined behaviour of lying and ruminating in dairy cows [28] or to detect 'gakel' calls in laying hens [29] which can be linked directly to the state of hunger [30]. Feed intake in broilers can be measured using sound analysis, correctly detecting 93% of pecking sounds and 90% of feed intake [31], or by monitoring the frequency of vocalisations to estimate weight, since this is highly correlated with growth rate [32]. Pig weight and growth rate can be estimated using cameras [33–35]. Thus, data pertinent to the assessment of hunger and thirst can be automatically collected [30].

PLF systems for monitoring animal health

Several sensor systems can be used to detect illness in farm animals, using animal-mounted sensors or sensors incorporated into farm infrastructure.

Body temperature can be measured directly with animal-mounted sensors or indirectly with thermographic cameras [36]. Thermographic cameras can detect mastitis in dairy cows [37] and vaccination response in piglets [38]. Body temperature can be monitored with rumen boluses in dairy cows; they can also monitor rumen motility and pH, as an indicator for metabolic disease [39–42].

Accelerometers measuring activity in dairy cows not only detect oestrus but also behavioural changes signalling disease [18, 43–46], such as lameness [47–51] or Johne's disease [52]. Accelerometers can also be used to score lameness in pigs [38]. In broilers, Avian influenza can be detected from analysing abnormal activity based on accelerometers [53, 54] and temperature variations [55].

Symptoms of disease can be detected with sound analysis, for example coughing in pigs [56–58] and in calves [59] and rale sounds in chickens, as symptoms for lung disease [60]. Lameness in cows, pigs or poultry can be detected with force plates or pressure mats [38, 61, 62]. Monitoring behavioural changes can be used to detect or predict disease, for example drinking behaviour that can be a sign of diarrhoea in pigs [20]. Cameras and vision systems can be used to monitor leg health in broilers, using optical flow [63] or using image-based activity monitoring in pigs and poultry [51, 64]. In milk samples, beta-hydroxybutyrate (BHB) and lactate dehydrogenase (LDH) can be measured automatically as an indicator for metabolic disease or mastitis in dairy cows [65].

PLF systems monitoring housing conditions and animal comfort

Most pig and poultry farms have an automatic climate control systems, including sensors that measure temperature and relative humidity (RH), air speed or carbon dioxide (CO_2). These sensors are used to regulate the indoor climate. Ambient conditions for pigs and poultry can be monitored using these data. In dairy farms, commercial climate condition monitoring is in development [40]. Indoor air quality can be monitored with several sensor systems [66].

Indirect measures of climate conditions are also possible. Sound can be used as a measure for thermal comfort in laying hens, recognising alarm calls, squawks and 'gakel' calls. These can be linked to a heat stress index (THI) [29]. In young chicks during the heating phase, thermal comfort can be assessed from the frequency and amplitude of the sound data [67]. Vision can also be used to determine thermal comfort. Measuring spatial distribution of pigs in a pen using colour vision can provide an indication of thermal comfort [68].

PLF systems monitoring animal behaviour

Behaviours of animals can be monitored using location or activity data from animal-mounted sensors in laying hens [69], dairy cows [70–73] and pigs [74]. In poultry, RFID can be used to monitor behaviour including locomotion, feeding and resting, and combined with pressure sensors in smart nest boxes, laying performance can also be monitored. Vision systems can detect body postures in poultry and monitor behaviours such as wing spreading, scratching and preening [75].

In dairy farms, activity sensors developed for heat detection are also used for behaviour monitoring and for reporting deviations in behaviour [25, 76–79]. Lying,

Table 2. Examples of PLF sensors commercially available for on-farm use at the time of writing.

