Case Study

Internet of Animal Health Things (IoAHT)

Opportunities and Challenges

Daniel Smith, Scott Lyle, Al Berry, Nicola Manning
Centre for Digital Innovation, Zoetis

Mohamed Zaki and Andy Neely
Cambridge Service Alliance, University of Cambridge

UNIVERSITY OF CAMBRIDGE
Cambridge Service Alliance

DATA AND ANALYTICS:
Internet of Animal Health Things

Traditional animal production techniques are usually labour intensive and driven by very slim margins. These margins are subject to variables such as meat and milk prices, growth rates of animals, governmental policy changes and seasonal changes in cereal and crop prices, coupled with the volatile risk of infectious disease resulting in livestock losses, increased veterinary inputs and reduced meat prices. However, the world population is rapidly increasing; world meat production is predicted to double by 2050 (FAO, 2009). As a result, farming techniques are shifting towards intensification.

For farmers, time is money, and recording farm data is traditionally a cumbersome task that is difficult to do on-the-go. However, consumers are increasingly demanding greater transparency of where their meat comes from, for example, the farm-to-fork concept, which has resulted in growing impact of farm assurance schemes such as Red Tractor, Freedom Food, etc. In addition to customer demand for transparency, policies are now changing. For example, farmers are now required to document antibiotic use in stricter controls in Germany (DART, 2008; USDA, 2011). The recent horsemeat scandal in Europe also highlighted the lack of traceability in the food chain (European Commission, 2014), undermining consumer confidence. The increasing requirement for transparency and documentation by farmers makes farm data management a topical issue.

The rapid expansion of the 'Internet of Things' in the last decade has made technology integral to daily activities and even our culture. The number of sensors shipped has increased more than five times from 4.2 billion in 2012 to 23.6 billion in 2014 (Elfrink, 2014). As a result, farming data management practices are also changing with the advent of 'Precision Farming'. The aim of this paper is to explore the opportunities and challenges of adapting IoAHT for the animal health industry. Furthermore, the authors used the DDBM Innovation Blueprint (Brownlow et al., 2015) as a practical lens to explore how the ethical use of collected data can improve animal health and welfare, improve transparency of production processes and construct a data-driven business model (DDBM) for precision livestock farming (PLF).

Farming information has traditionally been passed down the family generations. However, continually improving rural Internet connectivity means that the latest information is now readily available online; the Internet is changing social trajectories.

For years we have had the 'Internet', and the 'Things' such

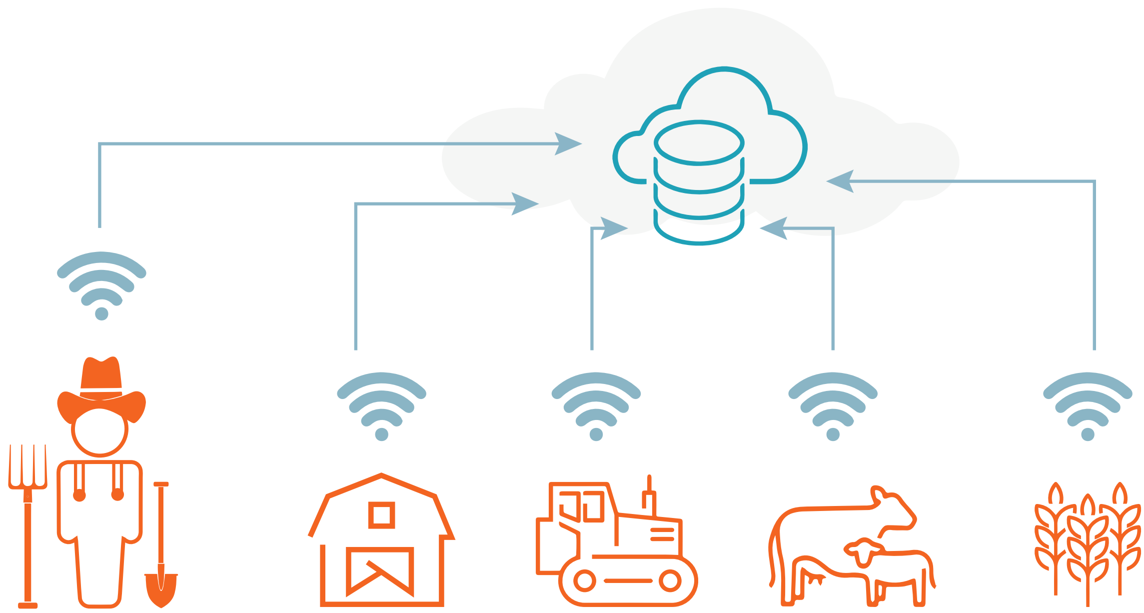

Figure 1: The Internet of Animal Health Things concept

The potential benefits of the 'IoAHT'

as farm animals, machinery and processes. However, only recently have these been integrated (see illustration in Figure 1). The 'Internet of Animal Health Things' not only offers the mechanism to make data collection streamlined, relevant and accessible, but it also makes data interpretable into meaningful information. Farming no longer relies on conventional wisdom; sensor-driven automated data collection in precision farming allows greater tracking of key parameters defining slim profit margins.

