A Proposal to Use Precision Livestock Farming for Epidemiology

Spyridon Manolidis

September 2025
DOI: 10.5281/zenodo.17021787

Abstract

This proposal explores how new Precision Livestock Farming (PLF) technology can be paired with existing epidemiological models to enrich disease control in animal farms. By utilising Artificial Intelligence (AI) to map the social interactions between livestock, we aim to create a 'social network' of the farm which can - amongst other things - be used to predict and model the spread of diseases. Whilst this approach mainly aims to promote animal welfare and reduce suffering, it may also have the positive implications of increasing productivity and protecting human health by mitigating zoonotic disease risks. Furthermore, the proposal acknowledges other ethical considerations and consequences, both positive and negative, to provide an unbiased view. Overall, this proposal outlines a framework for future research in this increasingly important field.

1 Introduction

Since the dawn of animal agriculture, diseases have ravaged and destroyed farms, killing many animals and severely affecting human health. This continues to occur even in the modern day, where disease outbreaks in animal farms pose a significant threat to both animal and human health, with millions of animals having lost their lives to rapidly spreading pathogens. Thankfully, in more recent human history, preventative measures have become available and the extent to which diseases demolish farms has (generally) decreased.[1] However, many farmers have (in the interest of cutting costs) resorted to unsustainable methods of disease prevention, such as the mass usage of antibiotics. This can foster antibiotic resistance and lead to the emergence of more dangerous bacteria (through the biological process of mutation). Hence, there remains an urgent need to find sustainable methods to reduce the spread of disease. This proposal addresses this need with a possible solution in which livestock populations are monitored by AI and then analysed to model the spread of disease (thereby helping farmers mitigate it).

There are three *primary* objectives to this proposal:

1. To propose and outline how the union of Artificial Intelligence (AI) in Precision Livestock Farming (PLF) can map the social interactions between livestock, which in turn can be used to create a 'social network' that reflects the farm's social dynamics (Section 4).

2. To show how this 'social network' can be mathematically represented as a graph, and how there already exist mathematical techniques within the field of *Graph Theory* which can be used for epidemiology (Section 3).

3. To provide other possible use-cases of a 'social network' as well as an ethical evaluation (Section 5).

Importantly, **this paper is a proposal.** Creating and fine-tuning an AI system which uses PLF to develop an accurate epidemiological model would require substantial resources, beyond those currently available to the author. Therefore the scope of this paper is not to provide a definite model, but rather to suggest a possible framework for how this could be achieved.

Furthermore, it is imperative to mention that this paper is written as a project in *Electric Sheep's 'Futurekind' Fellowship*, and thus is written in the hopes of reducing animal (and human) suffering by minimising the transmission of disease. The author strongly emphasises that the proposed methods should be used ethically, with animal and human welfare as a priority - above optimisation and profit. Notably, it is likely that this proposal cannot be used in battery farms (or more generally farms which house livestock in close proximity) as the much more stochastic contact patterns may make the model redundant. This will be discussed in greater detail further along in the paper.

[1] Very recently and in some situations, this is not true. However this has been a trend for most of modern history.

2 Overview of Precision Livestock Farming

The last few years have seen tremendous advancements and growth within the field of AI. It has become a household name, and with the ever-increasing adoption of it across various aspects of everyday life, it is considered by some an integral part of modern society.

Agriculture has not been immune to the widespread use of AI either. With recent advancements in AI, new technologies such as Precision Livestock Farming (PLF) have emerged. Particularly, PLF is a tech-driven approach to farming, whereby sensors (such as cameras, thermometers and RFID[2] chips) are used to monitor animals. AI can then analyse the provided data and provide valuable insight. For example, PLF can already be used to identify sicknesses in animals, and to recognise symptoms of animal stress. First and foremost, such already existing applications of PLF increase animal welfare - ensuring that otherwise possibly neglected animals are highlighted and given the care that they need. Moreover, they also increase environmental sustainability, and even the productivity of animals. [1]

3 The Social Network

3.1 Definition and Example

Throughout this paper, the idea of a 'social network' will be mentioned. For clarity, a social network is a model created by PLF technology that encapsulates the social dynamics of the farm. Particularly, it will show the 'contact intensity' between each relationship of the livestock.[3] This can then be 'mapped out' as a mathematical graph, and existing techniques from the field of *Graph Theory* can be used to model the spread of disease.

