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Artificial intelligence and animal farming: a scenario of drivers, barriers, and impacts in 2032

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Abstract

In animal farming, there is the hope that artificial intelligence (AI) will improve efficiency and increase profits while providing solutions to reduce pollution and pesticide use and improve environmental sustainability, animal health and welfare. However, many are also concerned about AI's ethical, legal, social, and economic impacts. These include the instrumentalisation of animals, bias caused by AI in how animals are portrayed, allowing the continuation of a harmful farming industry, and concerns around power asymmetries, data ownership, and copyright infringements. Therefore, there is a tension between the potential benefits and drawbacks of AI use in animal farming. This paper takes a forward-looking view of the benefits and challenges that AI may create in animal farming by the year 2032. Through several iterative rounds with stakeholders, this paper maps out a future scenario of AI in animal farming, identifying technological developments alongside potential drivers, barriers, and impacts. The scenario concludes with five recommendations for policymakers: 1. Initiate education programmes on AI in the sector; 2. Create ethical guidelines for AI in animal farming; 3. Science policy should be realistic and not only rely on technical solutions like AI; 4. Ensure public safety from harm caused by AI; 5. Implement better guidance on data-sharing in the sector.

Keywords Artificial intelligence · Agriculture · Livestock farming · Scenario · Animal welfare · Ethics

Introduction

The global population is set to increase to 11 billion people by 2100 (United Nations 2024). With this growth comes considerable pressure on the agricultural sector to provide enough food to sustain these demands. Humans have already used over 50% of the world's vegetated land for agriculture, and 26% of greenhouse gas emissions (GHG) come from food production and consumption (Ritchie et al. 2022). In particular, animal farming[1] is said to cause between 11 and 19% of global greenhouse gas emissions (Blaustine-Retjo and Gambino 2024), is a significant contributor to biodiversity loss (Ritchie et al. 2022; Ritchie 2022), and is a heavy burden on resources and the environment (Pickles 2017), and is criticised for its immoral treatment of animals (2024).

Despite these concerns, global meat consumption has consistently increased since 1990 (Statista 2024a) and is set to continue increasing globally until *at least* 2031 (Statista 2024b). However, it is unclear how animal farming can become more sustainable, efficient, and respond to some of these moral concerns. Digitalisation, specifically artificial intelligence (AI),[2] is being proposed as one way to respond to these challenges. There is hope that AI can help reduce

[1] . 'Animal farming' is used instead of 'livestock farming' or 'animal husbandry'. These two terms refer to animals as 'stock' or resources that should be managed and reserved. While changing terminology will not radically change the practice referred to, animal farming is a more neutral descriptor for this practice (i.e., animals are not necessarily stock or resources for human consumption).

[2] The definition of AI that we use is the understanding of AI in the European Union AI Act: (1) "'AI system' means a machine-based system that is designed to operate with varying levels of autonomy and that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments' (European Union, 'EU Artificial Intelligence Act' 2024).

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environmental impact, improve efficiency in the sector, and improve the health and welfare of farm animals (Bao and Xie 2022). AI is being used in many different ways in animal farming; for example, to test pigs for respiratory issues (Zhao et al. 2020), poultry health detection (Alex et al. 2019), optimising the input and output of chicken broilers (Amid and Gundoshmian 2017), and analysing lactating sow postures as determinants of their welfare (Zheng et al. 2018). However, the use of AI in animal farming is also not without problems, with recent research highlight several ethical and social concerns (Bossert and Hagendorff 2021). AI may provide biased results, for example, when searching for images of cows, pigs, and chickens, it was shown to bring back images of meat rather than animals – depicting their sole purpose as food (Hagendorff et al. 2022). Some have also stated that digital technologies such as AI could be used to objectify animals (Singer and Tse 2022), further dehumanise animal-human interactions (Bossert and Coeckelbergh 2024) and enable the further industrialisation of animal farming (Bos et al. 2018).

As AI use is mired with uncertainties, this paper provides a first step at identifying potential outcomes of AI use in animal farming in the future. It develops a scenario of AI in animal farming in Europe in 2032. This timeline (i.e., seven years) is soon enough to be realistic and context-specific enough for action (i.e., in Europe and related to land animal farming[3]). The scenario was formulated through three rounds (1. survey, 2. workshop, 3. feedback reviews) of stakeholder-led engagement ($N=28$) and validation at four events ($N=64$), resulting in this scenario of AI in European animal farming in 2032.

The paper is structured as follows: Section "Scenarios" begins with an overview of scenarios, highlighting several methodologies and why the 'policy scenario' was chosen. Section "Methodology" outlines the steps taken: 1. survey, 2. workshop, 3. feedback reviews, and 4. presentations at four events. Section "Scenario: AI in animal farming in 2032" presents the scenario developed for AI in animal farming in 2032. This section is subdivided into four subsections: 1. technological developments, 2. drivers, 3. barriers, and 4. impacts (ethical, legal, social, and economic). Section "Recommendations to policymakers in 2025" provides recommendations to policymakers on responding to many of the challenges and impacts outlined in the scenario.

Scenarios

As AI is set to develop rapidly and impactfully, it is important to evaluate how these developments may materialise, what types of impacts can occur, and how we can respond to these challenges. This paper uses a scenario approach to identify how stakeholders view the future developments, drivers, barriers, and impacts of AI in European animal farming. While AI research in animal farming is evolving, examining how stakeholders view these changes and their impacts on animals, farmers, the sector, and society is crucial. Using scenarios has a long history of helping individuals, organisations, and institutions make long-term decisions. Scenario 'planning', 'thinking', 'analysis', and 'prediction' all refer to developing strategic plans now to mitigate challenges and ensure a desirable future (Kahn and Wiener 1967). One of the underlying principles of scenarios is the understanding that many diverse events, actions, and relationships can change the future in surprising ways (Boenink et al. 2010). Using scenarios allows stakeholders to identify and map possible trajectories and respond accordingly (Stemerding et al. 2010). Scenarios are often used as a 'tool for ordering one's perceptions about alternative future environments in which one's decisions might be played out concretely, so people can help people make better decisions' (Schwartz 2012).

Researchers have used scenarios to evaluate technologies (Wright et al. 2014; Boenink 2013) like 5 G (Hutajulu et al. 2020), free and open-source software (Menéndez-Caravaca et al. 2021), electric cars (Deuten et al. 2020), nanotechnology (Karaca and Öner 2015), quantum computing (Pal et al. 2023), and the Hadron Collider (Carena et al. 2003). Scenarios have also been used to analyse Generative AI (Bjola and Manor 2024), ChatGPT (Ravipati et al. 2023), AI technologies that mimic people (Wright 2019b), AI in information warfare (Wright 2019a), smart cities (Alahi et al. 2023), self-driving vehicles (Fritschy and Spinler 2019; Ryan 2019), blockchain (Okoro et al. 2023), and AI in predictive policing (Macnish et al. 2020). Scenarios have also been used to analyse AI in different applications (e.g., nursing (Seibert et al. 2021), the oil and gas industry (Koroteev and Tekic 2021), agriculture (Ehlers et al. 2022; Daum 2021), testing groundwater quality (Shiri et al. 2021), drug discovery (Tripathi et al. 2021), education (Mouta et al. 2023; Xia 2020), and public health (Ogden et al. 2020)).

Researchers also use various scenario *methodologies* (see Cairns and Wright 2017; European Commission 2024b; Mietzner and Reger 2005; Thomas 2012; Wright et al. 2020).[4] The 'policy scenario' methodology (Ryan 2019;

[3] This paper will focus on what is traditionally understood as animal farming on land. Aquaculture is not included as this warrants a separate analysis because it is too large to fit within one paper.

[4] For this paper (AI in animal farming), many scenario methodologies fell short in their usefulness for this task. For example, some scenario methodologies are too vague, and it is difficult to identify what should be done based on the information in such scenarios (e.g.,

Wright et al. 2020), created in the SHERPA Project (Project 2024)[5] was chosen for this paper. The primary goal of a policy scenario is to 'explore possible consequences of current trends; to engage stakeholders; to uncover issues that might otherwise be overlooked; to help decision-making; to consider desired and undesired futures; to determine what steps should be taken to reach the desired future and avoid an undesired future' (Wright et al. 2019). It uses future medium-term (5–7 years) scenarios rather than distant futures because of the potential to divert into science fiction (Cairns and Wright 2017). This medium-term timeline is essential for AI in animal farming because it is urgent enough for policymakers to act now and is more plausible for stakeholders to take seriously than a scenario set 20 or 50 years in the future (Volkery and Ribeiro 2009).

The policy scenario is based on several iterative rounds of feedback from stakeholders[6], which is fundamental for the scenario's 'scientific plausibility and probability' (Ryan 2019). Stakeholder engagement allows diverse viewpoints to be included in the scenario. This engagement provides a nuanced account of perspectives within one scenario (Wright et al. 2020), which is essential for creating a compelling narrative involving many diverse stakeholders.

A fundamental reason for choosing the policy scenario was that it was explicitly designed for use in AI applications, making it an ideal choice for evaluating AIs impact on future animal farming. In the SHERPA project, the policy scenario methodology was developed and implemented to assess the future scenario of AI applications in predictive policing, self-driving vehicles, technologies that mimic people, their use in disinformation and information warfare, and robots in education (Wright et al. 2019). Therefore, the policy scenario methodology has demonstrated its usability in AI applications, making it suitable for this paper's focus (i.e., AI in animal farming).

However, the policy scenario methodology has two shortcomings. The first shortcoming is the brevity of the half-day workshop. This timeframe may prevent participants from deep-diving into the topic. Secondly, the policy scenario (Wright et al. 2020) holds a degree of naivety that there will be a 'consensus' on contemporary societal issues that are fundamentally 'contested' and 'wicked', such as AI. While these challenges are problematic, they were addressed during the implementation of this scenario methodology in this paper.

Firstly, to address the lack of time in the workshop, it may be possible to extend the half-day, given their busy schedules and the non-remunerative nature of the workshop (Wright et al. 2020) to a full-day workshop. While this would be ideal, it is often impractical. It is difficult to find a suitable date and time for such a large group of (voluntary) stakeholders without also asking them to attend a full-day workshop (i.e., given their busy schedules and because participation is non-remunerative). However, a half-day workshop may be sufficient if enough preparatory work is done beforehand. Specifically, compiling a list of the main themes, topics, and issues would allow for more in-depth discussions during the workshop. One way to achieve this is to send a survey to the participants a week before the workshop. The facilitator can then map out a comprehensive list of topics and issues retrieved from the surveys, so that the participants can do a deeper dive into these, rather than just spending time listing them in the workshop (Wright et al. 2020)).

In response to the second shortcoming, the survey could be used to identify potential convergences and divergences among stakeholders in advance. Once these divergences are identified, the workshop facilitator can create activities to explore the nuances and reasons underlying them. The surveys can be used as jumping-off points for discussion in the workshop. Furthermore, we disagree that participants *must* reach consensus on all topics to develop a scenario (Wright et al. 2020). Discussing and gathering insights into divergences strengthens the scenario by allowing for more nuance rather than taking a too one-sided view of the future, a point (Wright et al. 2020) criticised in other scenarios (e.g., dark scenarios' dystopian futures). While some level of agreement is essential, consensus should not be a fundamental guiding factor for scenarios. The approach taken to divergences is explained in the following section.

'orthogonal futures'). Some scenario methodologies provide engaging thought exercises but few recommendable actions (e.g., 'dark scenarios'). Therefore, when assessed by policymakers, these unclear or philosophically complex scenarios often require too much decoding to understand what should be done, reducing their effectiveness (Ryan 2019). Lastly, many scenario methodologies focus on the long term (20+ years from now), making it difficult to accurately predict what will happen and how to prepare for it.

[5] The SHERPA Project was a three-year project, consisting of 11 organisations from six European countries, to evaluate the ethical, legal, and social impacts of smart information systems (the combination of artificial intelligence and Big Data). It was one of the first large EU Horizon projects focusing specifically on the ethical, legal, and social aspects of artificial intelligence (2018–2021). The project involved an array of stakeholders and conducted 10 domain-specific case studies, a human rights analysis, standardisation recommendations, and guidelines for the development and use of AI. The project also achieved notable outreach to the general public by inviting several artists to create artworks based on the project's research. It also published 20+ scientific articles by the time the project commenced. In the context of this paper, the SHERPA project developed five scenarios, some of which were developed into scientific papers that have had a significant impact in the literature: cf. M. Ryan, 'The Future of Transportation: Ethical, Legal, Social and Economic Impacts of Self-driving Vehicles in the Year 2025', Sci. Eng. Ethics, Sep. 2019, doi: 10.1007/s11948-019–00130-2.

[6] Defining stakeholders as those who may experience or may anticipate experiencing actual or potential benefit or harm due to the actions or inactions being discussed. They can receive opportunities or threats from a particular course of action.

Methodology

This paper applies the policy scenario methodology to evaluate the potential future impacts of AI in the animal farming sector over the next 7 years (with a 2032 timeline).[7] Its primary geographical focus is Europe, but it also considers how global developments may impact Europe.[8] Europe was chosen to be more context-specific and realistic rather than too global and all-encompassing. The stakeholder group consisted of Europeans working and living in Europe, so they were most aware of AI applications in Europe, European law, and the animal farming sector in Europe. Stakeholder input was retrieved in three stages ($N=28$), and the scenario was validated through four events (see Fig. 1).

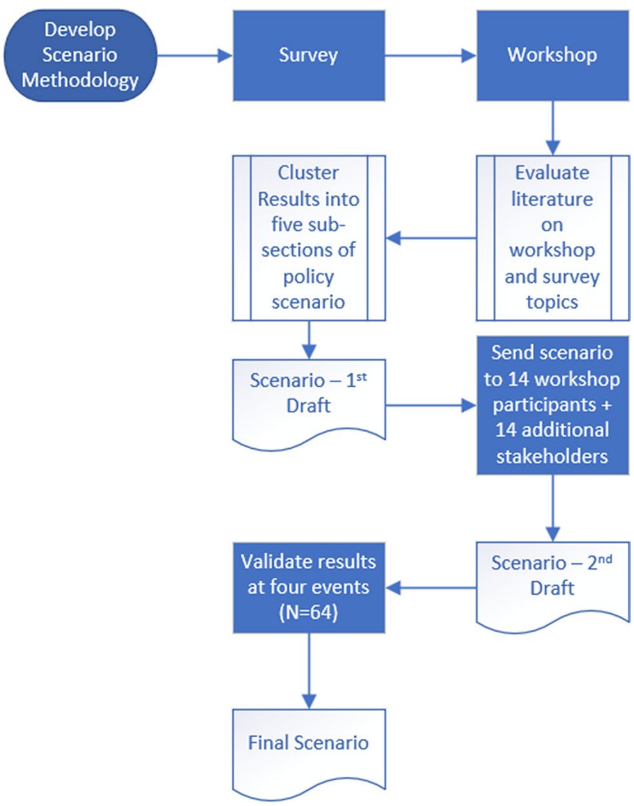

Fig. 1 Scenario construction process

Policy scenario survey and workshop

The policy scenario involves stakeholders throughout its development. Representatives from all four helices (government, civil society, academia, and industry) of the 'quadruple helix' (QH) were involved (Afonso et al. 2012; Carayannis and Campbell 2010, 2009; Miller et al. 2018). The stakeholders to invite to the workshop were selected through an extensive analysis of key figures involved in projects, product development, and AI research in animal farming in the Netherlands (e.g., Google searches, recommendations from peers, Scopus searches, and so forth). An initial list of 49 stakeholders was compiled and categorised into four QH helices: academia (18), civil society (7), government (7), and industry (17). Of this list of invitees, 14 agreed to attend the workshop, 14 were unavailable but expressed interest in reviewing the draft scenario, five were uninterested, and 16 did not reply.

The 14 stakeholders who participated in the survey and workshop came from government ($N=4$), civil society ($N=2$), academia ($N=6$), and industry ($N=2$). These individuals included philosophers, policymakers, economists, computer scientists, veterinarians, and animal welfare representatives.[9] While they had diverse backgrounds and skills, they were all experts on AI in animal farming.

The survey was sent to the 14 stakeholders ('stage 1' of stakeholder engagement) two weeks before the workshop. The survey contained seven questions: two multiple-choice questions on the background of the participants (i.e., the QH and disciplinary background they most closely relate to) and five open questions related to the subsections of a policy scenario (i.e., technological development, drivers, barriers, impacts, and recommendations) (see Appendix A for these questions). The survey data (see Table 1 for an overview of the survey results) was used to ground the workshop and scenario construction (the survey feedback is denoted in the scenario footnotes as 'stage 1').

The survey insights were used as discussion points in the workshop (stage 2 of stakeholder engagement). Before the workshops, all participants signed an informed consent form agreeing to participate and to have their feedback used in a scientific paper. The workshop was not recorded, but two dedicated note-takers took notes, and the workshop facilitator, and the notes were compared and contrasted afterwards for verifiability. The workshop consisted of five sections: expected technological progress, drivers, barriers, impacts (ethical, legal, social, and economic), and policy

[7] While this paper was written at the end of 2024, it was assumed that it would not be published until at least 2025.

[8] The reason for choosing Europe is for pragmatic and practical reasons: the project that this paper is funded from is European, the potential inclusion of workshop participants is European, and the presentation of results was mostly to a European audience. This is not to say that other regions are not important or AI will not have a significant impact on these regions (in fact, there may be a much bigger impact in other areas outside of Europe), it is simply that trying to cover all regions or implementing a global approach would be too broad, too difficult to organise in terms of stakeholder input, and outside of the scope of the funding body that this research is conducted for.

[9] Unfortunately, it was not possible to include all types of stakeholders (e.g., farmers, people working in food production, scientists using AI for animal genomics, and so forth) that we initially wanted to as it was too difficult to identify certain individuals from the stakeholder groups.

Table 1 Survey results

Survey Focus	Topics Discussed by Stakeholders (N = 11)
Technology: The main reasons for using AI in animal farming in the future	Monitoring animal health and welfare (7) Improving efficiency/quality of production process (e.g., for farmers or advisors) (5) Decoding animal communication (2) Phenotyping for animal traits (1) Reducing disease (1) Improve sustainability: emission reduction and harmful chemicals (1) Stimulating the positive welfare of animals (1) Identify animal activity patterns (1)
Technology: the leading advancements in technology	Computer vision technology (6) Sensors (4) Dashboards to visualise data (1) Data-driven farm management (1) Chatbots for client support and advice (1) Virtual reality (1) Audio Analytics (1) GenAI (1)
Drivers of AI development and use in animal farming	Economic and efficiency incentives (5) AI applications (like checks/audits) becoming mandatory (3) NGO/civil society pressure (2) Governmental support/political decision-making (2) Scientific advancements (2) Public opinion/consumer demand (2) Improve animal health and welfare (2) Shortage of human labour (1)
Barriers to AI development and use in animal farming	Lack of added value/incentives (6) High entry costs (5) Technological readiness/scientific merit (4) Lack of legislation (3) Mistrust in AI (2) Skills of end-user/lack of upskilling (2) Lack of enforceability to adopt (2) Data ownership (1) Lack of governmental support (1)
Impacts of AI development and use in animal farming	Risks of data-sharing and data ownership (4) Positive effect on animal care and welfare (3) Economic benefit of adoption if AI is better and cheaper (2) AI will make the farming sector more efficient/better (2) Farming becomes more distant – using technology remotely (2) Better ethical controls in place to reduce risks (1) What is allowed or compulsory for a farmer with AI is unclear (1) Consumer acceptance of AI use in animal farming (1) Farmers lose control (tech lock-in) and become employees of large food Manufacturers or tech companies (1) Change in the job/role of the farmer with the use of AI (1) Legislation cannot keep pace - power plays by large companies (1) Risk of greenwashing – pretending AI increases animal welfare (1)
Recommendations to Policymakers	Allow for experimentation and creativity in design and innovation (3) Focus on concrete examples and successful applications (2) Ensure inclusion of diverse stakeholders and interdisciplinarity (2) Be realistic and identify how to implement science into practice (2) Establish independent advisory board/committees (2)

recommendations. The workshop's first section focused on AIs main technological developments in animal farming in the next seven years (Section "Technological progress in 2032").

