Farmers' Use of Information Generated from Precision Livestock Farming Systems to Support Their Decision Making

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ATTESTATION OF AUTHORSHIP

I hereby declare that this thesis is my own work. To the best of my knowledge and belief, it contains no materials previously written or published by any other person, except for the authors defined in the acknowledgements. I also declare that this work has not been submitted to any other institution or university for the award of any other degree or diploma in any university or other institution of higher learning. The thesis work was conducted from July 2020 to November 2021 under the supervision of Dr. Maduka Subasinghage and Dr. Bill Doolin at Auckland University of Technology.

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ABSTRACT

This research explores how New Zealand farmers use the information from Precision Livestock Farming (PLF) systems to improve decision-making on farming operations. Farmers are being urged to improve operational efficiency under pressure to increase food supply for an increasing population. By having PLF systems alerting real-time abnormality of individual animals, farmers can proactively solve livestock-related operational problems (Halachmi, 2015). Six case studies of New Zealand farmers were conducted, along with insights from a PLF system provider, an information analyst, and a business analyst. Qualitative data were collected in semi-structured interviews and were analysed with secondary data collected from public websites. Findings show how the information from PLF systems encourage farmers to reflect on assumptions and provide tools to timely test and improve on solutions for different types of decisions (structured, semi-structure, unstructured). Detailed decision-making process flow models present the steps farmers take to receive, interpret, and act on the information before and after they adopt PLF systems. This study fills the research gap concerning post-implementation use of PLF systems with empirical case studies. It proposes how PLF systems encourage the development of double-loop learnings for decision-makers that challenge their original mental models and create innovative solutions. Practically, this study discusses barriers to realise the full benefits of information from PLF systems and recommends procedures developed to reduce the impacts of these barriers.

CHAPTER 1 INTRODUCTION

The world population is expected to grow to 9.1 billion by 2050, according to U.S. Census Bureau (2021). The rising population leads to increased food demands by 59% to 98% by 2050 (Elferink & Schierhorn, 2016). As meat is the primary source of nutrition for many people globally, the demand for meat is expected to triple in the next 50 years (Ritchie & Roser, 2017). However, beef and lamb production has more negative environmental impacts than pig and poultry. In New Zealand, livestock production generates 85.8% gross methane emissions—64.6% from cattle and 28.5% from sheep (StatsNZ, 2020). Farmers are urged to improve their operations to maximise production efficiency from individual animals. Precision Livestock Farming (PLF) systems, the integrated systems aiming to monitor individual animals in real time and inform farmers whenever there is an abnormality (Werkheiser, 2018), can play a significant role in improving the production efficiency of livestock farming.

Farmers can use videos, ear-tag, and neck collars to accurately monitor ruminants' behaviours (Paudyal et al., 2018). According to case interviews with 21 European farmers across 10 EU countries, PLF systems enable farmers to recognise problems significantly earlier than the traditional approach and better understand their animals (Hartung et al., 2017). Early warnings sent from PLF systems are believed to increase production by 10% because farmers save the data analysis process and are directly guided to the location of the problem when the systems automatically detect deviations (Van Hertem et al., 2017). Therefore, it is crucial to study how farmers are currently using PLF systems to optimise farming operations (feeding, stocking, productivity) to identify opportunities for improvements and guidelines for non-PLF-system adopters.

Few studies (Hartung et al., 2017; Kling-Eveillard et al., 2020; Van Hertem et al., 2017) have investigated the case practices of post-implementation of PLF systems. Hartung et al. (2017) studied European farmers' experience with PLF systems and concluded that, although PLF systems cannot automatically identify the root cause of the problems, they provide valuable support for farmers to trigger immediate response to prevent diseases or animals' suffering. Van Hertem et al. (2017) implemented their data visualisation tool on 15 farms and discussed the potential of PLF systems as an early warning system from six case studies. Kling-Eveillard et al. (2020) used case studies to investigate the human–animal relationships. However, there is a lack of research examining how farmers use PLF systems or studying the interaction between farmers and computers at the livestock farming operation. Thus, this research attempts to investigate "how farmers use information generated through PLF systems in their decision-making processes?". Contextual information such as the adopted technologies and systems, information collected through the systems, and the key livestock-related decisions should be clarified prior to investigating farmers usage of the information. Decision making study (bounded rationality theory, process) provides the theoretical foundation to explore different approaches to decisions and information ‘s role in decision makings. Thereafter, the case studies from New Zealand dairy and beef farmers are used as the data source for the discussion of this study.

The output of the study will fill the gap of PLF systems’ post-implementation studies with real case practices and enrich the topic by explicating the decision-making process using information from PLF systems. This study will also contribute to the systems thinking theory by providing examples and analysis of how different types of systems thinking affect farmers’ usage of the information and the learnings derived from it. Additionally, by use of the process flowchart that compares pre-PLF and post-PLF approaches, single-loop and double-loop learning processes are explored. As for practical contributions, this study provides general practices of PLF systems’ post-implementation stage for farmers to learn about what they can use the information from the system to improve their farming practices.

The thesis is organised thus: the Literature Review (chapter 2), Research Methodology (chapter 3), Results (chapter 4), Discussions (chapter 5), and Conclusions (chapter 6). The Literature Review introduces PLF systems and discusses theoretical decision-making concepts, including bounded rational decision-making and how decisions can be made using different systems thinking methods. Moreover, it summarises how former researchers expected information from PLF systems to improve decision-making. The Research Methodology section shares how this research was designed and amended to adapt to COVID-19 restrictions. The Results chapter unfolds the six individual cases of New Zealand dairy/beef farmers, including farm context, the PLF technology adopted, the information generated from the system, key decisions and decision-making processes. Details about how farmers and systems work together are demonstrated with examples, which provided foundations to examine systems’ effectiveness and limitations. The Discussion chapter is about how PLF systems expanded the bounded rationality of decision-makers and how the information was used to solve different types of problems, which leads to the discussion of how different stages of systems thinking affect farmers’ use of the information. The Conclusion shares theoretical and practical contributions, limitations, and recommendations for future researchers.

CHAPTER 2 LITERATURE REVIEW

This chapter examines previous studies reported in the literature on decision-making processes and how system-generated information was used to improve decision-making. To establish an understanding of how PLF systems improve the decision-making process, the definition of PLF systems, the expected commercial values, and how PLF systems function as integrated information systems were reviewed. Decision-making theories are discussed prior to the discussion of how different systems thinking approaches affect decision-makers' use of the information. Finally, the author summarises how PLF systems improve decision-making by widening the decision types to be answered by information systems and by deepening understanding of the problems through single-loop and double-loop learning.

2.1 PRECISION LIVESTOCK FARMING (PLF) SYSTEMS

2.1.1 Definition

PLF systems are integrated systems aiming to continuously monitor the *real-time* performance of individual animals and to inform farmers whenever there is an abnormality; they leverage the use of connected network devices and the built-in decision-making algorithms to deal with changes such as weather conditions, feeding, or reproduction (Werkheiser, 2018). PLF systems track the signals including "physiological, behavioural and production indicators" such as if the live weight meets the standard, if the animal has consumed the required food intake, and if the animals show any abnormal behaviours that are early signs of illness (Wathes et al., 2008). PLF systems can be used for 1) precision feeding; 2) monitoring rumination and feeding behaviour; 3) detecting lameness; 4) detecting mastitis; and 5) managing fertility for dairy cattle and sheep (Tullo et al., 2019). Such functionality is enabled by the PLF technologies using cameras, real-time image analyses, microphone, sound analyses, or by sensors around or on the animal (Berckmans, 2017). The individual animal is managed using electronic identification (EID) ear-tags (Morgan-Davies et al., 2018).

PLF systems have the following features: 1) ongoing tracking of the process responses at the frequency and scale set by the users; 2) a solid mathematical model that forecasts the best-estimated outputs of each process in real-time based on different inputs; 3) a target value and track for each process output such as a pattern for behaviour, the growth percentage, and the amount of emissions; and 4) model-based mechanisms that can predict and control the process inputs (Wathes et al., 2008).

2.1.2 Expected Commercial Values of PLF Systems

The expected commercial values of PLF systems are: 1) improving animal welfare; 2) increasing productivity; 3) reducing labour costs,4) reducing environmental impacts, and 5) financial advancement, which will be discussed in detail in the following paragraphs.

Improving animal welfare: Both local and international consumers are expecting more transparency throughout the food supply chain, which makes animal welfare an important selling point of animal products; the majority of respondents of the farmers' survey of 252 farmers indicate that they prioritise animal welfare (Kendall, 2018). The globally recognised gold standard in animal welfare includes the Five Freedoms that include both mental and physical well-being of animals, which are freedom from "1) hunger and thirst, 2) discomfort, 3) pain, injury and disease, 4) to express normal and natural behaviour, 5) fear and distress" (American Humane, 2016). PLF systems provide precision feeding to the individual animal, immediately notify farmers when there is an early sign of sickness (e.g., lameness, mastitis) therefore help to meet the gold standard to improve animal welfare. Moreover, PLF systems can improve animal welfare by alternating the environment (Croney et al., 2018) to fit the animal, and strategically breeding animals fit for the specific farm conditions (Morris, 2017).

Reducing labour costs: The fundamental commercial value of PLF systems is that they achieve the impossibilities apparent in human labour to track animal welfare: they can create 25 images per second, 20,000 sound samples per second or 250 sensor samples per second, 24 hours a day, 7 days a week, which significantly reduces labour costs and improves the accuracy of detection (Banhazi et al., 2012). The simulation showed that, using vocal cues, PLF systems improve the accuracy of estrus detection by 95% and efficiency by 79% (Devi et al., 2019).

Improving resource efficiency & productivity: Another expected commercial value of PLF systems is that they can improve profitability by reducing costs from efficient use of resources and increasing revenues from that improved productivity. Feeding costs are around 60% to 70% of the overall pig and broiler production costs; labour costs, veterinary and medicines, and lastly, energy costs are the next highest costs in a farm business (Hartung et al., 2017). Individually managing the large mountain of ewe flocks reduces the chance of producing anthelmintic products, and the labour handling costs and increases the economic returns (Morgan-Davies et al., 2018).

Reducing environmental impact: New Zealand Emissions Trading Scheme (NZ ETS) states that businesses will need to purchase 2,000 emission units on the New Zealand's ETS market if they emit 2,000 tonnes of Greenhouse Gases (GHG) (Ministry for the Environment, n.d.). The livestock and dairy industry have emitted at least 50% of New Zealand's GHG (Murray-Ragg, 2018). Farmers will need to pay higher taxes if they increase their production. Outputs from the simulations indicated that PLF systems can help reduce 27-32% of NO2 emissions by raising animal feeding efficiency, dropping stocking rates, and increasing productivity (Beukes et al., 2010).

Financial advancement: According to one simulation, PLF system is expected to increase pig prices by $.05/kg carcass by $.63 per kg. and sow sold//year to 28 by $.58/kg carcass (Banhazi & Black, 2015). Another estimation showed that PLF system can produce an internal rate of return of up to 75% if adopting the automatic cluster remover to reduce labour costs for dairy farms in Australia; however, all the stated benefits are generally not proven by real case practices (Rojo-Gimeno et al., 2019).

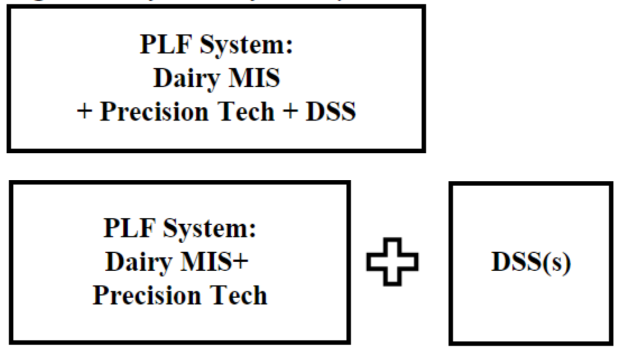
This research collects real case studies of farms in New Zealand that have implemented the PLF systems, which will extend the theoretical view of the values of PLF-systems' information. Moreover, this research will also explain how farmers interact with the systems and explore, theoretically, how information from PLF systems supports the decision-making process by applying the systems thinking concept, and single- and double-loop thinking.

2.1.3 PLF Systems as Information Systems

PLF systems are unique information systems given that they not only enable farmers to store operational data to make decisions (i.e., body condition score will affect feeding amount) but also provide tools to interact with farmers to alert abnormality and suggest solutions. There are four types of information systems: Transaction Processing Systems (TPS), Management Information Systems (MIS), Decision Support Systems (DSS), and Executive Support Systems (ESS) (Khan & Khan, 2011). TPS records daily business transactions of the organisation in sales and marketing, manufacturing and production, finance and accounting, and human resources (Laudon & Laudon, 2015). MIS support managers' decision-making by offering the past, present, and forecasted performance of internal operations and external information consistently over a period, which empowers managers to plan, control, analyse, and strategize the operation (Watson et al., 1991). DSS consolidate and analyse a large amount of data before producing reports that can be used for problem-solving and decision making; such systems can be operated by computers automatically or/and humans manually (Segal, 2020). DSS use input from TPS and MIS and occasionally import external information to run complicated mathematical models and statistics analysis to provide solutions to unique problems (Laudon & Laudon, 2015).

PLF systems are Dairy MIS as they function as one integrated MIS that provides historical, live, and projected figures to support management activities and functions. PLF systems support strategic and long-term executive decisions (Thomas & Callahan, 2002, as cited in Berger & Hovav, 2013). The PLF system such as AfiMilk® System is a leading global Dairy MIS; the AfiMilk® brand includes products such as milk measuring devices, individual cow identification, pedometers, milk analysers, sorting, weighing, and automatic individual feeding, which can all be integrated into the AfiMilk® MIS (Berger & Hovav, 2013). Besides the individual technologies that can be integrated into the MIS, farmers can choose to integrate DSS into the PLF system or to use independent DSS separately. If the PLF systems have the DSS, they can directly use the data collected from PLF systems to make automatic decisions or run simulations to test different possible practices. Alternatively, farmers can manually input data from PLF systems and run on the independent DSS. Examples of different combination of precision technology, Dairy MIS, and DSS can be seen in Figure 1.

Figure 1 *Definition of PLF Systems*



2.2 DECISION MAKING

2.2.1 Theories

There are mainly two strands of decision theories: *normative/prescriptive decision theory* that guides people on how decisions should be made, and *descriptive decision theory* which describes how decisions are made (Bell et al., 1988). The former expects decision-makers to be rational, objective, emotionless beings who use a logical, mathematical, and statistical approach to solve problems; the latter sees that humans are prone to make errors with numbers and statistics and have bounded capabilities to make decisions (Vazsonyi, 1990).

Rationality and Prescriptive Decision Theory

Prescriptive decision theory defines well-qualified decision-making that: 1) problems should be correctly defined; 2) values, preferences, and trade-offs should be clarified beforehand; 3) a diverse range of solutions should be explored; 4) reliable data should be used for evaluation; and 5) the reasoning should be supported by sound logic (Matheson, 1998). The *rational* model assumes that decision-makers have full access to all information and the cognitive capability, time, and resources to identify all possible alternatives and the associated consequences, with a clear evaluation scale to choose the optimal solution that maximises utility (Heracleous, 1994).

The foundation of the prescriptive decision theory is Subjective Expected Utility (SEU); SEU theory assumes that the rational actor has a consistent order of preference for all possible states of the world and the existing probabilities of the external event, which can be used to represent the utility of the event (Vazsonyi, 1990). The following steps can achieve SEU theory: 1) list all possible actions; 2) set all possible consequences; 3) assess both positive and negative impacts of the consequences; 4) allocate probability that it will occur; 5) compute the expected utility value by summing up the multiplication of the worth of each consequence and the possibility of occurrence; and 6) choose the one with the greatest expected worth (Fischhoff et al., 1981).

Rational decision-making has several limitations. It disregards qualitative information, such as ethics concerns (i.e., animal welfare, regulation compliance) and the limitation of human capacity, time, and resources. It only applies to simple problems clearly expressed, understood, agreed, and unambiguous cause–effect relations; such model does not fit in the real world where decisions are more complex and full of uncertainty and unpredictability (Heracleous, 1994). Very few businesses have taken a consistent decision-making approach; in fact, many of them ignored relevant information and made decisions based on most recent or unusual information than being reasonable (Krabuanrat & Phelps, 1998).

Bounded Rationality and Descriptive Decision Theory

Simon (1997) introduced *bounded rationality* to challenge the traditional assumption that all decision-makers are entirely "rational" to make the optimal decision due to the limitation of information, time, and humans' cognitive capability. The scholar argued these facts always limited humans in reaching full rationality: 1) inadequate understanding of the true nature of the problem due to the complexity of the environment; 2) inability to generate all possible alternative solutions; 3) incomplete evaluation of alternatives because of the impossibility of predicting the consequences of all alternatives accurately; 4) optimisation as the main judging criteria, but it is impossible to identify the optimal solution due to the inability to fully account for "3)". Therefore, no truly rational decisions can be made unless humans fully control the environment and their cognitive capability.

Satisficing: Decision makers do not examine and compare all options thoroughly or continuously try out different possibilities until achieving the optimal calculations (Martin-Clouaire, 2017) because of limited time and budgets (Narayanan, 2005, as cited in Lunenburg, 2010). Alternatively, decision-makers make satisfactory (or good enough) decisions based on their experiences (Simon, 1955, as cited in McFall, 2015). People usually choose the first alternative that satisficed the minimally acceptable criteria (Nielsen, 2011, as cited in Lunenburg, 2010). Because of an inability to identify all possible options with accurately predicted outcomes, decision-makers apply their rationality only after their options are greatly simplified to a few choices; therefore, decision-makers are "satisficers" who look for good choices, not optimal ones (Simon, 1955, as cited in Daydé et al., 2014).

Heuristics is defined as an experience-based technique for the problem-solving using rule of thumb, intuitive judgement, or common sense (Krabuanrat & Phelps, 1998). The heuristics model is more ideal than the rational model for dynamic strategic decision-making because of the uncertain nature of business decisions (Mole, 2007). Because it is impractical to undertake exhaustive research, using this experience-based technique will speed up finding a satisfactory approach. Some research shows that better decisions are made with heuristics rather than the theoretically optimal solution; individuals and organisations were found to rely on simple heuristics and ignore part of the information to have more accurate judgements for low recurrence and small samples (Gigerenzer & Gaissmaier, 2011). For dynamic environments, using subjective designs (heuristics) can enable organisations to learn more quickly from imperfect lessons than using a controlled objective approach such as SEU (Krabuanrat & Phelps, 1998).

2.2.2 Decision-Making Through Systems Thinking

Systems thinking is the opposite of linear thinking: it focuses on analysing in an integrated, not dissected way (Monat & Gannon, 2015). Systems thinking is a set of interconnected analytical skills used to strengthen the understanding of the systems, foretell future consequences, and make changes accordingly to achieve desired outcomes (Arnold & Wade, 2015). Modern systems thinking in agriculture can be classified into three structures: hard-, soft-, and complex-systems thinking (HST, SST, and CST) (Schiere et al., 2004).

Systematic and Systemic Approaches

HST, SST, and CST methodologies belong to two approaches: *systematic* approach and *systemic* approach. Schiere et al. (2004) summarise that systematic approach focuses on objective quantification, reductionist thinking, and mechanistic synthesis; the systemic approach presumes that people become part of the systems when choosing the parameters and methods. In other words, the previous approach can be programmed into computers to calculate the optimal option and the latter one requires people's inputs to interact with different options. The systemic approach emphasises the change within and surrounding the system and considers the qualitative information from the mind beside the hard facts about the matter (Schiere et al., 2004). This statement suggests that when farmers only choose to consider hard facts when making decisions are having systematic approach. Alternatively, when farmers choose to consider qualitative aspects of farming such as environmental impact, animal welfare during decision making process can be considered as having systemic approach.

Hard Systems Thinking

HST is established on the concept of reductionism, which is a practice of understanding a complicated concept by studying the separated individual pieces (Flew, 1984, as cited in Wood & Caldas, 2001). HST practitioner De Wit (1968, as cited in Schiere et al. (2004)) believes that companies should use heuristics to build agriculture systems so that the data relations align with the process and so the results can be explained by the observed phenomena. With much emphasis into proper measurements and the interrelationship between inputs and outputs, HST was credited to drive the success of agriculture, such as increasing the yield per area or animal by two- to three-fold (Brady, 1983). HST, however, was criticised for neglecting the human's mind and it marginalises uncertainty using *ceteris paribus* (everything else remains the same) (Schiere et al., 2004). Without considering the long-term side-effects of wastes such as nitrogen in the soil, farmers with HST thinking would fail to identify the trade-offs between agricultural production and the environmental impact. HST is therefore a systematic approach given its nature of following the pre-defined rules, methodology and system of thinking.

