ROADMAP

Rethinking of antimicrobial decision-systems in the management of animal production

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Case descriptions of Integrative real time intervention strategies animal health professionals to favour acceptability of AMU changes

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About the ROADMAP research project

The overall aim of ROADMAP is to **foster transitions towards prudent use of antimicrobials (AMs) in animal production in different contexts to manage antimicrobial resistance (AMR). Prudent antimicrobial use (AMU) will be achieved by enhancing antimicrobial decision-systems along the food and drug supply chains.** ROADMAP will focus on supporting animal health and welfare through prevention and health promotion actions.

AMR is recognized as a significant threat to global public health and food security. Overuse and improper use of AMs in many parts of the world contribute to the emergence and spread of AMR. Although human and animal health require AMs, it has been estimated that two thirds of the future AMU growth worldwide will be in animal production. Improving the management of AMU in farm animals is therefore a critical component of dealing with AMR and optimizing production in the livestock sector. Nevertheless, the variety of contexts of AMU in the livestock sector is a major challenge to managing AMR. **There is no "one-size-fits-all" solution to improve AMU and strategies must be contextually developed** (for instance, strategies used in the Danish pig industry are difficult to adapt and adopt in the French free-range poultry farming). Successful solutions must be combined and tailored to the production systems and the social and economic context in which they operate.

ROADMAP will meet three general objectives, in line with the EU AMR Action plan: i) **Rethink AM decision-systems and animal health management**; ii) **Develop options for encouraging prudent AMU in animal production**; iii) **Engage all actors in the food and drug supply chains in fostering a more prudent use of AMs.**

Project consortium

Part. N°	Participant organisation name (acronym)	Country
1	Institut National de Recherche pour l'Agriculture, l'Alimentation et l'Environnement (INRAE) **	France
2	Association de coordination technique agricole (ACTA) ***	France
3	Centre de coopération internationale en recherche agronomique pour le développement (CIRAD) **	France
4	University of Liverpool (ULIV) *	United Kingdom
5	Cardiff University (CU) *	United Kingdom
6	James Hutton Institute (HUT) **	United Kingdom
7	Alma Mater Studiorum - Università di Bologna (UNIBO) *	Italy
8	Aarhus Universitet (AU) *	Denmark
9	Eigen Vermogen van het Instituut voor Landbouw en Visserijonderzoek (EV-ILVO) **	Belgium
10	Research Institute of Organic Agriculture (FiBL) **	Switzerland
11	Stichting Wageningen Research (WR) *	Netherlands
12	Swedish University of Agricultural Sciences (SLU) *	Sweden
13	Southern Agriculture and Horticulture Organization (ZLTO) ***	Netherlands
14	European Forum of Farm Animal Breeders (EFFAB) ****	Netherlands
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** Universities/veterinary schools*
*** Research institutes specialized in both fundamental and applied agricultural and veterinary sciences*
**** Public and private advisory services Organisations*
***** Knowledge transfer and Innovation organisations*

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List of acronyms and abbreviations

AFSC	Agri-food supply chain
AI	Artificial intelligence
AIME	Artificial intelligence in medicine
AL	Application layer
AM	Antimicrobials
AMS	Automatic milking systems
AMU	Antimicrobial use
AR	Augmented reality
BC	Blockchain
BCT	Blockchain technology
BDA	Big data analytics
CL	Configuration layer
CS	Case Study
DLT	Distributed ledger technology
DSL	Domain specific language
EL	Encapsulation layer
FSC	Food supply chain
GPS	Geographical positioning system
ICT	Information and communication technologies
ID	Identification
IoT	Internet of things
IoTAH	Internet of things in animal healtcare
LLs	Living Lab
LL	Link layer
MCDM	Multicriteria decision-making
MGL	Management layer
ML	Machine learning
ML	Middelware layer
PA	Precision agriculture
PD	Precision dairy
PLF	Precision livestock farming

RFID	Radio frequency identification
RTLS	Real time locating system
RTRHMSs	Real-time remote health monitoring systems
SL	Sensor layer
TRU	Traceable resource unit
TTT	Trusted third party
WSN	Wireless sensor network
4P medicine	Personalized, predictive and participatory preventive medicine

1 Summary

In the ROADMAP project, stakeholders aim at designing new strategies to more prudent antimicrobial use in animal farming. Innovations in precision livestock farming (PLF) may contribute to it. To that extend, a few issues have to be addressed, especially in living labs aiming at an PLF innovation.