PLF sensor	Animal species	Where	What it measures	Why	Company website
Accelerometer	Dairy cows	Leg-mounted	Activity	Oestrus, health	Nedap.com; Icerobotics.com; Afimilk.com; Boumatic.com; Fullwood.com; Insentec.eu; Connecterra.io
Accelerometer	Dairy cows	Neck-mounted	Activity	Oestrus, health, rumination	Nedap.com; Nmr.co.uk; Lely.com; Rumiwatch.ch; Cowlar.com
Accelerometer,	Dairy cows	Rumen bolus	Activity	Oestrus, health	SmaXtec.com; Moonsyst.com
Accelerometer	Dairy cows	Ear tag	Activity	Oestrus, health	CowManager.com; Quantifiedag.com
Accelerometer	Dairy cows	Tail-mounted	Tail posture	Onset of calving	Moocall.com
Accelerometer	Sows	Ear tag	Activity	Oestrus, health, lameness, onset of birth	RemoteInsights.net
Temperature sensor	Dairy cows	Ear tag	Body temperature	Health	CowManager.com; Tekvet.com; Moonsyst.com
Temperature sensor	Dairy cows	Rumen bolus	Body temperature	Health	SmaXtec.com; Moonsyst.com; Smartstock-usa.com
pH sensor	Dairy cows	Rumen bolus	Body temperature	Health	SmaXtec.com; Moonsyst.com
milk characteristics	Dairy cows	Milking machine, online or inline	progesterone, BHB, urea, LDH	Pregnancy, ketosis, digestion, mastitis	Delaval.com
Milk characteristics	Dairy cows	Milking machine	Milk flow, colour, conductivity	Mastitis	*Several manufacturers*
Sound analysis	Dairy cows	Neck tag	Rumination	Health, stress	Fabdec.com; Scrdairy.com
Sound analysis	Pigs	Pig unit	Coughing	Health	Soundtalks.com
Vision	Dairy cows	Camera	Body Condition Score	Health, nutrition	Delaval.com
Vision	Dairy cows	Camera	Face recognition	Identification	Cainthus.com
Vision	Pigs	Camera	Body weight	Production, health	Fancom.com
Vision	Pigs	Tablet, smartphone	Body weight	Production	Itochu.co.jp
Vision	Pigs	Camera	Behaviour	Health status	Serket-tech.com
Vision	Pigs	Camera	Face recognition	Identification	m.yingzi.com
Vision	Broilers	Camera	Distribution and activity	Health, stress	Fancom.com
Positioning	Dairy cows	Beacons and neck tags	Locomotion, behaviour	Health, stress, reproduction	Nedap.com; Ibodairystore.com
Positioning	Dairy cows	Wireless sensor network	Locomotion, behaviour	Health, stress, reproduction	Omnisense.com; Ubisense.com
Positioning	Laying hens	UWB sensor in backpack	Locomotion, behaviour	Health	Sensolus.com
Weighing device	Dairy cows	Dairy farm, feeder	Weight and feed intake	Growth	Growsafe.com; Ricelake.com
Weighing device	Broilers	Poultry farm	Weight	Growth	Bigdutchman.com; Fancom.com; Veit.cz; Opticon-agri.com; Sodalec.fr; Choretime.com
Weighing device	Pigs	Pig pen	Weight	Growth, sorting	Pigscale.com; Osbornelivestock-equipment.com; Msschippers.com
Pressure sensor	Dairy cows	Floor sensor	Leg pressure	Lameness	Boumatic.com
Ultrasonic sensor	Dairy cows	Foot bath sensor	Claw shape	Lameness, claw health	Schippers.nl

walking, eating and standing behaviour of dairy cows can be measured quite accurately with activity meters on a leg, neck or ear tag [25, 76, 80]. Behaviour in pigs can be automatically monitored with several methods [81] such as vision systems based on pixel differences [82] or image analysis based on location in the pen [74]. Walking in pigs can be detected with a 'Kinect' motion-sensing camera [83].

It is also possible to detect some abnormal and damaging behaviours. An audio-based monitoring system for suckling piglets to detect crushing has been developed, but it generates many false-positives [84]. Sound analysis can detect feather pecking in laying hens based on squawks and total vocalisations [85]. Sound analysis can also detect pig screams and aggression [38]. Tail-biting in pigs can be

Table 3. Examples of PLF sensors in development and not yet commercially available for on-farm use at the time of writing.

PLF sensor	Animal species	Where	What it measures	Why
Accelerometer	Sows	Sensor in backpack	Posture, lying and standing	Farrowing sows, piglet survival
Accelerometer	Laying hens	Leg tag	Activity	Locomotion
Sound analysis	Pigs	Pig unit	Stress calls	Stress
Sound analysis	Laying hens	Poultry unit	Vocalisations, rale sounds, gakel calls	Health, stress
Sound analysis	Broilers	Poultry unit	Feed intake	Production, health
Sound analysis	Broilers	Poultry unit	Weight	Production, health
Vision	Dairy cows	Camera	Posture	Lameness
Vision	Pigs	Camera	Behaviour	Heat stress, thermal comfort
Vision	Pigs	Camera	Locomotion	Lameness
Vision	Pigs	Camera	Tail posture	Tail biting
Vision	Pigs	Camera	Location	Health, heat stress
Vision	Pigs	Camera	Behaviour	Aggression
Vision	Broilers	Camera	Locomotion	Lameness
Vision	Broilers	Camera	Body weight	Production, health
Vision	Broilers	Camera	Behaviour	Production, health
Vision	Broilers	Camera	Posture	Health, influenza
Positioning	Sows	UWB sensor	Locomotion, behaviour	Health
Positioning	Laying hens	RFID leg tags	Locomotion, resting	Health, activity
Light barriers	Sows	Farrowing crate	Activity	Parturition
Heart rate sensor	Dairy cows	Chest band	Heart rate	Health, stress

predicted using electronic feeder data, or using vision systems detecting lowered tail postures [86, 87].