Soft Systems Thinking

SST puts the human's mind and ethics at the core of the system thinking; different people have different perspectives, and the perspectives may change over time; humans' choices on the measurements will affect the outputs (Schiere et al., 2004). The example of the experimental dairy farm in the Netherlands shows that humans' participation matters: the optimal solution for one criterion (i.e., highest milk production) conflicts with the optimal solution for the other criteria (i.e., lowest NO3 production) (Van de Ven, 1996). Moreover, because SST practitioners see a cow as more than just a physical entity but also a living being that carries the emotional value (meanings, goals) (Ison et al., 2000), they take care of animal welfare. SST acknowledges the uncertainty of the environment and the dynamic changing property of the observance; it differentiates itself from HST by having changing goals, not a fixed defined goal. Therefore, humans play an active role in continuously learning by seeking information where systems change with the context (Schiere et al., 2004). Because the judgements are driven by human minds and cannot be separated as part of the thinking process, SST is a systemic approach.

Complex Systems Thinking

CST bridges the gap between SST and HST by extending the uncertainty from the human mind into physical matters (Capra, 1997, as cited in Schiere et al., 2004). Complexity thinking asserts that: 1) uncertainty exists everywhere; 2) different perceptions co-exist; 3) the system and context are interrelated; and 4) there is more than one coping strategy for the problem (Schiere et al., 2004). The discovery of the butterfly effect—which describes a slight change in the initial stage which can lead to significant differences in a later context, established the foundation of uncertainty; the fact that the butterfly effect can be diminished or amplified by other effects reinforces the level of uncertainty (Gleick, 1987). The perception of normal fluctuations varies among individuals in a different context (industry, situation). Furthermore, changes in one part of the system will have an affect elsewhere across the hierarchy; parts of the system interact and learn from each other (Schiere et al., 2004). Therefore, the *co-evolution* of the system and the context requires a mindset change from having one static solution for the problem towards the mindset of developing a combination of coping strategies. As part of the system, humans need to learn the lessons, choose the priorities, and create different coping strategies in a changing environment. Similar to SST, CST cannot be done without contribution of humans' input, it is a systemic approach.

2.2.3 Decision-Making Process

The decision-making process, in general, is comprised of problem statement identification, alternative solution creation and evaluation, and solution implementation (McKenna & Martin-Smith, 2005).

Problem Identification

The quality of the decision-making requires a good definition of the problem (Lunenburg, 2010). Failing to identify the root cause of the problems but putting all attention into solving symptoms will cost more in the long run. Verschaffel et al. (2010) state that constant supervision of the internal and external environment is necessary to capture issues. Reports from MIS are designed to make problems more noticeable (Lunenburg, 2010). Strategies such as comparing two similar objects, the "could be" and "is not" characteristics in all four dimensions (what, where, when, to what extent), can help to distinguish the features of the problem (i.e. an identical plant <what> could grow as much <how much> but it is not in the same time <when>, location <where> (Kepner et al., 2005, as cited in Lunenburg, 2010))

Alternatives Generation

After clearly identifying the specific factors closer to the root cause of the problems, decision-makers can proceed to cause-effect-analysis to generate possible alternatives (Kepner & Tregoe, 1981). But before brainstorming all possible solutions, decision-makers should first specify the goals they hope to achieve through this decision (Lunenburg, 2010). Company strategic goals should be used to guide this process. For instance, when facing a problem of product failure, companies with the strategy to gain market share of the product is more likely to investigate solutions to fix the technical issues to upgrade the product than the option to drop the product. The number of stakeholders affected by the decision will affect the time and budget allocated for the search for alternatives (Ehrgott, 2011, as cited in Lunenburg, 2010).

Evaluating Alternatives

Decision-makers should review the feasibility, satisfactory levels in solving problems, and the impact on stakeholders and the organisation to evaluate the alternatives (Grant, 2010). Feasibility depends on the resources available such as time, people, costs, and technology. Access to new information can support the generation of new alternatives; therefore, decision-makers should not conclude too early when more information is coming (Daydé et al., 2014). The satisfactory level is affected by the minimum acceptance level, an organisation's priorities, and goals. The clearer the evaluation criteria, the more objective the process can be. Decision-makers should carefully assess both short-term and long-term impacts; the current decision will affect the resources available for later activities; both benefits and risks should be considered (Daydé et al., 2014).

Solution Implementation

Decision-makers should evaluate a solution's effectiveness after implementation to decide if further decisions need to be made. Organisations that fail to assess the post-implementations of a solution continuously can fall into the trap of *single-loop learning,* and more problems can occur. Ineffectiveness of a solution can result from the wrong definition of the problem, inaccurate evaluation of the alternatives, and poor implementation (Lunenburg, 2010).

2.3 HOW PLF SYSTEMS' INFORMATION SUPPORTS DECISION-MAKING

2.3.1 Agility: Agile Information for Agile Decision-Making

The real-time information and execution from PLF systems will support more agile decision-making. Instead of waiting for the monthly or quarterly report to make informed decisions, farmers can make decisions with real-time information. The ability to understand the real-time conditions and daily performance of the herd enables farmers to manage the herd more proactively, to test different solutions quickly, and resolve problems effectively. *IS agility* is described as an IS's ability to notice and detect a change, choose, and implement a response in *real time*; real time is defined as the period when the task is performed, and the result of the task is produced (Chaudhary et al., 2017). Dodhiawala et al. (1989) introduced the four aspects of real-time performance: 1) speed (execution); 2) responsiveness (alert new events); 3) timeliness (react to meet deadlines, prioritise most critical and important tasks); and 4) graceful adaptation (adapt to changes in resource availability). PLF systems speed up the information-seeking time and responsiveness by directly sending visual and audio alerts to farmers when they detect abnormality at the rotary (Jantec, n.d.). The real-time information captured by PLF systems improves farming operations by comparing the current performance with the system-generated benchmark information. For example, PLF systems monitored 17 consecutive broiler flocks from the last two years; such an extensive dataset creates the benchmarking report and immediately sends early warnings to farmers when detecting deviations (Van Hertem et al., 2017). Agility can be expressed as an enterprise's aptitude to continually improve business processes. Six-Sigma is a set of techniques used for process improvement and quality delivery by identifying and removing the causes of defects to minimise operational/business process differences (Soleimannejed, 2004). Berger and Hovav (2013) suggest that the Dairy MIS (PLF systems) directly supports two of the Six Sigma steps—measuring and improving the operation. PLF systems' embedded technologies increase the measurements by filling in with real-time data, and calculated data (production worth, breeding worth, lactation worth) to enhance farmers' understanding of the performance. Furthermore, real-time outputs enhance the testing capability and support farmers to identify optimal solutions.

2.3.2 Accuracy: Accurate Delivery Using Precision Information

Precision information collected from the PLF systems supports the accuracy of decision-making. Using precision information and the system's *Decision Tree* (DT) analysis models, precision agriculture systems help farmers identify crops with the highest predicted outputs and profits (Dewi & Chen, 2019). The most common machine learning techniques used in precision agriculture are the *Support Vector Machine* (SVM) and DT: SVM can distinguish different kinds of data using kernels; DT can predict the outputs through decision rules inferred from the data features (García et al., 2020). DT was used to classify the plots according to two and then one factor, which resulted in high accuracy with 96% for the irrigation factor, 83% for the nitrogen, and 100% for weed control strategies (Waheed et al., 2006). DT can also be used to identify individual animal's behaviours such as grazing, rumination and moving (Fote et al., 2020). By having a system to monitor animals' behaviours 24/7, farmers can capture abnormal behaviours when they are away from their farms. Moreover, the machine learning techniques uses the data collected 24/7 to objectively distinguish between normal and abnormal behaviours, surpassing farmers' limited capacity to observe and subjectively judge within working hours on farms.

2.3.3 Breadth: Multiple Decision Types Supported by the Large Database

PLF systems provide information for farmers to make a wide breadth of decisions: structured, semi-structured, and unstructured. MIS users use the system to make *structured* and *semi-structured* decisions, which depend on both guidelines and human judgements that rely on existing information; DSS provides information for *semi-structured* and *unstructured decisions* requiring decision-makers to use judgement and analytics to draw conclusions (Laudon & Laudon, 2015). PLF systems that are Dairy MIS and integrated with DSS can support farmers to make all types of decisions.

Structured Decisions

Structured decisions are repetitive and routine decisions that can be made using standard procedures (Paginas, n.d.). Structured decision-making has a pre-arranged order of steps that engages multiple stakeholders in the conversation and considers both facts and values: 1) clarify the decision context (scope, budget, timeline); 2) specify objectives and measures; 3) create alternatives; 4) estimate consequences and identify uncertainties; and 5) evaluate trade-offs and 6) select, implement and monitor (Gregory & Long, 2009). More precise information will not change the overall decision making or intervening options; however, the preciseness of the information enables farmers to decide which treatment to give for a specific animal; in other words, it embarks a more precise implementation of existing management options (Rojo-Gimeno et al., 2019).

Semi-structured Decisions

Semi-structured decisions include both defined structured parts (e.g., fixed procedures, conventional algorithms) and inexplicit unstructured parts (e.g., intuition, common sense, neural networks) (Kaliardos, 1999). Semi-structured decisions require decision-makers to adapt their plans based on uncertain factors; they need to repeatedly review current data to identify trends and collect feedback from their performance to adjust their decision-making strategies (Remus & Kottemann, 1987).

Unstructured Decisions

Unstructured decisions are those that organisations have rarely seen before, so there are no pre-defined structures of responses (Mintzberg et al., 1976). Their objectives are ambiguous and conflicting; causes and evaluation criteria are hard to identify, so no clear actions can be pre-determined to affect the decision outcomes (Lee & Eom, 1990). Strategic decisions made by executives and directors are categorised as unstructured decisions (O'Brien & Marakas, 2011). Humans play a critical role in making these decisions. When making strategic decisions, they need to consider a wide range of data, especially nonquantitative data (values, emotions, politics) (Mintzberg et al., 1976). Decision-makers need to correctly select the objectives and evaluation criteria based on their priorities (Lee & Eom, 1990). However, systems can also use neural networks to make unstructured decisions but are restricted to special situations. A neural network modifies its rules using data given by humans; the amount of training will affect its ability to generalise from training to operational situations (Kaliardos, 1999).

Examples of the different decision types are shown on Table 1. Structured decisions are those that can be programmed to be calculated in the systems. Semi-structured decisions are those that require humans' judgements after some calculations. Unstructured ones are questions that rely heavily on humans' creative inputs, which can be generated through research, or lessons learned through other farmers.

Decision Types	Example Questions/Decisions
Structured Decisions	***Feeding***: Which groups of cows have best performance? ***Breeding***: Which breed has the best production? ***Animal Health:*** Which cow need to get vaccines?
Semi-Structured Decisions	***Feeding***: What kind of recipes generate the best outputs? ***Breeding***: When to perform artificial insemination? When to calve/ dry off the cows? ***Animal Health***: Which cows should be culled out?
Unstructured Decisions	***Feeding:*** How can we improve the recipe? Add new ingredient? ***Breeding:*** How to improve the in-calve rate? Try sexed semen or get a new bull? ***Animal Health***: How to reduce the somatic cell count? Reduce animal stress?

Table 1 *Decision Types*

2.3.4 Depth: Single-Loop & Double-Loop Learning

PLF systems and DSS encourage *single-loop and double-loop learning*, deepening farmers' understanding of the root causes of problems. With the enhanced breadth and depth of information that forms an integrated view of the farming operation, farmers have a better chance to learn and reflect on their decisions. PLF systems' reports eliminate the traditional prolonged data gathering and manipulation process, which frees up the time for farmers to reflect, think and learn from daily decision-making.

Single-Loop Learning

Single-loop learning is about correcting the errors in actions to achieve the same output more efficiently (Argyris et al., 1985, as cited in Greenwood, 1998). Single-loop learning does not challenge the "fundamental design, goals, and activities of organisations," which can be shown by the example of a thermostat system that learns the room temperature and takes corrective action to switch the heater on or off (Argyris, 1977, p. 6). It involves gradational adaptative changes to optimise resource management (Duru et al., 2012). In the form of linear thinking (Sellers et al., 2020), single-loop learning corrects actions based on existing cause–effect relations; instead of reflecting on root causes, single-loop learning offers short-term solutions to solve symptoms (Restrepo et al., 2018). Single-loop learning can therefore be misleading in the long run because, if the activities were incorrect initially, focusing on effectively achieving the results will not solve the real problems (Greenwood, 1998). What is worse, humans' confirmation bias will limit their choice of information to confirm their beliefs (Evans, 1989). Without challenging the fundamental assumptions or beliefs, humans can fail to recognise potential opportunities or threats that require change; therefore, it is vital to not to limit by the single-loop learning (Pahl-Wostl, 2009).

Double-Loop Learning

On the other hand, double-loop learning challenges the essentials of an organisation, which can be demonstrated by the thermostat system questioning the 68-degree threshold that controls the switch (Argyris, 1977). Double-loop learning is a reflective process that challenges the management team's *mental models* or theory behind the actions (Kim et al., 2013). Mental models refer to the individualised reasoning process that showcases how humans interact with the world around them and decide which controllable action to take (Johnson-Laird, 1983). They are perspectives (assumptions, generalisations) that guide people to choose and interpret information and decide what to do next (Senge, 1992). In the form of systems thinking (Sellers et al., 2020), double-loop learners integrate the experience into feedback during this reflecting and planning process (Pahl-Wostl, 2009) to solve the problems from the root cause instead of removing the surface symptoms (Kantamara & Ractham, 2014). By reframing the problems through reprioritising goals and adjusting the analysis boundaries, double-loop learners change assumptions on how goals can be achieved (Pahl-Wostl, 2009). Upon recognising new cause–effect relations, they replace traditional activities with new ones and test the strength of such relations (Restrepo et al., 2018). Farmers who have adopted double-loop learning tend to have revolutionary changes to their operations, such as raising a double herd with crossing calving periods to maximise the benefits of the autumn herbage growth (Duru et al., 2012). The change in systems' understanding, encouraged by double-loop learning, is a crucial step in developing organisational resilience when facing uncertainty (Howden et al., 2007, as cited in Restrepo et al. (2018). However, few organisations have developed double-loop learning because of a lack of awareness of their assumptions, absence of transparency or of incompleteness of information, and the heuristic approach that leads to inconsistency between actions and beliefs (Argyris, 1977). One strategy to develop this learning process is to share authority with those who have the decision capability or the ability to control the environment through deciding or implementing the action; any newly developed concepts are open to inspection by stakeholders who will use them (Argyris, 1976). Such a process encourages a mutual learning experience and an open space for reflection, learning, and development.

2.4 SUMMARY

PLF systems are unique Dairy MIS that not only store data and information but also enable configuration of DSS tools to use the information to calculate optimal solutions. With the accurate calculated information generated through the PLF systems, farmers can make informed decisions faster. In the context of bounded-rationality decision-making theory, farmers can have different approaches to decisions (hard-, soft-, and complex-system thinking). Theoretically, the more information they receive, the more likely farmers would have double-loop learnings in which they challenge their assumptions when making decisions. However, there is a lack of research that uses case studies to investigate this relationship. This research will fill this research gap by using case studies to analyse such relationships and investigate the role of information in each step of the decision-making process.

CHAPTER 3 RESEARCH METHODOLOGY

This chapter will discuss the research design, data collection, and data analysis process. Starting with the overall approach of the research, this chapter clarifies the definition of the research sample and describes the detailed process of how secondary and primary data were collected. Thereafter, the author explains how data were analysed to produce meaningful outcomes for this research topic.

3.1 RESEARCH DESIGN

The qualitative approach was adopted because the research topic seeks to understand a 'how' question and qualitative research is good for exploration (Williams & Gunter, 2006). Because of the lack of former studies on how farmers use PLF systems to improve decision-making related to farming practices, case study methodology was chosen from among all qualitative research design methods. The case study enables researchers to gain a solid, contextual, and thorough understanding of a topic by examining one or more cases in one study (McCombes, 2020). Because of the inseparable relationship between the context and the phenomenon, researchers will read the context of each case individually before drawing any generalisation (Yin, 2013). Additionally, as a triangulated research design method, researchers can confirm the validity of the processes by having multiple data sources to identify if the data remain the same in different contexts (Denzin, 2017).

This research collected data through secondary research and semi-structured interviews with the requirement to have multiple data sources. The researcher compared the expected usage of PLF systems' information usage from PLF systems' providers and information analyst with farmers' actual usage. The interviews discovered the PLF technology and system adopted, information collected, and specific examples of how they use the information from the systems to improve decision-making. The interview questions are listed in Appendix 1. Eight out of nine interviews were video recorded for transcribing purposes. One interview was not recorded as it was conducted over the phone. Qualitative data analysis-thematic analysis, process flowcharts (Figures 5 and 6), and a sequence diagram (Figure 7) were created to generalise the observations and insights from the cases.

As this study involves collecting primary data through the interview, the privacy and confidentiality of the participants should be respected and protected to minimise the risks or threats to both researcher and the interviewees. As farms are hazardous and due to Auckland's unstable COVID-19 lockdown situation in 2020, the researcher changed the original plan to conduct on-farm interviews to online Zoom interviews. This research received Ethics approval from the AUT Ethics Committee in December 2020. Interviewees received the Information Sheet (Appendix 2) that presents the research's objectives, interview procedures, and actions taken to protect their rights and the Consent Form (Appendix 3), allowing participants to decide if they approve of the interview being videotaped. After the interview, the recordings and notes were transcribed into Word documents for subsequent data analysis.

3.2 DATA COLLECTION

This research collected secondary data from websites, reports, existing research collected from Stats NZ, Dairy NZ, Beef + Lamb NZ, LIC, FarmIQ, Waikato Milking System and primary data from interviews. Interviews are one of the most important sources for case studies, and this research was conducted using semi-structured questions (Tellis, 1997).

3.2.1 Research Sample Definition

The researcher aimed to talk to both PLF systems' providers and PLF-systems' users (information/business analysts and farmers) to understand the expected and actual usage of the PLF systems' information to improve farming decisions. By talking to systems' providers, the researcher could understand what information was supposed to be collected from the system and their expected usage of the information. To explore the topic thoroughly using the case study research method, researchers must be flexible and open-minded in their search for types and sources of data (Denzin, 2017). Therefore, the only criterion for the research sample was a minimum of two years of PLF systems' implementation. This criterion was chosen because farmers would have passed through the trial period, which will be more likely to share insights such as key learnings and improvement opportunities.

Two PLF system providers were identified – one that provides an integrated system with different PLF technologies such as weight, health, breeding, automation, and environment; and one that offers a unique functionality such as tracking National Animal Identification and Tracing. The researcher contacted the systems' provider by emailing the Customer Experience Managers, whose contact details were shared on the websites. The researcher received only one reply from one of the PLF system providers, so secondary research was conducted to fill the gap of the expected usage of information from the integrated PLF system.

The difficulty of identifying PLF-systems' adopters is that PLF systems providers cannot share farmers' contact details due to data privacy. The plan to ask the PLF system's provider to share the interview request information to the system's users also failed as no farmers showed interest through email after being given three weeks for consideration. The research sample eventually got sourced through award winners' references and word of mouth introductions. The researcher chose to contact award winners because they are more likely to participate in the interview to share good case practices or lessons given the awards or titles they received.