There has been a whole range of proofs of concepts about the interest of sensors in an early detection processes. However, data acquisition is only the first step in a broader process where data storage, transfer, transformation, analytics and marketing have to be taken into account. Data transfer is a crucial stage in agriculture due to working with animals or lack of network connectivity. New techniques such as data mining or machine learning may support data analytics for higher quality of diagnosis. Decision making criteria and ease of use are of peculiar importance for the farm manager. Only an integrative approach provides with new monitoring practices.

Technical issues reveal only a small part of change in PLF. Work and team organization are redesigned by the implementation of these tool and the effects on mental charge of farmers are mixed. What's more, opponents to PLF argue that it may foster a higher objectivation of animals and then raise ethical concerns. Indeed are the farmers cautious in adopting PLF. They consider cost-efficiency of disposals, such as good farming norms and management of data. Industry and retailer levels may also be involved through information sharing thanks to blockchains.

Three examples are detailed to illustrate the way real-time strategies mays contribute to more prudent AMU: an integrative approach focused on a single pathology; the support of artificial intelligence to build decision-making tools supported by real-time assessment; a blockchain in a worldwide known retailer.

2 Introduction

2.1 Animal farming and health and disease data use: weaknesses to be overcome in prudent use of antibiotics

Reporting in prudent use of antibiotics has revealed quite efficient to favor awareness as well as change of practices in animal farming. Implementation of compulsory measure of antibiotic sales and use or biosecurity measures in European countries contributed to the decrease in use of antimicrobials. Measure take place either at the farm or vet levels ; both farm managers and health advisors are involved in steering (Canalli and Beber 2021).

However, some difficulties remain. In cattle sector, for instance, farmers find that diagnosis of disease by self-assessment is complex (Lind, Hansson, and Lagerkvist 2019), whereas early detection may help have a lower use of antibiotics in treatments. Researchers also report lack of diagnostic approach on farms (Mlala, Jarrige, and Gay 2018) or high likelihood of animals being treated at first symptoms (Olson et al. 2019), which may lead to misuses (Poizat et al. 2017). Traceability may also be incomplete, due to inappropriate incomplete recording (Doehring and Sundrum 2019) or manual recording (Neethirajan 2017) or even inappropriate storage practices (Rees et al. 2019). On top of that, the increasing size of farms and herds so as the search for better efficiency and productivity require new observation means (Neethirajan 2020; Neethirajan and Kemp 2021).

Precision livestock farming (PLF) may to a certain extend contribute to reduce these weaknesses and especially real time monitoring. PLF uses farmers' observations, sensors, automatic systems such as milking robots or feed distributors, aimed either at the animals or the farm environment, software including artificial intelligence (AI), information and communication technologies (ICT) or even augmented reality (AR) to exchange, transform, store data and provide notifications or reports (Caria et al. 2019; Hostiou et al. 2017; Valentin-smith et al. 2017). This concerns all farming systems, either intensive or extensive, even if PLF development in extensive farming is more difficult. Animals may be monitored in groups or individually. PLF improves indeed the individual monitoring whereas it is often associated to industrial farming. Precision agriculture was then defined in the early 1990 by the International society for precision agriculture as "*a management strategy that gathers, processes and analyzes temporal, spatial and individual data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, profitability and sustainability of agricultural production*" (Buller et al. 2020).

Whereas precision agriculture focuses on variability between individuals, smart farming also use context and situation awareness based on real time events. Hence actions may be supported by changes operational conditions or circumstances such as a disease alert. To that extend, humans are supported by machines in analyzing, planning and operational activities (Wolfert et al. 2017). In this document, we will consider that PLF includes that real-time and contextual dimension.

PLF focuses mainly on increased productivity thanks to identification of animals' needs; it may for instance contribute to more efficient utilization of nutrient (Tullo, Finzi, and Guarino 2019). As far as health and disease are concerned, PLF contributes to early detection of disease and disease pattern identification ; loss prevention in birth or early detection of estrus prior to insemination, reduction in pollutant emissions (Buller et al. 2020), but also extension of life-span or cut in antibiotics (Bos et al. 2018). Eventually, PLF provides resources to improve strategic management and reduce operational cost (Karthick, Sridha, and Pankajavalli 2020).

2.2 Real time monitoring in health: definitions

Although PLF is broader than real time monitoring, the latter is especially involved in early detection of imbalances or disease, which is likely to contribute or lead to more prudent AMU, because other actions and interventions can be appropriate and may solve the problem before AMU is necessary. We will therefore first illustrate the concept of real time monitoring to define the steps involved in an integrative real time intervention strategy.