As farming systems have intensified, lower fallow ratios mean more animals are raised on a smaller amount of land with higher labour and capital inputs. With more animals per farm, it is increasingly difficult for farmers to recognise individual animals due to batching techniques with highly automated methods for feeding and care. This is coupled with the lack of highly trained stockmen, which makes manual integration of observation and coordinated action more difficult. PLF utilises advanced technology to improve process management against these constraints, capturing and recording multiple attributes for each animal, for example, age, pedigree, growth rates, health, feed conversion rates, meat quality and killing out percentage. Consequently, farmers achieve better meat prices by slaughtering animals at optimal time points and minimise costs by strategic use of drugs and veterinary care.

While the world population is predicted to reach 9.6 billion in 2050 (UN, 2013), the World Bank predicts that the increases in demand for meat (Figure 2) must be sustained by 90 per cent of existing farmland (The World Bank, 2008); intensification is inevitable.

However, this intensification is still not sufficient to meet demand; total factor productivity (TFP) growth is not accelerating fast enough to meet the necessary agricultural output requirements of the future. In 2010 it was calculated that global agricultural TFP must grow by an average rate of at least 1.75 per cent annually in order to double agricultural output through productivity gains by 2050. However, the current global agricultural productivity (GAP) index falls 6 per cent short of the target when compounded over 40 years (Global Harvest Initiative, 2014).

Increased 'precision' of intensive farming provides an opportunity to maximise production efficiency and an attempt to mitigate the predicted shortfall in food supply. With increasing numbers of animals, data management is an ever more pertinent issue. The benefit of sensor-driven devices is that the data capture can be automated; it lowers bias in data entry and enables the farmer to dedicate time to animal care while maximising returns. In other words, data management is now both time- and cost-efficient for the farmer. But it is not just the farmer that benefits from the 'IoAHT'; there are a number of different stakeholders that have digital extensions to their products and services.

For veterinarians, the use of sensor devices provides a detailed history that could not be obtained in the typical consultation. Recovery of animals post-surgery or following medication can be measured, enabling quicker follow-up where needed, providing a better standard of care as a result. Trend data allows vets to make informed decisions that enhance conventional practices and experience. The communication network facilitated using the device on an animal with veterinary interaction promotes increased customer retention and client loyalty.

For feed providers and nutritional companies, the use of weight estimation devices provides real-time tracking of animal growth with a predictive capacity. This allows manipulation of feeding regimes in order to reduce batch variation and meet the optimum criteria for meat production; farmers therefore receive better meat prices at the abattoir. Retailers such as Morrison's are encouraging the use of electronic identification device (EID) ear tags to replace unreliable slap-marking of carcasses in the pork industry (O'Kane, 2015), thus providing better traceability of meat products and greater consumer assurance.

Pharmaceutical companies such as Zoetis use digital app extensions to their drug product portfolio to layer relevant data sets together to provide transparency into the status of an individual animal at any point in time along its lifecycle. Regulatory bodies and policy makers will also soon realise the benefits of improved data collection, as some European countries now require farm-level data and documentation on antibiotic use (Maron et al., 2013). In turn, these digital technologies are ushering in a new era of best practices by enabling farmers and veterinarians to increase clinical treatment performance, and improve farm productivity and overall animal welfare at the same time. The IoAHT will create a new level of transparency and become a necessity in the study of translational medicine and for global research initiatives such as 'One Health'.

Digital technology, and the transformational societal benefits that it promises, have an entirely different research and development process to drug technology and present a relatively new 'space' for pharmaceutical companies. This emerging 'space' presents new challenges, and not just for the pharmaceutical animal health company but rather for all stakeholders dependent upon our societal food production capabilities.

We carry a societal responsibility to use data in a positive way to maximise value to the production chain, while protecting the rights of individuals. With the development of the IoAHT and the intensification of farming driving the rise of PLF, we now have a potential mechanism to support the collection of redacted data from individual animals to utilise big data for societal benefit. The use of data in isolation does not fulfil its potential benefits: greater transparency of the food chain, improved traceability, as well as further improvements to animal health and welfare. This big data is essential when defining governmental policies, identifying new population trends and cultural shifts and allocating resources efficiently; think of the value of human census data, which is personal data used for a societal benefit. We have a moral responsibility to use big data effectively to oversee animal wellbeing, attempt to mitigate the forecast GAP index shortfall and to enhance food security as a result of a rapidly growing world population.