Following this, the workshop facilitator implemented the impact-likelihood technique from 'Orthogonal futures' (Ducatel 2010) to map the drivers and barriers collected from the surveys (see Appendix B). The participants were split into three groups of 4–5 people. They discussed and mapped the eight drivers (part two of the workshop) from Appendix B onto a four-quadrant orthogonal diagram poster. They did the same with the nine barriers (part three of the workshop) on a separate four-quadrant orthogonal diagram poster (see Fig. 2).

Part four of the workshop focused on AIs ethical, legal, social, and economic impacts in animal farming. The

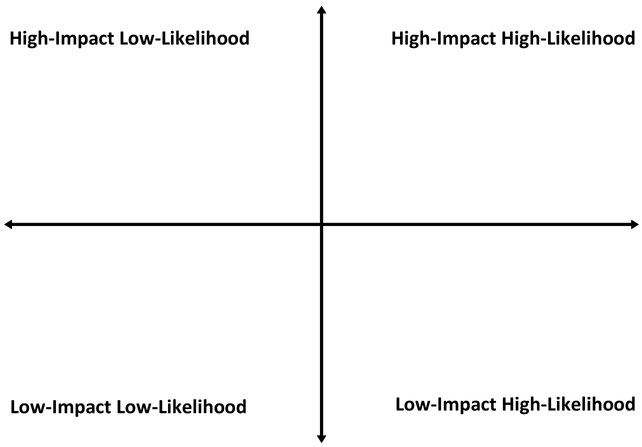

Fig. 2 Orthogonal impact likelihood quadrants

facilitator implemented the 'Two-sided Discussion' methodology (Gordijn et al. 2018), adapted from Lewis' Deep Democracy method (Lewis 2013). This approach was chosen to clarify several seemingly oppositional or divergent stances from the surveys. The participants listed a range of positive and negative impacts on key stakeholders, so it was essential to gather whether the overall impacts were seen as largely positive with some negative or the opposite (or somewhere in between).

The facilitator created two polarising viewpoints (A and B) and asked the participants to divide the room laterally into two and stand on the side of the room with the statement they felt more strongly toward (either left or right of the room, corresponding to the statements) (Gordijn et al. 2018) (see Appendix C). The facilitator also divided the room horizontally, telling the participants that the stronger they felt about the statement they supported, the closer they should stand to the front of the room. If they were less confident or their support for the statement was weaker, they would stand closer to the back of the room. This strong-weak division was a sliding scale so that they could position

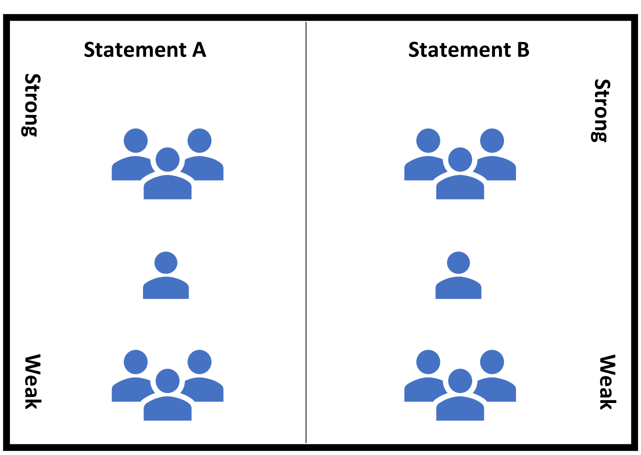

Fig. 3 Division of room for Statements

themselves in correspondence with the degree of support for the statement. A visualisation of the room can be seen in Fig. 3.

Each 'side' could give one argument from their position, taking this in turn from side to side for three rounds (Gordijn et al. 2018). This was done for three topics with polarising viewpoints in the surveys (see Appendix C). This method was chosen to clarify oppositional positions and provide greater nuance to surface-level divergences.

The fifth part of the workshop focused on policymaking recommendations (Wright et al. 2020) through a roundtable discussion, during which each participant was allowed to provide recommendations to policymakers based on the scenario discussions in the workshop. The focus was on recommendations to stakeholders, as this is the core focus of the policy scenario methodology. However, much of the scenario's content could also be applicable and implementable for a wide array of stakeholders. While this is beyond the scope of this paper, future research could identify the responsibilities of other stakeholders in the sector.

Constructing the scenario

A draft scenario was written based on the findings and input from the survey and the workshop. Verifying stakeholders' claims in scenario construction is essential as it supports the scientific credibility of the scenario. If unfounded claims, generalisations, or scientifically dubious remarks were made in the survey or workshop (unsupported by any studies or literature), they were not included in the scenario. However, this did not occur in practice, as everyone invited was a trained expert in their respective field and well-versed in the scientific plausibility of their statements. All feedback and input received from the survey and workshop were incorporated into the first draft of the scenario.

The stakeholders' input was categorised into the main sections of the workshop and the subsequent paper.[10] Within these sections and subsections, the stakeholders' feedback was also further grouped by the themes discussed; for example, several of them discussed GenAI in the context of technological progress over the next seven years. The overarching message of each theme and topic was based on stakeholders' feedback; for example, if stakeholders all referred to an impact positively, it was included in the scenario in the same light. However, when there was divergence, this nuance was accounted for by describing these differences in the scenario, which will be noted in the appropriate footnotes (Section "Scenario: AI in animal farming in 2032").

[10] Expected technological progress, drivers, barriers, impacts (ethical, legal, social, and economic), and policy recommendations.

The scenario was written in a narrative 'report' style from 2032 (following the outline by (Wright et al. 2020)), looking back at the preceding years and developments in AI in animal farming. Narrative scenarios are still somewhat novel in academia, so the presentation of the scenario is not written in a traditional social science manner (i.e., presenting results from empirical research with a discussion of the results and the literature). Instead, the scenario encapsulates the results from the stakeholder engagement exercises (the sources of which are denoted in the footnotes) alongside our engagement with the literature in a single narrative piece. The citations demonstrate the scientific basis for the stakeholders mentioned and referred to.

The first draft of the scenario was sent to the original group of workshop participants/survey respondents ($N=14$) for review to confirm whether their views were incorporated correctly, whether anything was overlooked, and to elicit further reflections and general commentary on the scenario. In addition, a group of experts ($N=14$) was asked to provide feedback on the scenario. This group consisted of those invited to the workshop and could not attend, but were interested in the topic. This process doubled the total number of stakeholders ($N=28$), following the policy scenario iterative step outlined in (Wright et al. 2020) ('stage 3' in the stakeholder engagement process). They were asked three questions: 1. Is the scenario convincing (why/why not)?; 2. Are there any aspects in the scenario that you think should be changed (if so, what parts and changed to what?); 3. After reading the entire scenario, what recommendations would you have to policymakers and key stakeholders now?

However, only six participants gave feedback at stage three-five workshop participants and one from the additional list of invited experts. While this feedback was rigorous, the low response rate (6/28) suggests difficulty obtaining feedback on a lengthy written text.

This observation made us reevaluate the final stage of stakeholder engagement, which (Wright et al. 2020) proposes sending the scenario to 100+ stakeholders for input. Instead, the scenario was presented at four events ($N=64$). In this way, we were guaranteed to receive more input on the scenario than we would have if we had expected people to provide feedback on an extensive written document.

The scenario was presented at a philosophy colloquium ($N=12$),[11] a technology ethics conference ($N=22$),[12] and two interdisciplinary agri-food innovation events ($N=30$)—for a total of $N=64$. The participants at these events ranged from ethicists, social scientists, computer scientists, agri-tech business developers, national government agri-tech managers, agri-tech providers, and representatives from transnational agri-food bodies. An overview of the sector's main technological innovations in AI over the past decade (4.1.) and what have been some of the main drivers (4.2.), barriers (4.3.), and impacts (4.4.), and policy recommendations (Section "Recommendations to policymakers in 2025") was presented at these events. The main themes, challenges, and solutions from each section were listed and explained, with figures illustrated in this paper used to visually illustrate the scenario.

The feedback from these four sessions focused more on the clarity of exposition, providing more detail or improved coherence in the scenario, definitions, refinements to the methodology, and discussions around the limitations of future research in the area. This input was used to peer-review the scenario and further improve it. For readability and conciseness, the findings from the survey (stage 1), workshop (stage 2), and stakeholder feedback (stage 3) are presented in footnotes to avoid detracting from the scenario's narrative. These footnotes highlight the sources of the findings and their impact on the scenario construction (footnotes beginning with 'stages' 1, 2, and 3 refer to the stakeholder engagement process from which the results were derived).

Scenario: AI in animal farming in 2032

This report examines events, activities, and progress in AI in the animal farming sector in Europe from 2022 to 2032. This report provides an overview of the sector's main technological innovations in AI over the past decade (4.1) and what have been some of the main drivers (4.2), barriers (4.3), and impacts (4.4). This report highlights the most significant events in AI in the animal farming sector over the past decade.

Technological progress in 2032

The use of AI in animal farming has grown dramatically in the past decade (2022–2032), particularly in sensors, drones, computer vision, machine learning, and GenAI.[13] The animal farming sector has seen many advancements in farm management systems that have helped improve the efficiency and quality of the production process for farmers and agribusinesses (for example, improvements in AI genomics and animal breeding (Chafai et al. 2023; Xiang et al. 2023; Hamadani et al. 2024)).[14] AI is also being used as a

[11] October 1st, 2024.

[12] October 3rd, 2024.

[13] Stage 1: These were the main technological areas the stakeholders proposed to be most significant in animal farming.

[14] Stage 2: The workshop participants did not indicate that there would be significant changes in the current research foci in the coming

recommendation system for better farm practices[15] through developments in dashboards to visualise data in the agricultural sector, which are now much more user-friendly than when they were first introduced in the early 2020s (many reported a steep learning curve at the time (Sahni and Singh 2024)). These AI-powered dashboards help visualise data, allowing many farmers to integrate it into data-driven management (Narra et al. 2020; Steup et al. 2019; van Klompenburg and Kassahun 2022; Niloofar et al. 2021). There has also been considerable growth in the use of AI chatbots for client support and advice in animal farming (Herrera et al. 2022) and audio analytics to evaluate the sounds that farm animals make (Bishop et al. 2017, 2019; Jung et al. 2021; Norton et al. 2019; Olczak et al. 2023; Tullo et al. 2013; Xie et al. 2024).

These developments have also been supported by advancements in GenAI (such as synthetic data generation, video analysis, automated annotation, and audio analytics) (Fowler 2024). Since the advent of GenAI in the early 2020s, there has been constant, steady progress in technological improvements in transformer-based deep neural networks, such as large language models (LLMs) (Zhao et al. 2024).[16] This allowed early innovators to develop advanced chatbots such as ChatGPT (OpenAI), Copilot (Microsoft), Gemini (Google) and LLaMA (Meta) (AlZu'bi et al. 2024; Teubner et al. 2023). The late 2020s saw increased partnership and cooperation between traditional agricultural companies (e.g., John Deere, Bayer, and Pioneer) and Big Tech companies developing AI recommendation systems (Ryan 2020).[17]

However, the effectiveness of GenAI in animal farming is still contentious (Biswas 2023; Ray 2023). Many have claimed that OpenAI and Big Tech companies are not transparent about AIs effectiveness, which has created mistrust toward large agribusinesses and Big Tech for overpromising and underdelivering.[18] This has led to a reluctance to adopt, with many farmers, particularly smaller farms, relying on traditional farming practices. In response to this, companies like Microsoft have begun implementing free 'Prompt Schools' and courses on prompt engineering for those in the agricultural sector to upskill and train farmers on correctly using Copilot for their business (Ekin 2023; Giray 2023; Henrickson and Meroño-Peñuela 2023; Ozdemir 2023). However, many working in animal farming have claimed that the 'prompt school' courses are more suited to crop farming and less for the animal farming sector.

What became visible in the early 2020s was that AI start-ups mainly focused on developing innovative solutions to tackle food security (Klerkx and Villalobos 2024) and this led them to concentrate on identifying solutions in crop farming, while to a lesser degree in animal farming (GreyB 2024). However, several AI start-ups began noticing this gap by the mid-2020s, which witnessed a slow and steady increase in start-ups focusing on AI in animal farming (Insights 2024; Europe 2024; 2024).[19] One of the significant advances of these AI start-ups (and large companies) has been in sensor development (Džermeikaitė et al. 2023; Tedeschi et al. 2021; Neethirajan 2020). Using IoT sensors to allow for massive amounts of data collection was fundamental for developing, training, and improving AI. In the past, there was often difficulty with sensors being damaged, bitten, moved, and hit by farm animals, thus impacting their effectiveness at retrieving data. Other factors, such as dust, moisture, and ammonia, impacted sensor functioning (Neethirajan and Kemp 2021). The late 2020s witnessed an explosion in the production of smaller, more durable, and cheaper sensors, which saw their uptake in animal farming around Europe increase (Kaswan et al. 2024).

Sensors (in particular, biosensors) have been implemented to detect shifts in animal behaviour, monitor stress indicators, and estimate increased animal welfare indicators (AWIs) (Kaswan et al. 2024). These have been implemented to monitor and improve the health and welfare of farm animals and identify diseases (and allow farmers and veterinarians to respond to them).[20] The data retrieved from these sensors have been analysed through the use of AI algorithms to detect abnormalities and physical ailments (e.g., computer vision to detect lesions and lameness) (Aydin 2017; Barney et al. 2023; Schlageter-Tello et al. 2018; Kang et al. 2021, 2020), symptoms of illness (e.g., audio recognition

decade, so one can assume that the figures taken from this snapshot of the literature would remain relatively unchanged for the most part.

[15] Stage 1: 5/11 survey respondents indicated this would be a huge focus of AI applications in the future.

[16] Stage 2: while GenAI was only mentioned by one stakeholder in the survey, it was discussed extensively throughout the workshop with the stakeholders, reflecting that it will significantly impact the sector.

[17] Stage 2: the stakeholders reflected that there would probably be a closer partnership between Big Tech and traditional agribusinesses in the coming years.

[18] Stage 2: This was discussed quite a bit during the workshops. One participant was very hopeful based on the recent OpenAI demonstration of ChatGPT and its potential capacity for solving many animal farming challenges. While the other participants were certainly optimistic about AI's future benefits to the sector, many felt Big Tech often overpromised on what it could deliver in practice. There was a lot of hype about AI and the wonderful things it could do, but in reality, these often fall short in practice. This was also strongly reflected in the literature and recent criticisms against OpenAI's 2024 demonstration of ChatGPT 4.0. See here (Chen 2024).

[19] Stage 2: The stakeholders stated that while AI use in animal farming has been slow to develop in the past, there are many indications that this is increasing and will continue to increase in the coming years.

[20] Stage 1: 7/11 survey respondents indicated that monitoring animal health and welfare would be a huge focus of AI applications in the future, the most discussed focus from the surveys.

of coughs from sick animals) (Zhao et al. 2020; Ijaz et al. 2022; Kim et al. 2015; Preethi et al. 2020), and signs of distress or aggression (e.g., pig tail-biting) (Drexl et al. 2024; Subedi et al. 2023; Wei et al. 2023; Han et al. 2023; Bati and Ser 2023).[21] However, some are still sceptical that AI can accurately detect animal welfare. Others claim that AI use is only guided by economic incentives to increase meat production rather than for the intrinsic welfare of the animals (i.e., improving animal health and welfare is only an instrumental byproduct of producing more and better quality meat and animal produce) (Bos et al. 2018).[22]

Lastly, there has also been considerable momentum to decode animal vocalisations (Andreas et al. 2021, 2022; Mustill 2023).[23] Researchers now believe that through AI, they have mapped many essential vocalisations from cows, pigs, and chickens that indicate specific meanings in human language (e.g., distress, play, and pain) (Gavojdian et al. 2024, 2023; Shorten and Hunter 2023; Bishop et al. 2023; Adebayo et al. 2023; Neethirajan 2023d, 2024b).[24] However, the scientific credibility of these findings is still being debated, with many claiming that they contain anthropomorphisms and human biases (Ryan and Bossert 2024).

Drivers of AI in animal farming in 2032

The landscape of animal farming across Europe witnessed enormous pressure in the 2020s to develop innovative solutions to many of its challenges and bottlenecks. For example, attracting young farmers to the sector has been an ongoing challenge for the past few decades (Eurostat 2024c), with a steady decline in the number of young farmers still entering the industry (Sutherland 2023). In 2005, 7.3% of European farm managers were under 35, which dropped to 6.5% in 2020 and 5.5% in 2030 (Eurostat 2024c). Some of the causes of this decline have been the high entry costs of farming (Forum 2024), importation of cheaper meat outside the EU has put pressure on farmers to produce more with less to be economically viable (Czubak et al. 2023), increased pressure to adhere to environmental regulations,

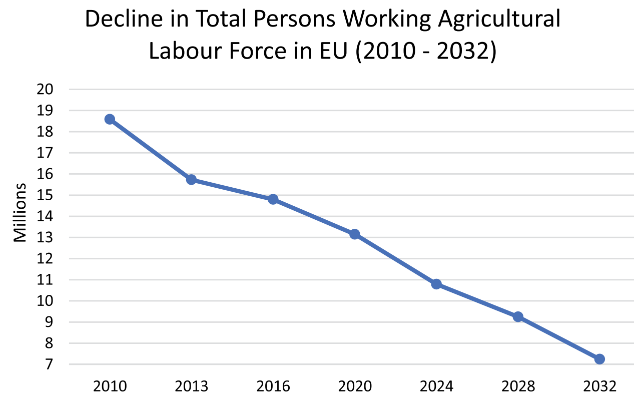

Fig. 4 The decline in the agricultural labour force in the eu over the past 22 years. This data is based on the Eurostat data on the decline of farmer numbers up to 2024 and uses a projected foresight (Excel) into the forthcoming years based on these trends. Data is calculated in total persons working in agriculture. Data can be found here https://ec.europa.eu/eurostat/databrowser/view/ef_lf_size__custom_12680385/default/table?lang=en

and assumptions about the profession (i.e., long hours, hard physical labour, and poor pay) (Nduati 2024; Lewis 2024). In addition to a decline in the number of young farmers, the sector has witnessed an overall decline in the number of people working in agriculture over the past 20 years (See Fig. 4).

Over the past several years, there has also been indirect consumer pressure on the animal farming sector to adapt due to demand (changes in European diets due to health and ethical concerns related to meat consumption) (2024). In response to changing consumer demands, there has also been considerable growth in the consumption of cultured meats (2024; Liu et al. 2023), meat substitutes (Research 2024; Statista 2024c), and dairy alternatives (Research 2024), (Global Insights 2024a), (Innova Market Insights 2024b).[25] This concern has led to a decrease in European meat consumption (European Commission 2023) despite an overall increase in meat consumption globally (World Economic Forum; Organisation for Economic Co-operation and Development OECD). As a result, farmers were forced to increase exportation levels of animal products because of the decreased demand in Europe.[26] These changes have also resulted in some farms closing or shifting towards crop production instead (Stone 2024; European Commission

[21] Stage 2: The stakeholders gave several examples of where sensor technology could advance and, in turn, benefit AI development.

[22] Stage 2: This point kept coming up throughout the workshop. In particular, many felt that health and welfare were often conflated and used interchangeably but that health does not necessarily imply that the animal's welfare is considered. Conversely, the animal's welfare could be considered simply as a means to produce more and better quality food rather than any consideration for the intrinsic well-being of the animal.

[23] Stage 1: 2/11 stakeholders mentioned these developments in the survey.