Three awards were used to identify farmers who have significant achievements in farming operations – Ballance Award, LIC Award, and New Zealand Dairy Industry Award. The researcher chose to source farmers from Ballance Farm Environmental Award winners as farms with excellent farm environmental practices are likely to have efficient farming operations (Ballance, n.d.). As Smeaton et al. (2011) suggested, farms could reduce GHG emissions through intensification (raising animal feed's efficiency and productivity, reducing stocking rates). The researcher also contacted farmers of the years of LIC's Sire Proving Scheme award that recognised outstanding performance in producing quality herds using LIC's semen – genetically superior bulls in New Zealand (LIC, n.d.-e). Because LIC is a main national provider of the PLF system, farmers who enrolled on the Sire Proving Scheme programme are more likely to adopt the PLF system. Dairy Industry Award's farmer of the year identified top national dairy farm's farm manager (Dairy Industry Awards, n.d.). More dairy farmers than other livestock (sheep, beef, deer) farmers improved farming practices with farm animals to be more environmentally sustainable (Ministry for Primary Industries, 2019). Therefore, contacting these award winners gave the researcher a higher chance of identifying farmers who have adopted PLF systems. The researcher contacted the organiser who gave out the award, and the organiser acted as a medium to request interview approval on behalf of the researcher. Upon such approval, the researcher received the email contact from the organisation. Besides, if the award authoriser did not reply, the researcher found the winners' contact (LinkedIn/phone/email) published online. Finally, the researcher leveraged word of mouth to identify participants for the research. A senior scientist referred two farmers from DairyNZ, and one interviewee was a friend of the farmer.

In the end, the researcher interviewed one PLF system provider's customer service manager, one corporate farm's national information analyst, and local business analyst, and five beef/dairy family farmers across New Zealand. Details of the interviewees, including the PLF technology and systems they use, are discussed in the Chapter 4 Results section of this research paper.

3.2.2 Qualitative Interviewing Process

The semi-structured interviews were conducted with a set of guiding questions and additional questions formed during the interview. The main topics of the discussion would be learning how they interacted with the PLF systems, interpreted the information generated from the system, and used the information to make decisions related to farming practices. Besides the initial introduction, the researcher adopted the order of the questions based on the answers and added additional follow-up questions to explore details of the discovery. All interviews, which took between 30 minutes to 1.5 hours, were carried out on Zoom except for one interview done over the phone. All farmers interviewed in their office or home, with minimum distractions except for one farmer taking care of a toddler during the interview. Few notes were taken during the interview to guarantee the smooth process of the online interview. Eight out of nine interviews were recorded successfully, except for the one phone interview as there was difficulty recording the phone call.

3.3 DATA ANALYSIS

3.3.1 Content Analysis

Without visiting the farms to see the actual operation, it was difficult to understand how PLF systems work purely through online interviews. Content analysis, systematic coding and categorising techniques to determine patterns and trends of words (Vaismoradi et al., 2013), were used to analyse the secondary data of this research. Because such techniques are not restricted to texts, but other media such as pictures, audio or video (Stemler, 2000), data such as systems' user manuals, online testimonial information and YouTube™ demonstration videos used were analysed. Given the limited existing theory or literature on this research topic, the researcher used conventional content analysis with the following steps: 1) read all data repeatedly to obtain a sense of the big picture; 2) make notes of the first impressions and initial analysis; 3) label for codes; 4) categorise codes into meaningful clusters; and 5) group subcategories into larger categories and define each category (Hsieh & Shannon, 2005). Such a technique is used throughout the data analysis. PLF systems' user manuals support categorising the information PLF system generates and the expected usage of the information to support on-farm decision-making. Online testimonial information (text and video) supports the codification of the effects and limitations of PLF systems. Finally, PLF system demonstration videos on YouTube™ provide visual evidence to support the interviewees' comments on how PLF systems work seamlessly with human labour on operations.

3.3.2 Thematic Analysis

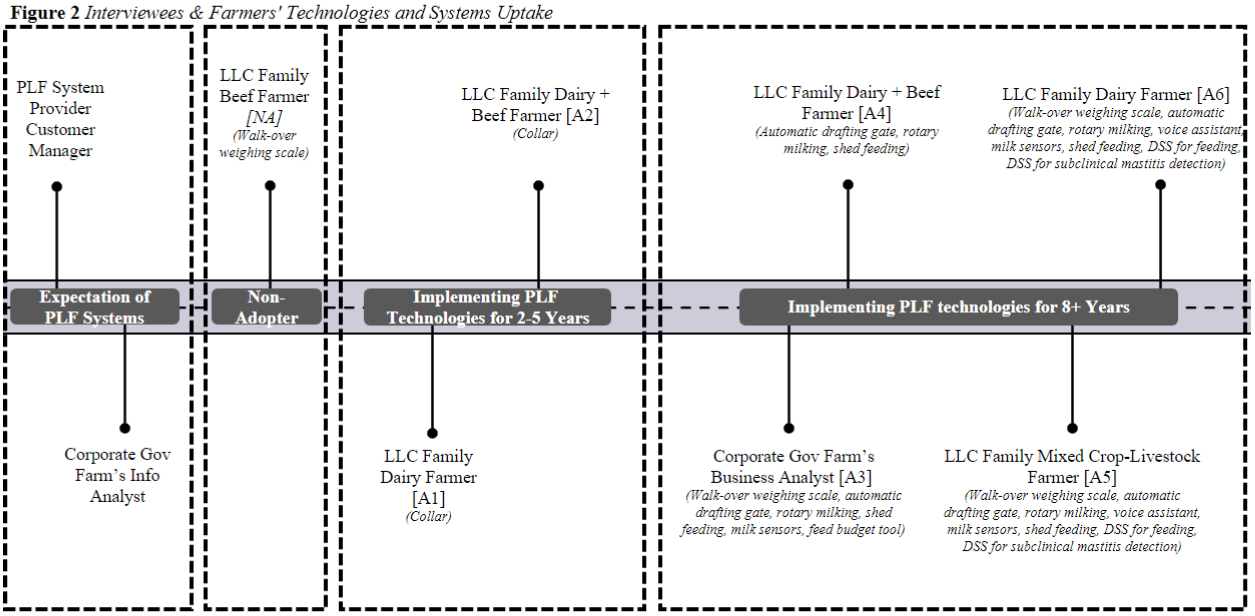
Because of the exploratory nature of this research, inductive thematic analysis, which is used to identify and analyse patterns in qualitative data (Clarke & Braun, 2014), was used to analyse the primary data collected from the interviews. Thematic analysis was used to develop a comprehensive and continuous extraction and thorough analysis process from the start to obtain the themes (Vaismoradi & Snelgrove, 2019). The researcher followed these steps: 1) transcribe data; 2) create initial code from data; 3) collage codes into themes; 4) review and define themes; and 5) produce the report (Braun & Clarke, 2006). The main themes (i.e., information generated and used from the system, types of decisions, and how they make decisions) were pre-coded and used to design the interview questions as a guiding framework to collect information related to the research topic. The sub-themes were developed by inductive thematic analysis of the interview data using the transcription, coding, and categorisation process. Appendix 4 presents a sample of how the interview data was categorized into main themes and subthemes Because of the small dataset generated from the nine interviews, the recorded results were transcribed without using the software – however, Word and Excel sheets were employed to identify common themes and differences among different cases. With the emphasis on context, inductive thematic analysis fills the gap of content analysis that focuses more on the frequency of the coded content (Vaismoradi et al., 2013), which can be shown with a thematic relationships map. The researcher analysed the context of each case and categorised them into different themes for analysis. Based on manifest characteristics such as the PLF technology adopted, farmers were grouped into different PLF-system implementation stages. Based on latent features such as systems thinking, farmers were divided into groups: hard systems thinking, soft systems thinking, and complex systems thinking. The thematic analysis enables multi-layered analysis using different theoretical lenses, which enriched the research findings. In combination with the process flowcharts and an information-flow sequence diagram, the researcher was able to draw connections among different themes (systems thinking, decision-making process, and double-loop learning), shown in Figures 5 and 6.

CHAPTER 4 RESULTS

Chapter 4 discusses key findings from the interviews. Figure 2 is a snapshot of the interviewees of the research, which included one PLF system provider, one information analyst, one farmer who used precision technology but not a PLF system (NA[1]), one business analyst (A3) for 10 corporate farms and five dairy/beef limited corporate's family farmers (A1, A2, A4, A5, A6[2]).

There are five production systems in New Zealand: system one - all feed self-contained, system two – import feed as supplements for dry cows., system three – import feed to extend lactation for dry cows, system four – import feed for both ends of lactation and for dry cows, and system five – import feed and used throughout the year for lactation & for dry cows (DairyNZ, n.d.-a). Farmer NA, A2, and A4 are system one farms that are self-sufficient and do not require importing feed from other farms; farmer A1 and A3's farms are system three, as they either move their cattle to other farms in certain season for feeds or they buy in feeds from other farms to extend lactation; farmer A5 and A6 run system five farms as they import supplements throughout the year aiming to achieve top performance.

Figure 2 *Interviewees & Farmers' Technologies and Systems Uptake*



The bracketed information summarised the PLF technology products and DSS farmers adopted. PLF systems are integrated Dairy MIS that use connected network devices and built-in decision-making algorithms to monitor the *real-time* performance of individual animals and to alert users to any abnormal situation (Werkheiser, 2018). Farmer NA is considered as a non-adopter of PLF system because the walk-over weighing scale does not monitor real-time performance or alert farmers to abnormalities to instruct

[1] NA = Non PLF System Adopter
[2] A1, A2, A3, A4, A5, A6 represent PLF systems adopters

decisions. However, farmer A1 and A2 are considered as adopters of PLF system although they use only one precision technology – the *collar*. The collar tracks real-time performance, temperature, behaviour of individual animals and present in the dashboard; it automatically generates graphics, colour-coded information, and notification messages to alert any suspicious deviation and remind farmers to perform activities such as artificial insemination when the cattle are on heat. Farmer A1, A2, A5 and the 10 farmers supervised by business analyst A3 all used multiple PLF systems to manage the farming operation because of unique functions provided by different systems, which have integrated DSS such as feed budget to support decision-making. Farmer A4, and A6 use only one PLF system, within which only A5 and A6 adopt independent DSS to support feeding and mastitis management.

4.1 OVERVIEW OF THE CASES

Six of the nine interviews were identified as cases because these represent farmers who adopt Precision Livestock Farming (PLF) technologies and systems. The interviews with the PLF system provider and the information analyst explained the expected use of the information from providers' perspective, which was compared against farmers' actual use to identify the information utilisation gaps. One non-PLF-system-adopter (NA) provided a perspective on why some farmers do not see the value of information from the PLF systems, and how they make decisions in their own way. Such information provides the contextual information to contrast with the cases to understand how the information from PLF systems becomes valuable to the selected groups of farmers.

Family Beef Farmer [NA]

The beef farmer, NA, raised over 1050 cattle on their grazing farm, together with her husband. They grow teenage cows and sell the grown-up bulls to another farm to slaughter for beef burgers in local and international markets. As a grazing/nursery farm, their priority is on feeding – determining where and when to move the cows to another cell of grassland. They only adopted one PLF technology – using electric scales to read EID tags and to automatically log in cows' weights into the system, which sped up the process, generated higher accuracy of the weights, and saved on labour costs. Controlling the feeding amount is crucial to the business as they want to grow their herds as much as possible; meanwhile, they would limit the ration in bad weathers so there will be enough feed when the grass is growing slowly. They use GPS mapping system to oversee the farmlands and their own economic model to reduce opportunity costs of selling the cows when they could have grown more. They relied more on external information, such as weather forecasts to determine the growing speed of the grass, the local and international beef pricing. NA chose not to use the PLF system because of the price, complications, internet coverage limitation, and because the costs of installing the technology outweigh the benefits it would bring to the beef farm.

Family Dairy Farmer [A1]

With a priority on reproducing dairy cows, farmer A1 (also a vet) raises 200+ dairy cows together with her husband in a system three farm; they have their heifers fed on other grazing farms. They use electric collars to track individual cow's activities (e.g., eating, ruminating, resting, walking) and especially, real-time animal temperatures. The real-time temperature can precisely capture cows' reproduction cycle and predict the optimal hours in the day for artificial insemination to improve the pregnancy success rate. As there was only one person working in the farm, the cows are artificially inseminated either in the morning or afternoon after milking. They kept the traditional way of tracking natural mating behaviours by applying paint on each cow in case the collars overlook these. The system provides a dashboard to show a list of cows that are ready for insemination, those who are *empty*, and when to conduct the pregnancy tests. The wide range of historical records of individual animals provide stronger foundations for the vet to diagnose any health issues. For instance, when the heifer has an abrupt change in eating behaviour, the vet can review previous eating trends and cross-check with the walking data to investigate if there are symptoms of lameness. Without such information, farmers can easily overlook the root cause of the problem and fail to take preventative actions to stop disease from spreading across the herd. Besides the collar technology, they adopted multiple other information systems to manage the livestock for different purposes, which requires them to double-enter the information to the systems to ensure all the necessary information is in one place: one system for health and safety compliance, and one system for herd testing.

Family Dairy + Beef Farmer [A2]

Beef farmer A2 raises 120 cows on a self-sufficient farm. Farmer A2 has adopted the collar technology for five years to track animal activities specifically tracking animals' heating status to predict the reproduction cycle better. Both farmer A1 and A2 kept to the traditional way – to use paint to identify natural mating behaviours because it had happened in the past that the paint was gone but the system failed to indicate it. Even though the system suggested the optimal hour for artificial insemination because there is only one person working on the farm, artificial insemination can only be performed in the morning and afternoon after milking. The system would show an alert when an individual animal eats 30% below average. Farmer A2 would check the animal's physical condition; however, learning from experience, it was normal for an animal to under-eat for a day and then come back to normal. The PLF system, for him, is not used for data analysis but as a day-to-day tool to run the farm.

Corporate Government Farm's Business Analyst [A3]

Business Analyst A3 works with 10 corporate farms that are system three (relying on imported feeds due to droughts), with an average of 650-1050+ cows. The farms have adopted multiple systems to run the farms, including: 1) one PLF system to have a holistic view of the farm and to comply with the national regulations to track animal movements across the farms; 2) one PLF system to record animal genetics, mating, biological information; 3) one PLF system that integrates all on-farm technologies such as smart shed, automatic drafting gate; 4) one DSS to forecast production and profits in different scenarios (pasture's growth, number of cows); and 5) one weather forecasting system using the corporate-owned weather station to predict grass growth. However, because there is no information exchange between systems, the business analyst plays a crucial role in ensuring the data in multiple systems are consistent before reporting back to the head office. Because the business analysts live near the farms, inconsistencies between the farm's reality and the reported system's data could easily be identified. Some farmers are self-sufficient in managing the data; other farmers who are not, will rely on the business analysts to enter, extract, and analyse the data. Business analyst A3 mentioned farmers who run farms purely on data cannot be successful because they would lose the instinct of managing farms; instead, data plays a supporting role in affirming what they observe in the farm.

Corporate Family Dairy Farmer [A4]

With over twenty years of experience running a 450-dairy-beef-farm, farmer A4 has adopted one PLF system for over 12 years. An external expert (who did not work on the farm) was invited to join the board to bring in external expertise to advise on the farming operation. Farmer A4 has three types of recipes to feed the cattle in different stages of the milking cycle (springers, dry cow, and milking), and the cows were fed in categorised groups to be efficient. Farmer A4 is a firm believer that, "What comes out from the system is probably only as good as what you put into it, and then it is only as good as how well you apply it." Therefore, farmer A4 would always double-confirm that the data captured in the system is accurate every time after milking to ensure the data in the system is accurate and truthfully reflects the situation. The system without technology such as the *collar* could not fully capture animal behaviours (e.g., a cow kicked over the milk bucket); therefore, it relies on human observations to fix errors and manually add the notes to the system. Overall, the system helped save money, time, labour, and supported farmer A4 to raise the top breeds in New Zealand. Instead of vaccinating the entire herd, farmers would only apply it to target animals. With the ability to track historical records of the ancestries, the system predicted which individual animals would have higher pregnancy success rates. Farmer A4 achieved well over the expected 50% heifer result (at 95%) because of consistent recording in the system.

Corporate Family Mixed Crop-Livestock Farmer [A5]

Farmer A5 is the CEO of a mixed farm with 650+ cows, crops, and fishponds and has used the PLF system for over eight years, together with two DSS to optimise feed for the animals and manage sub-clinical mastitis. Livestock is a small part of the farm, yet there are three ways to feed the cows: individual feed (springers, dry cow, and milking cow), group feeding (bulk supplements) using feed pad, and herd feeding (70% of times using grass feeding). Unlike some other farmers, farmer A5 would never overfeed the cows when they have more grass, as this would not match with their dietary requirements. They used a separate mastitis detection system, in which they take a sample, incubate and culture it to identify which type of mastitis. The system will suggest what kind of drugs should be given to the animals, and they will perform the procedure without having a vet to come to the farm. Given that the farm has so many technologies adopted to support feeding and animal health, they rely mainly on human observation for animal reproduction – having the vet record the animal's reproduction cycle in the PLF system and determining when the animal is ready for calving.

Corporate Family Dairy Farmer [A6]

Being one of the major suppliers for milk and cheese production, farmer A6 raises 2200+ cows, and. has adopted and used the PLF system for more than eight years and the feeding DSS and sub-clinical mastitis DSS for more than three years. The feeding DSS not only helped test if different recipes meet the dietary requirements, but also supported the feed budgeting to ensure the expected revenues are over the costs. Farmer A6 adopts a reward system to give more feed to cattle that produce more than the others and is able to individualise the feed by using PLF systems to automatically draft out the identified animals and provide more feed. He considered PLF system to be a *virtual labourer* that it will directly instruct farm workers using the shed's speaker on what to do to individual animal and farm workers can question the instructions from their experienced observations. Besides this, farmer A6 usually directly interrogated the systems with queries such as "show me cows that have somatic cell count under 400, have recently calved, and produce 30 litres of milk"; the system would show the list of cows that meet the criteria. Even with such well-developed systems, farmer A6, the same as farmer A2 and A4, kept the traditional painting method to indicate whether the cow had had natural mating that the system may fail to capture. The system can also automatically draft out cows that do not meet the conditions set by him. Farmer A6 is satisfied with the system given that it has helped make jobs faster, easier, and more cost-efficient.

4.2 PLF TECHNOLOGIES & SYSTEMS ADOPTED

4.2.1 Independent PLF Technologies

The interviewed farmers have adopted different levels of technologies. Companies that offer the dairy MIS usually provide a range of technologies for farmers to choose from to integrate with the system; meanwhile, farmers can choose to adopt the independent technologies without using the dairy MIS.

The most straightforward PLF technology is the *walk-over weighing scale***.** The machine reads the cattle's EID at the gate and automatically records the weight into the system. The system automatically generates the weight trends over the last 10 days; farmers can adjust the filter to see different weight categories' reports (Waikato Milking System, n.d.). By having the system monitor the real-time weight, farmers can have the most accurate information on time and take any necessary actions immediately. Farmer NA only adopted this PLF technology because buyers request the most precise weight's data at the gate; the scale is movable to be installed at different farm entrances. The animal can lose weight by walking from one end of the farm to the other; therefore, having the most accurate data at the gate is essential to guarantee fair trade. Furthermore, farmer A2 exemplified that if the cattle were lame, they could drop 30kg of weight overnight; such weight loss is hard to capture with the human eye. Another advantage is that farmers can directly see the results of the different feeding regimes immediately. Feed-to-yield is one of the key performance indicators for farmers to measure the feeds' return on investments. By closely monitoring the real-time weight of an individual cow, farmers such as A6 can more accurately predict the weight loss due to calving and prepare the ration (e.g., volume, recipe) to better achieve the weight's goal after calving.

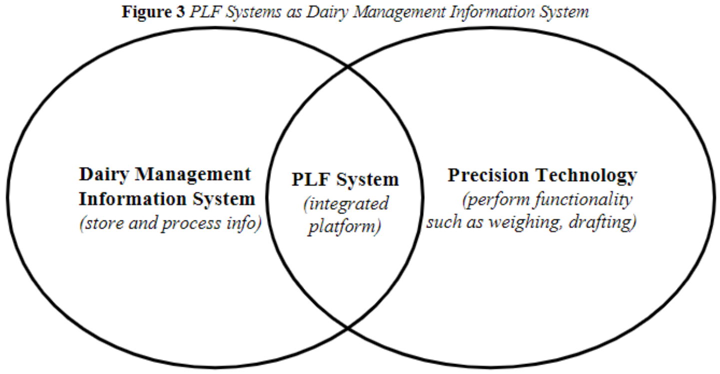
Another technology that New Zealand dairy farmers will mostly likely adopt is the *automatic drafting gate* (DairyNZ, n.d.-a). Farmers A4-A6, and the corporate farms all adopted this technology. Farmers saved a lot of time and reduced pressure on the animals as farmers needed to lead the way for individual cattle and sometimes run after the cows to sort the herds into different groups. The drafting gate (two-way, three-way) reads the EID and automatically changes the direction of the gate based on commands from the farmers (sent from the phone or tablets) or the pre-set criteria. The drafting function is enhanced if there is access to the herd records (Waikato Milking System, n.d.). Only when the technology is integrated with the Dairy MIS can the gate draft the cattle automatically with the pre-set threshold (DairyNZ, n.d.-a). Farmers can manually input the cow's data (e.g., cows scheduled for vets' check) or automatically record data such as somatic cell counts by installing other milk meters at the milking station. The automatic drafting gate enables agile farming practices if integrated with the Dairy MIS. Farmer A6 would, for instance, write a query to identify top cows that produce over the average litres of milk, and the system will seamlessly draft out the cows after milking. Farmer A6 then rewards these cows with extra rations. Such technology minimises the time needed for a logistical task and enables farmers to prioritise other value-adding activities.

