A framework for transparency in precision livestock farming

K. Elliott[1] and I. Werkheiser[2,*]
[1]*Department of Fisheries and Wildlife, Michigan State University, East Lansing, MI, USA*
[2]*Department of Philosophy, University of Texas Rio Grande Valley, Edinburg, TX, USA*
[*]Corresponding author: Ian Werkheiser, ian.werkheiser@utrgv.edu

Abstract

As precision livestock farming (PLF) technologies emerge, it is important to consider their social and ethical dimensions. Reviews of PLF have highlighted the importance of considering ethical issues related to privacy, security, and welfare. However, little attention has been paid to ethical issues related to *transparency* regarding these technologies. This paper proposes a framework for developing responsible transparency in the context of PLF. It examines the kinds of information that could be ethically important to disclose about these technologies, the different audiences that might care about this information, the challenges involved in achieving transparency for these audiences, and some promising strategies for addressing these challenges. For example, with respect to the information to be disclosed, efforts to foster transparency could focus on: (1) information about the goals and priorities of those developing PLF systems; (2) details about how the systems operate; (3) information about implicit values that could be embedded in the systems; and/or (4) characteristics of the machine learning algorithms often incorporated into these systems. In many cases, this information is likely to be difficult to obtain or communicate meaningfully to relevant audiences (e.g., farmers, consumers, industry, and/or regulators). Some of the potential steps for addressing these challenges include fostering collaborations between the developers and users of PLF systems, developing techniques for identifying and disclosing important forms of information, and pursuing forms of PLF that can be responsibly employed with less transparency. Given the complexity of transparency and its ethical and practical importance, a framework for developing and evaluating transparency will be an important element of ongoing PLF research.

Background

Precision livestock farming (PLF) is an important developing suite of technologies (see e.g., Benjamin and Yick 2019; Berckmans 2017; Neethirajan and Kemp 2021; Norton et al., 2019). The goal of PLF is "to manage individual animals by continuous real-time monitoring of health, welfare, production/reproduction, and environmental impact" (Berckmans 2017). It involves collecting information about the well-being of livestock through a range of sensors that can gather data through images, sounds, heart rate monitors, accelerometers, chemical analysis of waste, and a range of other tools. Some of these tools are currently in use, and many others are in development (e.g., Brier et al., 2020; Thompson et al., 2021; Vaintrub et al., 2021). These data are typically analyzed using algorithms that turn the low-level data into meaningful information that can guide the decision-making of farmers. PLF can also operate via a "closed loop" system, whereby systems can self-correct based on the collected data without depending on human guidance (e.g., Frost et al., 2003). These closed-loop systems can be facilitated by machine learning applied to large datasets of instrument data and outcomes, which can generate insights into connections between variables that human farmers would not look for or notice as well as faster and more accurate prediction of outcomes for animals based on limited information (Fernandes et al., 2020; Gauthier et al., 2022).

PLF has the potential to generate a number of benefits for farmers, consumers, and farmed animals. For example, as the number of animals on farms increases, it can be more difficult to ensure their welfare, but PLF can help farmers to keep closer track of their livestock (Benjamin and Yik 2019). For animals who experience stress in the presence of humans, PLF could also ease their stress by allowing them to be monitored with less direct human interaction (Werkheiser 2018). PLF could also ease the workload on farmers by creating automated systems that address potential problems without requiring human intervention (Frost et al., 2003). PLF can also promote sustainability (Tullo et al., 2019; Lovarelli et al., 2020), such as by enabling farmers to feed their animals with more precision, thereby avoiding waste (Pomar et al., 2009 and 2011), thus increasing both environmental and economic sustainability for the farm. PLF can even benefit consumers by facilitating more careful tracking of animals through the supply chain, thereby providing greater transparency for consumers who want to know where animals have been and how they have been treated (Neethirajan and Kemp 2021).

Nevertheless, PLF also generates ethical and social issues that need to be addressed if it is to be implemented in a socially responsible fashion. For example, PLF could contribute to the general trend toward consolidating smaller farms into larger ones, thereby altering rural communities and eliminating agricultural jobs (Werkheiser 2018). One might also worry that PLF could be used as a "cover" to argue that agricultural intensification is compatible with protecting animal welfare, whereas critics might contend that farm animals would actually be better off on smaller, more traditional farms (see Thompson et al., 2021). Privacy is another important ethical issue raised by PLF (Neethirajan and Kemp 2021). Given all the data collected through these systems, it will be essential to develop policies governing the sharing of these data with outside parties. Finally, one might worry about the ways that PLF could change the relationships between farmers and their livestock by eliminating the direct connections that farmers currently have as they assess the well-being of their animals (Bovenkerk et al., 2002; Werkheiser 2018).