[24] Stage 2: these examples were discussed in the workshop, and the potential to interpret animal vocalisations could have on the animal farming sector.

[25] Stage 3: One participant stated that the changing climate of food preferences, diets, cultured meats, and animal product substitutes is increasing and will put pressure on the current animal farming system in Europe. Based on current forecasts, this appears to be a potential issue for the sector.

[26] Stage 3: Three participants stated that there would be a clear customer push for changes in the animal farming; despite this not being a significant topic of discussion in the survey or workshops.

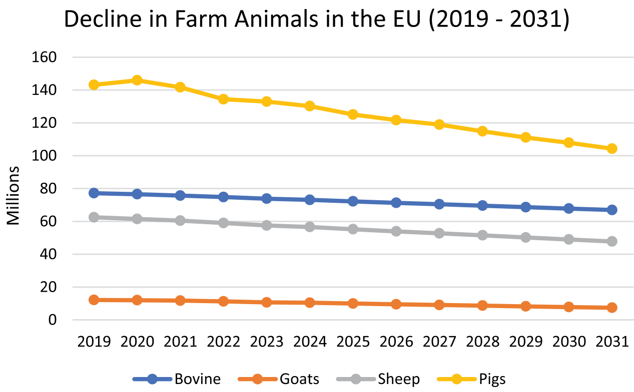

Fig. 5 Decrease in farm animals in the eu over the past 12 years. This data is based on the Eurostat data on the decline of farm animal numbers up to 2024 and uses a projected foresight (Excel) into the forthcoming years based on these trends

2024e).[27] As a result, there has also been an overall decrease in animal numbers in the EU, with bovine, pig, sheep, and goat numbers steadily declining since 2019 (Eurostat 2024b) (see Fig. 5).

The declining number of farmers, the decreased demand for animal products, and the pressure to reduce emissions have pressured the sector to adapt.[28] One significant push was encouraging digitalisation and technological solutions (e.g., AI) to meet the challenges needed for a just agricultural transition (Ryan and Hoes 2024; Baur and Iles 2023; Rai et al. 2023; Okengwu et al. 2023). Governmental support and political decision-making within the EU have also been paramount during this transition, and the European Commission has repeatedly emphasised the importance of digitalisation (such as AI) in animal farming (European Commission 2024d, 2024g, 2024c).[29] A key promise of AI was providing more significant insights into how farmers can deal with sustainability policy requirements and target management of reducing nitrogen, phosphate, and methane from animals (Nejad et al. 2024; Jeong et al. 2022; Neethirajan 2024d). Some farmers have been able to optimise the composition of their feeds, feed times, and feed quantities based on increased scientific research in this field and increased optimisations of their farming practices. This provided economic benefits and efficiency improvements on several farms (Kutyauripo et al. 2023; Javaid et al. 2023).[30]

Throughout the 2020s, AI was packaged as a way to make human labour more effective and efficient (Sharma et al. 2023; Mishra and Mishra 2023; Ryan et al. 2023), and those in the sector implemented it to improve their competitiveness in services and products. This was particularly appealing for farmers with larger herds/farms, and there has been a positive correlation between larger herds/farms and AI adoption (Abeni et al. 2019; Dilaver and Dilaver 2024; Carlberg and Jerhamre 2021). On these larger farms, adopting AI was seen as a way to make life easier for the farmer (Doidge et al. 2024, 2023) and to respond to an ageing labour force (Munnisunker et al. 2022a; Eurostat 2024a).[31] Farmers reported that they have to be on the farm (in person) less now because they can monitor most activities from the comfort of their homes (Munnisunker et al. 2022b). Many dairy farmers with large herds reported that AI-powered automated milking robots significantly reduced their workload, reduced overall labour needed for the job and gave them/their team more time (and energy) to concentrate on other jobs (Rodenburg 2012, 2017; Heikkila et al. 2010).

Early adopters of data-driven farm management software, for example, in the Netherlands (which has consistently been one of the top agri-tech pioneers), have reaped the benefits of this technology. It is estimated that over 90% of Dutch cows now wear sensors (either attached to their ear, collars, or legs) (Džermeikaitė et al. 2023; Neethirajan 2020; Kaswan et al. 2024; Shorten and Hunter 2023). The high saturation level of AI use in cattle farming is a result of the success rate of detecting diseases in cows (e.g., mastitis (Ghafoor and Sitkowska 2021; Coatrini-Soares et al. 2023; Fadul-Pacheco et al. 2021; Lakshitha and Sajja 2024; Luo et al. 2023; Singh et al. 2022)). In particular, dairy farmers have been the strongest adopters of AI throughout Europe (Groher et al. 2020). Therefore, farmers were incentivised to deploy AI in cattle farming more so than in other types of farms (e.g., in pig and poultry farming (Sadeghi et al. 2023; Dong et al. 2024; Neethirajan 2023c, 2023a; Veldkamp et al. 2023)).[32]

[27] Stage 3: One participant stated that there is a changing climate in animal farming in the EU, with much pressure being placed on farmers and that many would not be able to sustain their current practices in the face of changing demands, emission policies, and dietary patterns.

[28] Stage 3: One participant emphasised that there will be a myriad of issues and challenges in the sector that will need to be responded to and that it is not only one specific issue on its own.

[29] Stage 2: Two workshop groups placed the 'governmental support/political decision-making' post-it in the high-likelihood high-impact quadrant, while one group put it in the high-likelihood low-impact quadrant.

[30] Stage 2: All three workshop groups placed the 'economic and efficiency incentives' post-it in the high-likelihood high-impact quadrant.

[31] Stage 2: All three workshop groups placed the 'labour shortage' post-it in the high-likelihood high-impact quadrant.

[32] Stage 3: One expert was adamant that the main benefits of AI in animal farming is for disease detection and animal welfare. The biggest growth would be seen in cows, which corresponds to what is being most researched in the literature. The participant mentioned that it is/will be difficult to identify disease and improve health in pigs, broilers, laying hens, goats, and sheep. The increase in use of sensors and AI on the farm have to demonstrate an increase in profit to justify their use, as well. This is why it appears that one of the biggest potential growth areas will be AI use with cows (as it is easiest to detect disease with AI and also the reduction in disease outweighs the costs of investment).

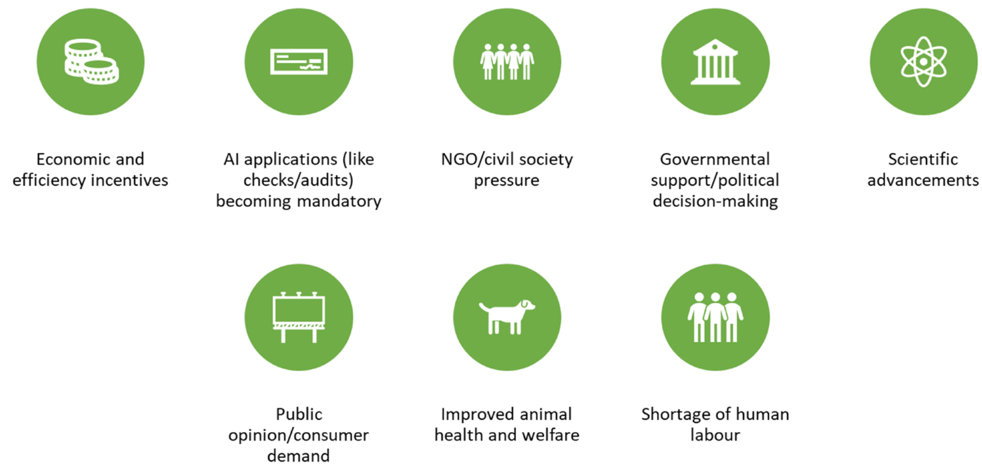

Fig. 6 Drivers of AI in animal farming

A contributor to the integration of AI in animal farming was the pressure from non-governmental organisations (NGOs) and civil society organisations (CSOs) on farmers to reduce the spread of disease on farms and improve animal welfare (Casnici et al. 2024).[33] These organisations had a strong presence and were vocal in ensuring certain types of AI were deployed in animal farming to reduce suffering, monitor diseases, and take effective action on farms. The agenda of NGOs and CSOs was very much focused on AI applications that supported their agenda of reducing disease (Nemitz 2024), improving animal welfare (SCAR Collaborative Working Group on Animal Health and Welfare 2024), and reducing carbon emissions in the sector (2023).[34] NGOs and CSOs also led public campaigns on AI audio analytics results to demonstrate pigs' suffering in many farms, which were quite effective at gathering public support and initiating policy discussions.[35] All Dutch slaughterhouses have implemented audio and visual analytics in their facilities (Voogt et al. 2023; Kim et al. 2023; Sandberg et al. 2023). The data retrieved from these sensors has helped farmers identify farm animal disease, lameness, location and movement patterns, eating and drinking patterns, body temperature, and as a form of risk management on the farm (Neethirajan 2023b, 2024a).[36] Discussions are underway about whether audio analytics methods should become mandatory on European pens, as they are in slaughterhouses across Europe (due to the AI in Slaughterhouses Act of 2029).[37] The work done by the European Food Safety Authority (EFSA) was paramount in defining and better understanding animal welfare in the context of AI use, particularly calves (EFSA Panel on Animal, Health and Animal, Welfare AHAW 2023), broiler chickens (EFSA AHAW Panel EFSA Panel on Animal Health and Welfare 2023), and pigs (EFSA Panel on Animal, Health and Welfare AHAW 2022).

Over the past several years, the European Commission has also opened funding calls for AI research projects in animal farming (e.g., HORIZON-CL6-2023-GOVERNANCE-01–14: Digital and data technologies for livestock tracking) (Rai et al. 2023). Many of these projects spawned new research and scientific developments, culminating in the emergence of numerous start-ups developing AI for animal farming.[38]

The overall list of drivers of animal farming is shown in Fig. 6.

33 Stage 2: All three workshop groups placed the 'NGO/civil society pressure' post-it in the high-likelihood high-impact quadrant.

34 Stage 2: Two workshop groups placed the 'improved animal health and welfare' post-it in the high-likelihood high-impact quadrant, while one group put it in the low-likelihood and high-impact quadrant.

35 Stage 2: One workshop group placed the 'public opinion/consumer demand' post-it in the high-impact high-likelihood quadrant, one in the high-impact low-likelihood quadrant, and one in the low-impact low-likelihood. Thus, it was indicated that it may have some likelihood of occurring and have some level of impact. Therefore, its importance was not overemphasised in the scenario as much as the other topics. They indicated in the workshops that public opinion would only have a significant impact in the case of a big scandal in the sector. Otherwise, it would be a much less significant driver of AI in animal farming.

36 Stage 3: One participant emphasised the importance of using AI for risk management on the farm. AI holds the potential to identify disease and prevent it on an individual farm basis, but identifiable patterns may also emerge among and between farms, where one can determine and manage risks.

37 Stage 2: Two workshop groups placed the 'AI applications (like checks/audits) becoming mandatory' post-it in the low-likelihood high-impact quadrant. In contrast, one group put it in the high-likelihood and high-impact quadrant. During the workshop discussions, there was a firm emphasis on the use of AI in slaughterhouses, with many success stories already being mentioned. The participants reflected that there was a strong possibility that AI applications would become mandatory in slaughterhouses to reduce unnecessary suffering.

38 Stage 2: All three workshop groups placed the 'scientific advancements' post-it in the high-likelihood low-impact quadrant.

Barriers to AI in animal farming in 2032

As a result of the many developments in using AI visual recognition, audio analytics, and sensor development in slaughterhouses in the mid-2020s (in Belgium (Locks 2024; 2024), the Netherlands (Janssen 2024; Deloitte 2024; VION Food Group 2024), and Germany (EuroMeatNews 'Monitoring animal welfare using AI' 2024)), demonstrating how AI can reduce animal suffering in these environments.[39] This early research was adopted in many Western European countries throughout the latter half of the 2020s, resulting in a push from the EFSA to stimulate policy further to improve the welfare of animals in slaughterhouses (2024).[40] The Slaughterhouse Act of 2029 was a pivotal document for the use of AI in animal farming, as it required all slaughterhouses to be able to monitor distress and animal welfare at the slaughterhouses (Voogt et al. 2023).

Despite the success in slaughterhouses, the lack of requirements to implement AI in other areas was a significant barrier to its adoption in many places where it could have been most beneficial.[41] Many NGOs and CSOs claim that Europe's worst animal welfare offenders should be forced to adopt animal welfare monitoring AI (Väärikkälä et al. 2020). However, this has been difficult to implement because those with high animal welfare offences do not want to be monitored (i.e., it would harm profit, they do not want their harmful practices public, and they do not want to face fines or sanctions). There has been pressure on the EU to implement better strategies and enforcement of adoption in these areas; for example, the animal rights organisation PETA has stated that these forms of AI need greater enforcement in other significant animal welfare offenders such as zoos and circuses (as one of their many objectives to reduce and altogether eliminate animal suffering and abuse in these places).[42]

Aside from adoption in slaughterhouses, AI use has been somewhat mixed throughout Europe, with a much greater propensity of adopters having larger farms where they viewed it as having more of a benefit than farmers with only a few animals (e.g., Romania (En V. Ministerie van Landbouw 2024)).[43] However, farmers with larger farms viewed it as more beneficial. Many indicated that they were not worried about high entry costs[44] or that AI use would bring them economic benefits[45]. This is because there has been a clear awareness within the sector for many years that farmers would not invest in AI unless there was an obvious economic benefit or it would make their lives easier (Ryan et al. 2023; Pedersen et al. 2024; Gemtou et al. 2024).[46] Therefore, agribusinesses developed approaches that would benefit both parties, such as allowing stakeholders to adopt AI-driven robots and recommendation systems for 'free' in exchange for the data retrieved or because the farmer is already paying for other technologies, the company is providing (e.g., milking robotics companies found it easier to attach sensors and cameras on their milking robots, which were already being sold or leased to farmers) (Ryan et al. 2023).

However, many farmers pointed out that they were uncertain whether AI would give them the correct recommendations and if the provided solutions would always fit for purpose (Chaterji et al. 2020).[47] There were many technical reasons for this; for example, in the area of audio analytics, there was a prevalent challenge with trying to identify which animal was making what sound on the farm and to reduce the level of the background noise (also known as the 'cocktail party' problem) (Liao et al. 2023), determining what the sounds of farm animals mean (Coutant et al. 2024; Neethirajan 2024c), and the difficulty of developing robots

[39] Stage 3: The participants pointed to many of these examples that were already currently underway in the field and illustrated that their current success is already being discussed at national and EU-levels.

[40] Stage 3: These efforts were addressed by the participants, emphasising the work that EFSA is already doing in the area. They mentioned that the EFSA is aware of the benefits of AI in slaughterhouses and they foresaw that further action would be taken in this area in the forthcoming years.

[41] Stage 2: One workshop group placed the 'lack of enforceability to adopt' post-it in the low-impact low-likelihood quadrant, one group placed it in the low-impact high-likelihood quadrant and one group placed it in the high-impact low-likelihood quadrant.

[42] Stage 1: Two survey participants clearly mentioned the need to implement animal welfare AI in circuses and zoos as well.

[43] Stage 3: One of the participants was adamant that a distinction needed to be made between farms with many animals and places with low animal density, giving the example of Romania. He felt this would greatly impact the level of AI adoption as these farmers would not see it as beneficial.

[44] Stage 2: One workshop group placed the 'high entry costs' post-in in the high-impact high-likelihood quadrant, and two groups placed it in the high-impact low-likelihood quadrant. Stage 1: Similarly to the high entry costs barrier, this was the second most mentioned barrier in the survey (5/11 mentioning it), despite two groups putting it in the low likelihood quadrant. This placement indicates that it is one of the most obvious and clear barriers, but the participants believed it would be resolved in the future.

[45] Stage 2: All three workshop groups placed the 'lack of added value/incentives' post-it in the high-impact low-likelihood quadrant. Stage 1: This contrasts with the surveys, as 6/11, who conducted the survey, described this as a barrier. It received the highest number of respondents, mentioning it as a specific barrier. This indicates that it is one of the most evident barriers. Stage 2: Still, the participants believed it would get resolved in the future (e.g., all three workshop groups placed it in low likelihood).

[46] Stage 3: One participant correctly pointed out that economic gain is not the only reason farmers adopt technologies; they also adopt them to make their lives easier.

[47] Stage 2: Two workshop groups placed the 'technological readiness/scientific merit' post-it in the high-likelihood high-impact quadrant and 1 in the high-impact and in-between high and low likelihood quadrant.

to navigate in unstructured environments (Gil et al. 2023). The lack of tangible results also exacerbated farmers' mistrust of companies and the sector's promise of AI solutions (Sullivan et al. 2024; Gardezi and Stock 2021; Gardezi et al. 2023).[48]

Another aspect was that many farmers believe that farming is a skill, and AI is incapable of replacing their knowledge and abilities (Ryan et al. 2023; Gardezi et al. 2023; Ryan 2022). This created a divergence throughout Europe between those embracing the latest innovations and technologies and others who remained sceptical, sticking to traditional farming methods. The latter believed AI was not a solution to the issues they faced, and greater digitalisation would harm their profession and the value of farming (van der Burg et al. 2022; Ryan et al. 2021). Many felt that AI was often designed without involving the end-user (e.g., veterinarians (Doidge et al. 2024) and farmers (Rose and Chilvers 2018; Bronson 2019)) and did not take into account their needs and experience.[49] Therefore, a considerable barrier to deploying AI on European farms was pushback on the explainability, usability, and transparency of AI and mistrust in the companies providing them (Doidge et al. 2024, 2023).

A contributing factor to this mistrust and an additional barrier to AI adoption in the EU was the challenge of upskilling and training end-users in AI (e.g., farmers, veterinarians, and farming advisors) (Doidge et al. 2024; Michailidis et al. 2024; Renda 2024; Ra et al. 2019)[50] and ensuring the user-friendliness and usability of AI on the farm (Doidge et al. 2024, 2023; Rotz et al. 2019a). While many AI recommendation systems and farm management tools were integrated into smartphone technology (Elbehri and Chestnov 2021; Mendes et al. 2020), many end-users reported that the learning curve was too challenging or that there was a lack of customer support to help them (or it was too time-consuming) (Javaid et al. 2023; Gardezi et al. 2023; Manning 2024). This led to a significant drop-out rate among those who initially adopted these on their farms.

In addition to this, many in the sector were worried about privacy and security[51] and who owns or controls the data

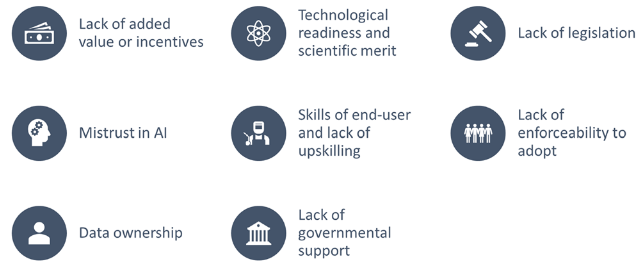

Fig. 7 Barriers to AI in animal farming

being shared (Rotz et al. 2019; Atik 2022) (often referred to as 'data ownership' or 'data sovereignty' (Ryan et al. 2024)).[52] Underpinning these issues were concerns around dependency on, and power dynamics of, large tech companies and agribusinesses (Ryan 2020; Sullivan et al. 2024; Bronson and Sengers 2022). Even though European legislation (e.g., the General Data Protection Regulation (GDPR) (European Union 2016), the Data Governance Act (DGA) (European Commission 2024f), and the Data Act (DA) (2024)) was created to help ensure more transparent and fairer data sharing in the EU; many felt that these laws often overlooked agricultural data because it was not considered 'personal' data (Atik 2023b, 2023a). The uncertainty concerning agricultural data-sharing hindered European AI development because of concerns around data-sharing, which impacted AI innovation because of the sector's dependence on agricultural data for training algorithms (Sullivan et al. 2024; Atik 2023a; Šestak and Copot 2023; Susha et al. 2023; Rozenstein et al. 2024).

