Data driven investment and performance management in the livestock sector

A.R. Peters* (1) & S. Thevasagayam (2)

(1) Centre for Supporting Evidence-Based Interventions in Livestock, University of Edinburgh, Easter Bush Campus, Midlothian, EH25 9RG, United Kingdom

(2) Bill and Melinda Gates Foundation, 500 Fifth Avenue North, Seattle, WA 98109, United States of America

*Corresponding author: andy.peters@ed.ac.uk

Summary

Evidence based decision making is now axiomatic in many sectors and it has become increasingly important in prioritising development in low and middle income countries. In the livestock development sector, there has been a lack of data on health and production on which to establish an evidence base. Thus, much strategic and policy decision making has been based on more subjective bases of opinion, expert or otherwise. However, there is now a trend towards a more data-driven approach for such decisions. The Centre for Supporting Evidence-Based Interventions in Livestock was established in Edinburgh by the Bill and Melinda Gates Foundation in 2016, to collate and publish livestock health and production data, lead a community of practice to harmonise livestock data-related methodologies and, to develop and monitor performance indicators for livestock investments.

Keywords

Data-driven – Decisions – Evidence based – Health – Livestock – Productivity.

Introduction

'With little or no knowledge regarding animal health, nutrition, production process, and reproduction procedures, and without a scientific plan and program, achieving a desired economic profit is absolutely impossible' [1].

Evidence based decision making has become broadly accepted as being necessary for optimal decision making in many professional settings. This has perhaps been most notable in the field of human medicine which began to emerge as a new paradigm for more rational clinical practice in the early 1990s [2] and has gained in wide global acceptance since then [3, 4, 5, 6] and has become adopted in veterinary medicine [7, 8, 9, 10] and many other professional and business sectors [11]. Evidence based medicine has been defined as the 'integration of best research evidence with clinical expertise and patient values' [12] and this principle has since been readily translated into other specific professional sectors.

The evolution of the livestock strategy in the Bill and Melinda Gates Foundation: a case study

A strategy for agriculture development in the smallholder sector of low and middle income countries (LMICs) was initiated in the Bill and Melinda Gates Foundation (BMGF) in 2006 and it soon became apparent that most smallholders rely both on livestock and crops for their livelihoods. However, there was a low base of understanding in the foundation of the livestock development priorities due to a distinct lack of data-based information on the needs of this sector [13]. Therefore a few initial investments were made in order to learn and to help inform future livestock investments; this process then resulted in the launch of a livestock initiative in 2012.

Seven countries in sub-Saharan Africa and two in South Asia were prioritised for dairy cattle (including water buffalo in South Asia), small ruminants and poultry, focusing on animal health and genetics, and the respective species' value chains. Fourteen infectious diseases considered to be causing the highest productivity losses were selected for investment. In genetics the focus was on identification and multiplication of appropriate genetic technologies applicable to smallholders, particularly in dairy and poultry. In prioritising and focusing these investments there was extensive consultation with partners and consultants in order to gain expert advice on the most impactful direction to take. However, as the learning and experience accrued over those early years, it became ever more apparent that much of the input was based on experience and expert opinion rather than objective evidence, largely because of the extensive gaps in data from the field on these livestock health and productivity issues. The above pragmatic approach to decision making, rather than being evidence based can be illustrated by the example of how livestock diseases were initially prioritised for intervention by BMGF. The 14 priority diseases referred to above were selected on expert opinion and largely based on the report by Perry *et al.* [13] commissioned by the United Kingdom's (UK) Department for International Development (DFID). The not for profit organisation the Global Alliance for Livestock Veterinary Medicines (GALVmed), originally the Global Alliance for Livestock Vaccines (GALV), was set up in 2005 with seed funding from the then UK DFID. This followed recognition that there was a market failure in terms of the provision of animal health products to small scale producers (SSPs) which applied particularly to vaccines for a large number of diseases. Thus, the need was identified for an organisation to support the development and production of livestock vaccines, diagnostics and other products for the control of these neglected tropical livestock diseases. Whilst there had been a considerable body of research on these diseases over the years, the gap in the livestock vaccine market was perceived to be due to the unwillingness of the animal health industry to invest in those diseases because of the relatively disparate, perceived low-demand and high-risk market segments. In 2008 BMGF then also invested in GALVmed along with DFID, this being the first major BMGF investment in animal health.