More advanced PLF technology used by A1 and A2 farmers are the *collars*. The collars track individual cow's real-time heating situations and activities (e.g., eating, ruminating, resting), enabling the prediction of the optimal hours for artificial insemination. Moreover, the collar technology also alerts the farmers when it detects any abnormal behaviours after benchmarking the current behaviour with the individual cattle's past behaviour and the behaviour of their peers (Waikato Milking System, n.d.). The collar was especially beneficial for farmer A1. Because the calves are fed and raised on another farm for nearly half of the year, having all cattle's activities captured online enables farmers to monitor the cows remotely. When the groups of cattle are on heat, farmer A1 will bring them back from the grazing farm for artificial insemination. The benefit of the collar is maximised if used together with other technologies such as the drafting gate, milking meters, and walk-in weighing scale. After the Dairy MIS integrates with the *collar* and the *drafting gate*, instead of waiting for farmers' command to draft them, it will automatically perform the task (Waikato Milking System, n.d.). The collar will alert farmers when the cattle are sick. Farmer can then compare the data (e.g., real-time weight, somatic cell counts of the milk) to investigate the health problem before treating the cow. Farmer A6 demonstrated that farmers would not want to cull out the cow right after any abrupt drop in milk performance but instead determine the root cause through analysis, find the proper treatment, and observe the performance.

4.2.2 PLF System as an Integrated Dairy MIS

Farmer A4 described the PLF system as an integrated Dairy MIS with a database to store all precise records of individual animals (historical and real-time performance, ancestries, events such as birth, calving and vaccinations).

Figure 3 *PLF Systems as Dairy Management Information System*



PLF system is one form of Dairy MIS which uses precision technology (one or many) to manage dairy cows' information (as shown in Figure 3). Because the independent PLF technologies are integrated into the PLF system, farmers can use the system directly to test the results of the different feed regimes by reviewing the differences in the daily weights (Waikato Milking System, n.d.). The 10 corporate farmers supervised by business analyst A3 and farmer A5 adopt more than one PLF system because of the need to comply to industry standards – using a certified herd tester's system to store the herd test results and genetic information. Prerequisites to run the herd test with the certified tester is that farmers should: 1) tag and record at least 95% of lactating cows, and 2) record the latest calving date for at least 75% of these cows into the system from this certified tester {LIC, n.d.-d #185}. Though the existing PLF system already captures such information, farmers cannot run herd-testing with it as the PLF provider is not a certified tester. However, farmers could not replace the existing system with the certified tester's one because all the installed hardware (smart shed, sorting gate, etc.) on farms was connected to this system they have been using for many years. Therefore, farmers would need to co-manage the existing PLF system to manage the operation (feeding, animal health) and to perform herd-testing and track genetic information with the certified tester's Dairy MIS. Because the two systems are not interconnected, farmer A5 said they needed to manually copy and paste the data from one system to another to enable another system to maximise its full functionality such as herd-testing, and relationship modelling between genetics and milk quality Similarly, farmer A2 needs to update the information collected from the collar (e.g., heating cycle, abnormal behaviours) PLF system to the independent dairy MIS routinely to ensure the Dairy MIS has the accurate data input to run herd tests. On the other hand, some systems can be compatible with each other: the vets can directly download their reports from the vets' system and upload into the Dairy MIS to seamlessly integrate the reproduction/health-related data and notes for individual animals.

Automatic walk-in weighing scale and *drafting gate technologies* individually only play a small role in the dairy management operations, which is why farmers A4, A5, A6, and farmers supervised by business analyst A3 all have a PLF system that integrates multiple technologies into an interconnected network to enable them to work together seamlessly throughout the daily dairy cow's operational cycle (shed-feed-breed-health treatment-shed).

The *smart shed* that A3-A6 farmers adopted can be used for milking, feeding, sanitising, and mastitis detection because of the integration of multiple technologies and machinery in one dairy MIS which becomes the PLF system. The most common milking parlours installed in the smart shed are the *rotary parlour* (a circular raised platform that rotates slowly for milking), and the *herringbone parlour* (in which the cattle stand at a 45-degree angle on a parallel milking platform) (Allen, 2017). The smart shed identifies the cattle once it enters and records the bail it enters. When the farmworker is attaching the milking clusters to each cow, the smart shed's *voice assistant* will announce an individual cattle's conditions and instruct any recommended actions. The parlour will automatically drop the ration into the container in front of the cattle when milking based on the feeding command set by the farmers. Farmers can choose to individualise the recipe and volume of the ration for individual cows in this setting. Parlours with the installed *SmartSpray* technology can automatically apply the teat spray before or after milking, which can help reduce chances of disease caused by bacteria. Farmers can automatically sort cows into different groups (e.g., cows that need to be dried off, cows to receive vaccines, cows to be artificially inseminated) based on pre-determined conditions when the *automated sorting gate* integrates into the dairy MIS. Farmers can also flexibly use the operator console at the milking station to command the system to sort out the cows. After integrating the collar into the dairy MIS, they can automatically draft out the cows whenever the cattle are on heat, which saves the effort to use paint to identify natural mating and reduces the pressure for farm workers to visually inspect the heating behaviour of the cattle (Waikato Milking System, n.d.). Instead of waiting till the next milking to perform the artificial insemination, farmers can increase the in-calve rate at the optimal heating time at this round of milking. After milking, with the support of the *milking meter* installed at the rotary parlour, farmers can review the milk quantity, milk contents (protein, fat, conductivity), and somatic cell counts, an important indicator in identifying clinical mastitis.

4.2.3 Decision Support Systems (DSS)

A5 and A6 farmers use DSS together with the PLF system. One DSS is to identify the optimal feeding recipe, and the other tool is to detect sub-clinical mastitis and determine the treatment (drug, vaccines).

The *feeding DSS* enables farmers to design new recipes that meet dietary requirements and optimise the feed's return on investment. Using this DSS, farmers can create a diet for up to 15 ingredients or mixes to meet the cow's dietary requirements; moreover, farmers can compare different ingredients and how one ingredient is more advantageous than another ingredient (Rumen8, n.d.). Farmers will need to input data generated from the integrated PLF systems, such as live weight, days pregnant, milk yield, milk fat, protein to make the recipe comparison for the individual cows or groups of cows. Farmer A6 specified that the DSS would project the outputs using a visual traffic-light system and easy-to-understand warning messages indicating if dietary requirements are not being met.

The *animal health DSS* supports farmers to better control mastitis by detecting sub-clinical mastitis and identifying the paring treatment of the specific type of mastitis. Besides using somatic cell count to detect clinical mastitis, farmers can take samples of the milk, culture them, and identify sub-clinical mastitis using the DSS. Specifically, farmer A5 demonstrated that the on-farm workers could use this DSS to identify the string of mastitis and it will generate recommendations on the specific type of drug or vaccines that can treat this mastitis. Such a system saves costs from the hidden mastitis and enables farmers to be more self-sufficient in controlling the disease; instead of waiting for external vets to come to the farm to investigate the issue and apply treatments, farmers can do it themselves.

4.2.4 Summary

Independent precision technologies each have unique functions and minor roles to play in the dairy cow's operational cycle. Farmer NA's automatic weighing scale is not considered as a PLF system because the PLF system is a dairy MIS that integrates individual technologies into one platform. They use the connected network and built-in decision-making algorithms to monitor individual animals' real-time performance and alert them to any abnormal situation (Werkheiser, 2018). Farmer A1 and A2 who adopted the collar based PLF system without other technology such as rotary parlours, drafting gates, have a less seamless experience. They need to copy and paste the information into another Dairy MIS to perform herd tests and identify relationships between genetics and milk performance. Farmers A3-A6 leveraged the integrated PLF system to seamlessly manage daily operations and directly run analytics to create insights to improve the operational processes. However, because of the existing investments of the PLF systems, farmers supervised by A3 and A5 would have to manage a PLF system and multiple Dairy MIS to comply with the industry standards to use the unique functions offered by the systems. To better support their decisions, corporate farmers supervised by A3 adopted the PLF system with integrated DSS such as the feed budget tool to manage the feed, and farmers A5 and A6 use independent DSS to optimize feed and manage sub-clinical mastitis.

4.3 INFORMATION GENERATED FROM THE PLF SYSTEMS

The PLF systems generate and store both quantitative and qualitative information captured through precision technologies, as shown in Appendix 4. The system self-generates measurements and reports for farmers to review. The Protrack® PLF system (LIC, n.d.-a) has a dashboard highlighting the genera category (i.e., animal count, animals drafted, milking plans, health indicators, heat, and production). The most critical data shown under each category, for example, are the number of cows with high somatic cell counts and averages of milk production.

4.3.1 Quantitative information

Real-Time Machine-Generated Data: In addition to the basic information (e.g., weights, milk volume) that farmers can record manually, PLF systems record additional descriptive information with their embedded technologies and predictive analytics models. On account of the technologies (e.g., collars, milking meters) integrated into the PLF systems, farmers can capture information that traditionally takes time to record through observation (e.g., animal heating or abnormal behaviours) or those that require tools from external professionals (e.g., somatic cell counts, milk fat percentages). Having the technologies to record the data into the system automatically reduces human errors, and the decision-making time. Farmer A6 wrote a query, "can we have all the cows with average cell count under 200K, milk quantity between 30-50 litters, and calved between these two days", and got a list of cows in seconds. Furthermore, having all accurate machine-generated data collected at the same time in one place avoids poor decisions being made from outdated, incomplete, or untrustworthy data.

Historical Information: PLF systems' ability to store historical information of each animal supports the breeding and health-related decisions. More historical data give decision-makers foundations to run statistical models to identify performance trends, associations among factors, and eventually create more accurate predictions of future performance. Farmers can cross-examine the trends with other factors (lifecycle stage, cow size, feeding amount, etc.) to identify if the trend is particular to the specific group or individuals. Farmers can also change the filter to observe the performance of the last three weeks, months, or years to observe the overall stability of an individual cow. Such historical information supports farmers to identify the root cause of the performance. Furthermore, the historical data of the ancestry can help predict the breed's performance. Farmer A2 demonstrated how PLF systems indirectly helped improve the exponential growth of in-calve rate by suggesting a list of cows to avoid and a list of ones to use for breeding based on the history analysis.

Calculated Information: Because of the diverse, real-time data PLF systems collected from individual animals, farmers can get more accurate calculated performance measurements. Getting precise performance measurements such as Breeding Worth and Production Worth are crucial to support farmers' decision making to determine which cow to breed or cull off. Calculating breeding worth requires accurate inputs such as herd-testing data, body condition score and weights (DairyNZ, n.d.-b). Farmer A2 showed that more regular measurements and progeny's data will improve the accuracy of Breeding Worth. With the historical records (protein, fat, volume, live weight, and somatic cell) of ancestry, individual, and offspring in the system, farmer A6 said Production Worth could be simply calculated with the data collected from PLF system. Farmer A2 added that with the heating data collected from the collars, the system can estimate the optimal hour of the day for artificial insemination. Farmer A3 concluded that such calculated information was helpful to improve the in-calve rate and reduces stress and time for farmers to observe the heating behaviours.

Benchmark Information: farmer A6 showed how the systems automatically generate benchmark information, or farmers can manually request through use of the query. Using the average performance of the entire herd as a benchmark, farmers can quickly categorise the 500-cow herd into different groups for treatments. The individual cattle's past behaviour and the peers' behaviour are used as benchmark information to detect abnormalities; such information can support farmers to distinguish the individual or the herd's problems (Waikato Milking System, n.d.). The benchmark information changes based on historical data. For instance, the walk-over weighing scale automatically benchmarks the current weight with the weights of the past 10 days. By having a floating benchmark that adjusts with real-time performance, farmers can have a more precise understanding of daily performance and how different treatments over different timeframes affect performance.

4.3.2 Qualitative Information

Visual Information: Farmer A 6 explained that, besides showing raw data on the table in the system, the system also produced easy-to-read visual information such as colour coding using the traffic-light system.

Farmer A2 showed how the onion graphs indicated the optimal hours for artificial insemination. The colour information sends visual alert information to farmers to pay more attention to the ones that are in red. Besides this, the systems produce charts and diagrams with trend lines to ease data interpretations. Farmers can easily observe the direction of the trend and if there is any abrupt change requiring special attention.

Events: Farmers can record special events for the individual cow such as artificial insemination performed, pregnancy date, calving date into the PLF system. Farmer A4 explicitly summarised that "the more information you record in the system, the more you can get out of it". Farmer A2 noted that they could easily integrate the vets' reports into the PLF system; information such as health information, drugs or vaccine treatments would therefore be in the PLF systems. Having this information is crucial for farmers' decision making, as farmer A6 demonstrated, farmers need quantitative data and qualitative data to make hard decisions, especially deciding which cow to cull off. By having the special events notes recorded in the PLF systems, farmers can better identify the root cause of any abrupt performance change. Moreover, it makes it easier to perform tasks such as comparing the performance outputs of different recipes.

Suggested Actions: Another differentiation between traditional analytics and PLF systems' analytics is that the latter produce suggested actions. With the information collected from PLF systems, the system can also generate a precise prediction of the optimal hour for farmers to conduct artificial insemination to increase the pregnancy success rate. PLF systems can calculate the optimal feeding amount based on the estimation of the weight loss from calving. Farmer A4 appraised the system for sending through a list of bulls that should avoid breeding after predicting the possibility of defects. A more vivid demonstration of the system's suggestive actions is that the speaker in the cowsheds will directly instruct farmworkers on the activities that need to be taken for that individual cow when the cow was at the rotary parlour.

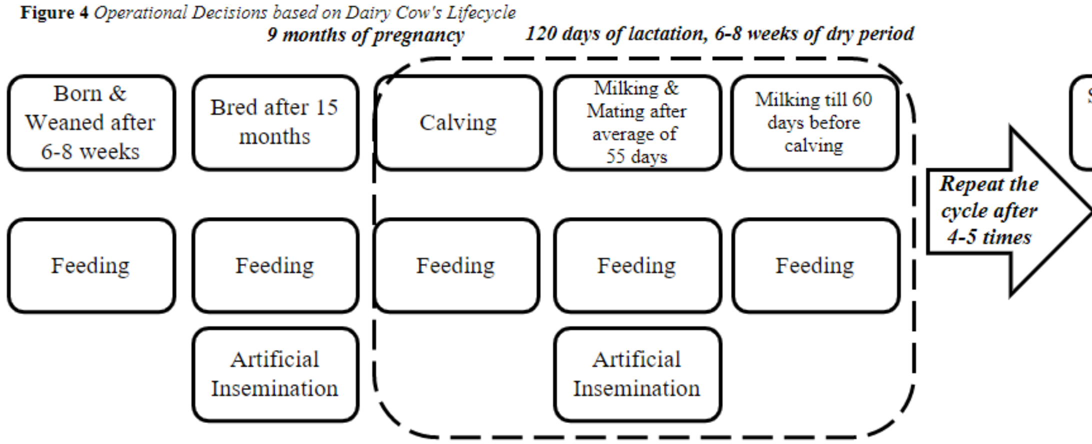
4.3.3 Summary

PLF systems use sensors to collect real-time data, process, and present quantitative and qualitative information to support farmers' decision-making. Quantitative information such as machine-generated data from parlour's *milk analyser* breaks through the traditional customs from understanding performance through quarterly herd-test reports to daily PLF system reports. Historical data, both quantitative and qualitative, give farmers the ability to identify the pattern, issues, or associated relationships to predict future performance. PLF systems' auto-generated calculated and benchmarking information speed up the data-interpretation process by putting the data into context. The PLF systems compare current performance against its past, peer, and other herds and alert farmers to abnormality through a visual assistant in the parlour or visual qualitative information such as colour-coded tables and graphics on the system's dashboard. Additionally, PLF systems allow farmers to record special events and add notes attached to individual cows, so farmers do not need to check the information across different platforms when they make decisions. Finally, PLF systems provide suggested actions when specific attributes meet the threshold through the system's embedded decision-making algorithm or farmers pre-setting.

4.4 LIVESTOCK RELATED OPERATIONAL DECISIONS

Farmer A5 introduced the notion that farmers need to make different decisions depending on the season's priority. As shown in Figure 4, the top three decisions farmers make regularly are feeding, breeding, animal health-related treatments. Most farming operational decisions are structured and semi-structured. Structured decisions (such as choosing the optimal feed amount to maximise the feed-to-yield or choosing the best performing cows to breed) can be answered by the computer systems' algorithms. Semi-structured decisions, such as identifying the best feeding recipe or the choosing when to dry off the cows, require systems' calculation and human judgements. Unstructured decisions such as deciding to add new ingredients to the feed or changing from frozen semen or sexed semen primarily relies on humans' judgements. Farmers would only ask for external support from the vets when they cannot identify the problems or solutions with the systems and experience.

Figure 4 *Operational Decisions based on Dairy Cow's Lifecycle*



**Health treatment is performed regularly based on the observation of any abnormal behaviours or the animal*

4.4.1 Feeding

While different seasons have changing priorities, as expanded on by farmer A5, feeding is the most fundamental animal-related task on the farm throughout the year. Farmer A6 stated that knowing what to feed in what quantity will affect feed efficiency and milk quality. System-one farms are self-contained, with no importing supplements; system-two to -five farmers will either import feeds or send their cattle to other farms for feeding (DairyNZ, n.d.-a). Farmers such as A2 paid another farm to feed the heifers before they are ready for milking. Farmer NA explained if pasture is the main feed, farmers rely on the weather forecast to decide how much to feed, where to move the cows and at what pace to guarantee that there is enough feed across different seasons. Corporate farmers decide how to move the animals across different grazing zones based on the forecasted pasture growth using the company-owned weather forecast station.

Farmer A3 and A4 commented that even though the parlour enables them to individualise the feed, they choose to mainly feed with the pasture because of limitation of time and budget. Farmers A5 and A6, who feed at least 30% of supplements to their animals have three feeding methodologies: 1) herd feeding at the pasture, 2) group feeding using the feed bunker, and 3) individualised feeding at the parlour. As explained by farmer A5, farmers can feed cows for up to 2kg at the parlour but 5kg at the feed bunker, which is why many farmers chose to feed the bulk supplements in groups instead of individually. Furthermore, Farmer A6 pointed out that to excel on feed-to-yield efficiency, the tricky question is how farmers can adapt the feed ingredients and volume based on the cow's body needs throughout the seasons; the change in the body conditions of the cattle will affect digestion capabilities.

Farmer A5 and A6 used the information from PLF systems to run simulations at a feeding DSS to create different recipes. Though the feeding DSS gave farmers individualised recommendations, farmers have different approaches to the suggestions. Farmer A6 used the feeding DSS to test recipes over time to optimise the feeds to generate the highest return on investments. Farmer A5 used the DSS to create three different recipes for three types of cows – springers, milker, and dry cows. The bulk supplements were fed to the entire herd after milking using feed pads. Herd-feed was chosen over individual-feed because the feeding amount is over the capacity of the container at the rotary parlour, and it would be time-consuming to individualise the group supplements. Furthermore, 70% of feeding comes from grass; farmer A5 controls it with another pasture's system to ensure that the animals do not overconsume.