Although many of these ethical issues have begun to be discussed in the scholarly literature on PLF, the issue of transparency about PLF has received relatively little attention thus far. There has been some discussion about the potential for PLF, in conjunction with technologies like blockchain, to provide transparency for consumers about the paths that animals have taken through the production process (Neethirajan and Kemp 2021), but this literature does not focus on the need for transparency about the nature of PLF technologies themselves. Although a few authors have begun to call for this kind of broader transparency about the values embedded in PLF systems (Thompson et al., 2021), there has been little discussion about how best to achieve this form of transparency or about the particular challenges that arise in doing so. This is an important gap because transparency will be crucial for pursuing PLF in a responsible fashion. The open science movement has recently highlighted the important role that transparency plays in promoting reproducible science, accelerating advances, and fostering public engagement with scientific research (Elliott and Resnik 2019; NAS 2018; Royal Society 2012). In the context of PLF, transparency is especially important because there are a number of values at play in this area of research (e.g., animal welfare, profit, sustainability, rural development, and so on). These values can come into conflict, and they can be interpreted in different ways (Werkheiser 2018), so transparency is important to enable farmers and consumers to decide what kinds of PLF systems actually help them to achieve their goals. However, transparency is not a simple concept. One might assume that it is merely a simple question of making information available, but in fact meaningful forms of transparency must typically be actively pursued. When achieved it can take many different forms, and it can come with costs as well as benefits (Elliott 2022). Some individuals might not even find transparency to be particularly helpful, especially if they have independent reasons for trusting scientific and technological systems. Thus, it is important to clarify what kinds of transparency are most important in different PLF contexts and how best to pursue them.

This paper proposes a framework for pursuing transparency about PLF. Building on a more general taxonomy of transparency developed by Elliott (2022), the framework consists of four parts: audience, content, challenges, and strategies (see Figure 1). According to this framework, those seeking to promote transparency about PLF should first consider, in specific contexts, the audiences toward which they are striving to provide information. Building on this consideration of audiences, they can consider the specific content that is most relevant to disclose. In order to communicate this content in a meaningful way, it is important to recognize the challenges that can make this difficult to achieve. Finally, drawing on the other elements of the framework, strategies can be developed for achieving meaningful forms of transparency. The following sections of this paper consider each of the four elements of the figure in the context of PLF. Although this framework has been developed specifically for application to PLF, many of its features could also be applicable to other areas of agriculture and biotechnology in general.

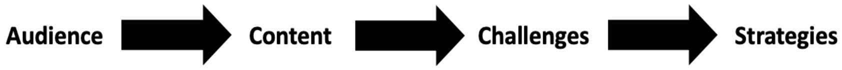

Figure 1: Representation of a framework for achieving transparency in the context of PLF.

Audience

In order to provide appropriate transparency, it is important to consider the audience toward which information is being directed because different audiences have different informational needs and different ways of obtaining information. Designers are often called on to consider "society," but this is too large a group with too disparate informational needs to be a single audience in this model. Instead, they need to be broken down into different interest groups. For example, the open science movement has focused on communicating information in ways that serve other scientists and technologists. While some elements of the open science movement can be helpful to non-specialists (e.g., publishing articles in open access formats), most features of the movement (e.g., making raw data available in publicly accessible databases) are geared primarily toward the scientific community. To meet the needs of non-specialists, it is often insufficient merely to make information available; the information generally needs to be interpreted in ways that are meaningful to them (Elliott and Resnik 2019). In the context of PLF, we suggest at least five different audiences that could have unique informational needs: scientists and engineers, farmers, consumers, industry groups, and regulators.

Scientists and engineers are likely to be interested in fairly traditional elements of open science such as open data and open access to research materials. In contrast, farmers are less likely to want this technical information and are more likely to want the "take-home" lessons about what these systems can do, how they work, and what their limitations are. Consumers would generally not even care about the working of the systems, but at least some consumers might be interested in the "implicit values" associated with the systems (e.g.., whether animal products from farms that employ PLF systems promote particular values concerning animal welfare or sustainability). Various industry groups, such as meat-packing companies, distributors, wholesalers, grocery stores, and restaurants, are likely to have a mixture of informational needs that could vary depending on how closely they work with farmers, regulators, or consumers. Finally, regulators are likely to be interested in the extent to which PLF systems can be designed to ensure compliance with regulations, whether they could inadvertently violate them, and whether compliance with regulations would become more or less difficult to verify when using the systems. These five categories do not include all the audiences that could be considered, and they elide important differences within specific audience categories, such as consumers or industry groups. Moreover, we acknowledge that we have characterized these groups in terms of likely informational needs, but it would be important to actually interact with these audiences in order to determine their informational needs in more concrete detail.