Early in the development of GALV/GALVmed, a committee of technical advisers comprising veterinary scientists experienced in international development and global vaccine developers including one of the present authors, was convened to advise the organisation on disease prioritisation for its initial focus. The recommendation for 12 infectious diseases was subsequently adopted as key priorities for GALVmed. These decisions were largely based on the advice given by experts on the basis of their experience and knowledge of the sector, but with little or no direct input of solid data. Further diligence was carried out to support the prioritisation, but it was noted at the time that there was a distinct lack of substantial data to support those decisions e.g. product demand, feasibility of product development and deployment, or the likely impact of product usage. Equally the decision making process here could be criticised for lack of due consideration to endemic production disease and non-infectious health problems.

The above example of non-data-based decision making is not unique. In fact the lack of data was becoming ever more apparent across the board in livestock development [14]. At the time of writing, BMGF now supports more than 60 programmes in the field of animal health, genetics, enabling systems, animal nutrition and offtake markets. As this investment portfolio expanded, the recognition of the need for better and reliable data became more urgent and acute for making informed management and investment decisions to optimise desired impact and to select future development programmes.

A number of reports in the grey literature and elsewhere have highlighted the need for more and better data relating to the LMIC livestock sector e.g. International Livestock Research Institute (ILRI), International Bank for Reconstruction and Development, the World Bank Group. Although there were a number of established international organisations engaged in collecting and disseminating livestock related data and statistics e.g. Food and Agriculture Organization of the United Nations (FAO), World Organisation for Animal Health (WOAH, founded as OIE), ILRI, World Bank Group, African Union–Inter-African Bureau for Animal Resources, BMGF took an alternative path. A new independent group was established with potential access to world-class expertise and competencies, to play a non-competitive, brokering role in bringing the livestock data community together, with the specific remit of improving availability, quality and reliability of livestock-related data to enable more evidence-based decision making for livestock investments in LMICs. This became known as Supporting Evidence-Based Interventions (SEBI).

SEBI developed a systematic approach as described below to answer some fundamental questions in an attempt to first understand and then address the root causes of the issues in order to enable data-based investment decisions.

Decisions for what? Decisions by whom? Who are the decision makers?

Within the current scope of SEBI, decision makers can be considered at least at four levels:

1) farmers, from SSPs to fully commercial, clearly need information on the health and productive performance of their stock in order to make rational management choices and decisions;

2) governments need information on the status and impact e.g. of livestock disease in order to prioritise, implement and monitor control programmes for economic reasons e.g. international trade and other potential official interventions such as breed improvement/artificial insemination programmes;

3) investors need information on the status of livestock production and their respective markets in order to make rational investment decisions e.g. animal health companies need information on numbers and types of species, prevalent diseases, most appropriate products, regulatory systems, knowledge of distribution networks, competitor information and other challenges;

4) international donors need information on the highest leverage investment opportunities for optimal outcomes from economic, social and environmental contexts, e.g. what impact they can have, what consequences (intended and unintended) they may cause and how best to shape future investment strategy. This information is needed in order to make the most rational and impactful choices regarding targeting of future funding. For example, should it be on dairy genetics, or foot and mouth

disease control programmes, or nutrition or some combination of these? Donors may be private or public organisations and in the latter case might be accountable to governments and therefore also integral to category 2 above.

Of course, none of the above categories of decision maker is homogeneous but rather a loose grouping of organisations with similar but individual needs. For example, a small scale producer with one or two cows will have different data needs from a commercial dairy with 200 cows. Thus data needs are very much dependent on the audience or 'customer' for the data.

One of SEBI's tasks was to establish, convene and lead the community of practice, Livestock Data for Decisions (LD4D). Its purpose is to drive better livestock decisions through improved data and analysis. Whilst making significant progress in bringing the livestock data community together, to find solutions for the most pressing livestock data needs, a valid criticism of LD4D is that the focus has been on the data collectors and analysts, that is the supply side of the equation, without much consideration of the decision makers (the customers). This consideration has now extended LD4D's focus to address the demand side by aiming to identify the specific needs of key decision makers.