PLF systems measuring distress

Stress calls in pigs can be detected using sound analysis [19, 88–90]; sound analysis can also detect heat stress in broilers [91] and different stress calls in cows can be recognised [92]. The rise in heat production during stress can be measured using a thermographic camera in pigs, cows and laying hens [93–95]. Finally, automatic heart rate measurements, corrected for activity, can be used to measure stress [96].

Welfare in farms with PLF systems

PLF to monitor welfare

Some attempts have been made to integrate several measures into an automated assessment of animal welfare. In a review on dairy cow technologies to automatically assess welfare, it was concluded that although manufacturers often claim to offer 'complete solutions', no system offers everything that could be achieved by using a full combination of all systems operating together, and almost without exception, the different technologies operate 'stand-alone' and will not communicate with each other [97]. In a broiler study, a Welfare Quality assessment was linked to vision data of a broiler flock. Relationships were found between deviations in distribution of the flock and footpad lesions, and between activity deviations and hock burns; activity and occupation pattern deviations were linked to the welfare assessments scores [98]. Similar results were found in a study where broilers were assessed by human experts and where gait scores could be predicted from flock data and automatic activity monitoring [64].

The human-animal relationship is important for animal welfare and could be measured automatically. The eYeNamic camera system can measure activity and distribution of broilers in the farm when someone walks through—an alternative to the human avoidance test of the Welfare Quality Protocol [99].

An integrated approach to animal welfare assessment should be possible (Fig. 1), but this approach needs to be further defined and validated.

Possible harm to welfare from PLF

The greatest uptake of PLF technologies to date has been in intensive animal production systems, and there is a risk the technology may be used to further intensify production in systems with little opportunity to enhance animal welfare by promoting positive experiences [100]. Another risk of on-farm automation is decreased contact between farmer and animals, and this may harm the human-animal