4.4.2 Breeding

Having the best breeds that produce quality milk and having less chance to become sick is crucial for the sustainable development of dairy farms. Farmers can identify the best breeds through the system-generated data such as Breeding Worth, Production Worth, and Lactation Worth; farmer A6 described how they review notes in the system (e.g., health history, drugs intake) to determine if the cows should be culled off (A6, 2021). Farmers such as A4 enrolled on a programme to produce New Zealand's best bulls, which was identified by looking into national ancestry records, DNA testing, and data from the daughter cows (LIC, n.d.-b). Besides being concerned about the best genetics on the farm, farmers care most about getting the insemination process done right to have the correct mix of drying cows, milking cows, and calves. Farmers can raise bulls in the herd for natural mating, or they can conduct artificial inseminations. They can choose between investing on sexed semen to increase the likelihood of reproducing heifers (adopted by farmer A2 and A4), or normal semen. Farmer A6 added that, to increase the in-calf rate, farmers conduct artificial inseminations to the same cattle multiple times after observing heating behaviours. After the ultrasound scanning, farmers can receive a more confirmed pregnancy date from the vet; after that, the vets enter the best-estimated calving date into the system; the system will automatically assign the dry-off date. Having the correct dry-off date is vital as it will affect the performance of the upcoming season – as explained by farmer A2, if drying off too early, farmers can overfeed the drying cows and not enough feed will be left for the upcoming season, especially if the upcoming season is winter when grass growth was much slower.

Farmers A1 and A2 have adopted the collar technology built to detect animals' behaviours, including mating behaviours. However, both farmers keep the traditional methodology – using paint on the tail to identify natural mating behaviours, the reason being that the collar technology sometimes would overlook such behaviours. Farmer A5 emphasised that "animal behaviours still rely heavily on human eyes to observe." Moreover, farmers A1 and A2 were the only farmers working on the farm, and they perform milking twice a day. Though the system suggested the optimal hour of the day for artificial insemination, both farmers could only do the job after the morning and afternoon milking activities. Other farmers who did not adopt the collar would keep track of the general calving cycle and animal's heating using the PLF system's information inputted from the vets and observation: PLF systems would notify farmers when the date approaches. Different farmers will react differently to this piece of information: Farmer A3 kept the tradition of choosing only the 10 best cows to inseminate; farmer A5 and A6 would perform this with all the cows ready for insemination.

4.4.3 Animal Health

Ensuring that the animals are healthy will affect animal welfare and the overall economic benefits of the farm. The number of vet visits is proportional to the size of the farm. Farmer A2, a vet herself, can investigate the issue whenever an abnormal behaviour signalled from the collar. Knowing at the right time which specific cow is sick is essential because cattle tend to hide away when they are sick; farmers find dead cattle in farm corners. Moreover, farmer A6 mentioned that knowing the origins of the disease will stop the infection from spreading across the entire herd and save nearly half on medical costs; similarly, farmers do not need to vaccinate the whole herd if they know which cattle specific should be vaccinated. To better control mastitis, farmers A5 and A6 used the somatic cell count to track clinical mastitis and a separate system to track sub-clinical mastitis.

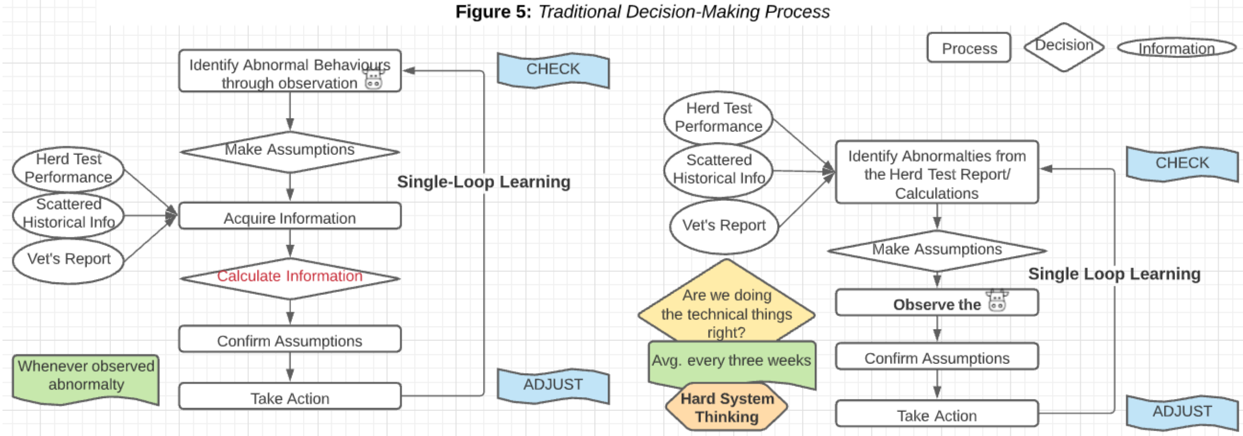
Out of all farm activities, animal health treatment is the one that is consistently applied individually, given the individual recommendation suggested by the systems. Using the somatic cell counts embedded in the rotary parlour system, farmers can detect the mastitis earlier and apply vaccines to individual animals. Farmer A2 expressed: "Instead of applying vaccines to all animals, we saved lots of money by applying it to individual ones." Moreover, PLF systems support farmers in tracking the animal family's health history, which helps farmers make difficult decisions on which individual animal to cull out of the herd. Farmer A6 talked about how he and the other farm manager discussed culling decisions one by one with all data pulled from the PLF system. They consider both quantitative information (performance, weight), and qualitative information (genetics, family health history) to decide which individual animal to cull.

4.5 DECISION-MAKING PROCESSES

Farmer A6 said the PLF system is *a* virtual labourer that is irreplaceable and plays a crucial role in the farm's operations. Farmer A6 has developed a systematic way of decision-making using data generated from the system: 1) receive reports from different departments to identify abnormalities; 2) drive around the farm to observe the conditions of the cows; 3) co-create the solutions with stations' managers; 4) move across different stations to ensure that the solutions delivered are consistent across all stations. When it comes to more difficult decisions (i.e., culling) farmer A6 will have formal meetings with another farm manager, during which they look through various data from the system to make decisions. The system is like a trustworthy and efficient virtual labourer that can accurately report the real-time status of the farm to support operational decision-making.

Figure 5 and Figure 6 show the decision-making process before and after the adoption of PLF systems. Traditionally, farmers could identify abnormalities only through observation or the quarterly herd-test reports before creating solutions, which is a process of *single-loop learning* where decision-makers adapt their actions based on the difference between actuals and expectations (Chiva, 2017). PLF systems enable farmers change from reactive to proactive problem-solving approaches by providing real-time data to reflect the reality and alerting abnormalities through daily system-generated reports. The PLF system's decision-making processes enable complex systems thinking because of the integration of information on one platform. With more information available to challenge traditional assumptions, PLF systems encourage double-loop learning by giving farmers the capability to plan and confirm assumptions using the platform.

Figure 5: *Traditional Decision-Making Process*



Traditionally, farmers need to identify illness symptoms and correctly score observed sickness for the vets to prioritise treatments to the animal: a score of 2 is a moderately lame cow that walks with short strides, a

3 is a severely lame cow that cannot bear weight on the affected limb (Coffey, n.d.). Detecting sickness merely through observation can be limited especially when there are hundreds or thousands of cows on the farm. Herd-test reports help complement farmers' visual limitations: if the milk contains high somatic cell counts, farmers will ask the vets to provide treatments for mastitis. Farmer A6 said if the herd test report shows that the milk's fat percentage increases, they would usually adjust the rations or the recipe because experience showed that higher fat percentage was associated with weight loss.

Figure 6: *PLF-Systems' Post-Implementation Decision-Making Process*

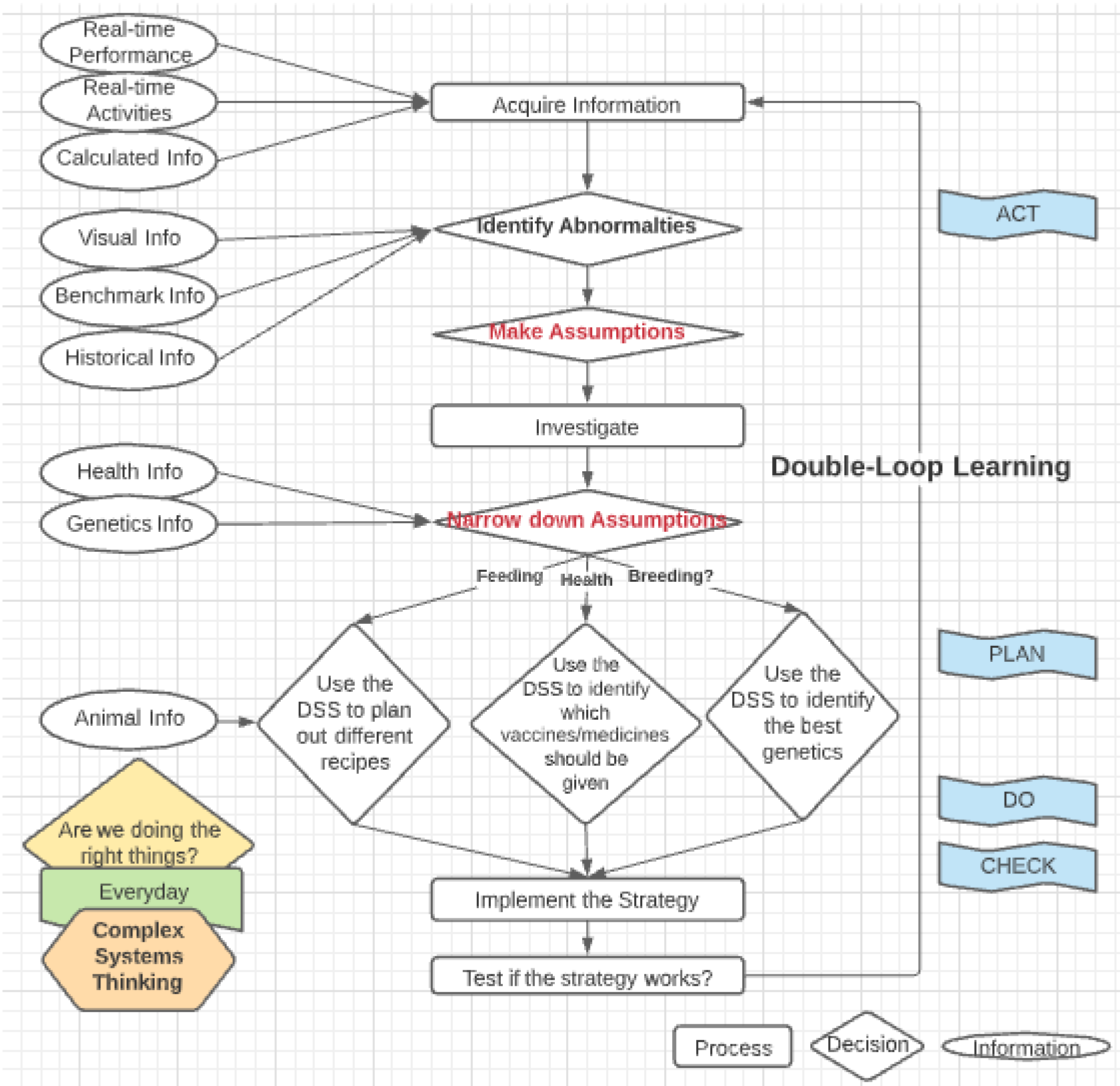


Figure 6 shows how PLF systems encourage farmers to move from thinking about "doing things right" to "doing the right things" by enabling the reflection process where farmers create and narrow down assumptions with data in the PLF system. Farmers such as A5 and A6 use DSS to create new solutions to before using system-generated data to test and confirm the assumptions. Such a process potentially prevents farmers from jumping to conclusions without knowing the root causes and expands possibilities. The following is a detailed, step-by-step decision-making process with the information from PLF systems based on Figure 6.

4.5.1 Acquire Information

Simple-to-Navigate Queries

Farmer A6 appraised PLF system's query tool as being flexible, simple, suitable for farmers' needs, and accurate in giving answers. The PLF system can answer queries as general as "Give me a list of low producing cows" and as specific as one with a combination of multiple characteristics (i.e., somatic cell count, body condition score, milk yield). Waikato Milking System (n.d.) provides an easy to navigate query table that allows farmers to select from a list of characteristics and input the threshold.

Easy-to-Customise Reports

Farmers have access to various reports generated from the system, including animal performance, drafting, sensors report (bulk somatic cell counts graph, health indicators, herd production, lactation, last milking) (LIC, n.d.-a). Farmers can *choose which measurements to show* in each report, such as showing yield instead of milk solids for the milk production report. Farmers can use easily *sort* the results within each report based on different factors, such as milk solids, yield. Farmers can also *adjust the date range* to identify trends over different periods. Farmers can customise their reports and download them for offline review. Instead of waiting for farmers to get the data and do the manual calculation, the self-generated measurements (breeding worth, production worth) make it more consistent, efficient, and accurate for farmers to obtain the information.

4.5.2 Identify Abnormalities

Graphs with Benchmarks

Besides showing the raw data on the side, the PLF system uses the "High" "Med" "Low" "Error" bar chart to indicate where the current performance is at and how many cows in the herd fall into each category (LIC, n.d.-a). Moreover, the systems show graphics that compare the current performance with historical performance and other benchmarks (i.e., individual animal's performance trend, whole herd's average performance, top and bottom 5%). The side-by-side trend line comparisons make it easy for farmers to identify how individual animals perform compared to themselves and their peers (too high, too low, average).

Visual and Audio Alerts

Protrack® PLF system provides standard alerts (i.e., blood in the milk, critical somatic cell count) for farmers to choose from and enables farmers to customise the alerts. Farmers can pre-set the alarm in the system, such as one when "the yield dipped 40% below her 14 days average" or when "previous milking's conductivity spikes as compared to her 15 days average" (LIC, n.d.-a). Farmers can change the system's setting to specify a colour for different warnings and to choose the alert audio between voice (customise what the computer should say such as “feed me more,” “feed group”) and tones (i.e., duck, cha-ching, doorbell). The system recognises the cow after matching the cow’s EID and the bail number and communicates (visually or verbally) to farmworkers if any treatment needs to be done to the cow identified with the bail number. As farmer A6 demonstrated, the system would announce a command such as “Bail number xxx, production worth has dropped significantly, and somatic cell counts increase by x%, please review the cow’s condition.” Red colours or any other specified colours are filled in the data cell in the report table to indicate abnormalities in the health indicator report. Because several characteristics and “number of alerts in the past 30 days” are shown in this report, it is easy to identify individual animals with more than one red flag and which require farmers’ special attention.

4.5.3 Make Assumptions

After receiving the alerts, farmers use their knowledge and experience to determine whether the performance is indeed abnormal and then make assumptions on the possible reasons. Farmer A6 explained cows’ fat percentage tended to rise when they lost weight; it was typical for cows that had milked for a long time to had dropping yields, but if the drop was abrupt, it became abnormal. Farmers can determine if the problem comes to the whole herd or the individual animal by comparing with the benchmarks. Farmer A4 showed how assumptions were made on the possible treatments on a certain day (i.e., the quantity of food, food recipe, vaccine treatment, heating) that contributed to the abrupt change by comparing the performance over different time ranges. Farmers can cross-examine the information generated from the PLF system and vet’s uploaded data to identify the possible health-related causes. An example given by farmer A4 showed that the system could experience error in getting the right data when the cattle kicked off the milk cups during milking.

4.5.4 Investigation

Farmers will investigate the problems by first examining the cows’ condition. The most common things they check are the cow’s dung, coating, grass levels. Farmer A6 said they observe these conditions to understand the digesting situation of the cow (any food waste or signals for sickness), the feed level (food supply), and the heating behaviours every single day. Farmers can capture information that the system might miss through double-checking through observation. Farmer A2 said although using the collars could monitor the real-time conditions of the cow, farmers still prefer seeing and touching the animals on the farm; the PLF system functions as a supporting tool to testify against the observations on the farm. Some farmers trust more in what they see on the animals than the data from the system. Business Analyst A3 found that some of the best-performing farmers did not rely much on the data from the PLF systems.

Therefore, investigation plays a crucial role in farming operations to cross-examine if the data on the system is correct and to catch information missed by the system.

4.5.5 Narrow down the Assumptions

Self-reflecting is a crucial step in double-loop learning, which is a reflective process that challenges the management team's mental model or theory behind the actions (Kim et al., 2013). In this step, farmers combine the information from the systems and the observed information on farms to challenge their original *mental models* and nullify any wrong assumptions. As explained by business analyst A3: farmers with more information have the advantage to cross-examine data from multiple sources and collect evidence to support their reasoning; on the other hand, farmers can get overwhelmed with too much information and end up choosing to decide with their instincts instead. Farmer A4 added that if they were still unsure about the possible cause after the cross-examination between the PLF system and observation, they would get the vets to come in to examine the situation. Instead of waiting to confirm the root cause, they will narrow down the possibilities and start trying some new changes. After testing with different treatments, farmers can then confirm the root causes.

4.5.6 Alternative Solutions Generation

Farmer A6 explained that if the diet was the assumed cause of malperformance, farmers would generate alternative recipes using the DSS. Farmers can add different ingredients to create a new recipe in the DSS. The DSS uses the traffic-light colour code to visually indicate if the designed recipe meets minimum dietary requirements. Besides this, the DSS also shows red warning messages when certain nutrients are too low/high and or there is high risk of ruminal acidosis (Rumen8, n.d.). This system helps automatically calculate evaluation criteria such as the feed efficiency and margins for farmers to compare the additional benefits of the different recipes. The prerequisite of producing the precise recipes is that farmers can enter the accurate individual cow's performance (milk yield, milk solid, live weight, etc.) and accurate external data (milk price, feed costs and nutritional information). The more precise the inputs, the more accurately the DSS's outputs will support the animals' diet management. Therefore, the PLF system plays a crucial role in developing effective alternative solutions that meet the minimum requirement and optimise the performance with the self-generated measurements to support the decision-making.

4.5.7 Alternatives Evaluation

DSS allow farmers to store and compare their own designed recipes to facilitate the evaluation process. Instead of manually calculating key measurements to evaluate the solutions, farmers can review the calculated measurements generated from the system. Rumen8 shows the calculated measurements to support the evaluation: feed costs (e.g. $/t DM, $/MJ ME), milk income (e.g. $/L raw milk, $/kg ECM), feed efficiency (e.g. kg ECM/kg DM, gm MS/kg DM, $ Milk/$ Feed), margin (e.g., $/cow/d, feed percentage income) (Rumen8, n.d.). Such information is calculated consistently through the embedded algorithms from the DSS. The accurate and efficient measurements help save time for farmers performing the calculation manually or in correcting errors. Farmers can directly evaluate and compare alternative solutions to quickly identify the most cost-efficient one to generate the maximised outputs.

4.5.8 Implementation and Testing

The decision-making process becomes agile because farmers can see the results one day after trying a new recipe. With the support of the milk analyser, the PLF system can directly record the testing results (e.g., milk solid, somatic cell counts) and compare the performance from the day before. With one day being the average lead time to see the results, farmers can test and trial different alternatives in a more efficient learning cycle. If the new recipe does not improve the performance, farmers will repeat the steps to adjust the recipe on the DSS programme and review the results on the PLF system until the problem is solved, which encourages double-loop learning. The AfiMilk® system indirectly supports the loop-back capabilities to adjust feed for individual cows based on milk yield (Berger & Hovav, 2013). If the performance still does not improve after multiple failures, farmers will change to another strategy or invite vets to examine the situation.

4.5.9 Summary

Key livestock-related dairy farm's operational decisions range across feeding, breeding, and animal health. Farmers should think systematically to maximise the dairy cows' value from milk production and reproduction while maintaining good animal welfare in the changing environment (weather, price and cost changes). Farmers who adopted PLF systems have changed from the traditional, reactive problem-solving approach in which they detected abnormality through observation and quarterly herd test reports. PLF-system-adopters can observe any deviations through the daily system-generated reports and cross-examine the data with the observed reality. PLF systems encourage farmers to move from single-loop learning to double-loop learning because of the increased availability of data and the computer's algorithms that alert farmers with traditionally overlooked information. Compared to the traditional decision-making process where farmers act based on the assumed interpretation of the herd-test data, the new process includes the assumptions-testing step. Farmers can use DSS and PLF-system-generated data to test and challenge traditional mental models to develop new learnings. Using PLF's data to run simulations on DSS, farmers can design innovative solutions tailored to the current reality. After that, farmers can test the results by reviewing the changes in the system-generated data.