To give a better understanding of what is meant, consider the following example: Let there be a dummy farm with animals A, B, C, D, E, F, G, H and I. Assume that the PLF technology has been able to create this social network. It can thus be displayed as a mathematical graph, as shown in Figure 1.

In the graph in Figure 1, each animal is represented by a node and each relationship that the animal has is represented by an edge. As with most epidemiological graphs, the weight of the edge connecting the nodes x and y, $w(x, y)$, is directly proportional to the contact intensity between animal x and y, $\iota(x, y)$.[4]

Hence, the graph shown in Figure 1 could signify many things. It could be that animal D is a mother pig, and her children are animals A, B and C. She has a high contact intensity with each of them, and they have even higher contact intensities between themselves - as represented by the graph. Moreover, animal E could be a horse that has very low contact intensity with animal D,

[2] Radio-frequency Identification.

[3] The contact intensity (ι) represents how intimate a relationship is. A more suitable name for non-epidemiological purposes would perhaps be social intimacy.

[4] Hence $w \propto \iota$.

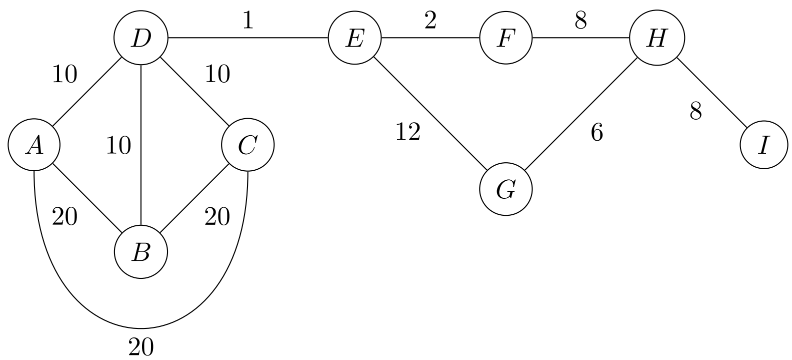

Figure 1: Basic example of a social network generated by PLF technologies. The weights of the edges are proportional to the contact intensity (ι).

this time represented by a low weight. Lastly, animal H could be a herding dog which has medium contact intensities with many animals. This of course is an example, but it shows how a mathematical graph and more generally a social network would encompass the social dynamics of the farm.

The purposes of this proposal are elementary. Therefore, throughout this paper the idea of a static graph is mainly mentioned. However, leveraging artificial intelligence and continuous monitoring through PLF would allow a more epidemiologically accurate *temporal* network to be made. Whilst not in the scope of this paper, this is something that could be pursued.

3.2 Existing Techniques for Epidemiological Analysis

Given the mathematical graph of the social network, existing techniques can be used for epidemiology. For instance, recent years have seen the relevance of graph theory in modeling the spread of COVID-19. [2][3] Particularly, perhaps models like the SIR (Susceptible-Infected-Recovered) model can be adapted to this network structure, where the probability of disease transmission depends on the edge weights. In general, many epidemiological models base themselves off of using graphs like these and a function (for example f) which maps the contact intensity, ι, to the probability of transmission, p (denoted by $f : \iota \mapsto p$) - with variable parameters which are adjusted for specific diseases and situations.

Additionally, the mathematical graph of the social network could be used to protect very vulnerable animals. For example, consider the social network that is displayed as a graph in Figure 1. Using the same social network, we can construct a graph where each weight (w) is *inversely* proportional to the contact intensity (ι), as shown in Figure 2.

Then, we can use existing algorithms such as Dijkstra's algorithm to find the shortest path between two nodes. The importance of this is that if an animal (e.g. E) is deemed very vulnerable to disease, and another animal has

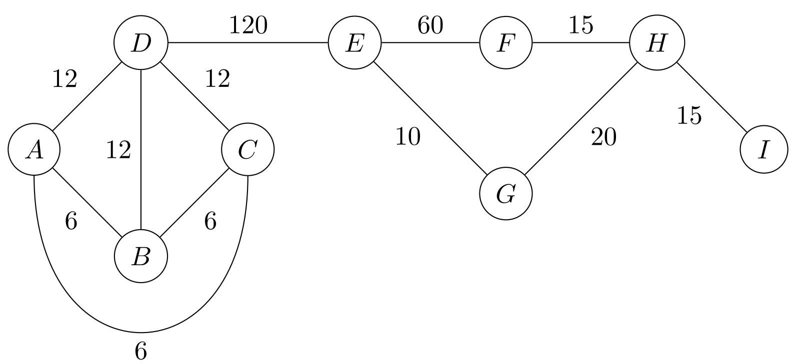

Figure 2: Basic example of a social network generated by PLF technologies. The weights of the edges are inversely proportional with the contact intensity (ι).

been infected (e.g. H), you can find the shortest path from the infector to the infectee (i.e. E and H do not directly share a connection, but using Dijkstra's algorithm you would find the shortest path to be $E \to G \to H$). Then, you could disrupt that path (i.e. by quarantining an animal in the path) so that the vulnerable animal is at less risk.[5] This is in situations where for some reason the infectee can not be quarantined.