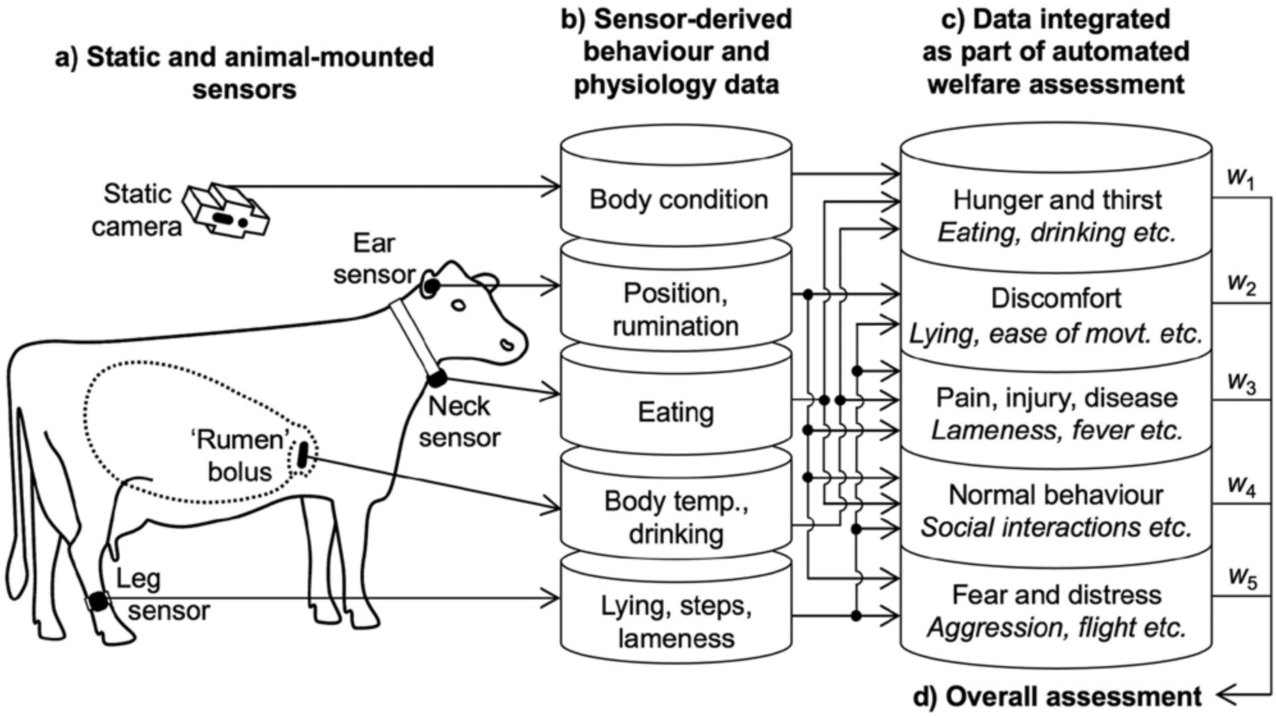

Figure 1. A simplified visualisation of the possible integration of PLF sensor data as part of an automated welfare assessment system. Several commercially available sensors (a) provide a variety of behavioural and physiological data (b). The use of multiple sensors on individual animals is currently not commercially viable. However, in future, lower sensor costs and better data integration will improve sensor-based health and welfare monitoring, improving the return on investment and making the use of multiple sensors per animal commercially viable. The data derived from the sensors are integrated into an automated welfare assessment (c). This example is based on the FAWC 'Five Freedoms', but other welfare assessment frameworks could be used. Some behaviour/physiology data will only be relevant to one welfare factor, but other data will be relevant to multiple welfare factors. This figure shows only a few examples of relevant data, and the system will be a lot more complex in practice. The assessment outcome from each 'Freedom' can be further integrated into a single overall welfare assessment (d) using factor weightings (w_1 to w_5). These weightings could be based on expert opinion or could be set dynamically in, for example, a smartphone 'app', letting consumers apply their own welfare assessment weightings to animal products whilst they shop.

relationship and decrease the opportunities to directly observe the health and well-being of the animals [101]. Farmers may become over-reliant on PLF and might miss signs of other diseases [102]. Techniques need to be understood prior to implementation, otherwise they will probably not be applied in an optimal way with maximum benefits for the animals and the farm [102]. In practice, farmers often do not understand PLF systems [103]. This also means that when PLF technologies malfunction, delays in repairing them can lead to welfare risks for the animals [104], and it is important to build in fail-safe mechanisms to reduce these risks [18]. PLF systems are intended to be tools to help expert stockperson manage their animals more effectively and not replace their skills [18].

PLF to improve animal welfare

In theory, PLF systems can improve welfare by optimising nutrient supply, based on automated growth monitoring or weight measurements [102], by early detection of disease, such as lameness or mastitis, as well as early detection of maladaptive behaviours such as feather pecking and tail-biting [102], and by improving housing conditions with devices such as robot scrapers and automated climate control systems [105, 106]. Webster [9] argues that giving animals the ability to make choices that promote their own quality of life could help improve welfare, and this could be achieved with technologies that facilitate 'choice', such as individual feeding, robotic milking or voluntary showering facilities [107]. PLF systems may increase welfare if the farmer responds adequately to the PLF system alerts; however, good tools do not automatically guarantee good utilisation by a stockperson.

In a field study with 23 farms that switched to an automatic milking system (AMS), many of the farmers reported that cows were calmer in comparison to cows milked in conventional milking systems (CMS). There was less of a herd hierarchy and less 'bullying'; yields increased and after an initial adjustment period, lameness and mastitis levels decreased [108]. In another study with five transitioned AMS farms, farmers spent less time interacting with the cows, but the cows were less fearful around people than in the CMS. The avoidance distance of cows in the AMS had decreased, and although when moving cows, farmers had to shout more, cows ran or slipped less often when trying to avoid the farmer [109].

In a large European study on PLF, most of the 13 pig and poultry farmers that were interviewed emphasised that the personal contact with the animals cannot be replaced by video cameras, but that PLF systems can be a great help in daily life. One farmer responded that he understands his animals much better after starting to use PLF monitoring [103].

Conclusion

The fact that animal welfare is a multidimensional phenomenon means that welfare assessment protocols are, by necessity, complex, and this complexity makes the manual assessment of welfare on farms a laborious, time-consuming and expensive process, limiting the utility of the protocols. A range of PLF sensors have been developed to improve the efficiency of animal production by optimising management. Data from these sensors could be integrated into automated welfare assessment systems although further research is needed to define and validate this approach. As well as providing a tool for the farmer to help monitor and manage animal welfare, PLF technologies also have the potential to improve farm animal welfare in several ways, such as improving the living environment, early detection of disease or by facilitating animal choice.

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