4.6 BENEFITS OF USING PLF SYSTEMS' INFORMATION

In general, farmers have reported that the overall performance has improved since the adoption of PLF systems and DSS. The common benefits they mentioned are: 1) saving time, 2) reducing costs, 3) improving performance continuously, and 4) adapting to changing environment.

4.6.1 Saving Time

Farmers who used the AfiMilk® system reduced milking time by approximately 40-50%, on account of the ability to draft out cows into different pens automatically (Berger & Hovav, 2013). Moreover, the remote monitoring capability through the online system reduces the need for farmers to be physically present on the farm to locate, seek, and manage large herds (Berger & Hovav, 2013). Farmer NA saved time weighing in and updating individual cow's data into the system. With the parlour and milk analyser installed on farms, farmers also saved time capturing the technical performance information (i.e., milk solid, somatic cell counts). Without waiting for an external company to examine the herd's performance four times a year, farmers can collect the information themselves through the milk analyser at every milking. Because of the frequent performance measurements, farmers can detect signals of problems earlier and act more proactively. Besides being efficient in capturing more precise and regular performance measurements, farmers can instantly test treatments by running simulations with DSS. The DSS help farmers to run different scenarios and complicated calculations to produce consistent, accurate, and efficient results. Such systems allow farmers to skip the prolonged calculation process and quickly build a new recipe that meets minimum requirements (i.e., nutrition, budget). Farmers can see the results in one to three days from cow's performance and behaviours with the support of the milk analyser. Additionally, farmers saved time providing health treatments to cows; instead of waiting for observable symptoms of disease to appear, farmers can start providing treatments by detecting high milk's somatic cell counts, abrupt change in milk performance and weight drops. Such a proactive approach reduces the time to detect abnormalities and early signs of disease and reduces the time through applying treatments to the entire herd rather than to individual animals.

The collaboration between humans and computers is strengthened when the systems are no longer being used purely for storing and analysing data but as "virtual labour" to instruct workers on the farms. The smart sheds integrated with farmers A4, A5, and A6's farms PLF systems instruct farm workers on what needs to be done with the individual cow on the rotary parlour. It will notify the farmworkers when it is time for artificial insemination and farm workers will draft out the cows to perform the job. The vets come to the farms to do the ultrasound scanning and input the expected calving date into the system and the system will automatically draft out the cows when the date approaches. Suppose a farm worker judges, from their experience, that the data from the system for a cow were wrong? In that case, the farm worker will mark the system without stopping the rotary parlour, and the worker in the next shift would draft out the cow to investigate the issue. The traffic-light visualisation graph in the feeding DSS allows farmers to compare the customised feeding recipes regarding diet, animal's health, milk price, and feed costs. Such a system supports farmers to optimise the feed to achieve their feed-to-yield objectives in a cost-efficient way. Moreover, farmers can avoid the weight loss from calving by inputting the predicted weight loss to the system to calculate the correct number of feeds.

4.6.2 Reducing Costs

The automatic PLF system saves at least one-labour cost per farm shed: the *electronic readers* and the automatic drafting gate save the costs of paying a farm worker to record the individual cow's conditions (weight, milk performance) and direct the cows to different pens; the smart shed function as a "virtual labourer" that instructs farmworkers on what needs to be done with the individual cow on the rotary parlour. Such automation minimises costs from human errors produced from manual records and miscalculations or vice versa. An example given by farmer A4 illustrates how the computer compensates for humans' limitations: the computer caught a significant weight drop in lame cows that could not be identified through human eyes. Besides reducing costs from errors, PLF systems enable farmers to reduce the opportunity costs of time spent from non-value-added logistical tasks to value-added tasks such as investigating the bottleneck of the farming operations and creating solutions. Getting the right breeding time can also reduce wastes of artificial insemination, which costs $17-27 per insemination (LIC, n.d.-c). The collar that connects with the PLF system will notify farmworkers when it is time for artificial insemination through the speaker in the smart shed. Farmers can then command the system to draft the animal out for artificial insemination. Such human–system collaboration reduces the costs of missing the prime time for breeding. Furthermore, because the system can automatically draft out the cows through three gates, farmers can quickly investigate the problematic cows by looking into the individual's performance and health history before identifying the solutions. Because farmers can detect mastitis earlier, they can identify which cow is the source of the disease and save the costs of vaccinating the entire herd. By tracking an individual animal's family history, farmers can identify animals with higher milk-to-yield efficiency and lower disease risks and reduce waste on breeding unproductive and sick cows. Business analyst A3 added that the feed budget tool embedded in the PLF system is efficient in managing the feed costs. With the precision information to support decisions, farmers can reduce costs that they could not prevent before.

4.6.3 Improving Performance Continuously

Farms who adopted PLF had shown significant improvements in farming operations compared to farms without PLF with improvements in daily milk production, fat and protein and calving success rate by 1.2, 0.08, .07kg, and 8.4% (Tomaszewski et al., 2000). Instead of waiting for the quarterly herd test to understand milk solids and somatic cell counts information, farmers have access to the daily milking performance with the milk analyser installed in the smart sheds. The more farmers measure their performance, the better they can understand what they can improve on. The change from quarterly measurement to daily measurement enables farmers to reflect on the daily performance and test against different treatments to improve continuously. The automatically calculated benchmarking information from *real-time* data supports the reflection process by alerting identify potential issues requiring attentions. PLF systems compare individual performance with its benchmark (i.e., weights from the last 10 days) and peers' benchmark (i.e., average real-time herd performance). Traditionally, farmers pick up abnormalities through observations and simple calculations, and could easily miss unapparent issues. Such quarterly benchmarking information is also outdated and can be misleading because of the number of different treatments given to the herd over the three months. Having real-time benchmarks enables farmers to understand current performance better, reflect on their daily farming practices and make changes. Farmer A6 used the real-time benchmarks, either generated by the system or created by him, to divide herds into groups and test different treatments such as feeding recipes, bull semen and health treatments. Through the queries at the system, farmer A6 found the threshold (i.e., the quantity of the milk produced) that can divide the herd evenly and reasonably. After that, farmer A6 designed controlled treatments and gave them to the controlled groups. PLF systems that track individual animals from farm to sheds enable farmers to manage the other affecting factors (i.e., resting location, vaccines), resulting in a more accurate conclusion of the relationship between performance and the controlled treatments (i.e., new recipe).

4.6.4 Adapting to Changing Environment

Farmers can continuously learn and optimise solutions to adapt to changing environments with the PLF systems and DSS. PLF systems function as databases that hold raw data and analytics information to support farmers' decisions. DSS help reduce the uncertainties from changing environments by enabling farmers to run simulations to produce calculated measurements to assist in decision-making. Traditionally, farmers could only estimate the general correlations between herd performance and treatments by comparing the performance change from different controlling factors (i.e., feeding amount, drafting timing, mating bull) every quarter after the herd test. As a result of the implementation of PLF system and DSS, farmers have daily evidence to determine the relationships between performance and daily treatments; farmers can also dissect multi-factor causal relationships by controlling all other factors and comparing the results within two to three days. By classifying the herds into different groups based on the characteristics (i.e., milk production, somatic cell count levels) and comparing the correlations, farmers can identify the trends, outliers, and optimal treatments. With the enhanced understanding of the causal relationships, farmers are more flexible and adaptable to changing environments. Additionally, DSS support farmers perform complicated calculations to identify the optimal solutions in different scenarios of changing environments.

PLF systems enables DSS to generate more accurate measurements for decisions by providing real-time data such as days of pregnancy, live weights, and milk fat percentages. DSS use the embedded algorithms to predict performance of certain treatments. Farmers can learn from farmer A6 to use the DSS to calculate the optimal feeding amount to individual animals to prevent weight loss due to calving. Because of the change in cattle's digestive capability in different seasons, farmer A6 used the DSS to try different recipes to adapt to the change that can maximise the feed-to-yield efficiency and minimise waste.

4.6.5 Summary

PLF systems help farmers do operational work on farms more efficiently by replacing at least one human labour cost and complementing human's physical limitations through observing on-farm 24/7. The systems replace logistical work time for more time to reflect, design and test new solutions. With PLF systems and DSS, farmers can create new solutions using complicated mathematical models and test the solutions in one to three days. Because of the ability to use the information generated from PLF systems to understand the situation in real-time, farmers gain more control of the changing factors (genetics, sickness), which empowers them to be more resilient to the changing environments.

4.7 BARRIERS TO REALISE THE BENEFITS

Farmer A4 explained the interaction between human and system, "it is like any technology, what comes out is probably only as good as what you put into it, and then it is only as good as how well you apply it." People can make incorrect decisions because the information they had was incomplete, erroneous, or misinterpreted.

4.7.1 Difficult to Integrate with Other MIS Systems

Only two out of the six interviewed farmers used one integrated PLF system. The majority of the farmers have adopted more than two systems to manage information for different purposes: tracking genetics and animal movements, detecting mastitis and/or mapping the farm. One PLF system is recommended by DairyNZ (n.d.-e) as they provide the nationalised evaluation measurements such as breeding worth, production worth and body condition scores. Though farmers already have one PLF system running, they may choose to adopt another one because the other system helps them comply with the national health and safety regulations and schemes such as National Animal Identification Tracing (NAIT). Farmers may not want to replace one with the other because of the sunk cost of the existing on-farm equipment such as the rotary parlour, the smart shed, and the automatic gate that were all connected to the old system. Business analyst A3 expressed concern over maintaining data accuracy and consistency across multiple systems as each PLF system has its own interconnected network that does not communicate with the other. Each system also has its unique algorithm and frequency (quarterly, monthly, weekly, daily) of data collection to produce measurements to reflect the farm’s performance. Without having all information in one PLF system, farmers or business analyst will need to cross-check the data to understand the actual reality before utilising them to produce valuable insights. Such information overload from multiple sources can overwhelm farmers to filter out irrelevant information, take away time to manage the farm, and cause confusion. As the business analyst A3 said, without “one accurate source of the truth,” farmers may eventually give up using data from the systems and decide with their instincts.

4.7.2 Lack of Quality Data

Having more accurate and consistent data is crucial to create quality insights to support operational decisions. Business analyst A3 showed how 10 years of historical trends could be irrelevant if the previous data were not captured accurately. DairyNZ (n.d.-e) suggests that using precision technologies to measure animals regularly and keeping track of all *kinship’*s performance can help produce a more accurate breeding value of a bull, which will affect the breeding decision. In other words, the earlier the farmers implement the integrated PLF system, the more accurate insights they can produce to maximise the benefits of the information generated from the systems. Besides restricting from a short period of implementation, PLF systems’ value can be limited without consistent information collected from all areas (feeding, breeding and animal health). Suppose farmers only have precision records of one area of the farming operation. In that case, they can easily be stuck with linear thinking and lose sight of how other factors interact with the system and evolve with the environment. However, farmers also need to avoid collecting too much irrelevant data that may confuse false statistical relationships. Statistical relationships can be drawn between unrelated factors such as the height of the grass and the animal’s somatic cell count. Farmers should use experience and instincts to judge the relevance of the information and distinguish between symptoms and root causes. Business analyst A3 said, “the biggest problem is that we try to collect everything, and we virtually use nothing from it; because there is too much to process from different platforms, we are not sure how to do with it”. Thus, PLF systems-generated insights can be limited by the length of usage, the amount of data collected, and decision-makers’ ability to determine relevancy.

4.7.3 Lack of Accurate Human Input

PLF systems’ information values are restrained by human inputs because, occasionally, there are computer errors or unexpected events such as when the animals damage the sensors. Outliers can skew the information because of such systems errors, which is why farmer A6 has built the standard operations procedures to ensure that farm workers can fix the systems errors and investigate the problems in real time. Besides, if the farm uses multiple PLF systems, humans’ accurate transition of the data from one system to the other will affect the quality of the output from another system. Farmers should develop habits to doubly confirm the data’s accuracy after transitioning data in order to avoid making decisions on wrongful data caused by human error. Human error can significantly impact the entire operations for the current and upcoming seasons. Most farmers depend on vets to determine the Body Condition Scoring, a visual assessment of the cows' body fat on the bones, which affects mating or post-calving decisions on how much to feed and when to dry off (DairyNZ, n.d.-c). Without farmers' qualitative inputs such as health information, decision-making with only quantitative information can be problematic. Making decisions without farmers' qualitative inputs such as health-related information and use of only quantitative information can be problematic. An example is that if farmers think the cattle are performing poorly and decide to feed less food, but then the cattle become pregnant and need more food. In addition, PLF systems' automatic functionality's effectiveness also depends on human input. Farmers can pre-set the threshold of a particular attribute to trigger the system to show different visual or audio messages (colour intensity, commands at parlour). If the pre-set threshold is too high or too low, cattle with issues can be hidden in the crowd, and resources can be wasted on non-problem cows. Farmers should also choose easy-to-understand colours to alert farm workers to avoid confusion. The audio commands at parlour should also be direct and succinct for farm workers, given that there are hundreds of cows that go through the parlour twice a day. Undoubtedly the co-dependent relationship between humans and computers will affect the maximised values of PLF systems' values.

4.7.4 Summary

Because of the difficulty of integrating information across multiple systems, errors can occur when farmers copy and paste data from one system to another, increasing the time for data analysis and affecting the outputs' accuracy. If farmers adopt multiple PLF systems, farmers can become disoriented without "one source of the truth" and not using the systems' information to make decisions. Additionally, without adequate historical data, PLF systems' generated insights can be biased towards most recent factors such as new feed and fail to recognise the influence from other general factors, such as genetics. Without accurate human input, PLF systems are also limited in their ability to produce accurate information to support decision-making. Knowing the barriers to realise the full benefits of information generated from PLF systems can help future adopters learn the lessons and improve the operational procedures to reduce the impacts from these barriers.

CHAPTER 5 DISCUSSION

The secondary research of multiple PLF systems provides the groundwork to understand how PLF systems theoretically support farmers to make decisions. The six farm cases, along with the insights from one information analyst, one business analyst, and one PLF system customer service manager provide the primary data to understand how farmers are using the information to improve their farming decisions. The author combines the theoretical concepts (bounded rationality, systems thinking) to discuss how PLF systems' information supports farmers' decision-making.

5.1 HOW PLF SYSTEMS EXPAND BOUNDED RATIONALITY

Bounded rationality states that decision-makers are not entirely "rational" to make the best decisions because they are bounded by limited information, time, and their own cognitive capability (Simon, 1997). As a result, people tend to stop looking for other options when they find the first *satisfying* alternative that meets the minimally acceptable criteria (Nielsen, 2011, as cited in Lunenburg, 2010). Moreover, people usually approach problems with heuristics, which includes common sense, rule of thumb, and intuition (Krabuanrat & Phelps, 1998). Systems thinkers approach problems by reviewing the entire system, and analysing the inter-relationships between different parts of a system (Eisner, 2011). Complex Systems Thinking (CST) combines hard systems thinking (focus on the *matter* to determine the cause–effect relationships) and soft systems thinking (focus on the *mind* to perceive the world to accept multiple ways of interpretation) by embracing the uncertainty of the changing environment, and accepting different perceptions; it states that there is more than one coping strategy to solve problems (Schiere et al., 2004).

CST acknowledges that parts of the systems interact, learn, and change together with the context; such trade-offs between resources in the systems in a changing environment make it impossible to use the cause–effect relationships to determine one optimal solution. The *co-evolution* of the system and the context requires a mindset change from having one static solution to developing a combination of coping strategies (Schiere et al., 2004). CST agrees with *bounded rationality* theory that it is impossible to have one optimal solution; however, it seeks to expand the boundary by reflecting on assumptions, choosing priorities, and creating new mental models to adapt to the changing environment. By constantly challenging the existing mental models for improvements, CST fosters the growth of double-loop learning. Double-loop learning involves reflection on the assumptions and correcting the fundamental standards, rules, and objectives, enabling an organisation to adapt and survive in changing environments (Bhatt, 2001). By becoming more self-aware of the assumptions and unconscious beliefs, decision-makers admit their limitations, learn how their actions affect this system-contextual dynamic ecosystem and eventually make changes to the rules, which is crucial for expanding bounded rationality.

PLF systems enable CST and expanded bounded rationality by providing more information, enabling more agile decision-making, and reducing human biases. The systems give farmers capability to understand the current situation better, to exploit information (quantitative and qualitative) from the past to explore possible inter-relationships and root causes of the problems. With the accurate real-time information from PLF systems, farmers can run simulation and what-if scenarios in DSS to predict outcomes, which complements farmers' limited capacity to run complicated mathematical models to make predictions. Moreover, PLF systems enables single-loop and double-loop learning. In single-loop learning, decision-makers adapt their actions based on the difference between actuals and expectations (Chiva, 2017). The drafting gate of PLF systems automatically draft cattle when a certain threshold is not met is an example of single-loop learning. PLF systems develop double-loop learning when they provide the integrated platform for farmers to, not only answer queries, but also the space to challenge and confirm their assumptions. Instead of looking at each operation (feeding, breeding, health treatments) independently, farmers are more likely to review the interactions of operations and the long-term impacts (animal welfare and environmental impacts). The ability to reflect on assumptions to develop new learnings and changes is a demonstration of double-loop learning. The following provides more details and examples of how PLF systems expand bounded rationality.

5.1.1 More Information

Farmers without PLF systems will have difficulty collecting the most up-to-date information to evaluate real-time performance and decisions. Instead, they must seek out all relevant information either through herd-test reports and observations. Herd-test reports only produce data such as the volume of the milk, fat percentage, protein, lactose, and somatic cell counts (LIC, n.d.-d). With only limited information available, farmers rely on observations (behaviour, skin, dung) to make decisions. Observations can be subjective and skewed depending on the observers' experience. Farmer A4 shared that the vet's wrongful judgement on the body condition score of the cattle could lead to underperformance of the upcoming season because of early calving. Having Internet of Things (IoT) sensors to determine the situation is crucial; farmer A4 also talked about how humans could not observe the significant weight drop from a lame cow. PLF systems' technologies complement humans' limited capability to capture real-time data 24/7 objectively and provide more well-rounded information. PLF systems integrated machine-generated data, historical information, vets' data, and farmers' notes on special events into one platform. Given so much information, farmers would have to select relevant information carefully because the selected information is only useful when combining several data sources and arranging them into understandable indicators (hindsight: patterns, foresight: predicting outcomes) (Martin-Clouaire, 2017). PLF systems help ease this process by automatically converting all relevant, raw data into understandable information: producing evaluation criteria (breeding worth), graphics (hindsight, colour-codes) and suggested actions (foresight).

In other words, PLF systems expand the amount of information for consideration and process it into relevant and comprehensible reports, which extends the 'limited-information boundary' stated *by* bounded rationality theory.

5.1.2 More Agile Improvements

Traditionally, farmers could identify abnormalities only through observations or quarterly herd-test reports and start solving problems when they appear. Using IoT sensors, farmers can record and detect both evident and inconspicuous abnormal behaviours whenever they occur. Before issues become serious, farmers have already taken action to minimise the negative impacts on the farming operations. Farmer A5 took samples of the milk, cultured these, and used the DSS tool to identify the specific strand of mastitis and pairing treatments. With such DSS, farmers can detect the disease earlier to limit the time lost on identifying the source of the infection and financial loss from the spread of the disease. Farmer A6 said it would only take him five minutes to review the customised PLF reports at different stations; if nothing seemed wrong, farmer A6 would move on to the next station and check the condition of the cows on the farm. Besides saving time waiting for symptoms to appear, farmers make faster decisions with the already processed information generated by PLF systems. Skipping the logistical steps to manually calculate data and cross-examine any human error in the calculations, farmers can prioritise validating a system-identified issue and determining the root cause and solutions. Furthermore, farmers are empowered to test different solutions using DSS and PLF. By inputting PLF systems' information and external data to run through various DSS, farmers can design and compare possible solutions in hours. Because PLF systems show daily treatment results with machine-generated data, farmers can see the testing treatment only in one day. Such agile interactions among farmer-PLF-DSS speed up the continuous improvement process (plan-do-check-act) from months to days. The change from reactively waiting for malperformance shown on cows to proactively optimising solutions enables more agile developments and expands bounded rationality.