It is important to mention that using Dijkstra's algorithm for Social Network Analysis is not unique to this paper; there is already a large amount of literature dedicated to this. [4][5]

3.3 Additional Techniques for Analysis

Additionally or otherwise, we may use the social network to identify animals which are more central and/or have higher connectivity, hence being more susceptible to infection (or themselves more likely to spread disease). To do this, we may use a social score (denoted by S_X for an animal X), a quantified measure of the centrality of an animal in the social network which we can then use to compare the sociability of animals. The methods in which we calculate social scores, such as Katz Centrality (likely the best option for this proposal) and Eigenvector Centrality are out of the scope of this paper. This social score is aimed at helping farmers to more accurately identify animals that are more vulnerable to disease or more likely to spread diseases, by implementing targeted monitoring or intervention strategies.

[5] Notably, this is not as useful in situations where you have many short paths, as you would need to disrupt many paths. Hence, this can be a heuristic simplification.

4 The Usage of Precision Livestock Farming to Create a Social Network

The notion of a social network that can be used for epidemiology so far mentioned in this paper is not entirely unique to this proposal. However, as mentioned in Section 1, the key idea of this proposal is how PLF can be used to create this social network.

PLF's most common use case is the utilisation of sensors to individually monitor animals. Therefore, to build upon current PLF infrastructure, this section will outline how existing sensors can be used to create a social network. Notably, we will outline which factors of contact intensity can accurately be surveilled and monitored by existing sensors, and their relationship with contact intensity (Section 4.1). We will then briefly mention how this can be used to create a social network (Section 4.2).

4.1 Factors to be Considered

There are many factors that have to be considered when trying to model the social dynamics of livestock. The following is a non-exhaustive list of possible factors that could be monitored using existing PLF sensors.

1. **The time two animals spend together.** Specifically, the duration in which two animals are in close proximity with each other (e.g. under a certain distance), per day.

2. **Average proximity.** This could be used contrary to the above. The distance between two animals could be recorded throughout the day for a certain period to calculate an estimated average proximity.

3. **Farm conditions.** Environmental factors such as temperature and humidity can have a profound effect on disease contagion. Different diseases can pose a greater risk to livestock, if the farm provides the optimal conditions.

Although something that is not easily measurable by PLF sensors, something to certainly consider is **disease-specific factors**. This includes things mentioned above, such as the temperatures in which the disease is more easily transmitted, but it also includes other characteristics of the pathogen. For example, its mode of transmission, possibility of antigenic escape, and possibility of cross-species transmission are all factors to be considered.

Examples of sensors which could be used to track and monitor the factors in the list above include:

- **Visual identification.** Cameras and CCTV, when paired with AI, have already been used to recognise individual animals. [6] The capabilities of this technology can perhaps be extended to record factors such as the time two animals spend together, among others.

Cameras and standard CCTV can still pose issues which make their implementation unfeasible, however. For example, most CCTV systems have limited coverage, and it would be a significant expenditure for large farms to ensure that the entire area is surveilled. Instead, drones (or more specifically UAVs[6]) could be used. There already exist systems which allow them to monitor individual animals [7], and their mobility solves the problem posed with CCTV.

- **RFID tags.** RFID tags can be used to identify and track livestock. Crucially, when multiple readers are installed, they can be used to determine when animals are in close proximity. [8] Active RFID tags can also provide real-time location updates for more precise tracking. [9]

  Importantly, RFID tags can still yield substantial error rates (due to things such as missed reads, for example), and their implementation will likely require techniques to account for error rates. It is also important to mention that RFID may be unfeasible in large-scale, outdoor farms for constant tracking as they likely wouldn't operate. A better approach would be in smaller-scale, indoor farming, by placing them on commonly used barn areas.

- **Thermometers and humidity sensors.** Thermometers and humidity sensors, as well as other sensors, can be used to track and measure the conditions of the farm.