Of course, the needs of the four categories of decision makers or customer groups above are quite different. For example farmers need information on individual animal performance, local markets, input prices, weather etc. and need the capability to evaluate the impact of management changes and interventions like disease prevention and breed improvement [15]. The other three sectors mentioned need different data sets but all consisting largely of aggregated livestock data.

What is meant by data and evidence?

'Data driven' has become a fashionable and possibly over-used expression and theme. However if it is for a strategic purpose then the specific problem, question or objective has to be posed first in order to inform what data is needed. So, while the answer may be data driven, the question first has to be asked i.e. what is it we are trying to solve or achieve? Thus, when someone or an organisation claims to employ a 'data-driven' approach, it should have first either asked what the objective or end goal is. It can then make strategic decisions based on the appropriate data, its analysis and interpretation.

What is data?

Data in the present context is purely an individual or set of non-contextualised numbers or observations. In order for this to be translated into evidence there has to be an opinion or hypothesis or question to add context (see Table I, [16], https://oxford-review.com/data-v-evidence/#summary). For example, a data point might be the average milk yield of cows in Tanzania. Then one might ask, has this changed in the last 20 years? For this one would need contextual information, evidence, and for this one would need a series of data collected over that period of time and one would need to analyse and interpret it to provide the evidence and then render it into a useful piece of knowledge that could be communicated to another party.

What is the overall objective of data processing?

Thus, in order to collect the right data, for the right metrics or indicators, a clear statement of the problem and/or objective(s) is needed. In the international development context, the usual device for this is to construct a Theory of Change (ToC) (Figure 1). Theory of change is an outcomes-based approach which applies critical thinking to the design, implementation and evaluation of initiatives and programmes intended to support contextual change [17]. A ToC is a tool to help describe the problem (objective) to be addressed, the changes that are to be made and the plan for activities to achieve that objective [18]. The key to this is the 'outcomes based' approach, i.e. starting with the end in mind, thus necessitating a clear understanding and definition of what is to be achieved and then planning the necessary steps to get there (termed the Theory of Action). It is also important to include some metrics or indicators and intermediate milestones, so that progress can be monitored during the course of the programme. An example of Theory of Change/Theory of Action is shown in Figure 1.

It will be clear from Figure 1 that as the focus moves up from the bottom, more context is added. Whilst the activities at the bottom of the figure are directly under the control of the acting organisation (SEBI in this case), as the context enlarges, it merges into sequential zones of influence and then interest where the actor has less and less control over subsequent events. This is important in terms of determination of cause and effect, because it can be extremely difficult in these cases to confirm any attribution with certainty. It is also important here to differentiate the terms outputs, outcomes and impact [19].

In the private sector the analogous tool or device would normally be constructed and termed a business plan (BP), essentially setting out the business objectives and then subsequently filling in the necessary activities, processes and resources necessary to achieve them. An important component of both the ToC and BP is the use of metrics or indicators, based on real data, to monitor progress and to ensure that the plan is on track and being adhered to. Thus, data is needed to measure the outputs of the programme and to inform the future direction. For this the trends in the data are also important e.g. is national milk production going up or down? Is egg production going up or down? How many more cattle are being vaccinated?

How we collect and use data to learn and adjust our course as necessary

Data gaps and flaws are well recognised in the international livestock development field [14]. While there are many sources of data on LMICs e.g. FAO, WOAH, ILRI, Centre for Agriculture and Bioscience International (more commonly known as CABI), World Bank Group, grey literature, peer reviewed publications, data is disparate and incomplete and, may even be extrapolated inappropriately from the industrialised world. Data on greenhouse gas emissions in LMICs are a case in point [20, 21].