Content

The second component of our framework for transparency about PLF is the content to be disclosed. We have already seen that different audiences are likely to care about different kinds of information. Without providing an exhaustive discussion of all the kinds of content that could be discussed, we can suggest five major categories of information about PLF that could be disclosed as part of a transparency initiative: the basic workings of a PLF system, including its major strengths and limitations; a second category of information focusing not so much on how PLF systems work but on the data generated by them; information concerning the operation of the machine learning algorithms associated with some PLF systems; information about whether the developers of the system share the same values as the audience, such as animal welfare or sustainability (including what the developers mean by these complex terms); and information about the implicit values embedded in the PLF system as a whole, such as the ways in which it optimizes some conception of efficiency or maximizes the agency of the user.

Challenges

The next component of our proposed framework is the challenges associated with pursuing transparency. Many of these challenges have already emerged from our discussion of different audiences and content. For example, one challenge is that those developing PLF systems might not have a clear understanding of the different audiences they need to be considering and the kinds of content they want to know. Even if they could identify the relevant audiences, they might have difficulty in some cases explaining the technical details of how their systems work. Especially in the case of closed-loop systems that gather information about the animals and make automatic corrections in response to the available information, the systems might be too complex to explain easily to those who might want to know how they operate.

But even if the developers could find a way to disclose all the detailed information that some audiences might want, another challenge is that the developers themselves might be ignorant of some relevant information. As discussed above, some audiences might want to know how PLF systems implicitly promote some values (e.g., particular conceptions of animal welfare) over others. However, when developing new technological innovations, it is often unclear—even to the developers—how they promote particular values or interests over others.

Another challenge to successful communication is trust between developers and potential users. If those trying to communicate the information do not trust the receivers, it is possible that they will try to manipulate rather than inform them to get a desired outcome or protect themselves, or simplify the information they are communicating to the point that it becomes unhelpful or even misleading or incorrect. If the receivers do not trust the communicators, they may not be able to take up any of the information they are being provided, even if it is in their own interest to do so. While some trust issues have to do with presentation style and other tools of rhetoric, and some trust issues have to do with the creation and maintenance of relationships between the various groups, it is also the case that previous harmful incidents can lead to justifiably low trust in ways that are quite difficult to overcome (Whyte and Crease 2010).

A separate but related challenge to achieving transparency involves the motivations and interests of those offering or receiving the information. For example, those promoting PLF systems might prefer not to acknowledge some of the systems' weaknesses or the ways the systems prioritize some values over others. In addition, those using the systems might not want to disclose certain kinds of data generated by the systems (e.g., about rates of disease or injuries or other animal welfare concerns). Although this reticence to share information might sometimes be narrow-minded and self-serving, it could also reflect the legitimate concern that those receiving the information could misinterpret it and draw illegitimate conclusions. It could also reflect companies' concerns about protecting their intellectual property and safeguarding confidential business information. These IP and related concerns might differ between different countries' IP regimes, making communication across national boundaries more difficult. For farmers, the fear of providing detailed information about their operations might even motivate some of them not to adopt PLF systems at all.

Finally, the use of machine learning algorithms in PLF systems raises special challenges, because unlike complex models which are understood by designers but difficult to explain to the public, even developers might not know what factors are responsible for the algorithms' outputs. As a result, the developers might be unable to provide a number of other relevant pieces of information. For example, they might not be able to identify the precise conditions under which the systems could become unreliable. They also might be unable to identify important biases, limitations, or "blind spots" that affect the systems. These limitations could be caused by biases in the training data used to develop the system, or they could be a function of the particular phenomena that the algorithms focus on. Without understanding how the algorithms work, it could be very difficult to provide detailed information about their strengths and weaknesses and the implicit values associated with them. This is particularly the case for the subset of machine learning commonly referred to as "deep learning" algorithms, in which programmers do not set which aspects of the environment the system is tracking.

Strategies

The final component of our transparency framework is to explore strategies for providing relevant content to audiences in a manner that overcomes major challenges. Although different situations and challenges are likely to call for different strategies, some general ones could prove helpful under a variety of circumstances. For example, one important kind of strategy is for the developers of PLF systems to collaborate with end users during the development process. One benefit of this co-creation process is that it helps the end users to understand the major features of PLF systems, and thus it provides a form of transparency that would be difficult to provide otherwise. In addition, when users and developers collaborate, they are more likely to identify ways in which implicit values could be embedded in the operation of the systems. Thus, this process of collaboration "early and often" (Yosie and Herbst, 1998) can be especially helpful for uncovering features of PLF systems that could be important to disclose but that would not have even been recognized otherwise (See Thompson et al., 2021's discussion of an "ethical matrix" for a useful framework for these stakeholders to express their ethical concerns).