Real time monitoring has been widely used in human medicine, especially to provide better health care to elderly and chronic patients, in relationship with their caregivers. The aim is to provide the health decision makers with indicators as often as possible, so as to adapt the decisions as fast and precisely as possible to the ongoing health status of their patients. These data are often collected and routed through connected networks of objects using embedded sensors, which is called Internet of things (IoT), hence the designation as Real-time remote health monitoring systems (RTRHMSs). As such they belong to the field of telemedicine, which is defined as 'the utilisation of medical information exchanged from one site to another via electronic communications to improve the clinical health status of patients'.

The Heart Rhythm Society defines remote monitoring as 'the automated transmission of data based on pre-alert related to device functionality, clinical events and clinical condition of patients' (Kalid et al. 2018). However, real time monitoring is not only useful to give an alert in case of any serious or even vital issue but gives insight on detection of abnormalities to the patient or health providers (Kalid et al. 2018). They may for instance be used to detect health troubles or drugs thanks to biosensors (Nelson et al. 2011; Zhou et al. 2020), predict sepsis in critical care (Nemati, Clifford, and Buchman 2019), deliver treatment to wounds thanks to smart bandages (Mostafalu et al. 2018) or electronically monitor AMU (Morquin, Ologeanu-taddei, and Reynes 2018). As such RTRHMSs also contribute to 4P medicine (personalized, predictive and participatory preventive medicine).

RTRHMSs as part of IoT are based on three tiers, all of which call on new technologies, such as monitoring sensors, communication systems, software analysis or even on artificial intelligence and machine learning, which have been used in medicine for over 30 years (Peek et al. 2015). In this document, we considered that a real time intervention strategy was integrative whenever all three tiers were completed.

Figure 1: The three tiers of RTRHMS

2.2.1 Tier 1: Data collection and big data

Data collection is based on connected devices (sensors and actuators) which may be called proximity network. Data may be heterogeneous or even come from different sources. The RTRHMSs are then integrated in the logic of big data which consists of using various data in large quantities. Six characteristics (called 6V) actually matter in big data (Kalid et al. 2018).

1. The *volume* i.e. the amount of data which increases daily
2. The *velocity* in relation to the rising demand
3. The *variety* of collected data due to numerous sources
4. The added value of collected data
5. The *variability* depends on heterogeneous formats or changes during processes
6. The *veracity* stands for data consistency and trustworthiness.

2.2.2 Tier 2: Edge gateway

Tier 2 Edge gateway layer deals with data aggregation. It gathers data in a secure and functional way and is more dedicated to architecture than to computing data in itself. The edge gateway computing power, so as the devices' one, is indeed limited. The key performance factors at this stage are:

- The global security
- The power used by devices which should send data while remaining autonomous whereas they are limited by battery-power or wireless communication
- The scalability and especially the capacity of the architecture to support the rising amount of data transmissions (use of bandwidth)
- The allocation of decision

The edge gateway may distribute the burden of computing data and analytics, either on the edge cloud, the edge analytics, the Internet or fog computing, i.e. using the processing capacity of data-generating devices themselves. In the latter case, the latency between input and response may be reduced as the devices the most likely to need the response is the very ones which generates the data. Used applications may also belong to the Internet, which is called the Internet of things; in that case, data have to be routed through the Internet and not only to the cloud.

In conventional IoT, a major head node is in charge of governing the whole system, whereas in decentralized IoT, sub-nodes have partial decision making.

2.2.3 Tier 3: Applications and multi criteria decision making

The generated health datasets are massive, mixed, complex, they require fast management and advance software, hardware and analytics. Tier 3 includes large database, as the volume of datasets rises due to the amount and variety of data but also use of time series, as well as applications to analyze them. Continuous real time signals provided by sensors in tier 1 and routed through tier 2 device are converted to records and analysed thanks applications. The first step in decision making then consists in simplifying data complexity and converting data to information. It may require modelling to compare collected data with expectations.

On the one hand, big data may contribute to better prevention or prediction strategies, or to identifying better treatments in regards to efficacy, efficiency or cost effectiveness. Mechanistic models and algorithms are then use to elucidate causality relation in complex systems. Artificial intelligence (AI) and machine learning (ML) will then provide decision makers with alerts adapted to the real time health status captured by sensors (Neethirajan 2020).

On the other hand, complex decision making may for instance lead to triage or prioritisation between patients (Albahri et al. 2018) then requires consistency and transparency. Accountable health managers then use explicit decision matrix to take multi criteria decisions or weight their choices trough different multi-criteria decision making (MCDM) methods. Specific applications are often built.