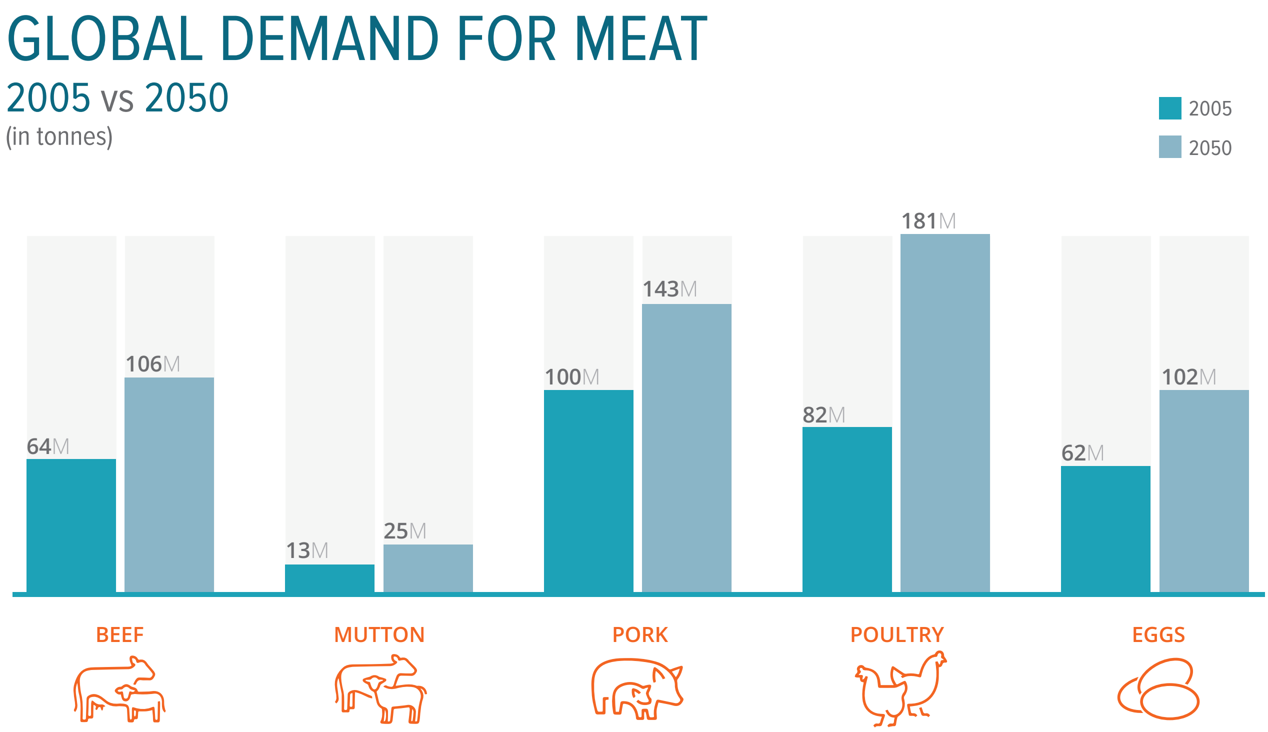

Figure 2: Global demand for meat in 2050 (adapted from FAO, 2012; Gates Notes 2013)

Data-Driven Business Model of Precision Livestock Farming (PLF)

PLF technologies can be incorporated into the Data-Driven Business Model (DDBM) framework, described by Brownlow et al. (2015), see Figure 3. In this section, we answer the six fundamental questions for PLF-DDBM innovation:

1. What do we want to achieve by using big data?
2. What is the PLF-DDBM desired offering?
3. What are the key data sources for PLF-DDBM?
4. What are the key activities?
5. What are the potential revenue streams?
6. What are the challenges to us accomplishing our goal?