- **UWB Tags.**[7] Whilst realistically only implementable for shorter distances (indoor farms/small-scale farms), UWB technology offers accurate and real-time location tracking for livestock. [10] This would be particularly useful for tracking the time and proximity factors.

- **GPS.**[8] This is generally implemented in larger-scale, outdoor (e.g. pasture) farms. GPS technology also offers location tracking for livestock [11], which can be used to track the time and proximity factors.

As mentioned in Section 1, this proposal is not intended to be used in intensive, battery farms. Instead, it is believed that this proposal would be most effective in extensive farms, such as pasture farms, grazing farms and free-range farms. In other farms where animals are kept too close, it might be futile to create a social network, as disease spread can often be stochastic because of the dense, cramped conditions.

It is still important to recognise however that PLF is a new technology for very many farms, which have not yet adopted it. Also, whilst it might be realistic and feasible on large-scale farms, small-scale farms might struggle to construct advanced and complex PLF systems. It is hoped that with the advancement of technology and PLF that these systems will place less of an economic burden

[6]Unmanned Aerial Vehicles.
[7]Ultra-Wideband Tags
[8]Global Positioning System.

on farmers - thus allowing for the more widespread use of PLF. If farmers are able to overcome this obstacle, then this should make the proposal feasible on small-scale farms (provided that it's a free-range/pasture farm).

4.2 The Creation of the Social Network

Using the factors mentioned in Section 4.1, after enough data has been collected, a prototype for the contact intensity (ι) of each connection can be made. The data could either be substituted into a formula (or a series of formulae) which yields the contact intensity, or neural networks which develop overtime to yield contact intensities with ever-increasing accuracy.

Next, industry-standard programming libraries from languages such as Python and R can be used to construct the graph and carry out further analysis. Each animal should be a node in the graph, and each predicted ι should be fed into the computer program. As time progresses and more data is collected, the corresponding ι values can be updated.

Importantly, whilst there may be a general graph which displays the social network, analysts and epidemiologists may want to create distinct graphs for distinct diseases. For example, animals H and I in Figure 1 have a contact intensity of 8 in the social network. However if they are not part of the same species, when modelling a disease that cannot transmit across species, one may choose to construct a new graph with their contact intensity lowered - representing the lowered risk of transmission.

5 Ethical Evaluation and Other Use-Cases

The application of PLF technology in this context (and more generally) raises several ethical considerations - both positive and negative.

5.1 Positive Implications

- **Improved disease control.** By accurately modelling disease spread, intervention by farmers can be more targeted, reducing animal suffering and mortality. More targeted measures also could result in less culling, again reducing animal suffering.

- **Reduced antibiotic use.** Again, through the modelling of the spread of disease, farmers can more easily identify which animals are more 'central' or social (using things such as the social score mentioned in Section 3.3) - thus incentivising farmers to only continuously administer antibiotics to central animals rather than the entire livestock population.

- **Support for animal rights.** Highlighting the social lives of animals may foster greater empathy and support for animal welfare campaigns.

- **Promotion of Extensive Farm Research.** Currently, it is mostly intensive farms that possess advanced technology, and hence, it is mostly intensive farms that benefit from research in fields such as these. However, by creating a proposal that is specifically tailored to extensive farms, it is within the author's hopes that this proposal helps accelerate and establish approaches for extensive farms, using PLF and other technologies.

5.1.1 Animal Psychology

Additionally, perhaps this proposal can accelerate advancements in **animal psychology as well.**

Notably, psychologists can use the social score to compare the social lives of animals. They can then investigate whether there is any correlation with animals who are less social, and increased signs of stress, depression, or inactivity.[9]

5.2 Negative Implications

- **Misuse in intensive farming.** PLF technology already poses some dangers that allow it to be used in ways that compromise animal welfare. [12] There is some speculation that this proposal could be used in battery farming to optimise animals' social lives in ways that neglect animal welfare and prioritise profits. It has also been suggested that farmers could use this proposal and PLF in a small-scale way, such that their reputation is enhanced, but the positive change to animal welfare is minimal. Thankfully, this concern might not be entirely plausible as the social network mentioned likely cannot be implemented in battery farms - where animals are in such close proximity that there may be no point in trying to model the farm's social dynamics; animals are so close that diseases spread much more unpredictably and stochastically.

- **Neglect of less social animals.** This is a much more concerning and realistic concern regarding the proposal and particularly the social scoring system. If farmers can quantify animals' social lives and the risk they pose, they might choose to only offer veterinary services and medicine to the more social animals, cutting costs.