5.1.3 Less Bias

Emotion is the critical differentiator between the rational and bounded rational model (Gigerenzer & Selten, 2002). Levy (1992) suggests that humans are likely to choose a solution because of the fear of negative outcomes; therefore, decisions are affected by individual risk-tolerance levels. Business Analyst A3 mentioned some farmers were more willing to try new strategies and some prefer staying with the normal activities. Humans can be biased with information received earlier in the search process (the primacy effect) or later in the search process (the recency effect) (Lunenburg, 2010). PLF systems can reduce such biases because computers give equal weight to information by comparing past and present data using tables and diagrams (dot plots, line graphs); moreover, farmers can adjust the period to see if identified trends occurred. By allowing farmers to test against historical data and interpretive data generated from new models (Kim et al., 2013), PLF systems also reduce the negative impacts of humans' poor memory. Another source of bias is *bolstering the alternative* (Bubnicki, 2013), in which decision-makers have a biased preference for one solution over another, so they only look for information that fits in with their judgements. PLF systems and DSS standardise the decision-making process by instructing farmers on the pieces of information needed and producing the evaluation criteria and the traffic-light bar charts to evaluate the recipe (Rumen8, n.d.). Such a standardised decision-making process cannot be affected by bias. Furthermore, compared to none-PLF systems-adopters who have access to only limited information from the quarterly herd-test reports, PLF systems-adopters receive more real-time information, which encourages *complex systems thinking*. Farmer A6 talked about the importance of observing the cow's situation to confirm the abnormality shown by the reports. However, without further information from PLF systems (notes of health treatment, calving), he and the manager would have difficulty narrowing down the assumptions to identify the root cause of an issue. Thus, PLF systems help remove subjective biases and challenge the "cognitive-capability boundary" set by bounded rationality.

5.2 HOW CAN PLF SYSTEMS' INFORMATION SUPPORT DECISION-MAKING?

PLF systems expand the boundary of bounded rationality by consolidating real-time all-rounded livestock's raw data into one database and processing the data into useful quantitative and qualitative information for farmers to aid in making decisions. The PLF systems simplify the data-interpretation process by enabling farmers to skip the steps to outsource data, calculate, and create diagrams to understand the performance. They allow farmers to codify the colours and change the colour intensity to represent the seriousness of the problem. The system-generated graphics contextualise individual animal's performance and simplify the data-interpretation process by comparing individual animals' performance against peers' average performance, and the worst performance. Such an automatic analytics process transforms complicated raw data into visual information simplifies the data interpretation and speeds the decision-making process. Farmers can easily identify abnormal behaviours, be aware of the seriousness of the problem, know exactly which individual cow requires special attention, and what actions are needed.

Without PLF systems, farmers were limited to the manually collected raw data, their own calculated information and observations to understand current performance and make decisions. The information generated from PLF systems enables farmers to enhance understanding of their managed livestock and change their decision-making approach from optimising performance of isolated operations (feeding, breeding, and health treatments) to systems thinking. Through observing the interactions among different factors, challenging and reaffirming their assumptions, farmers can create adaptive solutions to *structured*, *semi-structured*, and *unstructured* questions imposed by a dynamic environment. Structured decisions can be made using standard procedures because of its repetitive and routine nature (Paginas, n.d.). Semi-structured decisions can be enhanced with standard algorithms and human judgements (Kaliardos, 1999). Due to their unforeseen nature, unstructured decisions depend heavily on decision-makers' cognitive capability (Mintzberg et al., 1976). Table 2 shows the overview of how PLF systems' information support farmers to make different types of decisions. The following provides real case practices from farmers.

Table 2 *Detailed Quantitative and Qualitative Information that Supports Different Decision Types*

	Quantitative Information				Qualitative Information		
	Machine-Generated Data	Historical Information	Calculated Information	Benchmark Information	Visual Information	Special Events	Suggested Actions
Structured Decision	✓	✓	✓	✓			
Semi-Structured Decision	✓	✓	✓	✓	✓	✓	✓
Unstructured Decision	✓	✓	✓	✓	✓	✓	✓

5.2.1 Structured Decision-Making

PLF systems can be programmed to make automated structured decisions for farmers. Machine-generated data (i.e., heating, somatic cell counts) from PLF systems enable farmers to skip the structured decision-making process and act directly. For example, the collars that collect real-time individual animal temperature and activities information create an onion diagram with colour-coding information (bronze, silver, and golden period) to show the ideal period for artificial insemination. Besides having the PLF systems produce qualitative information such as diagrams, farmers can pre-set the PLF systems to automatically create other qualitative information such as colour code, alert command, and automatic systems' functions. For example, farmers know that cattle with low body condition scores need to be fed more food. They pre-set the command in the PLF system when the body condition scores threshold is not met. Farmer A6 described how the smart shed recognises such a situation. The voice assistant would announce the "feed more" command at the rotary parlour, and the drafting gate will automatically draft out cattle after milking. Similarly, PLF systems that generate somatic cell counts data from the milk analyser in parlours will inform farmworkers to inject antibiotics when such data fall in the mastitis alert range.

Besides having clearly defined thresholds to trigger the PLF systems to alert specific actions, farmers can also set the system to compare current performance with the real-time, system-generated performance benchmarks. The PLF systems expand human's limited cognitive capability by running multiple calculations simultaneously to compare current animal A's performance with its historical and predicted performance and its herd's performance. Based on the real-time benchmarking information, PLF systems can identify abnormality when animal A's performance is significantly different from its performance and its peers' performance; the significance of the difference can be determined by the default systems' setting or the farmer's setting. The process in which the PLF systems, triggered by its machine-generated data, inform farmers to take actions to fix inconsistencies is a process of single-loop learning.

Besides setting automated commands or actions in PLF systems, farmers have the flexibility to run queries to extract helpful information from PLF systems to make structured decisions. For example, farmer A4 used the query function in the PLF system to create a table of top-performing cows. The PLF system answered the query with its calculated measurements (production worth, breeding worth, lactation worth), computed with machine-generated data (milk quantity, protein/fat percentage, conductivity). Similarly, farmer A6 used the query to create a list of problem cows which consistently failed to meet the performance goal (quantity of milk production) and which have poor health history (determined by number of diseases). Thus, information from PLF systems enables farmers to make data-driven, structured decisions.

5.2.2 Semi-structured Decisions

The PLF systems process the "structured" part of semi-structured decisions by converting raw data into easy-to-understand measurements or graphics with its embedded algorithms; thereafter, farmers make the "unstructured" part of the decisions with observations, instinct and judgements. PLF systems provide farmers the ability to make decisions both from the backend (computer), and the frontend (parlour console, smart phone or tablet), which encourages seamless collaboration between farmers and computers.

PLF systems function as a farm assistant at the working station to perform the commanded actions or use visual or audio alerts to remind farm workers of possible activities (drying off, calving) that need to be taken regarding the individual cow. After farmers decide on the recipe or quantity that needs to be fed to individual animals, the PLF systems will automatically perform the feeding tasks. Protrack® (LIC, n.d.-a) recognizes individual animals, matches with the bail they enter and controls the feed head to drop the commanded amount of feed automatically during milking. Farmers can adjust the visual/audio alert command prior to milking; farmers can decide whether to take the recommended actions after observing the cow's situation at the parlour. The parlour console, allowing decision-making during milking at the smart sheds, plays a critical role in enabling such a semi-structured decision-making process. With the cows' data displayed on the parlour console, farmworkers are given the ability to create different groups based on chosen attributes. PLF systems present easy-to-read, colour-coded information (green, yellow, and red) through the interface to alert farmers to abnormalities (Van Hertem et al., 2017). What is more, the operator can input a specific cow's data (calving, heating and mating, culling, drying offs, health issues or status of treatment) into the PLF systems (Waikato Milking System, n.d.). Therefore, such interfaces assist humans to have well-defined control of the system and deliver feedback to humans by displaying information and graphics (Kaliardos, 1999).

Both quantitative and qualitative information stored in PLF systems encourages complex systems thinking and double-loop learning to do normal farming operations and solve emerging problems. For example, farmer A4 leveraged the use of the genetics and historical information from PLF systems to reproduce the top breeds in New Zealand. In addition to checking the machine-generated data and calculated data from PLF systems, farmer A4 reviewed other information (historical performance, health information), including those of the antecedents, to decide which individual cattle to prioritise or avoid breeding. Similarly, farmers A5 and A6 reviewed quantitative information (milk performance) and qualitative information (health history) to determine which cattle to cull out. Farmer A6 shared how he made decisions with another farm manager: one opened the PLF systems to consolidate all relevant data of an individual animal; the two discussed the assumptions and looked for more data to test the assumption. Such a discussion process with PLF's data is an example of double-loop learning, an improvement from the traditional single-loop learning approach in that there was no discussion space to doubt their assumptions. Farmer A6 found it beneficial to discuss with another experienced manager to make these semi-structured decisions because it enabled them to delve deeper into the issues, analyse the root cause of the problem, and think about the repercussions and trade-offs of actions. Farmer A4's example supports the argument that resource, and context are interconnected; drafting the cows earlier than they can result in poor performance in the upcoming season. Therefore, PLF systems enabled complex systems thinking to determine if farmers are *doing the right things* to solve the root cause rather than sticking with *doing things right*. PLF systems provide the platform for systems decision-making that considers the past and present, interrelations and trade-offs between different functions, and data-driven predictions.

As shown in the sequence diagram in Figure 7, seamless collaborations happen every day between farmers and the computer systems to make semi-structured decisions. Farmers such as A5 and A6 use the information generated from PLF systems to run models at DSS to create tailored recipes in adaptation to the changing conditions of the cattle. Using a combination of machine-generated data (i.e., milk quantity), systems' calculated data (i.e., lactation worth), vets' inputted data (i.e., calving date), and unstructured data (i.e., genetics, health history), farmers can create different feeding groups. Farmer A5 has mainly used the DSS to design three recipes based on the life stages of the cow: springer, milking, and calving; the vets determine such status inputted data (pregnancy detail, expected calving date) and upload the data into the PLF systems. Besides tailoring feeds based on the cycle, farmer A6 uses the DSS to constantly evolve the recipes to adapt to seasonal changes and used the PLF machine-generated data (i.e., milk performance, milk solids) to review the effect of any change. Farmer A6 also implements a reward system to individualise the feed quantity to encourage performance by offering bonus feed to top-performing cattle, answered by the PLF systems. He adjusts feeding amounts in DSS to ensure the bonus feed does not negatively affect the nutritional balance or the profit margin, which could be indicated by the traffic-light colour codes and warning messages in the DSS.

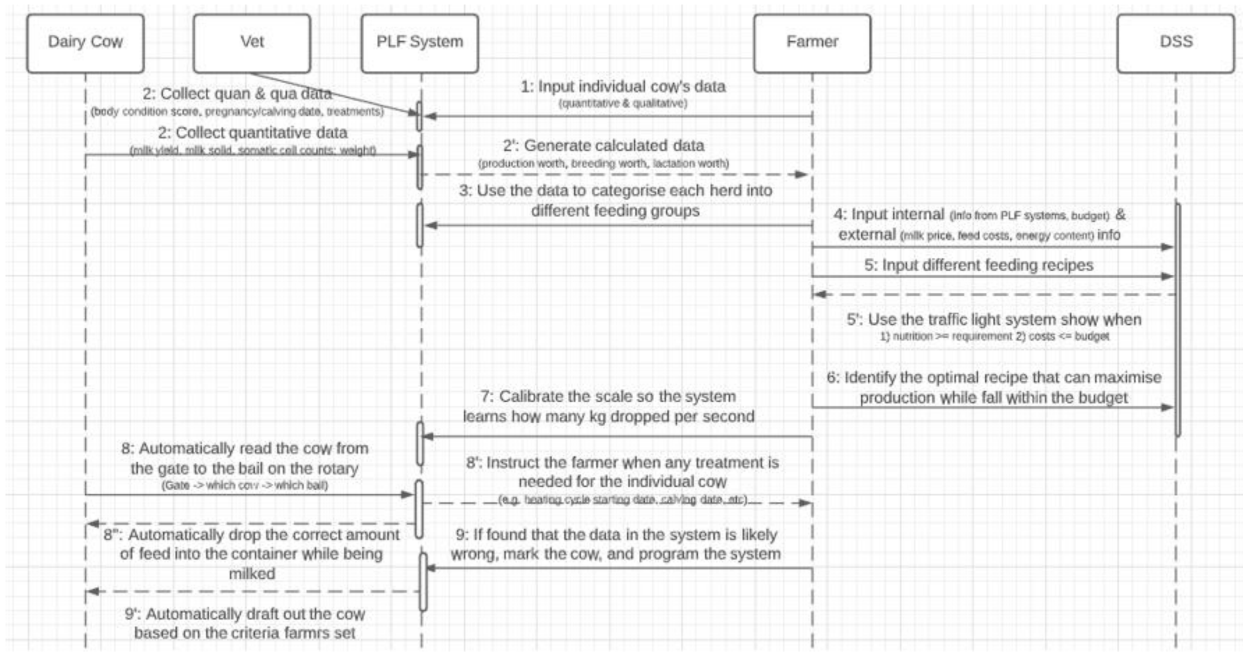


Figure 7 Information Flow among Cow-Vet-PLF-Farmer-DSS

PLF systems and DSS expand the solutions' possibilities by calculating and consolidating multiple dimensions of structured data for humans to examine (Lee & Eom, 1990). The systems integrate the internal (i.e., animal performance, activities) and external data (i.e., vets' reports, feed ingredients' information), quantitative and qualitative data in one place for decision-makers. The DSS can automatically adjust the feed budget following the stock's performance, factoring in supplements or nitrogen (FarmIQ, n.d.-a). Through running "what-if" scenarios, DSS with programmed interrelationships models can predict the outputs; managers can then quickly eliminate the options that do not satisfy the minimum, model-generated parameter values (Lee & Eom, 1990). DSS helped farmers A5 and A6 meet the minimum requirements of the feed using the traffic-light colour-codes and optimise the feed efficiency by calculating and comparing different recipes' feed-to-yield ratios and margins. Moreover, DSS challenges farmers' traditional mental model of maximising profits and shift to striving for a balance between profits and animal welfare. DSS sends red warning messages when a specific recipe has a high chance of ruminal acidosis (Rumen8, n.d.), which encourages farmers to consider the long-term impact of the feed on animal health and the sustainable growth of the herd. Calculated measurements (feed-to-yield, margin), colour-coded nutritional requirements, and health-related warning messages foster the development of systems thinking. Instead of optimising independent tasks (feeding, breeding, health), farmers are given the platform to review systematically all relevant information of the individual cow to make decisions. The back-and-forth interaction among PLF systems, farmers, and DSS is an excellent illustration of double-loop learning – constantly reviewing mental models to reaffirm their assumptions and using structured calculations to make decisions.

5.2.3 Unstructured Decisions

PLF gives farmers the ability to convert *unstructured decisions into* semi-structured decisions by enabling better control of all other factors (same genetics, same feed, same health condition) to test the effect of a possible solution. For example, suppose farmers are considering using sexed semen to replace normal frozen semen. In that case, they could convert a traditionally hard-to-measure unknown strategy to a measurable one because they can identify a list of cattle with the same conditions and set one group as the control group. Without PLF systems' generated data, farmers would have difficulty removing the different attributes of the herd. They could not run experiments because of an inability to identify and remove outliers or other impacting environmental factors that would affect the results. Farmers who use PLF systems to keep track of all attributes of individual animals and better control the context are given the capability to control all possible factors better to run experiments, converting a traditionally unstructured *q*uestion to a semi-structured question. After testing, farmers can compare daily, machine-generated data (milk quantity, conductivity, fat percentage) with historical data to determine possible correlations between the controlled treatment and the results. Furthermore, farmers can also cut the experimental lead time from weeks to as short as one to three days with PLF technologies such as the milk analyser integrated into the systems.

Though not all unstructured decisions can be converted to be semi-structured, the information from PLF systems will support farmers to run simulations to make best estimates to quantify the unknown. One breakthrough of DSS development is that farmers can quantify their environmental impacts. Farm Environment Plans will become essential to meet the 2025's carbon-neutral goal (FarmIQ, n.d.-b). To comply with the plans, farmers are asked to measure the environmental impacts of management practices (DairyNZ, n.d.-d). With the information stored in PLF systems, farmers have tracking records of the improvements of supplements' feed-to-yield, gains of milk and weight, reduced waste from inefficient livestock, improved pregnancy success rates to reduce number of dry cows because of the improved pregnancy success rate, and enhanced animal welfare information. After inputting the precise data from PLF systems to Overseer DSS, the DSS will estimate environmental impacts (methane, nitrous oxide, and carbon dioxide) with its the model built over ten years of research (Overseer, n.d.). Additionally, Kiwi farmers can also use the Farmax DSS built by AgResearch to connect data from PLF systems to run "what if” scenarios of certain events’ impacts on farm systems (Farmax, n.d.). Farmers can then create risk-mitigation plans for situations such as droughts or severe infections on the farm. After comparing simulated impacts of the changing elements on the physical and financial performance, farmers can be more prepared to answer the unstructured decisions that were once deemed to be overly complicated to resolve.

Unstructured decisions require farmers to also input external information (industry trends, price), and experts’ consultations to study the topics. Farmer A5 met with the board of directors every month to decide if keeping the same number of cows, importing new breeds, or adjusting feed budgets, which all require data to form arguments. The system-generated performance reports, the breeding/genetics development reports, the feed efficiency report, and health report all provide context for board members. During this unstructured decision-making process, board members are stimulated to practise double-loop learning because they need to reflect on their experience to generate knowledge and lessons to create future plans. Moreover, they may also reflect on how they questioned their assumptions and confirmed with information from PLF systems.

Together with DSS, PLF systems complement the limited cognitive capability of decision-makers by running complicated models and simulations to predict performance without actual implementation. PLF systems engage with single-loop learning by offering automation functionality and double-loop learning by providing alerts, insights, and tools to challenge assumptions. DSS plays a more prominent role in answering semi-structured questions because DSS has established mathematical models that enable farmers to run simulations. Farmers play a more significant role in answering unstructured decisions as these decisions are rare, and there were no clear measurement criteria or decision-making processes pre-arranged.

5.3 HOW DIFFERENT SYSTEMS THINKING AFFECTS THE USAGE OF PLF INFORMATION

Modern systems thinking in agriculture can be classified into three structures: soft-, hard-, and complex (Schiere et al., 2004). The different systems thinking determines the role of PLF systems in farming operations and how farmers perceive the information produced from the systems. The six interviewed PLF system-adopters have three observed relationships and interactions with the systems aligned with the different approaches to *systems thinking*.

5.3.1 Soft Systems Thinking (A2, A3)

Soft systems thinkers prioritise the human’s *mind* when making decisions because humans can use experience and intuition to adapt to different situations and determine priorities when there are conflicting goals (Schiere et al., 2004). Farmer A2 said the PLF system was no more than a tool to confirm what he sees on the farm; he trusts more of what he observes than he does the computer. Even though the collar captures all the cattle's activities, he prefers staying on the farm to watch the cows. Business Analyst A3, who managed 10 corporate farms, mentioned that some farmers prioritise making decisions with instinct over data from the PLF systems; they only use PLF systems as a formality to create reports for the office headquarters. Some farmers got the business analyst to do the data entry, analytics and reporting while working on their farms. Business analysts usually found differences between data in the systems and the reality on farms because farmers forgot to enter data into the system, which indicates a weak relationship between farmers and the PLF system. Hence, soft systems thinkers tend to use PLF systems as references or supporting evidence to support their instinctive decisions.

5.3.2 Hard Systems Thinking (A1, A3-A4)

On the contrary, hard systems thinkers believe it is more important to focus on the *matter* based on the *reductionism* concept as individual pieces form the complicated system (Flew, 1984, as cited in Wood & Caldas, 2001). By optimising the individual parts and leveraging the interrelationships, decision-makers can achieve better outcomes (De Wit, 1968, as cited in Schiere et al., 2004). Business analyst A3 shared how some farmers were more data-driven and made all decisions with data generated from PLF systems. They closely monitored the information in the PLF systems to ensure the system is always correctly representing the farm's reality. Farmer A4 emphasised the importance of double-checking the information collected from systems after each milking session. He once identified a data-entry error that happened because the cattle kicked off the milk cup and he quickly corrected the mistake on the same day. He is a firm believer that quality data entry will determine the quality of the system's performance. Because farmer A1 outsourced feeding, data from the PLF system is her primary source for understanding the current situation of the cattle. PLF system-generated information allows farmer A1 to discuss the feeding strategies and negotiate feeding costs with the feed supplier. When certain animals did not eat what they should have, there must be some problem, and they need to work out solutions with the feed supplier. As shown in the examples, farmers with hard systems thinking base their decisions on PLF systems' information.