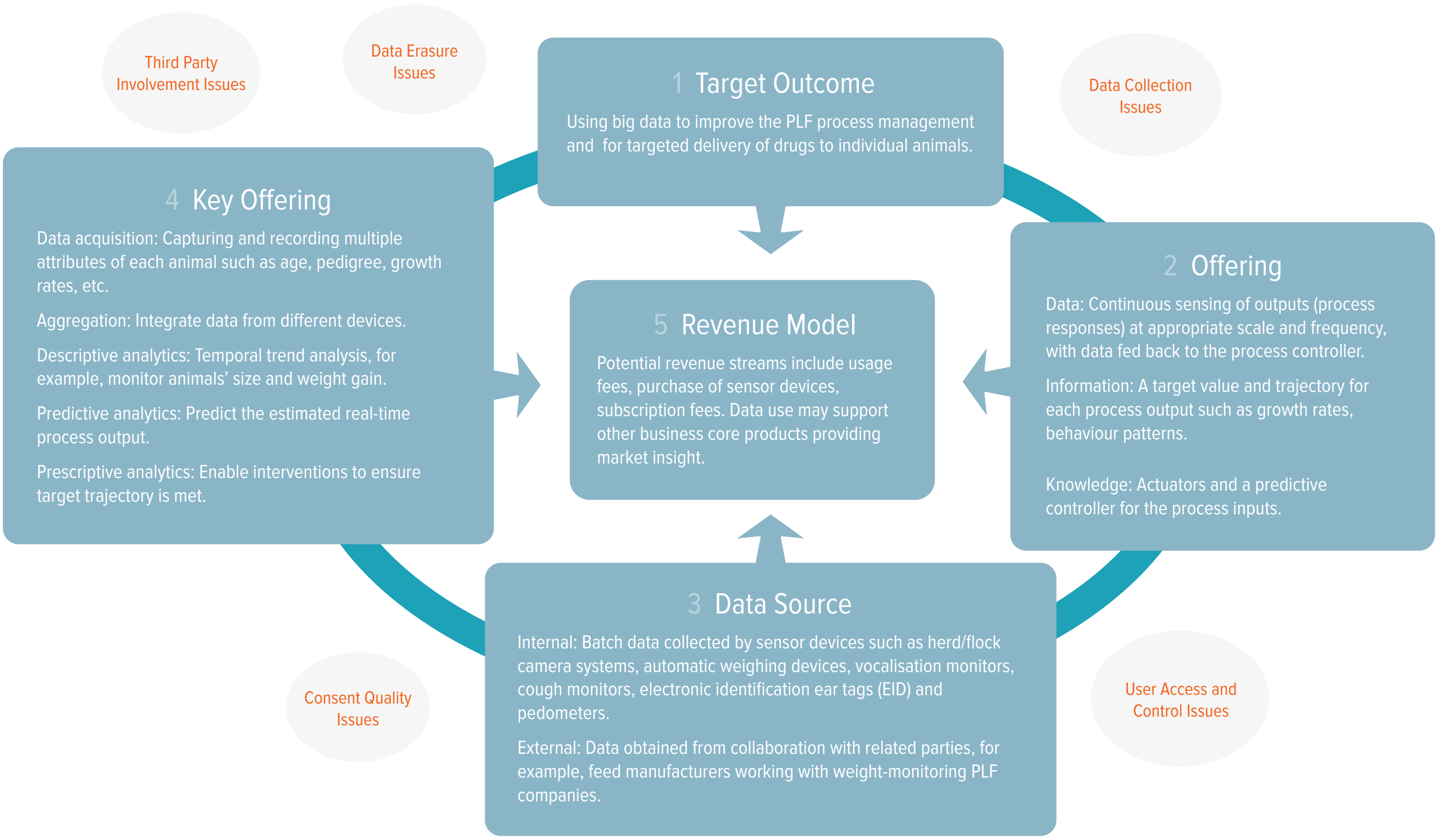

Figure 3: PLF-DDBM Innovation Blueprint

1. What do we want to achieve by using big data?

'Big data' collection by PLF technologies is facilitated by continuous, simultaneous measurement of a wide number of parameters with analysis of temporal trends – using methods of collection without the stress caused by animal disturbance or handling (Scott and Moran, 1993; Hamilton et al., 2004). The ease of data collection in farming activities makes it possible to collect a wider range of data from more parameters than ever before regarding animal health, in an unbiased and convenient way.

Some sensor-device technologies now allow the ability to distinguish between individual animals within traditional herd-level batching. Individual differentiation of pigs allows closer observation of individual health indicators, for example alterations in weight gain, feed and water intake, and activity levels could be indicators of disease. Earlier identification of health deterioration would allow earlier intervention, with quarantine of sick animals to minimise the impact of disease spread and timely use of the most appropriate drugs.

Sensor devices will vastly improve data collection and management methods on farms, which in turn means that more 'big data' is being collected than ever before. The use of 'big data' integrating multiple stakeholders along the value chain is promising for improving productivity and cost-efficiency of animal production, as well as animal health and welfare standards

2. What is the PLF-DDBM desired offering?

The first offering is the raw data, which is often collected using sensor devices incorporating continuous sensing of outputs (process responses) at the appropriate scale and frequency, with data fed back to the process controller (Wathes et al., 2008). The raw data will need some form of basic processing to be interpretable to the farmer, but this data in isolation may be beneficial in order to present a warning for system failures, such as water supply issues or air-conditioning failure. Earlier detection of system failures means that the farmer can intervene quicker to solve the

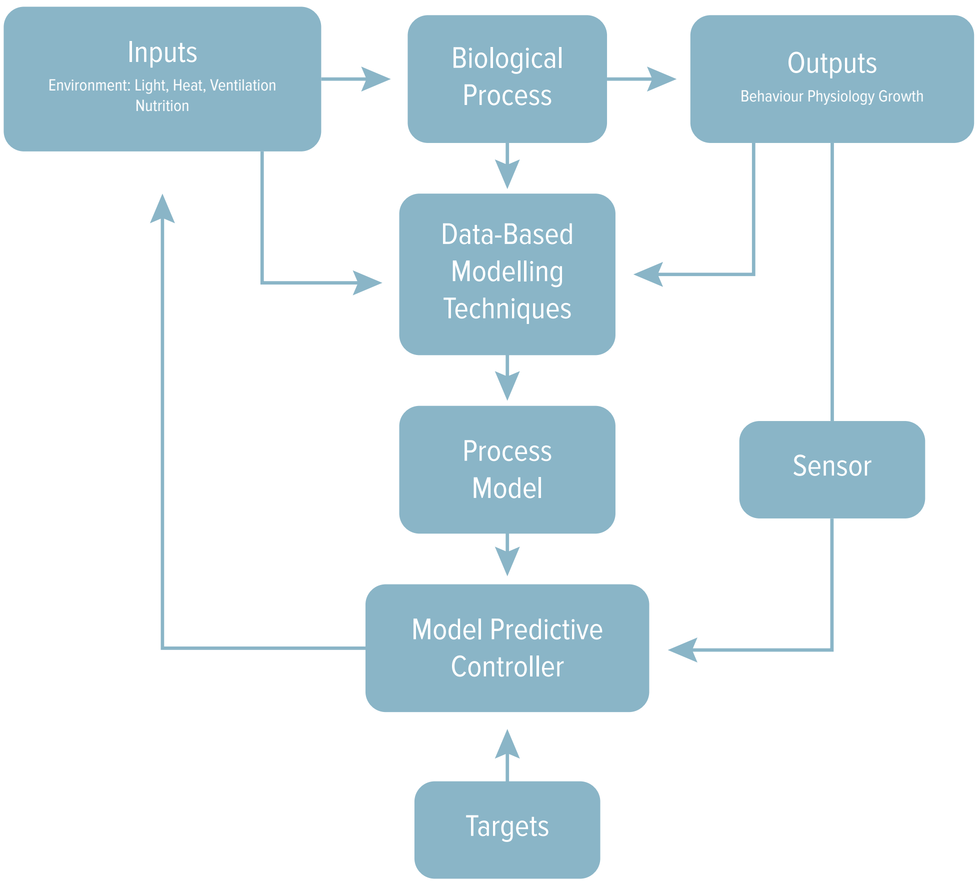

Figure 4: Schematic overview of the key components of PLF to control biological processes, such as animal behaviour, physiology and growth (adapted from Wathes et al., 2008)

problem, before the issue impacts on animal health and welfare. Figure 4 shows the basis of PLF for biological and physical processes, which can be applied at the pen, building or farm level.