The list of barriers to AI in animal farming can be seen in Fig. 7.

Impacts of AI in animal farming in 2032

In the past decade (2022–2032), AI development, deployment, and use in the animal farming sector have had many positive and negative impacts on stakeholders. While the development, deployment, and use of AI have brought many benefits to some stakeholders in the animal farming sector, others viewed these companies as overpromising and underdelivering. In addition, the development and use of AI created several economic, ethical, legal, and social impacts on animal farming.[53]

[48] Stage 2: One workshop group placed the 'mistrust in AI' post-it in the high-impact high likelihood category, one group in the high-impact and between high and low likelihood, and the third group put it between high and low impact and high likelihood.

[49] Stage 3: several participants emphasised this point and pointed out that veterinarians needed to be considered.

[50] Stage 2: One workshop group placed the 'skills of end-user/lack of upskilling 'post-it in the high-impact high likelihood, one group placed it in the high-impact and in-between high and low likelihood, and the third group placed it in the low impact and in-between high and low likelihood quadrant.

[51] Stage 2: Two workshop groups placed the 'lack of legislation' post-it in the low-impact low-likelihood quadrant, and one group placed it in the high-risk high-likelihood quadrant.

[52] Stage 2: All three workshop groups placed the 'data ownership' post-it in the high-likelihood high-impact quadrant.

[53] Stage 2: This was a serious point of agreement amongst the workshop participants. In the fourth part of the workshop, the participants all disagreed with a part of one of the statements that read: 'Using AI in animal farming reduces risks, and potential harms will be negligible'. There was general consensus in the room that the harms would not be negligible.

Economic

There were many early projections about the economic growth of AI in agriculture. These ranged from $1.5 billion (Pangarkar 2024) to $26 billion (Reports 2024), with many proposing somewhere between this amount (e.g., $6 billion (Intelligence 2024) to $7.5 billion (Sets 2024)). In reality, the market grew substantially from its level of $7 billion in 2023 (MarketsandMarkets 2024) to an estimated $12 billion last year (2031). AI in animal farming accounted for a considerable part of this investment, with many claiming that this growth was spurred by pressure on farmers to reduce emissions caused by farm animals, alongside increasing productivity (2024).

One of the biggest drivers for adopting and implementing AI in animal farming was the pressure to ensure efficient mass food production and a sufficient earning capacity for the farmer.[54] For the most part, AI has become cheaper and more accessible for farmers (Ryan et al. 2023) and has helped some farmers reduce their economic costs. For example, computer vision has allowed them to identify abnormalities and illnesses in farm animals (Sandberg et al. 2023; Chen et al. 2021; Fuentes et al. 2022; Jorquera-Chavez et al. 2020, 2021; Nasirahmadi et al. 2017; Okinda et al. 2020; Orandi 2023), which has helped aid decision-making and reduced veterinary visits or unnecessary antibiotic administration costs (Javaid et al. 2023; Fuentes et al. 2022).[55]

Ethical

Since the early days of AI deployment in agri-food, there have been many concerns surrounding the ethical impacts of its use (van der Burg et al. 2022; Ryan et al. 2021; Dara et al. 2022; Mark 2019). These concerns were related to 'transparency, justice and fairness, non-maleficence, responsibility, privacy, beneficence, freedom and autonomy, trust, dignity, sustainability, and solidarity' (Ryan 2022), the instrumentalisation of animals (Bos et al. 2018; Giersberg and Meijboom 2023), and farm surveillance (Stock and Gardezi 2021).[56]

One area that often came up in the agri-food literature, but which was often overlooked in many early AI ethics guidelines and frameworks, was animal welfare (Ryan 2022). An awareness of animal welfare in AI ethics discussions increased in the early 2020s (Bossert and Hagendorff 2021, 2023; Hagendorff et al. 2023; Singer and Tse 2023; Coghlan and Parker 2023; Debauche et al. 2021; Ziesche 2021). This significantly affected how AI was deployed in animal farming and the types of ethical impacts that resulted. Many have proposed that the increased deployment of AI on farms has dramatically improved the lives of farm animals (e.g., in slaughterhouses), while others have been sceptical about its effectiveness, often claiming that the industry as a whole is ethically flawed and nothing but its complete abolition would suffice (Reece 2018).[57]

On the one hand, proponents of AI claim that increased data has improved computer vision and audio analytics, enabling better individual animal care (e.g., in slaughterhouses). The Slaughterhouse Act has significantly reduced the suffering and distress of animals in abattoirs. It has also led to several companies installing sensors and using AI to monitor and reduce the stress and suffering of animals during transportation to slaughterhouses, which received early support and encouragement from the EFSA (EFSA Panel on Animal, Health and Welfare AHAW 2022).[58]

On the other hand, many others still claim that success in slaughterhouses is only one part of the animal's life and that AI does not fundamentally improve their overall welfare on the primary farm.[59] These 'small wins' are not enough and are used by industry to distract away from (or 'Greenwash') an entirely corrupt and abusive system toward animal welfare.[60] They propose that AI should not be seen as the solution to resolve an entirely broken and exploitative industry. If anything, AI is being used as simply another tool to

[54] Stages 1 and 2: This point was emphasised many times during the surveys and the workshops, and many felt it was a key point that would underpin the increased adoption of AI in the sector.

[55] Stage 2: The workshop participants discussed this, which was also a significant research focus in the literature (see previous footnote).

[56] Stage 3: One respondent felt that the instrumentalisation of animals and farm surveillance would be significant ethical issues in the coming years.

[57] Stage 1: In the survey and the third round of statements in Section "Scenario: AI in animal farming in 2032" of the workshop, the participants were very divided about whether or not AI will provide an overall benefit or harm to animal welfare. In stage 2, the group was split down the middle on both sides, and everyone (except for 1 person who strongly believed that AI use would produce an overall negative impact) was at the back of the room (they were least certain about their position). They stated that both impacts were already occurring (positive and negative impacts on animals) and that the situation largely depended on how it would be applied and regulated. Based on their comments and feedback throughout this workshop section, these mixed feelings were accounted for in the paper. All of the statements made were reflections by the workshop participants.

[58] Stage 3: One participant pointed toward the efforts being made by EFSA to monitor animal welfare during transportation better. They saw the success of AI in slaughterhouses, leading to the implementation of AI and the improvement of animal welfare in transportation, as well.

[59] Stage 2: This was a criticism of one of the participants in the workshop – while there are successes at slaughterhouses, there is still a long way to go in the sector to improve animal welfare in animal farming.

[60] Stage 2: The potential for greenwashing in the sector was a considerable concern in the workshop and was mentioned several times throughout the day. The participants reflected that there should be greater effort to implement AI that has a real impact on improving animal welfare and not only to give the appearance of ethical behaviour.

further dehumanise, objectify, and reject the intrinsic value of these animals (Bos et al. 2018; Neethirajan and Kemp 2021; Neethirajan 2023b).

Aware that abolishing animal farming is not realisable in the near term, many animal welfare organisations conceded to working with (rather than against) the sector. While they have been (and still are) against animal farming (the ‘ideal’), they claim AI has improved many aspects of animals’ lives and is a step in the right direction. They have often chosen to work with, rather than against, those integrating and using AI in animal farming while pursuing their goal of reducing animal suffering and eventually the abolition of animal farming altogether (often referred to as ‘non-ideal’ theory in animal ethics (Garner 2013; Bovenkerk et al. 2024)).[61]

Legal

The EU was one of the first to implement AI legislation (the AI Act in 2024) (European Commission2024a) and was a pioneer in providing guardrails to ensure AIs ethical development and use. However, many found implementing these recommendations in the agricultural sector challenging because they felt they did not apply to the sector or were too vague and generic to implement. It was also often unclear who was responsible for ensuring AI was legally implemented (Alexander et al. 2024). Farmers also felt that AI legislation was aimed more toward larger tech companies and those developing AI, and governments did not provide enough support for adopting AI or how to abide by legal requirements in practice (Adereti et al. 2024).[62]

Despite this, several legal concerns emerged related to large tech companies. For example, ChatGPT 7, released March 14th 2030, uses highly advanced voice, multilingual, and vision capabilities, allowing for direct communication and interaction between the farmer and the chatbot (2024), but there has been controversy that it has been trained on copyrighted data belonging to agricultural technology providers (ATPs) (Zia-Ul-Haq 2023; Lucchi 2023; McGee 2023). Several ATPs are filing large lawsuits against OpenAI for copyright infringement (The Guardian 2024; Krietzberg 2024).

Another legal impact of AI deployment in animal farming is the lack of clarity around who owns the data retrieved from farms[63] and who is allowed to share specific data (Doidge et al. 2024; Mark 2019; Maru et al. 2018; Sanderson et al. 2017; Wiseman et al. 2019; van der Burg et al. 2020). These concerns led to increased data legislation in the EU in the early 2020s. On the one hand, these efforts helped ensure greater privacy and security of farmers’ data, a significant concern in the early adoption rates of AI in the sector. On the other hand, it often made data-sharing more difficult, which some claim hampered the development of AI because of the dependence on data to train animal farming algorithms.[64]

Social

There have also been quite striking social impacts, particularly in how it has affected power asymmetries and market grabs by influential players (Ryan 2020; Bronson and Sengers 2022; Campolo and Crawford 2020; Clapp 2021). In the early 2020s, there was concern that if the legislation did not keep up with AI developments, it would allow influential food producers, supermarkets, and big tech companies undue influence and control over the sector. The AI Act in 2024 (European Commission 2024a), alongside several ISO and standardisation protocols, were implemented in Europe to try to counter these impacts. These policies and standardisation guided AI development and deployment in the agri-food domain (Laux et al. 2024; Garrido et al. 2023).

While the agri-food sector has felt many impacts from AI over the past decade, AI has also impacted the lives of farmers and farm workers. In a recent survey of farmers who adopted AI between 2025 and 2030, most indicated that they believed AI brought an overall benefit to their lives.[65] Despite this, some farmers reported uncertainty about AI or felt the downsides of adoption outweighed the benefits (particularly many of the social impacts on their profession, which will be discussed later).[66]

[61] Stages 2: This point became very clear throughout the workshop, with many of the different animal welfare organisation representatives stating that they have/are working with companies developing and deploying AI on farms and with animal farmers using these technologies. They believe that the industry will not change overnight and that improving animal health and welfare through AI tools is a step in the right direction.

[62] Stage 2: One workshop group placed the ‘lack of governmental support’ post-it in the high-impact high-likelihood quadrant, one group placed it in the high-impact low-likelihood quadrant, and one group placed it in the low-impact low-likelihood.

[63] Stages 1 and 2: This was one of the most discussed legal issues in the surveys and the workshop and was a key priority for the stakeholders.

[64] Stage 3: One respondent pointed out that data regulation could also have a negative impact in the sector, as well as protecting farmers.

[65] Stage 2: This estimate and input were retrieved in the fourth part of the workshop, as described in Section “Constructing the scenario” of this paper. In this section, 10/14 participants stood on the side with the statement that AI will bring an overall positive benefit to the lives of farmers. Statement A read: ‘The use of AI in animal farming will provide greater economic benefits, easier jobs, better farm management, better care for their animals, and more ethical farming for farmers’.

[66] Stage 2: These results emerged from the workshop, where only 4 participants stood on the side of statement B, which indicated a largely negative impact on farmers. However, all 4 participants stood right at the back of the room, indicating they were less confident that the overall impacts on farmers would be negative. Statement B read as

As a result of AI deployment and use, the nature and role of the farmer, veterinarian, and feed advisors have changed (van der Burg et al. 2022; Ryan et al. 2021; Giersberg and Meijboom 2023).[67] While some have claimed improvements in efficiency and production levels, others shared concerns about what their jobs have become and what it now means to be a 'good farmer' (Driessen and Heutinck 2015) or a 'good vet' (Doidge et al. 2024). Despite the improvement in their farms (Lundström and Lindblom 2021), some feel that the increased automation of their farms has led to a loss of control and freedom in their roles (Goodman 2023; Unay-Gailhard and Simões 2022; Ogunyiola and Gardezi 2022; Klerkx et al. 2019).

In addition, several farmers have reported losing out on their interaction with their animals, as there is less need for their physical presence in the barns and stables (van der Burg et al. 2019). They can do much of their work from their living room (on their computer), so it is difficult to justify going to the farm when the weather is bad. As a result, some have lost their sense of purpose or claim that the fun has been taken out of farming (van der Burg et al. 2022).

Some veterinarians embrace AI and data-driven solutions as supportive tools to assist them in their roles (Giersberg and Meijboom 2023). They see the benefits of working with (rather than against) AI (Giersberg and Meijboom 2023). However, other veterinarians are worried that farmers are becoming over-reliant on AI without consulting them and are apprehensive about the future of their profession and the accuracy of recommendations given by AI (Doidge et al. 2024). They warn that AI should not replace veterinarians because it is not always accurate or provides correct advice. Instead, farmers should consult with their local veterinarian regularly and also use AI (Giersberg and Meijboom 2023).

Recommendations to policymakers in 2025

The previous sections have focused on many potential challenges, issues, and opportunities AI may bring to the animal farming sector. This section will focus on the kinds of recommendations and actions policymakers should take now to ensure desirable outcomes from AI in animal farming, while addressing potential challenges and issues. These policy recommendations arose throughout the survey, workshop, and feedback sessions on the scenario. Providing clear-cut and precise policymaking recommendations is very challenging. Because AI in animal farming is relatively new, these recommendations provide a novel first step toward addressing these issues.

It must be noted that four policymakers were included in the initial survey and workshop and provided feedback on the drafting of these recommendations. At the same time, several policymakers also participated in the four events where the scenario was presented. This allowed for gathering insights from, and directly to, policymakers on the content of this scenario. In addition, the results of this scenario will be presented to Dutch and EU policymakers after the final version has been published, to provide them with insights into this scenario.

While AI offers great promise for the animal farming sector, policymakers must be open but realistic about its potential.[68] The first recommendation is that policymakers should implement adequate education on AI in animal farming.[69] Education policy should stimulate an open-minded, learning-focused, critical attitude towards these opportunities and AIs potential impacts and risks. This requires learning AI techniques and critically reflecting on their implications for farming practices. There should be an acknowledgement of what AI can and cannot achieve; for example, the limits of quantitative, generalisable methods to address qualitative, singular behaviour, animal integrity, and intrinsic value from an ethical perspective.[70] Policymakers should focus on concrete examples and successful applications of AI in the field.[71] However, they should not lose sight of the basics for animal welfare, such as the need for a good barn with sufficient space to perform natural behaviour.[72]

A second recommendation concerns the development of an ethical framework for using AI in animal farming with stakeholders.[73] Implementing such frameworks enables

follows: 'The use of AI in animal farming will result in less control of their farms because of technological lock-in with food manufacturers or tech companies; the role of the farmer will become a labourer on their farm, job loss, and more cumbersome regulations to follow'.

[67] Stage 3: One respondent added that they will dramatically also impact the role of veterinarians, feed advisors, and other stakeholders and not only farmers.

[68] Stages 1, 2, and 3: Recommended by 3/11 survey respondents. It was discussed in the workshop, and participants also mentioned it in their comments about the scenario in Stage 3 when asked again about recommendations to policymakers.

[69] Stage 3: The stakeholders emphasised the importance of education and appropriate training for people in the sector about AI in general and the benefits and potential impacts of using it in animal farming.

[70] Stages 1, 2, and 3: The stakeholders emphasised the benefits that AI could bring to the sector, but they also noted that these benefits should be met with openness and scepticism. AI's potential usability and benefits should not be taken for granted, and policymakers should make decisions based on sound scientific evidence.

[71] Stage 1: 2/11 stakeholders mentioned this as important.

[72] Stage 3: One stakeholder emphasised the need to focus on non-digital solutions to improve animal welfare, such as good barns and suitable living conditions for animals, rather than the incorporation of AI. They mentioned that these were essential prerequisites before deploying AI.

[73] State 2: This was a strong focus in the workshop, with several stakeholders referring to the need for ethical guidance through a set of

the assessment of AIs ethical implications in animal farming and exploring opportunities for redesign to prevent or address these implications.[74] The sector should not undertake such an assessment and exploration alone; it requires an interdisciplinary approach in which humanities scholars, social scientists, and engineers are stimulated to collaborate on sustainable, socially desirable, and ethically acceptable solutions.[75] Such an approach should also include representatives from the quadruple helix of industry (tech providers, farmers), policymakers (regional, national, and transnational), academia, and civil society (consumers, citizens, and NGOs). An ethical advisory board or committee at the EU level could facilitate the evaluation of particular ethical, legal, and social issues.[76]

A third policy recommendation concerns science policy.[77] Although many AI-based systems are already on the market, more advanced AI systems are still in the introductory science phase with low technological readiness levels (TRL). They provide sustainability, welfare, and health opportunities but require more investment to test their potential in high-level TRL applications and their scalability. Precise science policy requirements can help to prevent the development of costly AI-based systems to solve problems that conventional technologies can appropriately solve.[78] This is especially important to consider in light of the high environmental costs involved in AI development (energy costs to store data, train the models, and run the systems). Research policy should stimulate interdisciplinary research involving behavioural sciences (e.g., psychologists), humanities scholars, and technical sciences.[79]

A fourth recommendation concerns industrial policy and the connection between ICT and agri-food. The agri-food domain is a very particular and well-established sector with its knowledge base and dynamics, which requires alignment.[80] Policymakers must consider their responsibility for the public domain, their role in protecting society against AI-based systems and steering the employment of AI-based systems towards sustainable, ethically acceptable, and socially desirable use.

Lastly, while AI and data legislation are necessary and helpful for ensuring fair and transparent data sharing in Europe, greater clarity, translation, and assistance are needed for data sharing in animal farming. It should be clear to animal farmers how they can share data, to whom, and in what ways. There should also be proactive steps to ensure that farmers benefit from sharing their data, which trains LLMs and AI recommendation systems, which they may need to purchase to optimise their farms in the future. The steps towards data-sharing and use in animal farming should be made more accessible in the sector.

Conclusion

This paper took a forward-looking view of the benefits and challenges that AI may create in animal farming by the year 2032. Through several rounds of stakeholder engagement, this paper mapped a future scenario for AI in animal farming, identifying technological developments, potential drivers, barriers, and impacts. Although the scenario shows the opportunities of AI-based systems, like the potential positive impact on animal health and welfare and its assistance with food safety issues and increased environmental performance, it also shows that the discrepancy between the expectations of AI technology (e.g., access to training data) and concerns of farmers (e.g., risks involved in data sharing) will remain over time. A similar discrepancy can be observed between societal expectations regarding animal farming and the sector's actual performance, for instance, in animal welfare. It can be expected that AI provides opportunities to reduce this discrepancy (as indicated by the case of slaughterhouses). Still, it also poses the possibility that this discrepancy increases due to the digitalisation of animal farming (as indicated by concerns regarding the commodification of agricultural production).

Overall, this paper concluded with five recommendations for policymakers: 1. Initiate education programmes on AI in the sector; 2. Create ethical guidelines for AI in animal farming; 3. Science policy should be realistic and not only rely on technical solutions like AI; 4. Ensure public safety from harm caused by AI; and 5. Implement better guidance on data-sharing in the sector. These recommendations can, and should, be implemented at different levels from regional and local to national, international, and transnational

guidelines, an ethical committee, or an ethical advisory board.

[74] Stage 2: One stakeholder stated that behavioural sciences (psychologists) should be incorporated to better understand human-tech interactions.

[75] Stages 1, 2, and 3: Several stakeholders emphasised the importance of interdisciplinary collaboration, which policymakers should encourage and develop.

[76] Stage 1: The survey mentioned establishing independent advisory boards/committees twice.