2.3 Main aim of the report

In this report we aim at giving first an overview of concepts and processes implied in precision livestock farming; in peculiar we will raise the main technical limitations and perspectives. We will also deal with economic, organisational, ethical and personal data issues to help the stakeholders involved in designing innovations, especially living labs, address these issues (cf. part 3). Part 4 will be devoted to a few case descriptions to illustrate the different levels of integrative real time strategies.

3 Precision livestock farming and real-time monitoring in animal health: specific issues and limitations

In this part we will give some insight on main benefits and limitations of PLF and real time interventions. We do not aim at being exhaustive, but will present the main points of debate as food for thought.

3.1 Technical issues and traceability

Precision livestock farming has amazingly increased over the last years and includes all kinds of advanced technologies (sensors, algorithms, AI, ML) (Neethirajan and Kemp 2021). LPF and especially Internet of thing in animal healthcare (IoTAH) also faces specific issues linked to the livestock context. Technical issues do matter due to rural context, working with animals, constrained network connectivity due to remote locations with limited cellular coverage or distance between the fields and farm or a need of larger autonomy for sensors (Cf. Table 1).

Our aim here is not to give an overview on all developed devices and proofs of concepts related to proper early detection; we invite the interested reader to refer to the relevant literature reviews, e.g. on sensors (Karthick et al. 2020; Neethirajan 2017) or strategies in specific sectors such as pig farming (Tzanidakis et al. 2021) or poultry farming (Vidic et al. 2017). However, as a quick overview, we may cite the main types of used sensors: real time locating systems to detect position, accelerometers or gyroscopes to measure the movements, cameras coupled with image analyses, sound recording to detect coughing or vocalisations, temperature or humidity recording, weighing scales to measure intake and growth, sensors measuring biomarkers, electronic identification of animals (Buller et al. 2020). Even smart glasses have been tested and provide with the possibility of working free hand and sharing pieces of information with a remote technician while milking for example (Caria et al. 2019).

We also would like to point out that data which stem from sensors and devices are not the only ones to be involved in real time strategies, although literature is more abundant about devices-oriented disposals. We already pointed out human observations, and the know-how of farmers in identifying the needs of animals. We may also give example of the biological analyses, the results of which may be included in a real-time strategy intervention. Some authors also point out economic, strategic and historical data at the decision making stage (Hostiou et al. 2017).

Table 2: The three layers of IoTAH and devices' characteristics (based on (Karthick et al. 2020) *et* (Wolfert et al. 2017)

RTRHMSs	OSI model	Aims	Devices' characteristics	Key stages	Issue
Tier 1 Data collection / proximity network	1. Sensor layer (SL)	Sensors and devices for data acquisition	Biometric sensing and wearable or non-wearable sensors / Water resistant	Data capture	Availability, quality, formats
				Data storage	Quick and safe access to data
Tier 2 Edge gateway / Acess network	2. Link layer (LL)	Communication protocols for data transmission	Wireless sensor networks (WSN), among which Bluetooth, 3G, radio frequency identification (RFID), Geographical positioning systems tracking (GPS)…	Data transfer	Safety, agreements on responsabilities and liabilities
	3. Encapsulation layer (EL)	Establishing communication between the sensors and the external network : encapsulation and routines to regularize network traffic			
	4. Middleware layer (ML)	Transport and interoperability protocols			
	5. Configuration layer (CL)	Acquiring, synchronizing and aggregating of data at a sink node to be transformed and used in the processing	Databases		
				Data transformation	Heterrogeneity of data sources automation of data cleansing and preparation
Tier 3 Decision making / Service network	6. Management layer (MGL)	Data analytics and data mining and decision support system	Big data platform Digital data processing Object analysis Machine learning techniques for accurate prediction of abnormalities	Data analytics	Semantic heterogeneity, real-time analytics, scalability
	7. Application layer (AL)	Interface for the user	Visualization techniques, heat maps, graphs, two and three dimensional modelling	Data marketing	Ownership, privacy, new business models

Another concern in animal products is traceability, which was defined in 2002 by the EU as "*the ability to trace and follow a food, feed, food-producing animal of substance intended to be, or expected to be incorporated into a food or feed through all stages of production, processing and distribution*". PLF provides great opportunities to improve traceability from farm to fork. Blockchains (BC) contribute to reliability of information thanks to sharing databases identically among different participants. Traceable resource units (TRU) – i.e. in livestock, animals - are dealt individually with a unique identification (ID) all along its lifespan and timestamps are included in each transaction, which reveals of paramount importance in agrifood chains (Patelli and Mandrioli 2020). Each transaction creates a node, theses nodes are recorded into blocks (encapsulation layer) and blocks are linked thanks to unique hash codes into chains (Neethirajan and Kemp 2021). Each ledger of the distributed ledger technology (DLT) owns an identical copy which is updated at each change, and a trusted third party (TTT) is involved, which prevents from any falsification of data. BC are then decentralized, safe, immutable and transparent. (Patelli and Mandrioli 2020).