The raw device data can in turn be processed into information, enabling us to identify a process output and process trajectory such as growth rates and behaviour patterns of animals. Predictions of target outcomes allow the animal care to be tailored for the optimum result. For example, the use of trend data for pig weight can enable feed inputs to be tailored to ensure that pigs reach the optimum slaughter weight and fat ratio in the required time trajectory, resulting in cost-efficient distribution of inputs. Farming is an industry that is subject to huge variation of inputs and outputs; using big data enables the consequences of variation to be mitigated sooner, enabling real-time adjustment to meet output targets. This will generate knowledge and create a more resistant and stable market, which in turn offers consumers greater confidence in meat production standards in a competitive price-driven industry.

3. What are the key data sources for PLF-DDBM?

IoAHT data collected by PLF data-driven businesses can be from internal and external sources.

Internal data: Data is collected directly from the business in question, from its own audience and customers. It is highly valuable business data that is free to obtain, and is an asset to scale audiences, deepen consumer engagement and improve return of investment. Data collected from PLF devices is typically internal data, and will include temporal data from both animals and owners. The data collected by sensor devices may be batch data, such as herd and flock camera systems to monitor size and weight gain (Schofield, 1990; Whittemore and Schofield, 2000; White et al., 2004; Chedad et al., 2003; De Wet et al., 2003), automatic weighing devices (Turner et al., 1984; Lokhorst, 1996), and vocalisation and cough monitors (Van Hirtum and Berckmans, 2004; Hemeryck and Berckmans, 2015). Individual animal data can also be collected by sensors, most commonly in association with electronic identification ear tags (EID). Examples include sensors attached to the animal such as activity meters for monitoring dairy cow oestrus behaviour (Roelofs et al., 2004; Chanvallon et al., 2014; DeLaval, 2015a), milk yield monitors (de Mol and Ouweltjes 2001; Kohler and Kaufmann, 2003; Blom et al., 2015; DeLaval, 2015b), lameness detectors (Scheel et al., 2015; Salau et al., 2015) and sensors to measure telemetrics such as heart rate and temperature (Mitchell et al., 2004; Lowe et al., 2007; Hoffman et al., 2015). This individual sensor technology has also begun to be employed in companion animals.

External data: Basically data that is obtained directly from a source via a business deal, allowing high-quality data sharing with benefit to both parties (Lotame, 2013). An example in PLF could be the collaboration of a weight-monitoring PLF device manufacturer with a feed manufacturer, enabling both businesses to share data to increase chances of individual success. Another type of external data is generated from other platforms and is aggregated from other sources, and is often sold data accessible through many different avenues. PLF companies are typically data companies, so are highly likely to sell collected data onwards to other organisations. Customer-generated data from PLF businesses is usually the most significant data source for the individual company; it provides customer insight and ensures that potential revenue opportunities are not missed. However, the integration of external data sources into a data ecosystem presents a real opportunity; the use of 'big data' integrating multiple stakeholders along the value chain is promising for improving productivity and cost-efficiency of animal production, as well as animal health and welfare standards.

4. What are the key activities?

To develop a complete picture of the key activities for PLF to reveal the true value contained within the data, the different activities were structured along the steps of the 'virtual value chain': data acquisition, aggregation, descriptive, predictive and prescriptive analytics. The data acquisition infrastructure for PLF primarily relies on the use of sensor devices. These devices are relatively inexpensive; many new devices and systems are rapidly appearing in a similar fashion to that of human medicine, for example, wearable health-care devices.

The data collection and processing via IoAHT for a data-driven business model essentially involves two elements. Raw data is discrete data collected by PLF devices and apps, which may be geographical, contextual, specific and identifiable to the animal that is owned by the farmer. The device manufacturers have rights to this data, but it is only to be collected and kept for the stated purpose of the company that collected it; it cannot be allowed to be re-purposed for other intentions. This raw data then passes an inflection point, where the data is integrated, compiled and interpreted to become 'information', usually by an algorithm. This data processing signals a transition of data rights and ownership; the raw data is redacted and the information becomes the intellectual property of the data-driven business.

At the moment, many of the devices that make up the edge of the industrial Internet of Animal Health Things are being implemented without strict data encryption and security protocols. As the industry matures so will the use of increased data security practices. At the moment, it is important that the IoAHT devices collect and store activity information and personal identifiable information (PII) in separate ways that cannot be misused. It is recommended that the activity data of the animal should be stored in a physically segregated manner, isolated from the PII information on the pet owner, farmer or vet involved with the activity, in order to protect the privacy of all parties and to be compliant with the EU and US data privacy rules.

The key activity of PLF businesses is data insight using analytics, which may be descriptive, predictive and/or prescriptive. One of the main benefits of PLF is being able to use prescriptive analytics to inform decision making, and to measure the impact of a prescriptive intervention on the forecast trajectory from predictive analytics. Predictive analytics is considered the predicted trajectory calculated based on the descriptive analytics from the past, without an intervention. This then allows interventions to be used where it is cost-efficient or there is a benefit to animal health and welfare. For example, growth rates of pig batches over a time period can be predicted based on the descriptive data coupled with nutritional information from a feeding regime. The deviation from the optimum growth trajectory can then be measured in real time, allowing an intervention in the feeding regime to allow pigs to reach slaughter-weight on target. In a similar way, the health status of animals can also be monitored by movement cameras, allowing targeted use of medicine dosing where required in a prescriptive intervention.