Another, and somewhat less ambitious, kind of strategy to address transparency challenges is to design PLF systems in ways that require less transparency. One way to do this is to make systems less complex. For example, whereas a closed-loop system might leave farmers "in the dark" about why particular changes are being made by the system, an open-loop system might give the farmers more control and understanding of what is happening. For instance, in an open-loop system, farmers might be notified that something is wrong or sub-optimal. The farmers could then investigate and decide whether there is indeed a problem and how they want to address it. Because the PLF system would not be making as many decisions on their behalf, farmers would not need to demand as much transparency from it. Similarly, if a PLF system were designed so that the farmers could control more features of how it operated, that could also obviate some of the need for transparency. For example, if farmers could choose what temperatures they wanted the system to maintain, what amount of food to provide, what levels of activity they expected from the animals, and so on, they would be in control over more variables and thus less dependent on receiving assurances that the system would handle these variables in accordance with their preferences. This is a tradeoff with the kinds of efficiencies and emergent animal management practices sometimes promised by PLF but might be worth that loss for those with less trust in the technologies, at least initially.

Another general strategy for addressing transparency challenges is to provide Acknowledgements of the major values that guided the development of particular PLF systems. This strategy is an alternative to providing numerous details that could become overwhelming and impractical to disclose. For example, rather than providing endless details about all the input and output variables associated with a PLF system and the ways those values were analyzed, the developers of a system could focus on the main features of the system (e.g., animal welfare or economic efficiency) that the system was designed to maximize. In order to avoid being misleading, it would also typically be important to clarify how those features were defined or conceptualized (e.g., how animal welfare was measured) and how trade-offs are handled (e.g., what the system does when it would cost more to maximize particular features of animal welfare). Along these lines, the developers could also provide general information about how carefully their systems had been developed and under what range of conditions they had been implemented, which could serve as a proxy for more detailed information about the reliability of the systems. As mentioned above, it is sometimes the case that people might not be aware of the implicit values they hold or are expressing in their work. In such cases, going through guided processes of dialogue to draw these out could be an important step before acknowledging them (e.g., O'Rourke and Crowley, 2013; Thompson et al., 2021).

To address issues of trust and motivated communication, several strategies can be employed. For example, third-party experts who have higher trust from multiple parties, and who have different interests, can verify claims. This could include regulators, activist watch dogs, media, or engineers and designers working for a non-profit institution such as a university. Alternately, increasing the community epistemic capacities of both potential users as well as developers of a PLF system so that they can verify claims, formulate better questions, and communicate their values more clearly, can mitigate lack of trust (Werkheiser 2016).

Finally, although machine learning algorithms create significant complications for achieving transparency, there are some steps that can be taken to address these challenges. For example, the field of "explainable AI" (XAI) explores ways to clarify some of the features of machine learning algorithms even if they cannot be fully understood (Nyrup 2022) such as running "sensitivity analyses" to determine which input variables make the most difference to the predictions that a system provides. Sometimes uncertainty estimates can also be provided so that the users of a machine learning system have a sense of its reliability. Thus, the use of machine learning algorithms in PLF systems is not a barrier to providing at least some forms of transparency. Additionally, in keeping with the strategy discussed previously of making PLF less complex, machine learning could be added only in a gradual fashion so that its predictions could initially be compared to human judgment in open-loop processes. This comparison could provide its own form of transparency, as users could see the ways in which machine learning complemented, recapitulated, or differed from their own judgment.

Table 1: A sample of major audiences, content, challenges, and strategies to be considered as part of transparency efforts.

Audience	Content	Challenges	Strategies
• Other scientists and engineers • Farmers • Consumers • Industry groups • Regulators	• Basic operation, strengths, and weaknesses of PLF system • Data generated by the system • Basic goals of the designers • Implicit values of the system • Operation and nature of underlying ML algorithms	• Difficulty identifying and communicating with relevant audiences • Not knowing the information to be disclosed • Lack of trust • Problematic motivations of the developers or communicators • Opaqueness of ML algorithms	• Collaborations with end users • Design to minimize transparency needs • Acknowledgment of major guiding values • Independent verification • Community Epistemic Capacities • Explainable AI

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