Among the advantages, blockchains may help prevent distrust from the consumers who may be informed about race, feeding, farming system, use of drugs and especially antimicrobials, animal welfare. In case of an outbreak, real-time data may be available. However, blockchains have not been widespread until now and animal products industry is still among the least digitalised (Neethirajan and Kemp 2021).

We will now focus on the benefits and limitations for real time monitoring contributing to PLF and especially prudent AMU.

3.2 Economic and workload issues

Although the producer claim better performance on farm equipped with PLF technologies, technical improvement, some studies may show no impact on productivity (Steeneveld, Hogeveen, and Lansink 2015). As far as health and disease are concerned, LPF is supposed to be less expensive than vet visits in the preventive paradigm of health management, while AMU is a low cost but only reactive approach (Cf. Figure 2) (Neethirajan 2020). However, this analysis obviously underestimates many arguments. First of all, no precise study supports the comparison between vet services and PLF on the long run. What's more, even if thresholds are identified to raise alerts and dashboards elaborated to give an overview of the herds' health status, LPF cannot be opposed to expertise but can only be complementary to it; costs due to expertise can't then be erased even with LPF. On top of that, there are some missing costs in the comparative marginal budget: long term costs due to non-upcycled resource use in LPF (such as metal); amount of time of companies' engineers, technicians, patencies and other expenses; other authors point out that mainly big farms may afford for the investment.

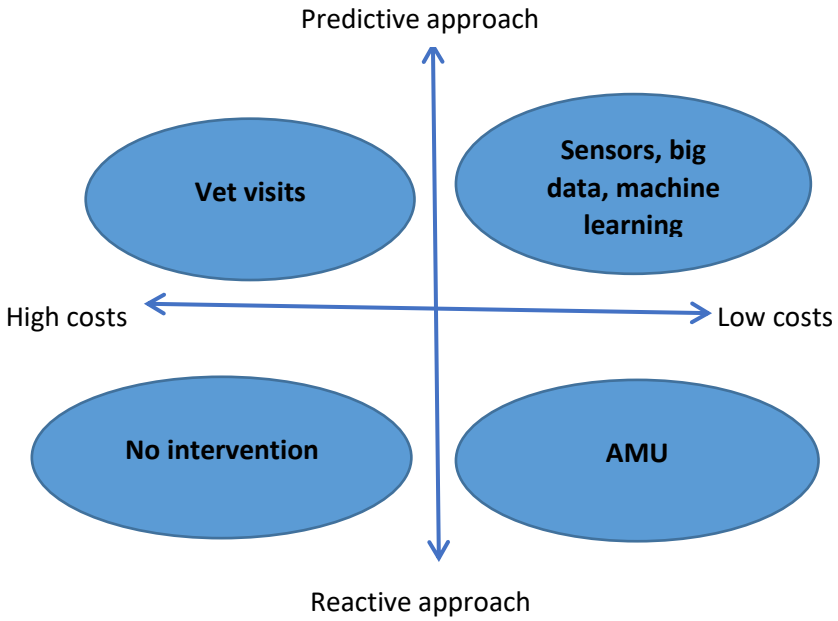

Figure 2 : Compared cost effectiveness of RTRHMSs over vet visits in prudent AMU (based on (Neethirajan 2020)

Proper cost benefit analyses then show that although PLF technologies are no less expensive, but they do improve the workload and the steering and management of herds. Saving time in repetitive tasks such as feeding or milking is the main motivation (Bos et al. 2018; Buller et al. 2020; Hostiou et al. 2017). This may either be a source of satisfaction for farmers who then spend more time observing their animals or demotivate the one who resent data management. Indeed, the nature of work evolves due to higher data management, equipment management and maintenance, interventions due to alerts (Hostiou et al. 2017), but of it may be share with remote advisors (Bos et al. 2018). Work and space organisation may be entirely redesigned according to the implementation of PLF technologies or automation (Driessen and Heutinck 2015; Rodenburg 2017). On the whole it seems that the workload does not really decrease, but the drudgery, as physically demanding tasks decrease and sleeping time increase – PLF technologies being able to measure continuously over time, contrary to human beings (Bos et al. 2018; Hostiou et al. 2017). This may help motivating young farmers to set up. Farmers also appreciate the higher flexibility in their work (time allocation but also space as they may remain remote) (Driessen and Heutinck 2015) although it may at once be counterproductive in farm team coordination. Using PLF may also ironically reduce opportunities for replacement due to the time it takes to get used to the specific PLF tools. (Hostiou et al. 2017). To some extend new allocation of tasks may also marginalize previous farm workers (Buller et al. 2020).