5. What are the potential revenue streams?

Some companies use 'big data' driven by PLF devices as value proposition to support their traditional revenue streams. For example, pharmaceutical company Zoetis invests in the Individual Pig Care programme (Pineiro et al., 2014), which is a PLF data-management system that essentially supports the core products of the company, improves animal health and welfare and promotes customer retention and loyalty. Newer start-up firms may rely almost entirely on data as their business offering, in the absence of an existing revenue stream. In order for data-driven PLF businesses to have a quantifiable benefit, a revenue model is crucial. Hartman et al. (2014) describes the seven main business revenue streams as: advertising, usage fees, subscription fees, brokerage fees, licensing fees, leasing fees and asset sales.

PLF businesses primarily rely on usage fees for their services, alongside purchase of sensor PLF devices. In the example of Zoetis, the Individual Pig Care programme has a revenue model consisting of survey usage fees for collecting information in the pens where the pigs are housed. The use of the system also supports the core products of the company, and provides further customer insight.

6. What are the challenges to us accomplishing our goal as an industry?

As a result of the inclusive nature of IoAHT, which incorporates 'everything', there are a number of challenges requiring appropriate oversight.

IoAHT data-collection methods are invasive, innocuous and unstructured. The seamless and frictionless nature of integration of devices into core user activities obscures the commitment and consequences of the data collection. In practice, it is unreasonable to assume that users of animal health applications that draw data actually understand the various entities participating in support of any data-collecting experience. Nor should it be expected that users understand the various places where their data resides and who could have access to it, especially after time passes. In the meantime, we need to ensure data is collected in a responsible manner with benefits to stakeholders in the value chain. It is of paramount importance therefore to set an industry standard for responsible storage and use of data, where unregulated use could result in triangulation of different data sets, which would infringe personal data rights.

User access and control over data is limited, allowing data recourse for different purposes. Animal data is a very different entity to human data; the animal is considered a 'Thing' in an industrial process where data laws are concerned, similar to other 'Things' where data is collected, such as light bulbs, windmills and other objects that are IoT devices. As a result, usage regulation is lacking, while a large amount of data is already being collected by IoAHT devices. This is less critical where the data is commoditised data, but where data collection is moving towards to medical data and prescription data, it is of paramount importance that this data cannot be exploited to the detriment of the IoAHT device owner.

Consent mechanisms used for user privacy approval of the IoT in general are often of low quality, making it hard for the user to understand what exactly they are consenting to. With the rapid expansion of the IoT and the rise of human wearable devices, updates have been made to human data laws in Europe (Rotenberg et al., 2013) and the US (The White House, 2012). Yet there has been recent publicity over concerns about data management for human wearable devices. A recent report showed 82 per cent of respondents are worried that wearable technology would invade their privacy (PWC, 2014). In a different study, 91 per cent of people felt that consumers had lost control of personal data (Pew Research Centre, 2014). Although animals do not have any privacy rights to their data, data protection laws exist to protect personal identifiable information (PII) collected with animal data. A critical problem is that human inference can be obtained from IoAHT data. For example, a companion animal activity tracking device that records dog walks could theoretically record where the owner lives, and owner activity levels and habits. It is the combination of this animal activity with the dimension of human activity information that requires special attention to ensure best practices are employed to restrict the use of PII in the IoAHT context.

The 'right to be forgotten' rule (Mantelero, 2013) needs to be enforced, enabling customer data to be deleted when requested by a member of the public, including data passed onto third parties. This is a very pertinent issue for PLF data collection with draft revision of EU policies calling for a fine of up to 1 per cent of annual turnover for firms that fail to 'erase personal data in violation of the right to erasure and "right to be forgotten"' (Reuters, 2015). PLF businesses need to consider carefully the type of data that their business is using, and ensure that data is deleted from sensor devices and related data-processing software.

Third party involvement is not identified by IoAHT applications, nor all of the places where raw and compiled data will reside. Animal health policies are changing; for example, German animal health policies now place great emphasis on data collection by farmers regarding the use of heavily restricted antibiotics (USDA, 2011); farmers may be reluctant to share data if they feel they may be penalised by government authorities. In the animal health context, does this mean governments should have access to farmers' individual veterinary data collected by herd management apps? It is important that users of IoAHT devices feel protected by data privacy laws.

To meet our goals, industry needs to be forward thinking for data-driven business models and establish a holistic data ecosystem that can fulfil its potential by overcoming a number of challenges. Zoetis is one of the companies working at the forefront of some of these critical challenges to shape the animal health industry in this area, ensuring the effective and intelligent use of big data for societal benefits with the appropriate level of privacy in a more systemic manner.

We believe that the use of 'big data' generated from PLF systems offers the ability to address a number of challenges currently facing the animal health industry. Whilst the intensification of farming can result in compromised animal health and welfare due to increased stocking densities of animals, the use of PLF sensor devices can help identify and mitigate these compromises sooner, resulting in improved health and welfare standards. Also, the recent European horsemeat scandal (European Commission, 2014) highlighted the flaws in traceability of the food production industry undermining consumer confidence, and the distrust in global organisations such as Monsanto (Monsanto, 2014; March-Against-Monsanto, 2015) demonstrates the need for greater transparency in the value chain.

Conclusion

Can the industry afford to wait to have data laws put in place by authorities, which could hinder societal benefit from big data in animal food production by limiting the wealth of information about animal health and welfare being offered by these IoAHT devices?