[77] Stages 2 and 3: Science policy was discussed during the workshop and in the feedback on the scenario. Many scientific advancements still need to be implemented at scale. To bridge this gap, policymakers should ensure a greater connection between the tech sector, agri-food, and academia.

[78] Stage 1: Two stakeholders mentioned that policymakers should be realistic and identify how to implement science into practice.

[79] Stage 1: Two stakeholders stated the importance of ensuring the inclusion of diverse stakeholders and interdisciplinarity in AI research.

[80] Stages 2 and 3: The stakeholders emphasised the importance of different data and AI legislation, stating that efforts should be made to ensure those using AI in animal farming are well protected.

collaborations. While the scenario focused on Europe, animal farming food systems are interconnected, so collaboration and interaction between regional policymakers are needed to achieve these objectives. Furthermore, these recommendations need to be initiated in collaboration with many other stakeholders to be effective. For example, developing AI ethics guidelines for animal farming is pointless if farmers, agribusinesses, slaughterhouses, and veterinarians do not integrate them into their practices. Overall, this paper provides a first step toward a set of recommendations for the ethical deployment of AI in animal farming. However, further research is needed to build on these recommendations and develop them into tangible, implementable steps for the responsible development and use of AI in the sector.

Limitations and future research

A limitation of the policy scenario methodology is the dependence on stakeholders for the content of the scenario. While stakeholder engagement for scenario construction is essential, the narrative's relative neutrality poses challenges when stakeholders overlook essential topics or events that could shift its direction. For example, the stakeholders did not mention the political shifts and turbulence in the EU, with many countries veering towards more right-wing policies. Nor did the stakeholders pay any attention to the environmental impact that developing and using AI would have (e.g., high water and electricity use in data centres), thereby contradicting the environmentally focused goals of using AI in the first place. These points were mentioned during the validation events, where the scenario was presented.

In addition, the study's geographical focus on Europe may limit its scope. While we earlier acknowledged the interconnectedness of the food system, the global scale of many AI actors, and the difficulty of separating geographical locations in a globalised system, it was essential to base the scenario on the knowledge, experience, and backgrounds of the stakeholders providing input on the scenario – namely, a European context. However, perhaps future research could develop several regional cases or conduct more geographically distributed scenarios to provide more geographically balanced scenarios.

A second limitation and a call for future research is the relatively short time frame of events in the policy scenario (i.e., 5–7 years), as evidenced by the four events we used to validate our results. It was mentioned that while the scenario was realistic and insightful, it should be complemented with more distant scenarios. This would allow for more robust postulation about controversial outcomes or starker future visions (e.g., a dark scenario, best-case, worst-case, or status quo scenario). Others also mentioned that using thought experiments may help complement scenario methodologies.

An additional limitation of the policy scenario methodology is how the information is presented to the reader. While it is essential not to take the reader out of the scenario, it is also vital to cite the source of the content, i.e., through footnotes. Unfortunately, it may be cumbersome for some readers to go back and forth between the footnotes and the text; it was felt that footnotes were the most suitable approach, as endnotes, appendices, or even in-text references would further pull the reader out of the narrative of the scenario.

Lastly, while many efforts were made to include and expand the number of stakeholders providing input on the scenario, implementing it in practice proved very difficult. While some of the most significant stakeholder groups were represented, we were unable to include all the stakeholder groups we wanted (see footnote 9). For example, it was not possible to include the most affected stakeholder in this technology, namely farmed animals, due to obvious communication barriers and logistical constraints (however, perhaps, someday with the help of AI, it may be possible to include animals in scenario construction, cf (Ryan and Bossert 2024). Despite this, several animal welfare groups were included to try to give animals a voice in the scenario construction.

Despite these limitations, this scenario offers a glimpse into the future of AI development and use in the animal farming sector in Europe, along with the probable drivers, barriers, and impacts that may result. Overall, it brings together a vast body of literature on the topic alongside several rounds of stakeholder engagement with individuals working in the field from government, academia, industry, and civil society. This scenario offers researchers a way to collectively evaluate the major trends, challenges, and opportunities in the development and use of AI in animal farming, while providing policymakers with insights and steps to be taken in the coming years.

Appendices

Appendix A: Questions asked in the survey

Questions
1. Which quadruple helix domain do you work in?
2. What is the primary focus of your work?
3. How do you think the use of AI in animal farming will develop in the next 5–7 years (e.g., what will be the focus? What new applications or uses will emerge? Possible breakthroughs or discoveries)?
4. What will be some of the most significant drivers for using AI in animal farming in the coming 5–7 years? (e.g., economic incentives, scientific research, competition, consumer demand, and government).
5. What will be some of the most significant barriers/inhibitors of using AI in animal farming in the coming 5–7 years? And why? (e.g., technological limitations, legislation, lack of incentive for adoption, high costs, political activism, etc.).
6. What will be some of the most significant impacts (positive or negative) of AI use in animal farming in the coming 5–7 years? Please describe some impacts in any of the following areas: ethical, legal, social, or economic impacts.
7. What recommendations would you give to policymakers and other stakeholders on how to mitigate the negative and accentuate the positive impacts of AI in animal farming in the coming 5–7 years?

Appendix B: Drivers and barriers from the survey

Drivers	Barriers
Economic and efficiency incentives	Lack of added value/incentives
AI applications (like checks/audits) becoming mandatory	High entry costs
NGO/civil society pressure	Technological readiness/scientific merit
Governmental support/political decision-making	Lack of legislation
Scientific advancements	Mistrust in AI
Public opinion/consumer demand	Skills of end-user/lack of upskilling
Improved animal health and welfare	Lack of enforceability to adopt
Shortage of human labour	Data Ownership
	Lack of governmental support

Appendix C: List of statements for part four of the workshop

Stakeholder	Statement A	Statement B
Farmer	The use of AI in animal farming will provide greater economic benefits, easier jobs, better farm management, better care for their animals, and more ethical farming for farmers.	The use of AI in animal farming will result in less control of their farms because of technological lock-in with food manufacturers or tech companies; the role of the farmer will become a labourer on their farm, causing job loss and more cumbersome regulations to follow.
Farming Sector	AI will make the farming sector more efficient and better. It will improve, become cheaper, and provide more benefits in the future. Using AI in animal farming reduces risks, and potential harms will be negligible.	AI will pose many challenges to the farming sector in the future. Legislation will be slow and follow technological developments, constantly playing catch-up. This will also lead to a dependency on wealthy companies, creating power imbalances in the sector.
Farm Animals	The use of AI in animal farming will dramatically increase the health and welfare of farm animals, reduce suffering, effectively respond to disease, and allow farmers to provide proper individual care of the animal.	The use of AI in animal farming will be used as a kind of ethics/greenwashing but will not truly alleviate the suffering and pain of farm animals. The animal farm industry will use AI to try to condone their practices and for the continuation of the industry and will only allow AI to perpetuate their narrative (e.g., no animal communication AI).

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References

ILVO. Animal Welfare Indicators at the SlaughterHouse - ILVO Vlaanderen. ILVO (English). 2024. Accessed August 27, 2024. https://ilvo.vlaanderen.be/en/research-projects/animal-welfare-indicators-at-the-slaughterhouse%92

MarketsandMarkets, Precision Livestock Farming market Size, Share, Industry Report, Revenue Trends and Growth Drivers, MarketsandMarkets. Accessed: May 28, 2024. https://www.marketsandmarkets.com/Market-Reports/precision-livestock-farming-market-29706557.html

RASE. Opportunities for Using Artificial Intelligence in Livestock Farming. Accessed June 26, 2024. https://www.rase.org.uk/news/opportunities-for-using-artificial-intelligence-in-livestock-farming/

VentureRadar. Top Livestock Start-Ups. Accessed June 25, 2024. https://www.ventureradar.com/startup/livestock

Abeni, F., F. Petrera, and A. Galli. A Survey of Italian Dairy Farmers' Propensity for Precision Livestock Farming Tools. *Animals* 9, no. 5 (2019): 202. *Animals*

Adebayo, S., et al. Enhancing Poultry Health Management through Machine Learning-Based Analysis of Vocalization Signals Dataset. *Data Brief*50 (2023): 109528

Adereti, D. T., M. Gardezi, T. Wang, and J. McMaine. Understanding Farmers' Engagement and Barriers to Machine Learning-Based Intelligent Agricultural Decision Support Systems. *Agronomy Journal* 116, no. 3 (2024): 1237–1249. https://doi.org/10.1002/agj2.21358

Afonso, O., S. Monteiro, and M. Thompson. A Growth Model for the Quadruple Helix. *Journal of Business Economics and Management* 13, no. 5 (October 2012): 849–865. https://doi.org/10.3846/16111699.2011.626438

Alahi, M. E. E., et al. Integration of IoT-Enabled Technologies and Artificial Intelligence (AI) for Smart City Scenario: Recent Advancements and Future Trends. *Sensors* 23, no. 11 (2023): 5206. https://doi.org/10.3390/s23115206

Alex, A. G. R., and G. J. Joseph. Real-Time Poultry Health Identification Using IoT Test Setup, Optimization and Results. *In Advances in Signal Processing and Intelligent Recognition Systems*, edited by S. M. Thampi, O. Marques, S. Krishnan, K.-C. Li, D. Ciuonzo, and M. H. Kolekar, 30–40. Communications in Computer and Information Science. Singapore: Springer, 2019. https://doi.org/10.1007/978-981-13-5758-9_3

Alexander, C. S., M. Yarborough, and A. Smith. Who Is Responsible for 'Responsible AI'?: Navigating Challenges to Build Trust in AI Agriculture and Food System Technology. *Precision Agriculture* 25, no. 1 (February 2024): 146–185. https://doi.org/10.1007/s11119-023-10063-3

AlZu'bi, S., A. Mughaid, F. Quiam, and S. Hendawi. Exploring the Capabilities and Limitations of ChatGPT and Alternative Big Language Models. In *Artificial Intelligence and Applications*28–37, 2024. Accessed June 25, 2024. http://ojs.bonviewpress.com/index.php/AIA/article/view/820

Amid, S., and T. Mesri Gundoshmian. Prediction of Output Energies for Broiler Production Using Linear Regression, ANN (MLP, RBF), and ANFIS Models. *Environmental Progress & Sustainable Energy* 36, no. 2 (2017): 577–585. https://doi.org/10.1002/ep.12448

Andreas, J., et al. Cetacean Translation Initiative: A Roadmap to Deciphering the Communication of Sperm Whales. April 17, 2021. arXiv:2104.08614. Accessed November 21, 2023. http://arxiv.org/abs/2104.08614

Andreas, J., et al. "Toward Understanding the Communication in Sperm Whales. *Iscience* 25, no. 6 (2022): 104393.

Animal Welfare Institute. "Inhumane Practices on Factory Farms." Accessed January 19, 2024. https://awionline.org/content/inhumane-practices-factory-farms

Atik, C. Towards Comprehensive European Agricultural Data Governance: Moving Beyond the Data Ownership Debate.*IIC - International Review of Intellectual Property and Competition Law* 53, no. 5 (May 2022): 701–742. https://doi.org/10.1007/s40319-022-01191-w

Atik, C. Addressing Data Access Problems in the Emerging Digital Agriculture Sector: Potential of the Refusal to Deal Case Law to Complement Ex-Ante Regulation. *European Competition Journal* 19, no. 3 (September 2023): 380–409. https://doi.org/10.1080/17441056.2023.2200618

Atik, C. 2023b, Nov. Horizontal intervention, sectoral challenges: Evaluating the data act's impact on agricultural data access puzzle in the emerging digital agriculture sector. *Comput. Law Secur. Rev.* 51: 105861. https://doi.org/10.1016/j.clsr.2023.105861

Aydin, A. Development of an Early Detection System for Lameness of Broilers Using Computer Vision *Computers and Electronics in Agriculture* 136 (2017): 140–146

Bao, J., and Q. Xie. "Artificial Intelligence in Animal Farming: A Systematic Literature Review. *Journal of Cleaner Production* 331 (2022): 129956

Barney, S., S. Dlay, A. Crowe, I. Kyriazakis, and M. Leach. Deep Learning Pose Estimation for Multi-Cattle Lameness Detection. *Scientific Reports* 13, no. 1 (2023): 4499

Bati, C. T., and G. Ser. SHEEPFEARNET: Sheep Fear Test Behaviors Classification Approach from Video Data Based on Optical Flow and Convolutional Neural Networks. *Computers and Electronics in Agriculture.* 204 (2023): 107540

Baur, P., and A. Iles. Replacing Humans with Machines: A Historical Look at Technology Politics in California Agriculture. *Agriculture and Human Values* 40, no. 1 (March 2023): 113–140. https://doi.org/10.1007/s10460-022-10341-2

Bishop, J., G. Falzon, M. Trotter, P. Kwan, and P. Meek. Sound Analysis and Detection, and the Potential for Precision Livestock Farming—A Sheep Vocalization Case Study. In *Proceedings of the 1st Asian-Australasian Conference on Precision Pastures and Livestock Farming,* Hamilton, New Zealand, 2017, 1–7. Accessed May 31, 2024. https://www.researchgate.net/profile/James-Bishop-9/publication/325006988_Sound_Analysis_and_Detection_and_the_Potential_for_Precision_Livestock_Farming_-_A_Sheep_Vocalization_Case_Study/links/5af104da0f7e9ba36645283a/Sound-Analysis-and-Detection-and-the-Potential-for-Precision-Livestock-Farming-A-Sheep-Vocalization-Case-Study.pdf

Bishop, J., M. Welch, D. Paul, P. Kwan, and G. Falzon. Automated Livestock Vocalisation Detection in Farm Acoustic Environments. 2023. Accessed June 25, 2024. https://rune.une.edu.au/web/handle/1959.11/57067

Bishop, J. C., G. Falzon, M. Trotter, P. Kwan, and P. D. Meek. Livestock Vocalisation Classification in Farm Soundscapes. *Computers and Electronics in Agriculture* 162 (2019): 531–542

Biswas, S. Importance of Chat GPT in Agriculture: According to Chat GPT. March 30, 2023. Rochester, NY: 4405391.

Bjola, C., and I. Manor. Digital Diplomacy in the Age of Technological Acceleration: Three Impact Scenarios of Generative Artificial Intelligence. *Place Branding and Public Diplomacy*(2024). https://doi.org/10.1057/s41254-023-00323-4

Blaustine-Retjo, D., and C. Gambino. Livestock Don't Contribute 14.5% of Global Greenhouse Gas Emissions.*The Breakthrough Institute*.Accessed January 19, 2024. https://thebreakthrough.org/issues/food-agriculture-environment/livestock-dont-contribute-14-5-of-global-greenhouse-gas-emissions

Boenink, M. Anticipating the Future of Technology and Society by Way of (Plausible) Scenarios: Fruitful, Futile or Fraught with Danger? *International Journal of Foresight and Innovation Policy* 9, no. 2–3–4 (January 2013): 148–161. https://doi.org/10.1504/IJFIP.2013.058608

Boenink, M., T. Swierstra, and D. Stemerding. "Anticipating the Interaction between Technology and Morality: A Scenario Study of Experimenting with Humans in Bionanotechnology. *Studies in Ethics, Law, and Technology* 4, no. 2 (August 2010). https://doi.org/10.2202/1941-6008.1098

Bos, J. M., B. Bovenkerk, P. H. Feindt, and Y. K. van Dam. "The Quantified Animal: Precision Livestock Farming and the Ethical Implications of Objectification. *Food Ethic* 2, no. 1 (December 2018): 77–92. https://doi.org/10.1007/s41055-018-00029-x

Bossert, L. and T. Hagendorff. 2021, Nov. Animals and AI. The role of animals in AI research and application - An overview and ethical evaluation. *Technology in Society* 67 (November 2021): 101678. https://doi.org/10.1016/j.techsoc.2021.101678

Bossert, L., and T. Hagendorff. "The Ethics of Sustainable AI: Why Animals (Should) Matter for a Sustainable Use of AI. *Sustainable Development*(2023)

Bossert, L. N., and M. Coeckelbergh. From MilkingBots to RoboDolphins: How AI Changes Human-Animal Relations and Enables Alienation towards Animals. *Humanities and Social Sciences Communications* 11, no. 1 (2024): 1–7.

Bovenkerk, B., M. Bracke, and A. Valros. Ethical Aspects of Tail Biting and Docking. *In Tail Biting in Pigs : A Comprehensive Guide to Its Aetiology, Impact and Wider Significance in Pig Management,*2024. Brill

Bronson, K. Looking through a Responsible Innovation Lens at Uneven Engagements with Digital Farming. *NJAS - Wageningen Journal of Life Sciences* 90 (2019): 100294

Bronson, K., and P. Sengers. "Big Tech Meets Big Ag: Diversifying Epistemologies of Data and Power. *Science as Culture* 31, no. 1 (January 2022): 15–28 https://doi.org/10.1080/09505431.2021.1986692

Cairns, G., and G. Wright. *Scenario Thinking: Preparing Your Organization for the Future in an Unpredictable World.*Springer, 2017. Accessed May 7, 2024. https://books.google.com/books?hl=en%26lr=%26id=NFs6DwAAQBAJ%26oi=fnd%26pg=PR5%26dq=Cairns,+G.,+Wright,+G.,+2018.+Scenario+Thinking:+Preparing+Your+Organization+for+the+Future+in+an+Unpredictable+World,+second+ed.+Palgrave+Macmillan %26ots=e6iU1phCBf%26sig=99g3C8pZ4XyE-AygGCRQQMc0owA. Springer

Campolo, A., and K. Crawford. Enchanted Determinism: Power without Responsibility in Artificial Intelligence. *Engagement Science, Technology and Society* 6 (January 2020): 1–19. https://doi.org/10.17351/ests2020.277

Carayannis, E. G., and D. F. Campbell. Triple Helix, Quadruple Helix and Quintuple Helix and How Do Knowledge, Innovation and the Environment Relate to Each Other?: A Proposed Framework for a Trans-Disciplinary Analysis of Sustainable Development and Social Ecology. *International Journal of Social Ecology and Sustainable Development* 1, no. 1 (2010): 41–69

Carayannis, E. G. and D. F. J. Campbell. 2009. "Mode 3" and "Quadruple Helix": toward a 21st century fractal innovation ecosystem. *International Journal of Technology Management* 46, no. 3/4 (2009): 201. https://doi.org/10.1504/IJTM.2009.023374

Carena, M., S. Heinemeyer, C. E. M. Wagner, and G. Weiglein. Suggestions for Benchmark Scenarios for MSSM Higgs Boson Searches at Hadron Colliders. *European Physical Journal C* 26, no. 4 (2003): 601–607. https://doi.org/10.1140/epjc/s2002-01084-3

Casten Carlberg, C. J., and E. Jerhamre. Artificial Intelligence in Agriculture: Opportunities and Challenges." 2021. Accessed September 2, 2024. https://www.diva-portal.org/smash/record.jsf?pid=diva2:1559051

Casnici, C. V. C., G. G. Reis, D. Schulzmann, M. Papanastassiou, and J. Clegg. The Role of NGOs in the Transition Towards More Sustainable and Innovative Agri-Food GVCs. *In Walking the Talk? MNEs Transitioning Towards a Sustainable World: Tribute Volume to Alain Verbeke*373–392. Emerald Publishing Limited, 2024. Accessed June 26, 2024. https://www.emerald.com/insight/content/doi/10.1108/S1745-886220240000018023/full/html. Accessed: Jun. 26, 2024. [Online]. Available

Chafai, N., I. Hayah, I. Houaga, and B. Badaoui. A Review of Machine Learning Models Applied to Genomic Prediction in Animal Breeding. *Frontiers in Genetics* 14 (2023): 1150596.