The impact of PLF on farmers' mental workload is controversial. Long term alerts, such an estrus detection does decrease the mental workload because it helps the farmer to anticipate, whereas continuous disturbance due to short term alerts do increase the mental workload. This may lead either to a learning process and the farmers sort the appropriate alerts; or to farmers giving up reacting to alerts. (Hostiou et al. 2017). Therefore, farmers prioritize system with a low rate of alerts (Mollenhorst,

Rijkaart, and Hogeveen 2012) and research focused on reducing it (Dominiak and Kristensen 2017). This is also a reason why the dashboards are so important.

3.3 Ethical issues

What's more, concerns are raised about the more distant management of husbandry, with reduced number and length of human-animal interactions, which may lead to farmers ignoring or misunderstanding health or welfare issues. The animals may also become more fearful of interactions with humans, this ones being focused on unpleasant interventions, or have restrained opportunities to enter into intersubjective relationship to humans which would reduce their well-being (Bos et al. 2018; Buller et al. 2020; Hostiou et al. 2017). Some authorities such as the UK Farm animal welfare council even defined in 2006 good farming practices including "*an affinity and empathy with livestock, patience and keen observational skills amongst others" whilst the European Union charged in 2008 "farmers and stock persons with the responsibility to inspect animals at regular interval (usually, at least once a day) to verify their wellbeing"* (Buller et al. 2020). New relationship routines may also purposively be created (Hostiou et al. 2017).

Indeed, good farming norms in relation to PLF have to be redefined, as the technology integrates new arrangements between farm and value chain stakeholders. PLF reshape not only processes with better functionalities in improving control and performance but also practices. The implantation of milking robots did for instance redesign the whole dairy farming system into automated milking system (AMS) (Driessen and Heutinck 2015). The standardized processing of data embeds new unified norms, for instance for health or animal welfare, which become institutionalized without any debate (Bos et al. 2018). Some authors are thus concerned by the fact that productivity data are preferred to welfare monitoring, which does not contribute enough to welfare improvement (Buller et al. 2020; Harfeld, Kornum, and Gjerris 2016) Indeed the used paradigms are engineers' ones (Wathes et al. 2008) and reinforces the perception of animals as "production units" only (Harfeld et al. 2016). The animal is considered as a biological production process and measured inputs are managed to obtain a target performance level, which may be a multi-criterial one (including economics, environment, quality for instance). Therefore, opponents to PLF denounce animals being treated as objects and instrumentalised in the Kantian perspective – i.e. animals are not considered as an end in themselves, but as a mean (Bos et al. 2018), as "living part of a machinery"(Harfeld et al. 2016). PLF could reinforce lack of agency of animals on farms. The criteria for animal welfare may for instance be decided by consumers or regulation even remain far from animals' needs (Driessen and Heutinck 2015) or be based on measurable indicators and give up qualitative insights (Bos et al. 2018). PLF may for instance induce a bias in the animal selection, the ones being keen enough on wearing sensors or using the milking robot being more selected than others (Driessen and Heutinck 2015; Wathes et al. 2008).

However, this may be intensive farming more than PLF in itself that leads to animals' objectivation: de-animalisation, commodification, alienation and quantification have been noticeable even before PLF development. PLF may even improve animals' agency and welfare. For instance, AMS, depending on the way space is organised to prevent farmers from the duty to force animals to the automat, may either restrain or give more freedom and autonomy to animals and herds, to the price of being disciplined and undergoing new forms of control (Driessen and Heutinck 2015). Market use of behaviour data also foster compliance with welfare new standards by farmers. Contribution of PLF to objectivation of animals then may depend on the way PLF technologies leave space for care and sentient human-animal relationships (Bos et al. 2018). PLF ethics may then be analysed thanks to pragmatism

considering the relationship (Driessen and Heutinck 2015). Some authors even claim for new farming environment which would help to restore such a relationship, no matter if PLF technologies are used or not (Harfeld et al. 2016).

3.4 Willingness (or not) to adopt and personal data

Although proofs of concept abound about PLF, only RFID and accelerometer technologies already found a viable market share (Buller et al. 2020). (Borchers and Bewley 2015) described a few years ago the decision criteria of producers in dairy farming. Producers make take many points into account before acquiring PLF equipment: benefit to cost ratio, total investment cost, simplicity and ease of use. (Schukat and Heise 2021) add criteria such as influence of social environment, expected effort for implementation, general trust in smart products and technology readiness of farmers.