Instead, could the Animal Health industry proactively:

- Create a responsible model to meet the dual needs of privacy and on-demand personal data redaction?
- Integrate privacy and redaction models in a manner that can achieve the promise of improved animal medical outcomes that drive precision farming?
- Standardise technology infrastructure and practices to ensure proper data privacy, security and management, while enabling the wider benefits of increased transparency and information sharing along the value chain?
- Work together to ensure data practices are trusted by users and society as a whole, and set the standard for the responsible use of data?

References

Blom, J.Y., Christensen, J.M., Ridder, C. 2015. Real-time analyses of BHB in milk can monitor ketosis and its impact on reproduction in dairy cows. http://dx.doi.org/10.3920/978-90-8686-815-5_7.1

Brownlow, J., Zaki, M., Neely, A., Urmetzer, F. et al., 2015. Data and Analytics - Data-Driven Business Models: A Blueprint for Innovation. http://www.cambridgeservicealliance.org/uploads/downloadfiles/2015%20March%20Paper%20-%20The%20DDBM-Innovation%20Blueprint.pdf

Chanvallon, A., Coyral-Castel, S., Gatien, J., Lamy, J.M., Ribaud, D., Allain, C., Clement, P., Salvetti, P., 2014. Comparison of three devices for the automated detection of estrus in dairy cows. Theriogenology, 82(5), 734-741.

Chedad, A., Aerts, J.-M., Vranken, E., Lippens, M., Zoons, J., Berckmans, D., 2003. Do heavy broiler chickens visit automatic weighing systems less than lighter birds? Br. Poult. Sci. 44, 663–668.

DART, 2008. DART: German Antimicrobial Resistance Strategy.http://www.bmg.bund.de/fileadmin/dateien/Publikationen/Gesundheit/Sonstiges/DART_-_German_Antimicrobial_Resistance_Strategy.pdf

DeLaval, 2015a. Activity Meter System. http://www.delaval.com/en/-/Product-Information1/Management/Systems/Activity-meter-system/

DeLaval. 2015b. Herd Navigator: Mastitis detection. http://www.delaval.com/en/-/Product-Information1/Management/Systems/herdnavigator/Mastitis-detection/

de Mol, R.M., Ouweltjes, W., 2001. Detection model for mastitis in cows milked in an automatic milking system. Prev. Vet. Med. 49, 71–82.

De Wet, L., Vranken, E., Chedad, A., Aerts, J.M., Berckmans, D., 2003. Computer-assisted image analysis to quantify daily growth rates of broiler chickens. Br. Poult. Sci. 44, 524–532.

Elfrink, W., 2014. The Internet of Things: Capturing the Accelerated Opportunity. Cisco Blog, 15 October 2014. http://blogs.cisco.com/ioe/the-internet-of-things-capturing-the-accelerated-opportunity

European Commission, 2014. Horse Meat: One year after - actions announced and delivered. http://europa.eu/rapid/press-release_MEMO-14-113_en.htm

FAO, 2009. How to feed the World in 2050. http://www.fao.org/fileadmin/templates/wsfs/docs/expert_paper/How_to_Feed_the_World_in_2050.pdf

FAO, 2012. World Agriculture towards 2030/2050: The 2012 Revision. ESA Working Paper No 12-03. http://www.fao.org/fileadmin/templates/esa/Global_persepctives/world_ag_2030_50_2012_rev.pdf

Gates Notes, 2013. Meat Market: The Future of Food http://www.gatesnotes.com/About-Bill-Gates/Future-of-Food

Global Harvest Initiative, 2014. 2014 Global Agricultural Report, Global Revolutions in Agriculture: The Challenge and Promise of 2050. [Online] Available at: http://www.globalharvestinitiative.org/GAP/2014_GAP_Report.pdf

Hamilton, D.N., Ellis, M., Bertol, T.M., Miller, K.D., 2004. Effects of handling intensity and live weight on blood acid-base status in finishing pigs. J. Anim. Sci. 82, 2405–2409.

Hartmann, P.M., Zaki, M., Feldman, N., Neely, A., 2014. Big Data for Big Business? A Taxonomy of Data Driven Business Models used by Start-up Firms. http://www.cambridgeservicealliance.org/uploads/downloadfiles/2014_March_Data%20Driven%20Business%20Models.pdf

Hemeryck, M., Berckmans, D., 2015. Pig cough monitoring in the EU-PLF project: first results. http://dx.doi.org/10.3920/978-90-8686-815-5_5.4

Hoffman, G., Schmidt, M., 2015. Monitoring the body temperature of cows and calves with a video-based infrared thermography camera. http://dx.doi.org/10.3920/978-90-8686-815-5_6.1

Kohler, S.D., Kaufmann, O., 2003. Quarter-related measurements of milking and milk parameters in an AMS-herd. Milk Sci. Int. 58, 3–6.

Lokhorst, C., 1996. Automatic weighing of individual laying hens in aviary housing systems. Br. Poult. Sci. 37, 485–499.

Lotame, 2013. 1st, 2nd, 3rd Party Data: What Does it All Mean? http://www.lotame.com/resource/1st-2nd-3rd-party-data-what-does-it-all-mean/

Lowe, J., Abeyesinghe, S.M., Demmers, T.G.M., Wathes, C.M., McKeegan, D.E.F., 2007. A novel telemetric logging system for recording physiological signals in unrestrained animals. Comput. Electron. Agric. 57, 74–79.