Chaterji, S., et al. Artificial Intelligence for Digital Agriculture at Scale: Techniques, Policies, and Challenges. January 21, 2020. arXiv:2001.09786. https://doi.org/10.48550/arXiv.2001.09786

Chen, B. X. The New ChatGPT Offers a Lesson in AI Hype. *The New York Times 2024*. Accessed June 21, 2024. https://www.nytimes.com/2024/05/31/technology/personaltech/chatgpt-4o-openai-review.html. Accessed: Jun. 21, 2024. [Online]. Available

Chen, C., W. Zhu, and T. Norton. "Behaviour Recognition of Pigs and Cattle: Journey from Computer Vision to Deep Learning. *Computers and Electronics in Agriculture* 187 (2021): 106255.

Clapp, J. The Problem with Growing Corporate Concentration and Power in the Global Food System. *Nature Food* 2, no. 6 (2021): 404–408.

Coatrini-Soares, A., et al. 2023. Microfluidic E-tongue to diagnose bovine mastitis with milk samples using Machine learning with Decision Tree models. *Chemical Engineering Journal* 451 (2023): 138523

Coghlan, S., and C. Parker. Harm to Nonhuman Animals from AI: A Systematic Account and Framework. *Philosophy & Technology* 36, no. 2 (2023): 25.

Coutant, M., A. S. Villain, and E. F. Briefer. 2024, Jun. A scoping review of the use of bioacoustics to assess various components of farm animal welfare. *Applied Animal Behaviour Science* 275 (June 2024): 106286. https://doi.org/10.1016/j.applanim.2024.106286

Custom Market Insights. Europe Cultured Meat Market Size, Share, Forecast 2032 - CMI. Accessed August 28, 2024. https://www.custommarketinsights.com/report/europe-cultured-meat-market/

Czubak, W., K. Pawlak, and P. Kotyza. Small Farms Managed by Young Farmers." 2023. Accessed June 25, 2024. https://www.researchgate.net/profile/Pavel-Kotyza/publication/376609660_SMALL_FARMS_MANAGED_BY_YOUNG_FARMERS_UNDER_NEW_FARM_-TO_-FORK_STRATEGY/links/65804e7956e52916af53c707/SMALL-FARMS-MANAGED-BY-YOUNG-FARMERS-UNDER-NEW-FARM-TO-FORK-STRATEGY.pdf

Dara, R., M. Hazrati, and J. Kaur. Recommendations for Ethical and Responsible Use of Artificial Intelligence in Digital Agriculture. *Frontiers in Artificial Intelligence* (2022): 176

Daum, T. Farm Robots: Ecological Utopia or Dystopia? *Trends Ecol. Evol.* 36, no. 9 (September 2021): 774–777. https://doi.org/10.1016/j.tree.2021.06.002

Debauche, O., M. Elmoulat, S. Mahmoudi, J. Bindelle, and F. Lebeau. "Farm Animals' Behaviors and Welfare Analysis with AI Algorithms: A Review. *Revue d'Intelligence Artificielle* 35, no. 3 (2021)

Deloitte. AI4Animals. Deloitte Netherlands. Accessed August 27, 2024. https://www2.deloitte.com/nl/nl/pages/consumer/solutions/ai4animals.html

Department of Food Science. Most Europeans Are Reducing Their Meat Consumption, EU-Funded Survey Finds. Accessed August 27, 2024. https://food.ku.dk/english/news/2023/most-europeans-are-reducing-their-meat-consumption-eu-funded-survey-finds/

Deuten, S., J. J. Gómez Vilchez, and C. Thiel. Analysis and Testing of Electric Car Incentive Scenarios in the Netherlands and Norway. *Technological Forecasting and Social Change*.(2020). Accessed June 19, 2024. https://www.sciencedirect.com/science/article/pii/S0040162519301210: Jun

Dilaver, H., and K. F. Dilaver. Robotics Systems and Artificial Intelligence Applications in Livestock Farming. *Journal of Animal Science and Economics* 3, no. 2 (2024): 63–72.

Doidge, C., et al. A Living Lab Approach to Understanding Dairy Farmers Needs of Technologies and Data to Improve Herd Health: Focus Groups from 6 European Countries. *Journal of Dairy Science*. (2024). Accessed August 27, 2024. https://www.sciencedirect.com/science/article/pii/S0022030224005502

Doidge, C., A. Burrell, G. van Schaik, and J. Kaler. A Qualitative Survey Approach to Investigating Beef and Dairy Veterinarians' Needs in Relation to Technologies on Farms. *Animal* 18, no. 4 (2024): 101124

Doidge, C., L. Palczynski, X. Zhou, A. Bearth, G. van Schaik, and J. Kaler. Exploring the Data Divide through a Social Practice Lens: A Qualitative Study of UK Cattle Farmers. *Preventive Veterinary Medicine* 220 (2023): 106030

Dong, Y., et al. PigSense: Structural Vibration-based Activity and Health Monitoring System for Pigs. *ACM Transactions on Sensor Networks* 20, no. 1 (January 2024): 1–43. https://doi.org/10.1145/3604806

Drexl, V., I. Dittrich, T. Wilder, S. Diers, H. Janssen, and J. Krieter. Prediction of Tail Biting in Pigs Using Partial Least Squares Regression and Artificial Neural Networks. *Computers and Electronics in Agriculture* 216 (2024): 108477

Driessen, C. and L. F. Heutinck. 2015. Cows desiring to be milked? Milking robots and the co-evolution of ethics and technology on Dutch dairy farms. *Agriculture and Human Values* 32, no. 1 (2015): 3–20

Ducatel, K.U. 2010, 2001. européenne T. de la société de l'information, U. européenne I. d'études de prospectives technologiques, and U. européenne S. de l'information conviviale, 'Scenarios for ambient intelligence in. Accessed: May 7, 2024. [Online]. Available. http://www.ist.hu/doctar/fp5/istagscenarios2010.pdf

Džermeikaitė, K., D. Bačėninaitė, and R. Antanaitis. 2023, Jan. Innovations in Cattle Farming: Application of Innovative Technologies and Sensors in the Diagnosis of Diseases. *Animals* 13(5, Art. no. 5). https://doi.org/10.3390/ani13050780

EFSA AHAW Panel (EFSA Panel on Animal Health and Welfare),. 2023. Welfare of broilers on farm. *EFSA J.* 21(2): e07788. https://doi.org/10.2903/j.efsa.2023.7788

EFSA Panel on Animal, Health and Animal, Welfare (AHAW),. 2023. Welfare of calves'. *EFSA J.* 21(3): e07896. https://doi.org/10.2903/j.efsa.2023.7896. et al

EFSA Panel on Animal, Health and Welfare (AHAW). 2022. Welfare of pigs on farm. *EFSA J.* 20(8): e07421. https://doi.org/10.2903/j.efsa.2022.7421

EFSA Panel on Animal, Health and Welfare (AHAW),. 2022. Welfare of cattle during transport. *EFSA J.* 20(9): e07442. https://doi.org/10.2903/j.efsa.2022.7442. et al

Ehlers, M.-H., et al. 2022. "Scenarios for European Agricultural Policymaking in the Era of Digitalisation. *Agricultural Systems* 196: 103318. https://doi.org/10.1016/j.agsy.2021.103318

Ekin, S. 2023. Prompt Engineering for ChatGPT: A Quick Guide to Techniques, Tips, and Best Practices." May 4, 2023. https://doi.org/10.36227/techrxiv.22683919.v2

Elbehri, A. and R. Chestnov. 2021. *Digital agriculture in action: Artificial intelligence for agriculture*. Food& Agriculture Org

N. en V. Ministerie van Landbouw, Fewer animals in pig and cow farms in Romania - Nieuwsbericht - Agroberichten Buitenland. May 17, 2023. Accessed September 4, 2024. https://www.agroberichtenbuitenland.nl/actueel/nieuws/2023/05/17/fewer-animals-in-pig-and-cow-farms-in-romania: Sep. 04

EuroMeatNews '2024. "Monitoring Animal Welfare Using AI." Accessed August 27, 2024. https://euromeatnews.com/Article-Monitoring-animal-welfare-using-AI/6057

Europe, Animal AgTech. 2024. [Online]. Available: Meet 11 start-ups Advancing sustainable livestock and aquaculture production. In Animal AgTech innovation summit - AMSTERDAM. Accessed: Jun. 25, https://animalagtecheurope.com/meet-11-start-ups/

European Commission, Directorate General for Agriculture and Rural Development.*EU Agricultural Outlook* 2023-2035. Luxembourg: Publications Office. Accessed August 28, 2024. https://data.europa.eu/doi/10.2762/722428

European Commission. Artificial intelligence act. 2024a. Accessed: Jun 25. https://www.europarl.europa.eu/thinktank/en/document/EPRS_BRI(2021)698792

European Commission. 2024b. *Cluster*, 6: Food, Bioeconomy, Natural Resources, Agriculture and Environment - European Commission. https://research-and-innovation.ec.europa.eu/funding/funding-opportunities/funding-programmes-and-open-calls/horizon-europe/cluster-6-food-bioeconomy-natural-resources-agriculture-and-environment_en%92. Accessed: Jun. 27

European Commission. Commission welcomes political agreement on AI Act. European Commission - European Commission. Accessed: Mar. 28, 2024a. [Online]. Available: https://ec.europa.eu/commission/presscorner/detail/en/ip_23_6473

European Commission. 2024c. [Online]. Available: Digital transformation in agriculture and rural areas - European Commission. *Accessed: Jun* 26. https://research-and-innovation.ec.europa.eu/research-area/agriculture-forestry-and-rural-areas/digital-transformation-agriculture-and-rural-areas_en

European Commission. 2024d. The Digitalisation of the European Agricultural Sector *Shaping Europe's digital future.* 26. https://digital-strategy.ec.europa.eu/en/policies/digitalisation-agriculture

European Commission. 2024e. August 27. EU agricultural outlook 2023-35. a transitioning and resilient EU farming sector will cope with challenges and embrace opportunities - European Commission. Accessed. https://agriculture.ec.europa.eu/news/eu-agricultural-outlook-2023-35-transitioning-and-resilient-eu-farming-sector-will-cope-challenges-2023-12-07_en

European Commission. 2024f. European Data Governance Act. Accessed: Jun. 27 https://digital-strategy.ec.europa.eu/en/policies/data-governance-act%92

European Commission. The Scenario Exploration System (SES) | Knowledge for policy. Accessed: May 7, 2024b. [Online]. Available. https://knowledge4policy.ec.europa.eu/foresight/tool/scenario-exploration-system-ses_en

European Commission. '*Digital Agriculture*', EIP-AGRI - European Commission. 2024g Accessed: Jun 26. https://ec.europa.eu/eip/agriculture/en/digitising-agriculture
European Commission, 'Data Act' 2024d. Accessed: Jun. 27https://digital-strategy.ec.europa.eu/en/policies/data-act
European Food Safety Authority. 2024e. Animal Welfare at Slaughter | EFSA. Accessed August 27, 2024. https://www.efsa.europa.eu/en/topics/topic/animal-welfare-slaughter
European Union. 2016. General Data Protection Regulation
European Union, 'EU Artificial Intelligence Act'. 2024. Accessed: October. 08, https://artificialintelligenceact.eu/article/3/
Eurostat. 2024a. "Agricultural Labour Force by Size of the Farm and NUTS 2 Regions Accessed June 3, 2024. 3. https://ec.europa.eu/eurostat/databrowser/view/ef_lf_size/default/table?lang=en
Eurostat. 2024b. Decline in EU livestock population in 2023 - Eurostat. https://ec.europa.eu/eurostat/en/web/products-eurostat-news/w/ddn-20240521-2%92. Accessed: Jun. 03
Eurostat. 2024c. Farmers and the agricultural labour force - statistics. Accessed: June 3. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Farmers_and_the_agricultural_labour_force_-_statistics
Fadul-Pacheco, L., H. Delgado, and V. E. Cabrera. 2021. Exploring Machine Learning Algorithms for Early Prediction of Clinical Mastitis. *International Dairy Journal* 119: 105051
Forum, European Youth. 2024. The Challenges of Young Farmers in the European Agricultural Sector: A Discussion with CEJA. Accessed: June 25. https://www.youthforum.org/the-challenges-of-young-farmers-in-the-european-agricultural-sector-a-discussion-with-ceja
Fowler, G. A. 2024. How Generative AI is Reshaping Agriculture: A Farmer's Guide to the Future. Medium. Accessed: June 25. https://gafowler.medium.com/how-generative-ai-is-reshaping-agriculture-a-farmers-guide-to-the-future-d8fc5e8a4d01
Fritschy, C. and S. Spinler. 2019, Nov. The impact of autonomous trucks on business models in the automotive and logistics industry-a Delphi-based scenario study. *Technological Forecasting and Social Change* 148: 119736. https://doi.org/10.1016/j.techfore.2019.119736
Fuentes, S., C. G. Viejo, E. Tongson, F. R. Dunshea, H. H. Dac, and N. Lipovetzky. 2022. Animal Biometric Assessment Using Non-Invasive Computer Vision and Machine Learning as Predictors of Dairy Cows' Age and Welfare: The Future of Automated Veterinary Support Systems *Journal of Agricultural and Food Research* 10: 100388
Fuentes, S., C. Gonzalez Viejo, E. Tongson, and F. R. Dunshea. 2022. The Livestock Farming Digital Transformation: Implementation of New and Emerging Technologies Using Artificial Intelligence. *Animal Health Research Reviews* 23(1): 59–71. https://doi.org/10.1017/S1466252321000177
Gardezi, M., et al. 2023. Artificial Intelligence in Farming: Challenges and Opportunities for Building Trust. *Agronomy Journal*
Gardezi, M. and R. Stock. 2021. Growing Algorithmic Governmentality: Interrogating the Social Construction of Trust in Precision Agriculture. *Journal of Rural Studies* 84: 1–11
Garner, R. 2013, 2024. *A theory of Justice for animals: Animal rights in a nonideal world*.Accessed: OUP USA Sep. 02 https://books.google.com/books?hl=en%26lr=%26id=onbqyYaMviAC%26oi=fnd%26pg=PP2%26dq=Garner,+R.,+2013.+A+Theory+of+Justice+for+Animals.+Oxford:+Oxford+University+Press.%26ots=V89-8mkobn%26sig=2P9VOXlOfYK5r3ufUbXQxrD22CU
Garrido, J. Soler, et al. 2023, 2024, Analysis of the preliminary AI standardisation work plan in support of the AI Act. *Publications Office of the EU. Https: //Publications. Jrc. Ec. Europa. Eu* …Accessed:June. 25. https://publications.jrc.ec.europa.eu/repository/bitstream/JRC132833/JRC132833_01.pdf?trk=public_post_comment-text
Gavojdian, D., T. Lazebnik, M. Mincu, A. Oren, I. Nicolae, and A. Zamansky. 2023, Available 'BovineTalk: Machine Learning for Vocalization Analysis of Dairy Cattle under Negative Affective States. http://arxiv.org/abs/2307.13994. Accessed: June. 25, 2024.
Gavojdian, D., M. Mincu, T. Lazebnik, A. Oren, I. Nicolae, and A. Zamansky. 2024. BovineTalk: machine learning for vocalization analysis of dairy cattle under the negative affective state of isolation. *Frontiers in Veterinary Science* 11: 1357109
Gemtou, M., et al. 2024, Jan. Farmers' Transition to Climate-Smart Agriculture: A Systematic Review of the Decision-Making Factors Affecting Adoption. *Sustainability* 16(7, Art. no. 7). https://doi.org/10.3390/su16072828
Ghafoor, N. Abdul and B. Sitkowska. 2021. MasPA: A machine learning application to predict risk of mastitis in cattle from AMS sensor data. *Agri Engineering* 3(3): 575–583
Giersberg, M. F. and F. L. B. Meijboom. 2023, As if you were hiring a new employee: on pig veterinarians' perceptions of professional roles and relationships in the context of smart sensing technologies in pig husbandry in the Netherlands and Germany. *Agriculture and Human Values* 40(4): 1513–1526. https://doi.org/10.1007/s10460-023-10450-6
Gil, G., D. E. Casagrande, L. P. Cortés, and R. Verschae. 2023, Feb. Why the low adoption of robotics in the farms? Challenges for the establishment of commercial agricultural robots. *Smart Agriculture Technology* 3: 100069. https://doi.org/10.1016/j.atech.2022.100069
Giray, L. 2023, Prompt Engineering with ChatGPT: A Guide for Academic Writers. *Annals of Biomedical Engineering* 51(12): 2629–2633. https://doi.org/10.1007/s10439-023-03272-4
Global Insights, '2024a. Trends in dairy products and dairy alternatives in Europe', figlobal.com. Accessed: Aug. 28, https://insights.figlobal.com/trends/trends-dairy-products-and-dairy-alternatives-europe
Goodman, D. 2023 2024. 21–35. Precision agriculture: Adoption, "re-scripting", farmer identity, path dependence, and "appropriationism 4.0". In Transforming agriculture and foodways. Accessed: Bristol University Press: June. 26, https://bristoluniversitypressdigital.com/display/book/9781529231489/ch003.xml
Gordijn, F., N. Eernstman, J. Helder, and H. Brouwer.2018 *Reflection methods: Practical Guide for trainers and facilitators: Tools to make learning more meaningful. Wageningen Centre for development Innovation,*. Accessed: May 14, 2024. https://library.wur.nl/WebQuery/wurpubs/fulltext/439461
GreyB, T. 10 Innovative AI Agriculture Startups in 2024. GreyB. Accessed: May 31, 2024. https://www.greyb.com/blog/ai-agriculture-startups/
Groher, T., K. Heitkämper, and C. Umstätter. 2020. Digital Technology Adoption in Livestock production with a special focus on ruminant farming. *Animal* 14(11): 2404–2413
The Guardian. 2024. Eight US newspapers sue OpenAI and Microsoft for copyright infringement.*The Guardian* April. 30, 2024. Accessed:Jun 26. https://www.theguardian.com/technology/2024/apr/30/us-newspaper-openai-lawsuit.
Hagendorff, T., L. N. Bossert, Y. F. Tse, and P. Singer. 2022. Speciesist bias in AI: how AI applications perpetuate discrimination and unfair outcomes against animals. *AI Ethics* 1–18
Hagendorff, T., L. N. Bossert, Y. F. Tse, and P. Singer. 2023. Speciesist bias in AI: how AI applications perpetuate discrimination and unfair outcomes against animals. *AI Ethics* 3(3): 717–734
Hamadani, H., A. Hamadani, and S. Shabir. 2024. Artificial intelligence in animal farms for management and breeding. In A Biologist s Guide to artificial intelligence. 167–182. Elsevier. https://www.sciencedirect.com/science/article/pii/B9780443240010000117. Accessed: Jun. 25, 2024. [Online]. Available
Han, J., et al. 2023. Evaluation of computer vision for detecting agonistic behavior of pigs in a single-space feeding stall through

blocked cross-validation strategies. *Computers and Electronics* 204: 107520

Heikkila, A. M., L. Vanninen, and E. Manninen. 2010, 2010, March. Economics of small-scale dairy farms having robotic milking. http://www.precisiondairy.com/proceedings/s3heikkila.pdf. Accessed: Aug. 30, 2024. [Online]. Available', in *Proceedings of the First North American Conference on precision dairy management*, Toronto, Canada

Henrickson, L. and A. Meroño-Peñuela. 2023, Sep. Prompting meaning: a hermeneutic approach to optimising prompt engineering with ChatGPT. *AI & Society*. https://doi.org/10.1007/s00146-023-01752-8

Herrera, K., J. Miranda, and D. Mauricio. 2022. Milchbot: App to Support the Process of Feeding and Caring for Dairy Cows in Peru. *AGRIS - Line Papers on Economics and Informatics* 14(4): 27–37

Hutajulu, S., W. Dhewanto, and E. A. Prasetio. 2020, Nov. Two scenarios for 5G deployment in Indonesia. *Technol. Forecast. Soc. Change* 160: 120221. https://doi.org/10.1016/j.techfore.2020.120221

Ijaz, A., et al. 2022. Towards using cough for respiratory disease diagnosis by leveraging Artificial Intelligence: A survey. *Inform. Med. Unlocked* 29: 100832

Innova Market Insights, 'European Dairy Market: Dairy and Dairy Alternative Drinks'. Accessed: Aug. 28, 2024b. [Online]. Available. https://www.innovamarketinsights.com/trends/european-dairy-market/

Innovation for Cool Earth Forum, 2023. Artificial Intelligence for Climate Change Mitigation Roadmap

Insight Ace Analytics, 'Artificial Intelligence in Livestock Farming Market Market Latest Trends Analysis Report 2024'. https://www.insightaceanalytic.com/report/global-artificial-intelligence-in-livestock-farming-market/1323. Accessed: May 28, 2024. [Online]. Available

Insights, StartUs. 2024. '5 Top Precision Livestock Farming Startups', StartUs Insights. Accessed: June 25. https://www.startus-insights.com/innovators-guide/precision-livestock-farming-startups/

Intelligence, Mordor. 2024 AI in Agriculture Market - Companies, Research & Trends. https://www.mordorintelligence.com/industry-reports/ai-in-agriculture-market. Accessed: May 28, 2024.