In their report 'Investing in the livestock sector: why good numbers matter', Pica-Ciamarra *et al.* [14] drew attention to the deficit in good quality data on LMIC livestock production and went on to describe the institutional necessity for the routine collection and analysis of data at an official level but they pointed out that such routine data currently is of poor quality partly because of inadequate training of extension officers who are responsible for the process. Furthermore, routine data are collated on a complete enumeration basis which makes it extremely demanding and time consuming and thus the authors advocate a statistically based sampling approach which could make data collection more efficient and convenient. It should be noted that it is not only livestock data that is lacking in many LMICs. The 50 by 2030 project a multi-lateral initiative to produce, analyse and apply data to decision making across the whole agricultural sector has recently launched (https://www.50x2030.org) to attempt to address these issues on an international scale.

There are many publications on livestock health and productivity in LMICs in the peer reviewed and grey literature, but the evidence has rarely been systematically categorised and reviewed. A key objective of SEBI has been to systematically describe the available data and evidence on the high impact livestock diseases in SSA. Highly detailed academic studies of the epidemiology of livestock disease have been carried out in limited areas [22] but these can be prohibitively expensive and therefore unsustainable for the purpose of providing long-term routine evidence. Data collection and processing comes at a cost. It is important to have reliable data and it should be fit for purpose. The law of diminishing returns can be applied to the quality of data. Starting at a low base of quality, increased investment will lead to an increase in the quality and hence reliability of the data. However, as investment level increases eventually the pace of quality improvement will begin to level off eventually leading to a point where there is little or no improvement irrespective of increases in investment. Thus, the question should be asked, how good does the data have to be, when is it good enough, what is the cost: benefit?

SEBI has used a variety of methodologies to collect data on ruminant disease in several countries to engage with governments in the selection of priorities for intervention (https://www.livestockdata.org/data-object/farmer-surveys-and-key-informant-questionnaires-cattle-and-small-ruminant-mortality).

SEBI has also developed a protocol for systematic mapping using Ethiopian literature on ruminant diseases over the last ten years as a pilot [23] and the map is currently in press I[24]. The aim of this study was to collate and synthesise the published evidence on ruminant disease frequency and disease-associated mortality in Ethiopia, by identifying knowledge gaps and clusters in the literature to provide the basis for a decision-making tool. Search results were screened for relevance at title, abstract and full text levels, which identified 716 articles relevant to the research question. The study suggested that despite the high output of epidemiological publications, further understanding of a considerable number of diseases is required and where evidence is abundant, synthesis of information could be carried out to better inform decisions on disease control priorities in the country. An example of the output from the systematic map is shown in Figure 2. The output has been developed into a visualisation format that can be interrogated for individual species, regions diseases etc. and is available online at https://www.livestockdata.org.

Since the performance of such reviews is highly laborious this process has now been automated such that this can now be achieved with machine learning protocols [25] and the intention is to extend this process to other species, languages, and countries, to add more structure to the body of data on the impact and prevalence of tropical livestock disease.

Monitoring and learning for continuous improvement

The BMGF team needs a constant flow of data in the form of 'dashboards' from funded programmes, particularly the farmer-facing ones so that their outputs can be monitored, data aggregated across programmes with the objective of being able track progress, identify opportunities to improve and to adjust operational directions if necessary. These and other data coming into SEBI are cleaned and processed as described in Figure 3. Standardising the format and structure of incoming data is a work in progress.

In addition, the team depends on these data to calculate the impact of investments and to inform future investment decisions. Calculations are also carried out by SEBI on the economic return for SSPs on their investments in animal health and genetics. Examples of these models are illustrated in Figures 4 and 5.

Examples of data collected and considerations to inform future directions

Investigation of mortality rates/risk

To investigate the use of a single metric e.g., mortality as a measure of a country's animal health status, the mortality rates were estimated (or more correctly, risk [26]) in three countries, Ethiopia, Tanzania and Nigeria. A further aim for this effort was to determine the most prevalent diseases causing mortality with a view to be identifying priorities for implementing control interventions. A variety of methods were used including government institutional data, farmer recall surveys, expert opinions, living standards measurement study surveys, literature review, laboratory data and real time diagnostic surveillance. All these methods have recognised flaws [14]. Thus, it soon became apparent that the estimates within and between years were highly variable to the extent that the use of such a single measure was considered unachievable particularly given the huge gaps in systematic data collection. On further analysis since a high proportion of livestock mortalities in LMICs occur during the early weeks of life (SEBI, unpublished data) we have suggested the use of a young stock mortality metric as a more reliable indicator of overall animal health status of a country [26].