Mantelero, A., 2013. The EU Proposal for a General Data Protection Regulation and the roots of the 'right to be forgotten'. Computer Law & Security Review 29 (3): 229–235.

March-Against-Monsanto, 2015. March Against Monsanto http://www.march-against-monsanto.com/home/

Maron, D.F., Smith, T.J., Nachman, K.E., 2013. Restrictions on antimicrobial use in food animal production: an international regulatory and economic survey. Globalization and Health. 9:48. doi: 10.1186/1744-8603-9-48.

Mitchell, K.D., Stookey, J.M., Laturnas, D.K., Watts, J.M., Haley, D.B., Huyde, T., 2004. The effects of blindfolding on behaviour and heart rate in beef cattle during restraint. Appl. Anim. Behav. Sci. 3–4, 233–245.

Monsanto, 2014. Monsanto Opinion Leader Research. http://monsantoblog.eu/wp-content/uploads/2015/02/Monsanto-Media-Research-Report.pdf

O'Kane, K., 2015. Breakthroughs in Electronic Identification for Pigs: Morrissons. BPEX Innovation Conference, Stoneleigh Park, 13 May. https://www.youtube.com/watch?v=CWJpmv6q-hw

Pew Research Centre, 2014. Public Perceptions of Privacy and Security in a Post-Snowden Era. http://www.pewinternet.org/files/2014/11/PI_PublicPerceptionsofPrivacy_111214.pdf

Pineiro, C., Morales, J., Dereu, A.,Wuyts, N., Azlor, O., Vizcaino, E., Doncecchi, P., 2014. Individual Pig Care program improves productive performance and animal health in nursery-growing pigs. J. Swine Health Prod. 22 (6): 296-299. https://www.aasv.org/shap/issues/v22n6/v22n6p296.pdf

PWC, 2014. The Consumer Intelligence Series: The wearable technology future. http://www.pwc.com/us/en/industry/entertainment-media/publications/consumer-intelligence-series/wearable-technology.jhtml

Roelofs, J.B., van Eerdenburg, F.J., Soede, N M., Kemp, B., 2005. Pedometer readings for estrous detection and as predictor for time of ovulation in dairy cattle. Theriogenology, 64 (8), 1690-1703

Reuters, 2015. Firms to face stiffer fines for breaking EU's 'right to be forgotten' rules. http://www.reuters.com/article/2015/05/20/us-eu-dataprotection-fines-idUSKBN0O529X20150520

Rotenberg, M., Jacob, D., 2013. Updating the law of information privacy: The new framework of the European Union. Harvard Journal of Law & Public Policy; Spring 2013, Vol. 36 Issue 2, p605.

Salau, J., Haas, J.H., Junge, W., Leisen, M., Thaller, G., 2015. Development of a multi-Kinect-system for gait analysis ans measuring body characteristics in dairy cows. http://dx.doi.org/10.3920/978-90-8686-815-5_2.3

Scheel, C., Traulsen, I., Krieter, J., 2015. Detecting lameness in sows using acceleration data from ear tags http://dx.doi.org/10.3920/978-90-8686-815-5_2.1

Schofield, C.P., 1990. Evaluation of image analysis as a means of estimating the weight of pigs. J. Agric. Eng. Res. 47, 287–296.

Scott, G.B., Moran, P., 1993. Fear levels in laying hens carried by hand and by mechanical conveyors. Appl. Anim. Behav. Sci. 36, 337–345.

The White House, 2012. Consumer data privacy in a networked world: A framework for protecting privacy and promoting innovation in the global digital economy. https://www.whitehouse.gov/sites/default/files/privacy-final.pdf

The World Bank, 2008. World Development Report 2008: Agriculture and Poverty Reduction. http://siteresources.worldbank.org/SOUTHASIAEXT/Resources/223546-1171488994713/3455847-1192738003272/Brief_AgPovRedctn_web.pdf

Turner, M.J.B., Gurney, P., Crowther, J.S.W., Sharp, J.R., 1984. An automatic weighing system for poultry. J. Agric. Eng. Res. 29, 17–24.

UN, 2013. World Population Prospects: The 2012 Revision, Volume I: Comprehensive Tables. ST/ESA/SER.A/336.

USDA, 2011. Global Agricultural Information Network: Stricter Control on Antibiotics in Animal Husbandry. http://gain.fas.usda.gov/Recent%20GAIN%20Publications/Stricter%20Control%20On%20Antibiotics%20In%20Animal%20Husbandry_Berlin_Germany_11-9-2011.pdf

Van Hirtum, A., Berckmans, D., 2004. Objective recognition of cough sound as a biomarker for aerial pollutants. Indoor Air 14, 10–15.

Wathes, C.M., Kristensen, H.H., Aerts, J.M., Berckmans, D. 2008. Is precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall? Computers and Electronics in Agriculture 64: 2 - 10.

White, R.P., Schofield, C.P., Green, D.M., Parsons, D.J., Whittemore, C.T., 2004. The effectiveness of a visual image analysis (VIA) system for monitoring the performance of growing/finishing pigs. Anim. Sci. 78, 409–418.

Whittemore, C.T., Schofield, C.P., 2000. A case for size and shape scaling for understanding nutrient use in breeding sows and growing pigs. Livest. Prod. Sci. 65, 203–208.

UNIVERSITY OF CAMBRIDGE
Cambridge Service Alliance

Cambridge Service Alliance
www.cambridgeservicealliance.org
email: contact@cambridgeservicealliance.org