Janssen, C. 2024. Argus changes how we look at data - Butcher Gosschalk no longer hides anything thanks to Artificial Intelligence. Foodlog. Accessed. August 27 https://agrifoodnetworks.org/afn/article/slaughterhouse-gosschalk-no-longer-keeps-anything-hidden-due-to-artificial/

Javaid, M., A. Haleem, I. H. Khan, and R. Suman. 2023, Mar. Understanding the potential applications of Artificial Intelligence in Agriculture Sector. *Advances in Agrochemicals* 2(1): 15–30. https://doi.org/10.1016/j.aac.2022.10.001

Jeong, S., M. L. Fischer, H. Breunig, A. R. Marklein, F. M. Hopkins, and S. C. Biraud. 2022, April. Artificial Intelligence Approach for Estimating Dairy Methane Emissions. *Environ. Sci. Technol.* 56(8): 4849–4858. https://doi.org/10.1021/acs.est.1c08802

Jorquera-Chavez, M., et al. 2020. Remotely sensed imagery for early detection of respiratory disease in pigs: a pilot study. *Animals* 10(3): 451

Jorquera-Chavez, M., et al. 2021. Using imagery and computer vision as remote monitoring methods for early detection of respiratory disease in pigs. *Computers and Electronics in Agriculture* 187: 106283

Jung, D.-H., et al. 2021. Deep learning-based cattle vocal classification model and real-time livestock monitoring system with noise filtering. *Animals* 11(2): 357

Kahn, H. and A. J. Wiener. 1967. The next thirty-three years: A framework for speculation. *Daedalus* 705–732

Kang, X., X. D. Zhang, and G. Liu. 2020. Accurate detection of lameness in dairy cattle with computer vision: A new and individualized detection strategy based on the analysis of the supporting phase. *J. Dairy Sci.* 103(11): 10628–10638

Kang, X., X. D. Zhang, and G. Liu. 2021. A review: development of computer vision-based lameness detection for dairy cows and discussion of the practical applications. *Sensors* 21(3): 753

Karaca, F. and M. A. Öner. 2015, Feb. Scenarios of nanotechnology development and usage in Turkey. *Technological Forecasting and Social Change* 91: 327–340. https://doi.org/10.1016/j.techfore.2014.04.004

Kaswan, S., et al. 2024. Applications of sensors in livestock management⊗. In Engineering applications in livestock production, eds., A. Tarafdar, A. Pandey, G. K. Gaur, M. Singh and H. O. Pandey, 63–92. Academic Press. https://doi.org/10.1016/B978-0-323-98385-3.00004-9

Kim, H., J. Sab, B. Nohc, J. Leed, Y. Chung, and D. Park. 2015. Automatic identification of a coughing animal using audio and video data. 18–19. https://pos.sissa.it/264/008/pdf. Accessed: Jun. 25, 2024. *Proceedings of the Fourth International Conference on Information Science and Cloud Computing-PoS (ISCC2015), Guangzhou, China*

Kim, J., Y.-K. Kwon, H.-W. Kim, K.-H. Seol, and B.-K. Cho. 2023. Robot technology for pork and beef meat slaughtering process: a review. *Animals* 13(4): 651

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

Klerkx, L., and P. Villalobos. Are AgriFoodTech Start-Ups the New Drivers of Food Systems Transformation? An Overview of the State of the Art and a Research Agenda. *Global Food Security* 40 (March 2024): 100726. https://doi.org/10.1016/j.gfs.2023.100726

Koroteev, D., and Z. Tekic. Artificial Intelligence in Oil and Gas Upstream: Trends, Challenges, and Scenarios for the Future. *Energy AI* 3 (2021): 100041.

Krietzberg, I. Here Are All the Copyright Lawsuits Against ChatGPT-Maker OpenAI. *TheStreet*. Accessed June 26, 2024. https://www.thestreet.com/technology/copyright-lawsuits-against-openai-microsoft-chatgpt

Kutyauripo, I., M. Rushambwa, and L. Chiwazi. Artificial Intelligence Applications in the Agrifood Sectors. *Journal of Agriculture and Food Research* 11 (March 2023): 100502. https://doi.org/10.1016/j.jafr.2023.100502

Lakshitha, S. L., and P. S. Sajja. Designing AI-Based Non-Invasive Method for Automatic Detection of Bovine Mastitis. In *Soft Computing and Its Engineering Applications*, edited by K. K. Patel, K. Santosh, A. Patel, and A. Ghosh, 301–313. *Communications in Computer and Information Science*, vol. 2030. Cham: Springer Nature Switzerland, 2024. https://doi.org/10.1007/978-3-031-53731-8_24

Laux, J., S. Wachter, and B. Mittelstadt. Three Pathways for Standardisation and Ethical Disclosure by Default under the European Union Artificial Intelligence Act. *Computer Law & Security Review* 53 (2024): 105957.

Lewis, L. Why European Farming Faces a Demographic Crisis. Accessed August 29, 2024. https://www.foodunfolded.com/article/european-farming-is-facing-a-demographic-crisis-what-is-being-done-about-it

Lewis, M. Deep Democracy. Deep Democracy – Lewis Method, 2013. Accessed May 14, 2024. https://download.boekhuis.nl/9789089840196_fragm-docb.pdf

Liao, J., et al. Domestic Pig Sound Classification Based on Transformer-CNN. *Applied Intelligence* 53, no. 5 (March 2023): 4907–4923. https://doi.org/10.1007/s10489-022-03581-6

Liu, J., et al. Perception of Cultured 'Meat' by Italian, Portuguese and Spanish Consumers. *Frontiers in Nutrition* 10 (June 2023). https://doi.org/10.3389/fnut.2023.1043618

Locks. AI Analyses Belgian Pork Group's Animal Welfare. Accessed August 27, 2024. https://www.locks.be/en/ai-analyses-belgian-pork-groups-animal-welfare

Lucchi, N. ChatGPT: A Case Study on Copyright Challenges for Generative Artificial Intelligence Systems. *European Journal of Risk Regulation* (2023): 1–23.

Lundström, C. and J. Lindblom. Care in Dairy Farming with Automatic Milking Systems, Identified Using an Activity Theory Lens. *Journal of Rural Studies* 87 (October 2021): 386–403. https://doi.org/10.1016/j.jrurstud.2021.09.006

Luo, W., Q. Dong, and Y. Feng. Risk Prediction Model of Clinical Mastitis in Lactating Dairy Cows Based on Machine Learning Algorithms. *Preventive Veterinary Medicine* 221 (2023): 106059.

Macnish, K., D. Wright, and T. Jiya. Predictive Policing in 2025: A Scenario. In *Policing in the Era of AI and Smart Societies*, edited by H. Jahankhani, B. Akhgar, P. Cochrane, and M. Dastbaz, 199–215. Cham: Springer International Publishing, 2020. https://doi.org/10.1007/978-3-030-50613-1_9

Manning, L. Innovating in an Uncertain World: Understanding the Social, Technical and Systemic Barriers to Farmers Adopting New Technologies. *Challenges* 15, no. 2 (June 2024): 32. https://doi.org/10.3390/challe15020032

Mark, R. Ethics of Using AI and Big Data in Agriculture: The Case of a Large Agriculture Multinational. *ORBIT Journal* 2, no. 2 (2019): 1–27.

Maru, A., et al. Digital and Data-Driven Agriculture: Harnessing the Power of Data for Smallholders. *Global Forum on Agricultural Research and Innovation*, 2018. https://cgspace.cgiar.org/bitstream/handle/10568/92477/GFAR-GODAN-CTA-white-paper-final.pdf. Accessed: Jun. 26, 2024. [Online]. Available

McGee, R. W. ChatGPT and Copyright Infringement: An Exploratory Study. SSRN, 2023. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4578430

Mendes, J., et al. Smartphone Applications Targeting Precision Agriculture Practices—A Systematic Review. *Agronomy* 10, no. 6 (June 2020): 855. https://doi.org/10.3390/agronomy10060855

Menéndez-Caravaca, E., S. Bueno, and M. D. Gallego. Exploring the Link between Free and Open Source Software and the Collaborative Economy: A Delphi-Based Scenario for the Year 2025. *Technological Forecasting and Social Change* 173 (December 2021): 121087. https://doi.org/10.1016/j.techfore.2021.121087

Michailidis, A., et al. A First View on the Competencies and Training Needs of Farmers Working with and Researchers Working on Precision Agriculture Technologies. *Agriculture* 14, no. 1 (January 2024): 1. https://doi.org/10.3390/agriculture14010099

Mietzner, D., and G. Reger. Advantages and Disadvantages of Scenario Approaches for Strategic Foresight. *International Journal of Technology Intelligence and Planning* 1, no. 2 (2005): 220. https://doi.org/10.1504/IJTIP.2005.006516

Miller, K., R. McAdam, and M. McAdam. A Systematic Literature Review of University Technology Transfer from a Quadruple Helix Perspective: Toward a Research Agenda. *R&D Management* 48, no. 1 (January 2018): 7–24. https://doi.org/10.1111/radm.12228

Mishra, H., and D. Mishra. Artificial Intelligence and Machine Learning in Agriculture: Transforming Farming Systems. *Research Trends in Agricultural Science* 1 (2023): 1–16.

Mouta, A., E. M. Torrecilla-Sánchez, and A. M. Pinto-Llorente. Design of a Future Scenarios Toolkit for an Ethical Implementation of Artificial Intelligence in Education. *Education and Information Technologies* (October 2023). https://doi.org/10.1007/s10639-023-12229-y

Munnisunker, S., L. Nel, and D. Diederichs. The Impact of Artificial Intelligence on Agricultural Labour in Europe. *Journal of Agricultural Informatics* 13 (March 2022). https://doi.org/10.17700/jai.2022.13.1.638

Munnisunker, S., L. Nel, and D. Diederichs. The Impact of Artificial Intelligence on Agricultural Labour in Europe. *Journal of Agricultural Informatics* 13, no. 1 (2022b). https://www.magisz.org/journal/index.php/jai/article/view/638

Mustill, T. Can AI Help Us Talk to Whales? *The Alan Turing Institute*. Accessed November 23, 2023. https://www.turing.ac.uk/blog/can-ai-help-us-talk-whales

Narra, N., et al. A Data Driven Approach to Decision Support in Farming. In *Information Modelling and Knowledge Bases XXXI*, vol. 321, 175–185. Amsterdam, The Netherlands: IOS Press, 2020. https://books.google.com/books?hl=en%26lr=%26id=4mTIDwAAQBAJ%26oi=fnd%26pg=PA175%26dq=data-driven+farm+management%26ots=cSgIwicjsn%26sig=Wac-ddHEAUZ-jNu9gio6Jfu-jAE

Nasirahmadi, A., S. A. Edwards, and B. Sturm. 2017. Implementation of machine vision for detecting behaviour of cattle and pigs. *Livest. Sci.* 202: 25–38

Nduati, R. Germany: Why Are Young People Shunning Farming? *DW*, July 18, 2024. https://www.dw.com/en/germany-why-are-young-people-shunning-farming/a-69619001

Neethirajan, S. The Role of Sensors, Big Data and Machine Learning in Modern Animal Farming. *Sensors and Bio-Sensing Research* 29 (2020): 100367.

Neethirajan, S. Artificial Intelligence and Sensor Innovations: Enhancing Livestock Welfare with a Human-Centric Approach. *Human-Centric Intelligent Systems* 4, no. 1 (2024a): 77–92. https://doi.org/10.1007/s44230-023-00050-2

Neethirajan, S. Decoding the Language of Chickens—An Innovative NLP Approach to Enhance Poultry Welfare. *bioRxiv* (2024b): 2024–04.

Neethirajan, S. AI in Sustainable Pig Farming: IoT Insights into Stress and Gait. *Agriculture* 13, no. 9 (2023a): 1706.

Neethirajan, S. From Predictive Analytics to Emotional Recognition–The Evolving Landscape of Cognitive Computing in Animal Welfare. *International Journal of Cognitive Computing in Engineering* 5 (2024c): 123–131. https://doi.org/10.1016/j.ijcce.2024.02.003

Neethirajan, S. Net Zero Dairy Farming—Advancing Climate Goals with Big Data and Artificial Intelligence. *Climate* 12, no. 2 (2024d): 15.

Neethirajan, S. The Significance and Ethics of Digital Livestock Farming, *AgriEngineering*, vol. 5, no. 1, Art. no. 1, Mar. 2023c, https://doi.org/10.3390/agriengineering5010032

Neethirajan, S. SOLARIA—SensOr-driven resiLient and adaptive monitoRIng of farm Animals, *Agriculture*, vol. 13, no. 2, p. 436, 2023c.

Neethirajan, S. Vocalization patterns in laying hens—An analysis of stress-induced audio responses, *bioRxiv*, pp. 2023–12, 2023d.

Neethirajan, S., and B. Kemp, Digital livestock farming, *Sensors and Bio-Sensing Research*, vol. 32, p. 100408, 2021.

Nejad, J. Ghassemi, et al. 2024. Advances in Methane Emission Estimation in Livestock: A Review of Data Collection Methods, Model Development and the Role of AI Technologies. *Animals* 14(3): 435

Nemitz, E. Can AI Help Us Build a More Sustainable Food System? *FairPlanet*. Accessed June 26, 2024. [Online]. Available:https://www.fairplanet.org/story/artificial-intelligence-sustainable-food-meat/

Niloofar, P., et al. Data-Driven Decision Support in Livestock Farming for Improved Animal Health, Welfare and Greenhouse Gas Emissions: Overview and Challenges. *Computers and Electronics in Agriculture* 190 (2021): 106406.

Norton, T., C. Chen, M. L. V. Larsen, and D. Berckmans. Precision Livestock Farming: Building 'Digital Representations' to Bring the Animals Closer to the Farmer. *Animal* 13, no. 12 (2019): 3009–3017.

Ogden, N. H., et al. Artificial Intelligence in Public Health: Modelling Scenarios of the Epidemic of COVID-19 in Canada. *Canada Communicable Disease Report* 46, no. 8 (2020): 198.

Ogunyiola, A., and M. Gardezi. Restoring Sense out of Disorder? Farmers' Changing Social Identities under Big Data and Algorithms. *Agriculture and Human Values*, July 2022. https://doi.org/10.1007/s10460-022-10334-1

Okengwu, U. A., L. N. Onyejegbu, L. U. Oghenekaro, M. O. Musa, and A. O. Ugbari. Environmental and Ethical Negative Implications of AI in Agriculture and Proposed Mitigation Measures. *Scientific African* 22, no. 1 (2023): 141–150.

Okinda, C., et al. A Review on Computer Vision Systems in Monitoring of Poultry: A Welfare Perspective. *Artificial Intelligence in Agriculture* 4 (2020): 184–208.

Okoro, E. M., A. O. Umagba, B. A. Abara, Z. S. Isa, and A. Buhari. Towards Explainable Artificial Intelligence: History, Present Scenarios, and Future Trends. In *XAI Based Intelligent Systems for Society* 5.0, 29–59. 2023. https://doi.org/10.1016/B978-0-323-95315-3.00006-1

Olczak, K., W. Penar, J. Nowicki, A. Magiera, and C. Klocek. The Role of Sound in Livestock Farming—Selected Aspects. *Animals* 13, no. 14 (2023): 2307.

Orandi, J. A. *A Computer Vision System for Early Detection of Sick Birds in a Poultry Farm Using Convolution Neural Network on Shape and Edge Information*. PhD diss., University of Nairobi, 2023. Accessed June 24, 2024. http://erepository.uonbi.ac.ke/handle/11295/164009. Accessed: Jun. 24, 2024. [Online]. Available: PhD Thesis, University of Nairobi

Organisation for Economic Co-operation and Development (OECD) and the Food and Agriculture Organization (FAO). *OECD-FAO Agricultural Outlook 2021–2030*. Food and Agriculture Organization of the United Nations. Accessed August 28, 2024. https://www.fao.org/policy-support/tools-and-publications/resources-details/en/c/1449704/

OOzdemir, S. *Quick Start Guide to Large Language Models: Strategies and Best Practices for Using ChatGPT and Other LLMs*. Addison-Wesley Professional, 2023. Accessed June 25, 2024. https://books.google.com/books?hl=en%26lr=%26id=aDvVEAAAQBAJ%26oi=fnd%26pg=PT18%26dq=correct+prompt+training+for+chatgpt%26ots=9hY6C9J1RO%26sig=1qiHGNTxgYoSNaeXSMp5nXV6xHw. Addison-Wesley Professional

Pal, O., V. Kumar, V. Thakur, and B. Alam. Quantum Computing: A Global Scenario. In *Cyber Security Using Modern Technologies: Artificial Intelligence, Blockchain and Quantum Cryptography*, 1–12. 2023. https://doi.org/10.1201/9781003267812-1

Pangarkar, T. AI in Livestock Farming Market Towards USD 2.9 Bn by 2033. *Market Scoop*. Accessed May 28, 2024. https://scoop.market.us/ai-in-livestock-farming-market-news/

Pedersen, S. M., et al. Drivers and Barriers to Climate-Smart Agricultural Practices and Technologies Adoption: Insights from Stakeholders of Five European Food Supply Chains. *Smart Agricultural Technology* 8 (August 2024): 100478. https://doi.org/10.1016/j.atech.2024.100478

Pickles, M. The Ethical Arguments Against Eating Meat. University of Oxford. Accessed January 19, 2024. https://www.ox.ac.uk/news/arts-blog/ethical-arguments-against-eating-meat University of Oxford

Preethi, S. R., A. R. Revathi, and M. Murugan. Exploration of Cough Recognition Technologies Grounded on Sensors and Artificial Intelligence. In *Internet of Medical Things for Smart Healthcare*, edited by C. Chakraborty, A. Banerjee, L. Garg, and J. J. P. C. Rodrigues, 193–214. Studies in Big Data, vol. 80. Singapore: Springer Singapore, 2020. https://doi.org/10.1007/978-981-15-8097-0_8

SHERPA Project. *Project SHERPA – Shaping the Ethical Dimensions of Smart Information Systems: A European Perspective*. Accessed June 19, 2024 https://www.project-sherpa.eu/

Ra, S., M. Ahmed, and P. S. Teng. Creating High-Tech 'Agropreneurs' Through Education and Skills Development. *International Journal of Training Research* 17, no. sup1 (July 2019): 41–53. https://doi.org/10.1080/14480220.2019.1629736

Rai, A. K., N. Kumar, D. Katiyar, O. Singh, G. Sreekumar, and P. Verma. Unlocking Productivity Potential: The Promising Role of Agricultural Robots in Enhancing Farming Efficiency. *International Journal of Plant & Soil Science* 35, no. 18 (2023): 624–633

Ravipati, A., T. Pradeep, and S. A. Elman. The Role of Artificial Intelligence in Dermatology: The Promising but Limited Accuracy of ChatGPT in Diagnosing Clinical Scenarios. *International Journal of Dermatology* 62, no. 10 (2023): e547–e548. https://doi.org/10.1111/ijd.16746

Ray, P. P. AI-Assisted Sustainable Farming: Harnessing the Power of ChatGPT in Modern Agricultural Sciences and Technology. *ACS Agricultural Science & Technology* 3, no. 6 (June 2023): 460–462. https://doi.org/10.1021/acsagscitech.3c00145

Reece, J. *The End of Animal Farming*. Boston, MA: Beacon Press, 2018.