Data on national Veterinary Services

The World Organisation for Animal Health publishes regular reports on national Performance of Veterinary Services. A tool was developed to extract data from such reports so that it can be manipulated into a summary and analysable form at https://www.livestockdata.org/data-object/performance-veterinary-services-pvs

This interactive visualisation can be interrogated to focus in on specific countries, years, etc. and is illustrated in Figure 6.

Data for farmers

Record keeping is a necessary element of good livestock business management. With no written records, farmers have to depend on their memory while making decisions regarding their farm practices (https://vikaspedia.in/agriculture/livestock/cattle-buffalo/importance-of-record-keeping-at-livestock-farm). The sophisticated livestock industries of the developed world have been built with the vital support of on-farm performance (phenotypic) data recording and this has usually necessitated the precursor of institutional development such as livestock federations and related organisations e.g., national dairy federations. The International Committee for Animal Recording is an international non-governmental organisation and network with members from 120 countries and aims to set standards for livestock identification, performance recording and genetic evaluations, thus a future aspiration would be for LMIC livestock data generation to work towards alignment with these international standards.

Thus, the necessity of on-farm recording as a prerequisite for livestock performance improvement is well recognised but clearly systems are not in place to be able to fully exploit this in most LMICs. One of the main obstacles is the need for individual animal data and until the advent of digital methods of data collection this relied on 'pen and paper' or worse, farmer recall. Digital methods of phenotypic recording are rapidly advancing in industrialised settings e.g. the use of activity meters, physiological measures, sound monitors, cameras, environmental monitors, oestrus detection devices, etc. The concept of precision livestock farming (PLF) was introduced during the last decade or so, the aim of which is to manage individual animals by continuous real-time monitoring of health, welfare, production/reproduction, and environmental impact [27]. A recent systematic review of PLF in the poultry sector [28] revealed that a very low (4.9%) proportion of research papers had come from LMICs and even in high income countries most of the technologies are still at prototype stage. The main limitation in LMICs is the fact that much of the livestock production is small scale, pastoral in nature, often remote and, the sensing technologies and networks are not sufficiently available in convenient, low-cost forms to be widely applicable [29]. The lack of a consistent and mandatory animal identification system remains a fundamental barrier. Whilst there have been promising developments in LMICs e.g. Stellapps (https://www.stellapps.com) which aims to provide 'one stop dairy chain digitisation via the internet of things', and MoooFarm (https://mooo.farm) which provides digital livestock management, veterinary and other market related information services for small scale livestock producers in India, they are yet to be adopted at scale to reach their promised impact. Numerous mobile phone apps have been developed for use in remote areas e.g. iCow (https://icow.co.ke) for support in veterinary diagnostics, phenomics, market and other information services but they remain small scale and are yet to develop with sustainable business models.

Conclusions

The goal of data driven investment and performance management in the LMICs livestock sector is a work in progress. However, it is apparent that:

1) improved systems of data availability are necessary for evidence-based decision making on livestock priorities in LMICs;

2) data collection and collation first need to be contextualised in terms of the decision maker (farmer, investor, government, donor) and tailored to the question(s) being asked so that there is a favourable cost–benefit and fitness for purpose;

3) ideally data collection systems should be introduced that are sustainable so that they do not require continuous donor funding;

4) finally, data is only one component of decision making and all organisations have their own specific individual cultures, needs

and methodologies. Other factors necessarily come into play such as personal preferences and biases at all levels, influence of competing strategies and policies, levels of understanding etc. Nevertheless, if the factual data-based information is available this at least can provide a rational basis for further discussion and evidence-based decision making.