On top of that, there is a concern that data provided may be used inappropriately. Undoubtedly are data ownership and related privacy and security issues of paramount importance. (Wolfert et al. 2017) points out that not only data protection is concerned, but also speed in innovation which may be slown down if data requirements are too restrictive. However, data sharing is also an issue, especially with animal health farm advisors and veterinarians.

4 Cases description of integrative real time interventions

In this section we will provide with some case descriptions of integrative strategies. Our aim is to illustrate key points animal health professionals should be aware of. The first example then deals with an example based on a single pathology; the second example deals with artificial intelligence helping defining best treatment strategies to reduce AMU; the third example is about a blockchain to inform the consumer.

4.1 Focus on Tier 1: An example on lameness detection based on machine learning

Taneja et al. are interested in lameness in cattle. Detection based on visual inspection is much likely to be late detection and widespread detection is limited due to a lack of trained and equipped professionals. That the reason why Taneja's team developed a comprehensive IoT device to detect them. (Taneja et al. 2020). An animal expert is mobilized at the data acquisition stage.

Due to literature study, Taneja et al. chose three predictors of lameness, namely step counts, lying time, swaps and confronted machine learning to an animal expert for locomotion scoring. Individual cow data were compared with the mean of the herd, considering that they graze under similar conditions. Individual deviation to the mean activity was taken into account in a former clustering and cows were qualified as active, normal or dormant. Authors then defined two regions, namely normal activity region and lame activity region to classify animals.

One of the issue was to deal with limited network connectivity; part of analytics was then performed at the fog nod to reduce the flow of data to the cloud and backward (5 times more data is processed at fog nod level than at cloud level). The application synchronizes with the cloudant database once a connection is established. Similarly, the notifications on anomalies (cows being qualified as lame and not already in a lameness cycle) are sent to the farmer's mobile device (See Figure 3).

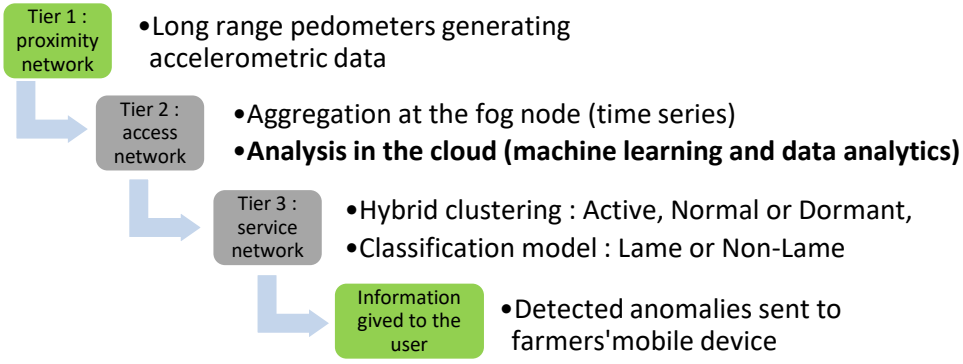

Figure 3: The three tiers of Teneja et al.'s strategy to detect lameness

The approach was tested on a herd of 150 cattle on an Irish dairy farm. The end-to-end IoT application detected lameness in an early stage (3 days before visual inspection did) with a good accuracy (87 %).

4.2 Focus on Tier 3: A decision-making design thanks to AI in BRD in beef cattle

Although this example uses proof of concepts in data acquisition and designing decision-making strategies, it can't indeed be considered as fully integrative but rather like prerequisite to an integrative strategy. Animal health professionals are mobilized thank to new AI tools at the decision making stage.

Picault et al. (Picault, Ezanno, et al. 2019) are interested in bovine respiratory diseases (BRD) in beef cattle at small fattening operations. Reasoning AMU requires tradeoffs between metaphylaxis and selective treatment following early detection. Use of reticulo-rumen boluses has proved useful to provide proper early detection compared to clinical signs alone. However early detection revealed indeed efficient to reduce AMU in case of positive animals but counter-productive in case of false positive animals due to non-infectious hyperthermia.

The authors then aimed at designing efficient control strategies in regard with health, economics and AMU. They designed a stochastic mechanistic individual based model including infection processes, detection method and treatment protocol thanks to a generic agent-based modelling framework using AI methods called EMULSION (Picault, Huang, et al. 2019). This framework fostered exchange loops between computer scientists, modellers and epidemiologists thanks to a domain specific language (DSL) and contributed to quick design of the model. The model included time span between infection and detection of hyperthermia by visual appraisal or boluses concerning the first detected case and the subsequent ones, and duration of hyperthermia.