- **Forced adoption of PLF.** If this approach and others regarding PLF drastically increase productivity, farmers who reject the adoption of PLF on their farms might be out-competed and forced into bankruptcy. Therefore, farms will have less choice as to whether or not they accept the implementation of PLF.

6 Additional Remarks

As briefly mentioned in Section 3.1, an accurate epidemiological model using Social Network Analysis would more than likely be temporal. This is because,

[9] This was suggested by Mr. Max Taylor.

whilst the behaviors of livestock are not entirely stochastic, they are dynamic, and interactions can slightly alter depending on a multitude of factors. [13]

Additionally, the author would like to mention a potential factor which was not mentioned in Section 4.1, but which could be important for more complex social networks: the infectability/vulnerability rates of each animal. This would be a much harder factor to compute, and is out of the scope of this paper (which aims for a simple model), but it likely could be calculated using PLF.

6.1 Social Variance

As mentioned in Section 5.1.1, there are many implications of this proposal in the field of animal psychology. To anyone considering pursuing research in this using this proposal, the author suggests a simple method to compare the variance of centrality/sociability between groups of animals.

Say that you have two **equal** groups of animals[10], group ζ and ξ. From here, we can mathematically define ζ and ξ, with each being the non-increasing sequence of the group's animals' social scores. So, for example, say ζ is a group of animals with social scores 4, 5 and 3 and that ξ is a group of animals with social scores 6, 16 and 12. In this case, we would say $\zeta = (5, 4, 3)$, and $\xi = (16, 6, 2)$. Next, we want to ensure that the summation of the sequences are equal. If they are not (as in the case of $5 + 4 + 3 \neq 16 + 6 + 2$), then multiply one sequence by a scale factor to achieve this (for the purposes of this example, we will multiply ζ by a scale factor of 2.) Now that we have two non-increasing sequences which, when summed, are equal to each other, we can check if one sequence majorises the other.[11]

If we find that one sequence, for example ξ, majorises 2ζ (denoted by $\xi \succ 2\zeta$), then the social scores in group ξ exhibit greater inequality and disparity compared to those in group ζ (i.e. the social scores in group ζ are more similar whilst in group ξ they have a bigger range).

This may be used to evaluate and study hierarchies and the sociability variance of a species, for example (compared to another species).

7 Conclusion

This proposal suggests an original approach to epidemiology: through the marriage of PLF and epidemiological techniques we can create and analyse a social network as a model of disease dynamics, reducing antibiotic usage and helping farmers tackle widespread outbreaks. Whilst there are ethical considerations that will require further assessment, the possibilities of increased animal welfare and reduced fatalities, among others, make this a promising area for future research and development.

[10] Here, equal groups means they have the same amount of animals.

[11] For a formal definition of majorisation, see Appendix A.

8 Acknowledgments

As mentioned in Section 1, this proposal is the author's project for *Electric Sheep's 'Futurekind' Fellowship*. Therefore, many of the ideas mentioned in this paper have been developed only after much correspondence and feedback with the *Electric Sheep Community*. Whilst the author would like to thank everyone who helped him throughout the writing of this paper, he would like to especially commend Mr. Max Taylor for his help overall, and especially in Section 5, and everyone in the *Group 9* cohort. Gratitude is also expressed to Ms. Bárbara Buril, who led the *Group 9* cohort, providing guidance throughout, and Mr. Lee Wall, who peer-reviewed this paper and provided valuable insight. Furthermore, the author also honours the invaluable help of Ms. Borbala Foris, whose revisions and suggestions (particularly in Sections 4.1 and 5.1) greatly improved the quality and depth of this paper.

It is also important to mention that whilst (to the author's knowledge) using PLF technology to create a social network is novel, many approaches have already been taken and explored in the field of Social Network Analysis regarding Veterinary Medicine and Epidemiology. [14][15] Moreover, there already exists literature which demonstrates using sensors (such as those mentioned in this paper) for social network analysis. [16] This proposal is aimed at building on those foundations by offering some unique and novel considerations, with the ultimate goal of serving as a framework for future work.

