



# 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

## 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

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(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 (Alsaad 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; Alsaad 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 be 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; Gygas, 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 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; Gygas, 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 of smart farming technology.

## AUTHOR CONTRIBUTIONS

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

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