Renda, A. Chapter 6: AI and the Transformation of Agricultural Work: Economic, Social, and Environmental Implications. 2024. Accessed June 27, 2024 https://www.elgaronline.com/edcollchap/book/9781800889972/book-part-9781800889972-14.xml

Valuates Reports. *Artificial Intelligence in Livestock Farming – Market, Report Size, Worth, Revenue, Growth, Industry Value, Share 2024*. Accessed May 28, 2024. https://reports.valuates.com/market-reports/QYRE-Auto-17L8896/global-artificial-intelligence-in-livestock-farming

Expert Market Research. *Europe Dairy Alternatives Market Report and Forecast 2024–2032*. Accessed August 28, 2024. https://www.expertmarketresearch.com/reports/europe-dairy-alternative-market. Accessed: Aug. 28, 2024. [Online]. Available

Grand View Research. *Europe Plant-Based Meat Market Size | Industry Report, 2030*. Accessed August 28, 2024. https://www.grandviewresearch.com/industry-analysis/europe-plant-based-meat-market-report. Accessed: Aug. 28, 2024. [Online]. Available

Ritchie, H. Wild Mammals Make Up Only a Few Percent of the World's Mammals. *Our World in Data*. Accessed January 24, 2024. https://ourworldindata.org/wild-mammals-birds-biomass

Ritchie, H., P. Rosado, and M. Roser. Environmental Impacts of Food Production. *Our World in Data*, December 2022. Accessed January 19, 2024. https://ourworldindata.org/environmental-impacts-of-food: Jan. 19

Rodenburg, J. The Impact of Robotic Milking on Milk Quality, Cow Comfort and Labor Issues. In *Proceedings of the National Mastitis Council 51st Annual Meeting, St. Pete Beach, FL*, 125–137, 2012

Rodenburg, J. Robotic Milking: Technology, Farm Design, and Effects on Work Flow. *Journal of Dairy Science* 100, no. 9 (2017): 7729–7738.

Rose, D. C., and J. Chilvers. Agriculture 4.0: Broadening Responsible Innovation in an Era of Smart Farming. *Frontiers in Sustainable Food Systems* 2 (2018): 87

Rotz, S., et al. Automated Pastures and the Digital Divide: How Agricultural Technologies Are Shaping Labour and Rural Communities. *Journal of Rural Studies* 68 (May 2019): 112–122. https://doi.org/10.1016/j.jrurstud.2019.01.023

Rotz, S., et al. The Politics of Digital Agricultural Technologies: A Preliminary Review. *Sociologia Ruralis* 59, no. 2 (April 2019): 203–229. https://doi.org/10.1111/soru.12233

Rozenstein, O., et al. Data-Driven Agriculture and Sustainable Farming: Friends or Foes? *Precision Agriculture* 25, no. 1 (February 2024): 520–531. https://doi.org/10.1007/s11119-023-10061-5

Ryan, M. The Future of Transportation: Ethical, Legal, Social and Economic Impacts of Self-Driving Vehicles in the Year 2025. *Science and Engineering Ethics*, September 2019. https://doi.org/10.1007/s11948-019-00130-2

Ryan, M. Agricultural Big Data Analytics and the Ethics of Power. *Journal of Agricultural and Environmental Ethics* 33, no. 1 (February 2020): 49–69. https://doi.org/10.1007/s10806-019-09812-0

Ryan, M. The Social and Ethical Impacts of Artificial Intelligence in Agriculture: Mapping the Agricultural AI Literature. AI & Society, January 2022.*AI Soc*. https://doi.org/10.1007/s00146-021-01377-9

Ryan, M., and L. Bossert. 2024. Dr. Doolittle Uses AI: Ethical Challenges of Trying to Speak Whale. *Biological Conservation*. Accessed June 24, 2024. [Online]. Jun. 24 https://doi.org/10.1016/j.biocon.2024.110648.

Ryan, M., P. Gürtler, and A. Bogucki. Will the Real Data Sovereign Please Stand Up? An EU Policy Response to Sovereignty in Data Spaces. *International Journal of Law and Information Technology* 32, no. 1 (2024): eaae006.

Ryan, M., and A.-C. Hoes. Justice and Sustainability Tensions in Agriculture: Wicked Problems in the Case of Dutch Manure Policy. *Ethics, Policy & Environment* 0, no. 0 (2024): 1–18 https://doi.org/10.1080/21550085.2024.2360369

Ryan, M., G. Isakhanyan, and B. Tekinerdogan. 2023. An interdisciplinary approach to artificial intelligence in agriculture. *NJAS Impact Agric. Life Sci.* 95(1): 2168568

Ryan, M., S. van der Burg, and M.-J. Bogaardt. Identifying Key Ethical Debates for Autonomous Robots in Agri-Food: A Research Agenda. *AI Ethics* (2021): 1–15.

Sadeghi, E., C. Kappers, A. Chiumento, M. Derks, and P. Havinga. Improving Piglets Health and Well-Being: A Review of Piglets Health Indicators and Related Sensing Technologies. *Smart Agricultural Technology* (2023): 100246.

Sahni, V., and M. Singh. Smart Indian Agriculture Farm Using an IoT Dashboard. *Educational Administration: Theory and Practice* 30, no. 5 (2024): 2872–2888.

Sandberg, M., et al. Applications of Computer Vision Systems for Meat Safety Assurance in Abattoirs: A Systematic Review. *Food Control* (2023): 109768.

Sanderson, T., A. Reeson, and P. Box. *Cultivating Trust: Towards an Australian Agricultural Data Market*. Commonwealth Scientific and Industrial Research Organisation, 2017. Accessed June 26, 2024. https://www.researchgate.net/profile/Todd-Sanderson/publication/321307402_Cultivating_Trust_Towards_an_Australian_Agricultural_Data_Market/links/5a1ba04aaca272df080f1f37/Cultivating-Trust-Towards-an-Australian-Agricultural-Data-Market.pdf

SCAR Collaborative Working Group on Animal Health and Welfare. *European Partnership on Animal Health and Welfare – Strategic Research and Innovation Agenda*. 2024. https://scar-europe.org/images/AHW_CWG/Documents/working-draft_AHW-SRIA_25-10-2022.pdf

Schlageter-Tello, A., T. Van Hertem, E. A. Bokkers, S. Viazzi, C. Bahr, and K. Lokhorst. Performance of Human Observers and an Automatic Three-Dimensional Computer-Vision-Based Locomotion Scoring Method to Detect Lameness and Hoof Lesions in Dairy Cows. *Journal of Dairy Science* 101, no. 7 (2018): 6322–6335.

Schwartz, Peter. *The Art of the Long View: Planning for the Future in an Uncertain World*. New York: Crown Currency, 2012. Accessed May 7, 2024. https://books.google.com/books?hl=en%26lr=%26id=T-r36bIZA44C%26oi=fnd%26pg=PR13%26dq=Schwartz,+P.+(1998).+The+art+of+the+long+view.+%26ots=1UWdRpWXJ2%26sig=w2oecCZ5VrFajrsBhJLNGNLuXBI

Seibert, K., et al. Application Scenarios for Artificial Intelligence in Nursing Care: Rapid Review. *Journal of Medical Internet Research* 23, no. 11 (2021): e26522.

Šestak, M., and D. Copot. Towards Trusted Data Sharing and Exchange in Agro-Food Supply Chains: Design Principles for Agricultural Data Spaces. *Sustainability* 15, no. 18 (January 2023). https://doi.org/10.3390/su151813746

Future Data Sets. *AI in Precision Livestock Farming Market Size & Industry Growth 2030*. Accessed May 28, 2024. https://www.futuredatastats.com/artificial-intelligence-in-precision-livestock-farming-market

Sharma, S., K. Verma, and P. Hardaha. Implementation of Artificial Intelligence in Agriculture. *Journal of Computer and Cognitive Engineering* 2, no. 2 (2023). https://doi.org/10.47852/bonviewJCCE2202174

Shiri, N., et al. Development of Artificial Intelligence Models for Well Groundwater Quality Simulation: Different Modeling Scenarios. *PLOS ONE* 16, no. 5 (2021): e0251510.

Shorten, P. R., and L. B. Hunter. Acoustic Sensors for Automated Detection of Cow Vocalization Duration and Type. *Computers and Electronics in Agriculture* 208 (2023): 107760.

Singer, P., and Y. F. Tse. AI Ethics: The Case for Including Animals. *AI Ethics* (2022): 1–13.

Singer, P., and Y. F. Tse. AI Ethics: The Case for Including Animals. *AI Ethics* 3, no. 2 (2023): 539–551.

Singh, P., R. Sharma, and V. Kumar. Prediction of Clinical Mastitis in Dairy Cows Using ANN. *Journal of Pharmaceutical Negative Results* (2022): 3655–3665.

Statista. *Global Meat Consumption by Type*. Statista. Accessed January 19, 2024a. https://www.statista.com/statistics/274522/global-per-capita-consumption-of-meat/

Statista. *Per Capita Meat Consumption by Country Group Worldwide 2032*. Statista. Accessed January 19, 2024b. https://www.statista.com/statistics/1270102/meat-consumption-worldwide-per-capita/

Statista. *Meat Substitutes – Europe | Statista Market Forecast*. Statista. Accessed August 28, 2024c. https://www.statista.com/outlook/cmo/food/meat/meat-substitutes/europe

Stemerding, D., T. Swierstra, and M. Boenink. 2010, Dec. Exploring the Interaction Between Technology and Morality in the Field of Genetic Susceptibility Testing: A Scenario Study. *Futures* 42(10): 1133–1145. https://doi.org/10.1016/j.futures.2009.12.001

Steup, R., L. Dombrowski, and N. M. Su. Feeding sthe World with Data: Visions of Data-Driven Farming. In *Proceedings of the 2019 on Designing Interactive Systems Conference*, 1503–1515. San Diego, CA, USA: ACM, June 2019. https://doi.org/10.1145/3322276.3322382.%92

Stock, R., and M. Gardezi. Make Bloom and Let Wither: Biopolitics of Precision Agriculture at the Dawn of Surveillance Capitalism. *Geoforum* 122 (2021): 193–203.

Stone, K. EU Must Help Animal Farmers Transition to Plant-Crop Farming to Benefit from Plant-Based Boom, Experts Tell MEPs. *Humane Society International*. Accessed August 27, 2024. https://www.hsi.org/news-resources/eu-plant-crop-farming-031119/

Subedi, S., R. Bist, X. Yang, and L. Chai. Tracking Pecking Behaviors and Damages of Cage-Free Laying Hens with Machine Vision Technologies. *Computers and Electronics in Agriculture* 204 (2023): 107545.

Sullivan, C. S., M. Gemtou, E. Anastasiou, and S. Fountas. Building Trust: A Systematic Review of the Drivers and Barriers of Agricultural Data Sharing. *Smart Agricultural Technology* (2024): 100477.

Susha, I., B. Rukanova, A. Zuiderwijk, J. R. Gil-Garcia, and M. Gasco Hernandez. Achieving Voluntary Data Sharing in Cross Sector Partnerships: Three Partnership Models. *Information and*

Organization 33, no. 1 (March 2023): 100448. https://doi.org/10.1016/j.infoandorg.2023.100448

Sutherland, L.-A. Who Do We Want Our 'New Generation' of Farmers to Be? The Need for Demographic Reform in European Agriculture. *Agriculture and Food Economics* 11, no. 1 (February 2023): 3. https://doi.org/10.1186/s40100-023-00244-z

Tedeschi, L. O., P. L. Greenwood, and I. Halachmi. Advancements in Sensor Technology and Decision Support Intelligent Tools to Assist Smart Livestock Farming. *Journal of Animal Science* 99, no. 2 (2021): skab038.

Teubner, T., C. M. Flath, C. Weinhardt, W. Van Der Aalst, and O. Hinz. Welcome to the Era of ChatGPT et al.: The Prospects of Large Language Models. *Business & Information Systems Engineering* 65, no. 2 (April 2023): 95–101. https://doi.org/10.1007/s12599-023-00795-x

Thomas, C. *Types of Scenario Planning*. Futures Strategy Group, 2012.

Tripathi, M. K., A. Nath, T. P. Singh, A. S. Ethayathulla, and P. Kaur. Evolving Scenario of Big Data and Artificial Intelligence (AI) in Drug Discovery. *Molecular Diversity* 25, no. 3 (August 2021): 1439–1460. https://doi.org/10.1007/s11030-021-10256-w

Tullo, E., I. Fontana, and M. Guarino. Precision Livestock Farming: An Overview of Image and Sound Labelling. *Precision Livestock Farming* 13 (2013): 30–38.

Unay-Gailhard, İ., and F. Simões. Becoming a Young Farmer in the Digital Age—An Island Perspective. *Rural Sociology* 87, no. 1 (March 2022): 144–185. https://doi.org/10.1111/ruso.12400

United Nations. *World Population Projected to Reach 9.8 Billion in 2050, and 11.2 Billion in 2100*. United Nations. Accessed January 19, 2024. https://www.un.org/en/desa/world-population-projected-reach-98-billion-2050-and-112-billion-2100

Väärikkälä, S., T. Koskela, L. Hänninen, and M. Nevas. Evaluation of Criminal Sanctions Concerning Violations of Cattle and Pig Welfare. *Animals* 10, no. 4 (April 2020): 715. https://doi.org/10.3390/ani10040715

van der Burg, S., M.-J. Bogaardt, and S. Wolfert. Ethics of Smart Farming: Current Questions and Directions for Responsible Innovation towards the Future. *NJAS - Wageningen Journal of Life Sciences* 90 (2019): 100289.

van der Burg, S., E. Giesbers, M.-J. Bogaardt, W. Ouweltjes, and K. Lokhorst. Ethical Aspects of AI Robots for Agri-Food: A Relational Approach Based on Four Case Studies. *AI & Society* (2022): 1–15.

van der Burg, S., L. Wiseman, and J. Krkeljas. Trust in Farm Data Sharing: Reflections on the EU Code of Conduct for Agricultural Data Sharing. *Ethics and Information Technology* (2020): 1–14.

van Klompenburg, T., and A. Kassahun. Data-Driven Decision Making in Pig Farming: A Review of the Literature. *Livestock Science* 261 (2022): 104961.

Veldkamp, F., T. I. Garcia-Faria, V. L. Witjes, J. M. Rebel, and I. C. de Jong. Validation of Non-Invasive Sensor Technologies to Measure Interaction with Enrichment Material in Weaned Fattening Pigs. *Applied Animal Behaviour Science* 263 (2023): 105923.

VION Food Group. *Artificial Intelligence Camera – Vion Food Group*. Accessed August 27, 2024. https://www.vionfoodgroup.com/en/ai-camera-system

Volkery, A., and T. Ribeiro. Scenario Planning in Public Policy: Understanding Use, Impacts and the Role of Institutional Context Factors. *Technological Forecasting and Social Change* 76, no. 9 (2009): 1198–1207.

Voogt, A. M., R. S. Schrijver, M. Temürhan, J. H. Bongers, and D. T. Sijm. Opportunities for Regulatory Authorities to Assess Animal-Based Measures at the Slaughterhouse Using Sensor Technology and Artificial Intelligence: A Review. *Animals* 13, no. 19 (2023): 3028.

Wei, J., X. Tang, J. Liu, and Z. Zhang. Detection of Pig Movement and Aggression Using Deep Learning Approaches. *Animals* 13, no. 19 (2023): 3074.

Wiseman, L., J. Sanderson, A. Zhang, and E. Jakku. Farmers and Their Data: An Examination of Farmers' Reluctance to Share Their Data through the Lens of the Laws Impacting Smart Farming. *NJAS - Wageningen Journal of Life Sciences* 90 (2019): 100301.

The World Counts. *World Consumption of Meat*. Accessed June 21, 2024. https://www.theworldcounts.com/challenges/foods-and-beverages/world-consumption-of-meat

World Economic Forum. *Meat: The Future – A Roadmap for Delivering 21st-Century Protein*. World Economic Forum. Accessed August 28, 2024. https://www.weforum.org/publications/meat-the-future-a-roadmap-for-delivering-21st-century-protein/

Wright, D. AI and Information Warfare in 2025. In *2019 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI)*, 317–322. August 2019. https://doi.org/10.1109/SmartWorld-UIC-ATC-SCALCOM-IOP-SCI.2019.00098.%92

Wright, D. Creating Companions for Senior Citizens with Technologies That Mimic People. In *2019 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI)*, 311–316. August 2019. https://doi.org/10.1109/SmartWorld-UIC-ATC-SCALCOM-IOP-SCI.2019.00097.%92

Wright, D., et al. Ethical Dilemma Scenarios and Emerging Technologies. *Technological Forecasting and Social Change* 87 (September 2014): 325–336. https://doi.org/10.1016/j.techfore.2013.12.008

Wright, D., et al. *D1.2 SIS Scenarios*. June 1, 2019. https://doi.org/10.21253/DMU.8181695.v2

Wright, D., B. Stahl, and T. Hatzakis. Policy Scenarios as an Instrument for Policymakers. *Technological Forecasting and Social Change* 154 (May 2020): 119972. https://doi.org/10.1016/j.techfore.2020.119972

Xia, P. Application Scenario of Artificial Intelligence Technology in Higher Education. In *International Conference on Applications and Techniques in Cyber Intelligence (ATCI 2019)*, edited by J. H. Abawajy, K.-K. R. Choo, R. Islam, Z. Xu, and M. Atiquzzaman, 221–226. *Advances in Intelligent Systems and Computing*, vol. 1017. Cham: Springer International Publishing, 2020. https://doi.org/10.1007/978-3-030-25128-4_29.%92

Xiang, T., T. Li, J. Li, X. Li, and J. Wang. Using Machine Learning to Realize Genetic Site Screening and Genomic Prediction of Productive Traits in Pigs. *FASEB Journal* 37, no. 6 (June 2023): e22961. https://doi.org/10.1096/fj.202300245R

Xie, Y., et al. Sound Identification of Abnormal Pig Vocalizations: Enhancing Livestock Welfare Monitoring on Smart Farms. *Information Processing & Management* 61, no. 4 (2024): 103770.

Zhao, J., et al. DNN-HMM Based Acoustic Model for Continuous Pig Cough Sound Recognition. *International Journal of Agricultural and Biological Engineering* 13, no. 3 (June 2020). https://doi.org/10.25165/ijabe.v13i3.4530

Zhao, W. X., et al. A Survey of Large Language Models. arXiv preprint arXiv:2303.18223 (November 24, 2023). Accessed June 25, 2024. http://arxiv.org/abs/2303.18223

Zheng, C., X. Zhu, X. Yang, L. Wang, S. Tu, and Y. Xue. Automatic Recognition of Lactating Sow Postures from Depth Images by Deep Learning Detector. *Computers and Electronics in Agriculture* 147 (April 2018): 51–63. https://doi.org/10.1016/j.compag.2018.01.023

Zia-Ul-Haq, M. 2023. ChatGPT & Copyright: Key Legal and Moral Implications. *Bull. Transilv. Univ. Braşov Ser. VII Soc. Sci. Law* 16(Suppl): 151–158

Ziesche, S. 2021. AI ethics and value alignment for nonhuman animals. *Philosophies* 6(2): 31

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