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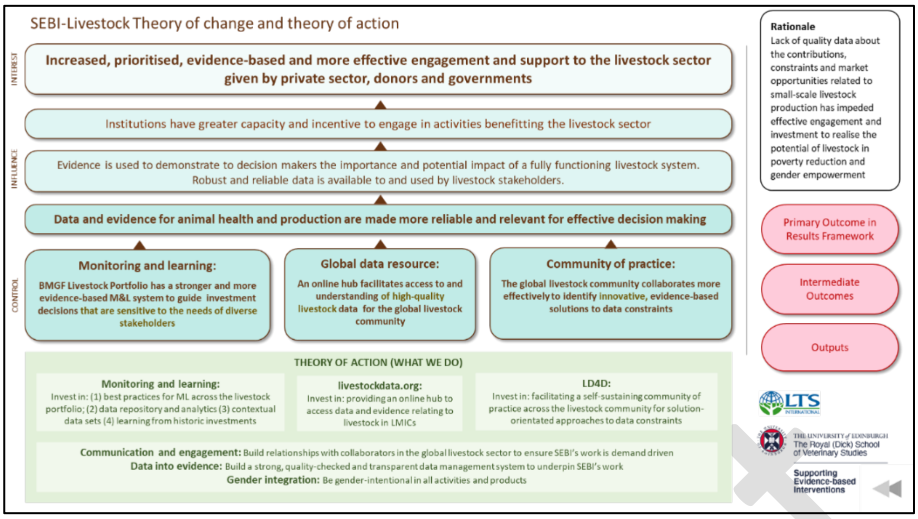
Table I

Definitions of data and evidence (modified from Dammann [16])

Term	Description	How it is generated	Generator	Purpose
Data	Numbers, symbols, text, images, etc.	Collected from experiments, observations, field research	Data collector (person or automated)	Generation of information
Evidence	Relevant contextualised data	Comparison with standards or other reference information	Scientist, advisor to decision/policy makers. In present context could also be a farmer	Used as a basis for decision making



BMGF: Bill and Melinda Gates Foundation
LD4D: Livestock Data for Decisions
LMICs: low and middle income countries
M&L: monitoring and learning
SEBI: Supporting Evidence-Based Interventions

Figure 1

Theory of change and action for Supporting Evidence-Based Interventions in Livestock