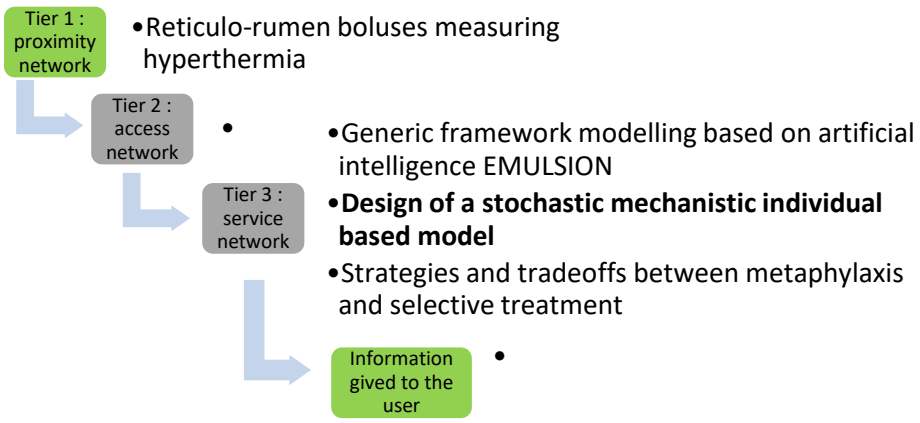

Figure 4: The three tiers of Picault et al.'s strategy to detect BRD

The results show a higher efficiency of boluses over visual appraisal. Metaphylaxis also revealed less cost-efficient especially when pathogen transmission is moderate. No combination of detection through clinical signs and early detection through boluses proved efficient. At a small batch level, metaphylaxis increased AMU due to false positive animals. What's more, the generic modelling framework may be used to deal with other pathologies.

4.3 Focus on blockchains: A blockchain in swine

Although their potential advantages are documented, blockchains are still at an early age in agrifood sector (Kamble, Gunasekaran, and Gawankar 2020). We will then give an example of current blockchain ; we will invite the reader to read the reviews citing blockchains in animal product industry if interest (Neethirajan and Kemp 2021; Patelli and Mandrioli 2020).

The chosen example is the blockchain developed by Walmart on an IBM Hyperledger-based blockchain to trace pig meat after slaughter, in the States and in China (Kamath 2018; Neethirajan and Kemp 2021; Xu et al. 2020). Walmart collaborated to design the blockchain with One health experts and administration (Kamath 2018).

Each pork receives an identification in pen where the animals are tracked by sensors such as cameras. Even in shipping trucks sensors do measure transport conditions (temperature and humidity). The blockchain has been designed and tested, even across border, to demonstrate reliability.

In that case, information is not analysed not transformed, the aim is about informing the consumer without any change in data.

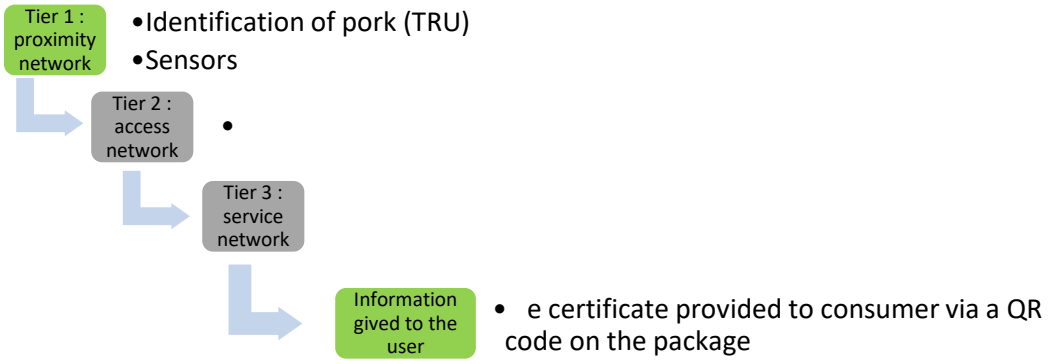

Figure 5: The three tiers of Walmart blockchain strategy

5 Conclusion

Integrative real-time monitoring strategies offer undoubtedly great perspectives in adapting AMU very precisely to the situation, hence reducing AMU. Early detection associated to visual appraisal leads for instance to reduced doses of antibiotics compared to large metaphylaxis. However, some key issues have to be addressed. There might be a risk than usual advice relationship may be discarded due to data sharing issues or fewer farm autonomy in decision making processes. That is the reason why, in changes induced by precision livestock farming, human-animal relationship should remain central.

6 Literature

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