A Definition of Majorisation

The mathematical principle of majorisation, using the definition found in [17, Definition A.1], is:

"For any $x,\ y \in \mathscr{R}^n$,

$$x \prec y \text{ if } \begin{cases} \displaystyle\sum_{i=1}^{k} x_{[i]} \leq \sum_{i=1}^{k} y_{[i]},\ k = 1,\ \ldots,\ n-1, \\ \displaystyle\sum_{i=1}^{n} x_{[i]} = \sum_{i=1}^{n} y_{[i]}. \end{cases}$$

When $x \prec y$, x is said to be *majorized* by y (y majorizes x)."[12]

References

[1] Bing Jiang, Wenjie Tang, Lihang Cui, and Xiaoshang Deng. Precision livestock farming research: A global scientometric review. *Animals*, 13(13), 2023.

[12] This paper uses the term 'majorisation' instead of 'majorization' because it is written in British English. It still conveys the same concept, however.

[2] Rasim Alguliyev, Ramiz Aliguliyev, and Farhad Yusifov. Graph modelling for tracking the covid-19 pandemic spread. *Infectious Disease Modelling*, 6:112–122, 2021.

[3] I. Adamopoulos, A. Valamontes, N. Syrou, J. Adamopoulou, and A. Bardavouras. Utilizing graph theory algorithms for the modeling and analysis of covid-19 infection dynamics. *Mesopotamian Journal of Artificial Intelligence in Healthcare*, 2025:1–11, Jan. 2025.

[4] Boštjan Šumak and Maja Pušnik. *Analysis of the Shortest Path Method Application in Social Networks.* January 2023.

[5] Arul, Sharmila Mary, Senthil, Gowri, Jayasudha, S., Alkhayyat, Ahmed, Azam, Khalikov, and Elangovan, R. Graph theory and algorithms for network analysis. *E3S Web Conf.*, 399:08002, 2023.

[6] William Andrew, Jing Gao, Siobhan Mullan, Neill Campbell, Andrew W. Dowsey, and Tilo Burghardt. Visual identification of individual holstein-friesian cattle via deep metric learning. *Computers and Electronics in Agriculture*, 185:106133, June 2021.

[7] Juliana T.C. Marcos and Simukai W. Utete. Animal tracking within a formation of drones. In *2021 IEEE 24th International Conference on Information Fusion (FUSION)*, pages 1–8, 2021.

[8] C. Aquilani, A. Confessore, R. Bozzi, F. Sirtori, and C. Pugliese. Review: Precision livestock farming technologies in pasture-based livestock systems. *Animal*, 16(1):100429, 2022.

[9] Nancy L. Scott, Bernard Hansen, Chase A. LaDue, Carlson Lam, Albert Lai, and Lowell Chan. Using an active radio frequency identification real-time location system to remotely monitor animal movement in zoos. *Animal Biotelemetry*, 4(1):16, Aug 2016.

[10] Philippe Hindermann, Stefan Nüesch, Daniel Früh, Andreas Rüst, and Lorenz Gygax. High precision real-time location estimates in a real-life barn environment using a commercial ultra wideband chip. *Computers and Electronics in Agriculture*, 170:105250, 2020.

[11] G. Ramesh, K. Sivaraman, V. Subramani, P. Yoga Vignesh, and S. Venkata Veera Bhogachari. Farm animal location tracking system using arduino and gps module. In *2021 International Conference on Computer Communication and Informatics (ICCCI)*, pages 1–4, 2021.

[12] Juliette Schillings, Richard Bennett, and David Christian Rose. Animal welfare and other ethical implications of precision livestock farming technology. *CABI Agriculture and Bioscience*, 2(1):17, May 2021.

[13] Shi Chen, Brad J White, Michael W Sanderson, David E Amrine, Amiyaal Ilany, and Cristina Lanzas. Highly dynamic animal contact network and implications on disease transmission. *Sci Rep*, 4:4472, March 2014.

[14] B. Martínez-López, A. M. Perez, and J. M. Sánchez-Vizcaíno. Social network analysis. review of general concepts and use in preventive veterinary medicine. *Transboundary and Emerging Diseases*, 56(4):109–120, 2009.

[15] Matthew J. Silk, Darren P. Croft, Richard J. Delahay, David J. Hodgson, Mike Boots, Nicola Weber, and Robbie A. McDonald. Using social network measures in wildlife disease ecology, epidemiology, and management. *BioScience*, 67(3):245–257, 02 2017.

[16] Suresh Neethirajan and Bas Kemp. Social network analysis in farm animals: Sensor-Based approaches. *Animals (Basel)*, 11(2), February 2021.

[17] Albert W. Marshall, Ingram Olkin, and Barry C. Arnold. *Inequalities: Theory of Majorization and Its Applications*. Springer, 2nd edition, December 2009.