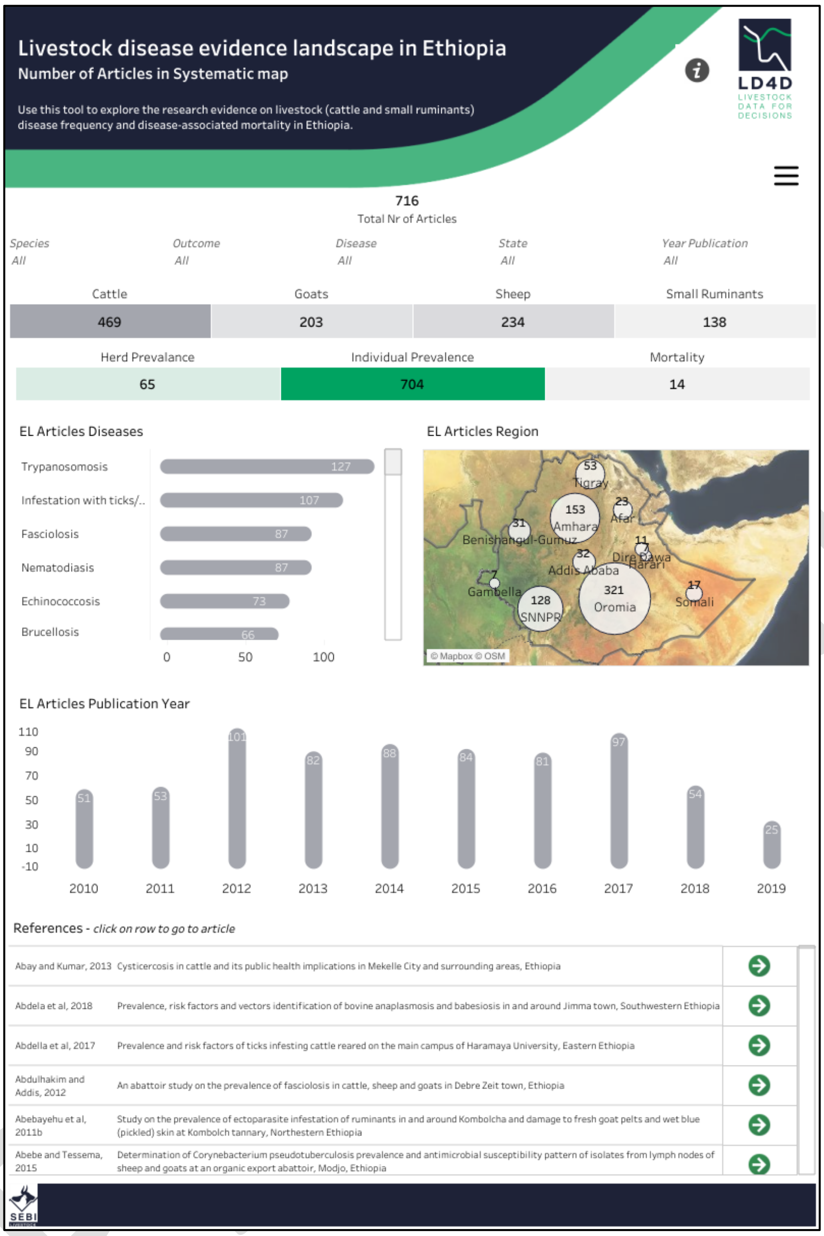


Figure 2

A static example of the output from the systematic map of literature on ruminant disease in Ethiopia [24, 25]

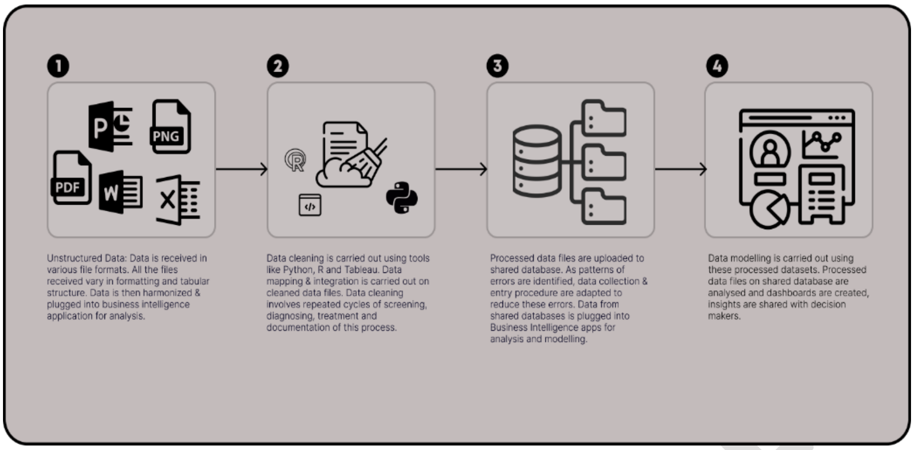


Figure 3

The data cleaning process used in Supporting Evidence-Based Interventions

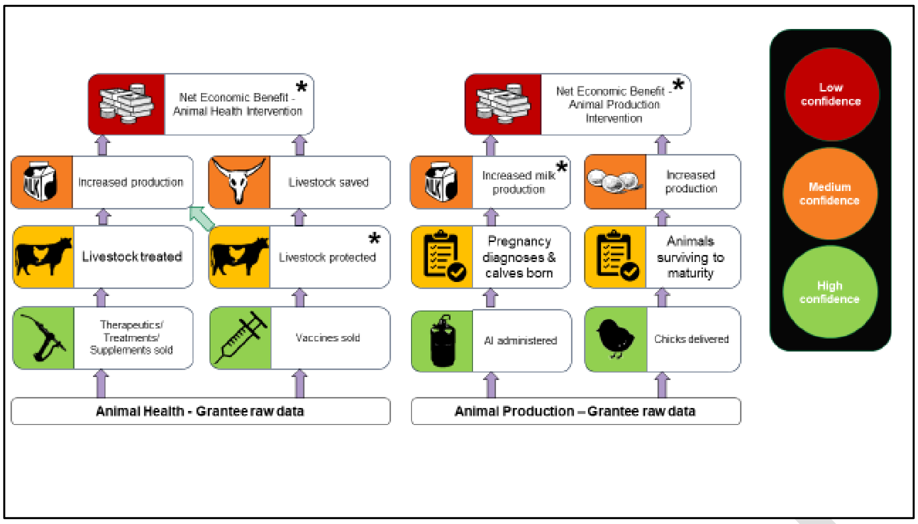
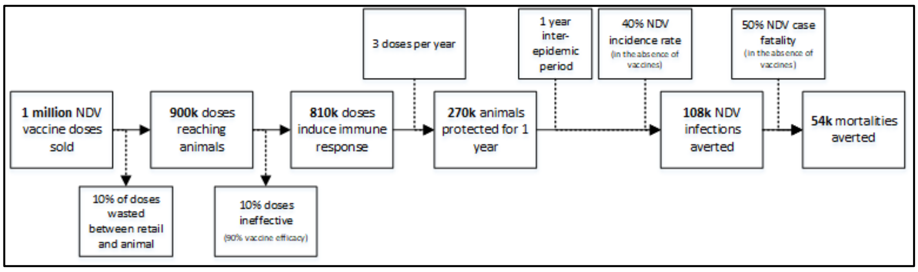


Figure 4

Simple models used to estimate net economic benefit of the use of veterinary medicines or improved genetics in small scale producer livestock (courtesy of Gareth Salmon, Supporting Evidence-Based Interventions)



NDV: Newcastle disease vaccine

Figure 5

Simple model used to estimate the impact of Newcastle disease vaccine from the knowledge of the number of vaccine doses sold by a vaccine manufacturer (courtesy of Gareth Salmon, Supporting Evidence-Based Interventions)

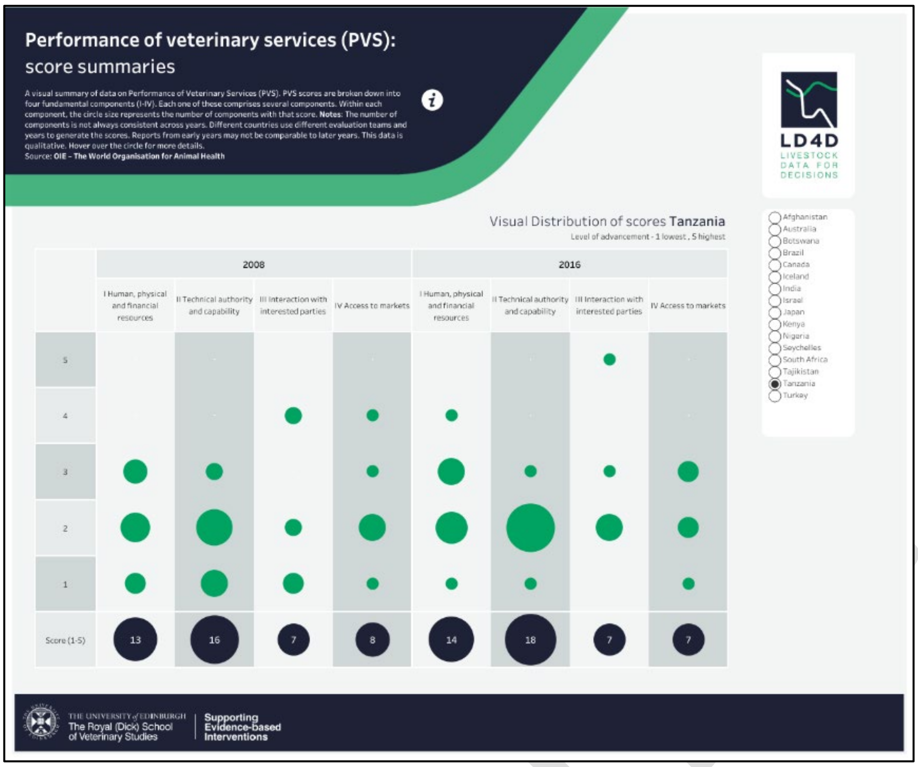


Figure 6

Example visualised screenshot of Performance of Veterinary Services (PVS) scores for Tanzania in 2008 and 2016 derived from published World Organisation for Animal Health's PVS reports (courtesy of Louise Donnison, Supporting Evidence-Based Interventions)