5.3.3 Complex Systems Thinking (A5, A6)

Complex systems thinkers combine both *mind* and *matter* in decision-making because they believe the systems and context's *co-evolution* can lead to more possibilities. Moreover, parts of the systems interact with and learn from each other, which requires constant learning to adapt to such dynamics (Schiere et al., 2004). Farmer A6 saw PLF systems as an irreplaceable virtual labourer and the PLF system became an integral part of the farming operation. Putting equal trust in farm workers and the PLF system, farmer A6 developed standard operations procedures to ensure seamless collaboration between the two. Farmer A6 leveraged the strengths of humans (instincts and experience) and computer (real-time data and analytics) by providing opportunities for farm workers to identify or correct system errors and for the computer to instruct specific actions or remind farm workers of details they may overlook. When farm workers recognised system errors during milking, they would mark the system, and the system will draft the cattle out for investigation. PLF systems would remind workers via visual or audio announcement at the parlour *o*n the calculated recommended insemination date; farm workers would observe the heating situation of the cattle and determine if such action should be taken. The standard procedures enable PLF systems to participate in the decision-making process and reduce the pressure for farm workers to stay on the farm to observe individual animals. Farmers have more time and space to reflect on assumptions and identify root causes using observation and system-generated information. Both farmers A5 and A6 also use PLF's input to improve feed recipes and health treatments to tailor these to the changing conditions of the cow and the environment. Through the constant practice of double-loop learning, farmers stay vigilant to discoveries from the matter, make the best use of the human's mind to correct errors, develop new solutions, and utilise the system-generated data to evaluate the effectiveness of new solutions. Farmer A6 never stops exploring options to improve operations because he believes that the environment changes, and farmers need to stay open-minded to changes.

CHAPTER 6 CONCLUSIONS

6.1 IMPLICATIONS FOR THEORY

Through exploring how farmers use the information from PLF systems to improve decision-making on farming practices using case studies, this research adds value to the previous literature on post-implementation of PLF systems. The majority of the studies (Berger & Hovav, 2013; Devi et al., 2019; Laudon & Laudon, 2015) discussed theoretically how PLF systems could add value to farming operations – encouraging agile growth of operations with its Six Sigma's capability, enhancing decision accuracy with the decision tree algorithms embedded in the systems, and supporting farmers to answer multiple decision types. However, the value of PLF systems' information is only theoretically discussed; no research has investigated how farmers use the information from PLF systems to improve operational decisions on farming practices in the real world. The uniform resource locator flowchart (see Figure 6) presents the farmers' decision-making process and demonstrates how PLF systems support the farmers' thinking processes.

Besides being the first to study the information usage of post-implementation of PLF systems, this research also applies a multiple theories lens to examine the case practices from six New Zealand farmers. In addition, this research enhances the literature by discussing:

1) how farmers at different stages of PLF system implementation apply systems thinking in agriculture.
2) how PLF systems expand the boundaries set by bounded rationality.
3) how quantitative and qualitative information generated from PLF systems support farmers to make structured, semi-structured, and unstructured decisions.
4) a detailed, agile decision-making process.
5) the sequence diagram among PLF-vet-farmer-DSS.

The author identified that farmers at different stages of PLF systems implementation have other systems thinking approaches to problems. For example, farmers at stage one only applies PLF technology, but not the PLF system adopting soft systems thinking because they only see PLF technology to support their intuitive decisions. Farmers at stage two apply one PLF system and multiple MIS to generate as much information and as many insights as possible; they are practising hard systems thinking because they emphasise capturing reality and using data to make decisions. The next stage farmers are practising complex systems thinking by combining both "mind" and "matter" by giving equal weight to human and computer insights, systematically considering different interpretative options, and using data to test the assumptions.

Furthermore, this research uses case studies to explore the relationship between different systems thinking approaches and single- and double-loop learnings. Farmers at various stages have different approaches to information received from PLF systems because of data availability. In addition, the different settings of the systems give them unique abilities to utilise the information to develop learning. The first two group stages of farmers tend to be limited by single-loop thinking, in which decision-makers seek to make improvements to reduce the gap between actuals and expectations. The last stage of farmers is more likely to expand to be involved in the double-loop learning process because the integrated information they receive gives them the overall big picture and encourages them to challenge existing assumptions and develop new learnings through solution testing. This research accepts that humans have bounded rationality when making decisions because of limitations of time, budget, and cognitive ability but shows how PLF systems expand the boundaries. PLF systems create a seamless operational process that reduces the data interpretation time, labour costs and enhances cognitive ability by leveraging the computer algorithms from DSS. Moreover, PLF systems quickly convert raw data into easy-to-understand quantitative (machine-generated, calculated, and benchmarking information) and qualitative information (special events, visual information, suggested actions), empowering an agile decision-making process. Such information enables farmers to use the system to make structured decisions (identifying top performers), semi-structured decisions (creating optimised feed-to-yield feed), and unstructured decisions (creating an environmental plan).

The detailed decision-making process expands researcher Martin-Clouaire (2017)'s theoretical model and highlights the "assumptions testing process" enabled by the PLF system. Additionally, it presents how farmers with PLF system and DSS practice the "plan-do-check-act" process to continuously examine the process, optimise performance, review the alternatives, and act on the solutions. With the enhanced ability to measure and assess the impacts of different factors, farmers are in better control of the farming operations. PLF-systems adopters leverage well-rounded transparent real-time information to develop adaptive solutions to the changing environment (changing weather, number of cows).

Lastly, this research contributes to the PLF studies by providing a real-case sequence diagram of how information flows among PLF-vet-farmer-DSS. This diagram provides a concrete example of how data get converted into information and how humans and computers work seamlessly together in this decision-making process. Both humans and computers play irreplaceable roles in this process, and each has its unique strength to complement the other's weaknesses.

6.2 IMPLICATIONS FOR THE FARMING INDUSTRY

In light of the pressure to provide more food to support a growing population while reducing their environmental impact, farmers should improve operational efficiencies, such as lowering dry cows and food waste. Because of the increased availability of well-rounded, real-time data, farmers spend less time on non-value-adding logistical work, such as manually pushing cows into different groups. Instead, they spend more time reflecting on the performance, planning strategically, and testing alternative solutions. Farmers have developed the mindset from optimising "how to do things right" to "how to do the right things."

This research explores how farmers use the information from PLF systems to improve decision-making through the six New Zealand farmers' actual case practices. Farmers are at different stages of PLF systems' implementation: One group of farmers had just started using PLF technology to perform heat detection and automatic weighing. Another group of farmers uses a PLF system and multiple MIS to conduct herd and genetics tracking activities. The last group of farmers use only one PLF system and some DSS to create alternative solutions such as creating a new feed or identifying on-farm treatments to sub-clinical mastitis, without hiring vets. Different stages of PLF systems usage determine farmers relationship with the systems and how they use the information to improve the operations. The first stage is where farmers only use the systems' data to confirm what they observed on the farm. The second stage is where farmers try to get as many insights as possible by running one or more PLF systems and multiple MIS. The last stage is where farmers use the PLF system as the only MIS and see it as the virtual labourer that works cohesively with human labourers. Without lessening the value of humans' contribution, farmers in this stage give equal value to computer and farmers' insights and provide opportunities for both to collaborate using interfaces such as the parlour consoles. Overall, PLF systems can effectively reduce time, costs, and improve farming's operations and enable farmers to adapt to a changing environment.

The research findings discussed the limitations of PLF systems when there is too much information across different platforms – and when there is not enough historical data from one platform. Both extremes will prohibit the usage of the PLF system; therefore, farmers should choose one PLF system that enables them to keep track consistently of farming operations from the beginning. This system should have the ability to run basic analytics to transform raw data into easy-to-understand information (graphics, colour-coded information) and answer farmers' queries. Moreover, it should enable farmers and computers to participate in the decision-making by having interfaces such as the parlour console at the smart shed. Because of the co-dependent relationship, farmers should develop procedures to ensure the data in the system are an accurate reflection of the on-farm reality, and the system can communicate with farmers to remind them of any overlooked information. Having "one source of the truth" will simplify the data-interpretation process, and farmers can use the trusted data to drive more insights. Using PLF system-generated data to run simulations at DSS, farmers can accelerate the decision-making process, challenge traditional beliefs and assumptions, and create innovative solutions.

6.3 LIMITATIONS & FUTURE RESERACH

The output of the research is limited to references from six farmers' cases. A larger sample size of real case practices should be collected to test if the findings and the PLF systems' decision-making model accurately represent the general practices. Specifically, future researchers could review how different stages of PLF systems implementation affect the relationship between humans and systems and how that affects the systems thinking approach when making decisions. More evidence should be collected to identify if other factors support, or prevent, complex systems' thinking, or double-loop learning given the information from PLF systems. Besides reviewing the model with more real cases, future researchers could also investigate different farm types (mixed, deer, sheep, private, public farm) and compare their different information usages to improve their decision-making. Moreover, they could apply the sequence diagram model to other MIS decision-making cases to challenge and improve the model.

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APPENDICES

Appendix 1: Indicative Interview Questions

Project Title

How do farmers use information generated from Precision Livestock Farming (PLF) systems to support their decisions in relation to farming practices?

Basic Information

- Could you please briefly tell me about your farm
- How long have you been using the PLF system? And what kind of PLF technologies you have installed in your farm?

Decision Making

- What are some key decisions in relation to farming practices that you need to make on a regular basis? (individual decision-making or group decision-making or hierarchical decision-making? External stakeholders?)
- How has PLF system change your decision-making process?

AC: Knowledge Acquisition/ Data Collection

- How often do you review the data collected from the systems?

AC: Knowledge Assimilation

- How do you analyse the data collected through the PLF system??

AC: Knowledge Transformation

- Can you talk me through some examples of how you interpret the analysed data in the context of your decision making (individual/ farm/external) (business value? legitimacy?)

AC: Knowledge Exploitation

- How do you translate the decisions into actions? (are there any automated actions triggered by the system? Any decisions affected by farm's structure)

Outputs & Performance

- What are the effects of those actions on your farming practices? (examples)

Appendix 2: Participant Information Sheet

Date Information Sheet Produced:

23 November 2020

Project Title

How do farmers use information generated from Precision Livestock Farming (PLF) systems to support their decisions in relation to farming practices?

An Invitation

Kia Ora! My name is Gladys Lai and I am conducting research on farmers' use of Precision Livestock Farming (PLF) systems as part of my Master of Business degree at Auckland University of Technology. I would like to invite you to participate in my research. The aim of the study is to develop a richer understanding and insights into how farmers use the information generated from PLF systems to make decisions related to farming practices.

What is the purpose of this research?

While prior research has examined the development and adoption of PLF systems, there is less understood about the post-implementation use of such systems. This research aims to fill this gap with a study of New Zealand farmers' use of information from PLF systems. In particular, the research focuses on the processes of information recognition, assimilation and exploitation from PLF systems.

How was I identified and why am I being invited to participate in this research?

You indicated your interest in participating in the research by replying to an advertisement or a contact email. You are being invited to participate in this research because of your experience and information of PLF systems on New Zealand farms. Ideally, your farm should have implemented and used a PLF system for at least two years.

How do I agree to participate in this research?

Your participation in this research is voluntary (it is your choice) and whether or not you choose to participate will neither advantage nor disadvantage you. You can agree to participate in this study through a reply email to me. You are able to withdraw from the study at any time. If you choose to withdraw from the study, you will be offered the choice between having any data that is identifiable as belonging to you removed or allowing it to continue to be used. However, once the findings have been produced, removal of your data may not be possible. A consent form will be provided for you to complete if you wish to participate in this study.

What will happen in this research?

Your participation in this study would involve a one hour video interview with myself. The interview will take place on Zoom (or similar software), at a day and time depending on your preference. During the interview, I will take notes of our conversation. I would also like to audio record the interview to assist with my data collection and analysis. However, I will only do so with your permission. Only I and my supervisors (Dr Maduka Subasinghage and Dr Bill Doolin) will have access to the data collected for this study. Only aggregated findings from the research analysis will be reported in my Master of Business thesis and in any subsequent publications or presentations.

What are the discomforts and risks and how will these risks be alleviated?

There should be no discomfort or risk arising from your participation in the research. If you consider your use of a PLF system as a competitive advantage you may wish to not share your experiences or participate in the research. No commercially sensitive information will be sought. Further, your name and your farm's name will not be used in any reporting of the findings. The interview will only be conducted upon your consent.

What are the benefits?

There is a no direct benefit to you in participating in this research. However, I am hoping that you will find it valuable to share your experience and to reflect on how you use your PLF system. The findings from this research will contribute to the body of knowledge on effective use of PLF systems, which may be beneficial to the New Zealand farming community.

How will my privacy be protected?

Confidentiality will be upheld. Your name and that of your farm will not be used and you will not be identified personally in the research findings. Only my supervisors and I will have access to the data during the data collection and analysis stages of the research. All data will be kept securely for a period of six years, after which it will be destroyed.

What are the costs of participating in this research?

There are no financial costs involved in participating. However, it is anticipated that the interview will take around one hour of your time.

What opportunity do I have to consider this invitation?

I would ask you to contact me within two weeks of receiving the invitation to participate in this research.

Will I receive feedback on the results of this research?

Not specifically. The findings will be reported in a thesis lodged in AUT's Tuwhera Institutional Repository, which is open access. The findings may potentially also be disseminated in industry conferences and/or publications..

What do I do if I have concerns about this research?

Any concerns regarding the nature of this research should be notified in the first instance to the primary research supervisor, Dr Maduka Subasinghage, maduka.subasinghage@aut.ac.nz, 09 921 9999 ext 5048.

Concerns regarding the conduct of the research should be notified to the Executive Secretary of AUT Ethics Committee, ethics@aut.ac.nz, 09 921 9999 ext 6038.

Whom do I contact for further information about this research?

Please keep this Information Sheet and a copy of the Consent Form for your future reference. You are also able to contact the research team as follows:

Researcher Contact Details:

Gladys Lai

Email: nff0869@autuni.ac.nz

Phone: 021 258 5520

Project Supervisor Contact Details:

Maduka Subasinghage

Email: maduka.subasinghage@aut.ac.nz

Phone: 09 921 9999 ext 5048

Bill Doolin

Email: bill.doolin@aut.ac.nz

Phone: 09 921 9999 ext 5807

Approved by the Auckland University of Technology Ethics Committee on *type the date final ethics approval was granted*, AUTEC Reference number *type the reference number*.

Appendix 3: Consent Form

Project title: ***How do farmers use information generated from Precision Livestock Farming (PLF) systems to support their decisions in relation to farming practices?***

Project Supervisor: ***Dr. Maduka Subasinghage, Dr. Bill Doolin***

Researcher: ***Gladys Lai***

- I have read and understood the information provided about this research project in the Information Sheet dated 23 Nov 2020.
- I have had an opportunity to ask questions and to have them answered.
- I understand that notes will be taken during the interviews and that they will also be audio-taped and transcribed.
- I understand that taking part in this study is voluntary (my choice) and that I may withdraw from the study at any time without being disadvantaged in any way.
- I understand that if I withdraw from the study then I will be offered the choice between having any data that is identifiable as belonging to me removed or allowing it to continue to be used. However, once the findings have been produced, removal of my data may not be possible.
- I agree to take part in this research.

Participant's signature: ....

Participant's name: ....

Participant's Contact Details (if appropriate):

………………………………………………………………………………………..

Date:

Approved by the Auckland University of Technology Ethics Committee on type the date on which the final approval was granted AUTEC Reference number type the AUTEC reference number

Note: The Participant should retain a copy of this form.

Appendix 4: Sample of the Thematic Analysis

Themes	Subthemes	Quotes
Info from PLF Systems	**Quantitative Information**	"measure fat, protein, lactose, somatic cell count five times per week randomly" - A5
		"can write a query search and get the answer in 30 seconds... can ask the system the low producing cow and group the cows into herbs of 200" - A6
		"the system shows the ancestral information of a particular cow, which helps to keep track of the best breed"- A4
		"the system tells exactly when to draft the cows for the artificial insemination to optimise the chance of pregnancy"-A1
		"measure cow activity- eating, ruminating, how much time resting... will send alerts when observed abnormality" -A1
	Qualitative Information	"farmers can add notes into the system, such as ultrasound scanning result can be uploaded to the system" -A6
		"when suspected of disease, farmers add notes on potential health issues and wait for the vets to examine" - A4
		"the vets can add the medical health history into the system to include details such as diagnosis of a certain disease, and the possible costs of the disease" -A1
Key Decisions	**Feeding**	"it's crucial to know when and where to move the cow to avoid over or under feeding, which can affect the performance of both the current and the upcoming season" -NA
		"feeding properly is fundamentally the most important in the farm in order have good quality outputs."-A3
		"we have one manager skilled in feeding to create the diets that is tailored to a cow's lifecycle and the season" - A5
	Breeding	"important to know exactly when to inseminate the cows based on their heating condition, even 12 hours can have huge difference on the pregnancy success rate"- A1
		"the decision on exactly which cow should be dried off at what time will affect the performance of both the current season and the upcoming season" - A4
		"culling decisions are difficult and require us to look into the family history, the malperformance reasons, and should we give it another chance" -A6
	Animal Health	"we care about the animal welfare and we want to ensure animals get treated whenever they are sick" - A3
		"we take an proactive approach to diagnose non-clinical mastitis in order to prevent the disease from spreading before it becomes a bigger problem" - A5
How they use the information to make decisions	**Examine daily performance through system' reports**	"use the easy to read traffic light system to get the max out of the cow to get the most economic ration for each herd" - A6
		"use the dashboard from the system to oversee and manage the entire herd" -A1
		"get the reports from the managers everyday to review the herds' data.. check performance out of expectation if everything is normal the process can only take 5 mins..go across managers to examine the situation and make assumptions on the root cause of the difference.. he will use the Rumen8 DSS tool to create the precision feed based on the assumption and coordinate the team to make the changes. This cycle of change can take 2-3 days and repeat the same process till the performance is back to normal" - A6
		"we will calibrate the computer so it learns how many kg it will have in a certain time frame" - A6

	Collaborate in the operations	"we program the computer to automatically draft cows that do not meet certain criteria" -A5
		"you can just click a button at the shed to automatically draft out the cow after milking" -A4
		"the system alerts us when the milk's indicator exceed the threshold we set and so we can proactively respond and prevent the disease is spread across the herd" -A5
		"the system will automatically draft out the cows if the body condition score is below a pre-set threshold" -A3
		"The system will send you a list all the bulls you shouldn't use over certain calves because of the defects in the past" -A4
	Create new precise solutions <i.e. diets>	"computer will calculate that the cow needs 5kg of feeds.. it will speak out a command if there is a program for it.. and the rotary will automatically drop the feeds amount" -A6
		"use the DSS to optimise the ration to get the maximum weight, what weight gain, estimate weight loss, and get pretty accurate results" -A6
		"use the system to ensure that no cows are underfeed and better reach the cows/hectare goal per season" -A4
		"use the DSS tool to create the seasonal diets and feed the calves differently based on the calving date" -A5
		"depending on the body condition score, we group the cows into different herds and we adjust the feed volumes for different herds" -A3
How the decisions are improved with the information from the PLF systems (benefits)/ Benefits	**Reduce costs**	"reduce the feed costs and increase milk production... ten years ago, feed 2kg a day, 1.6 tons grains a day, now average feed reduced to 1kg + 1.4 tons per day but the milk went up a litre and half across the whole herd."
		"cut down labour costs as previously need skilled labour for heat detection but can have mistakes lead to wastes because if missing calving will be empty calf and will need to wait for another cycle"
	Save time	"the system directly talk to people in the shed when it observed abnormality" -A6
		"before you have to write down all information in the book and update them on the computer after calving, which can take 2-4 weeks after you finish calving. We used to use fax to send the report through, which can be 5-10 days after each testing.. now we can just enter information on the phone and the information will be automatically updated on the system and the system can automatically draft out the cow that has the issues right after each milking"-A4
	Improve performance	"the system help better manage and minimise poor decision making.. if the calving decision is wrong it can affect both the current and the next season because there won't be enough grass and the cow will be underfed... farmers have to think in the long-term goals and adapt to the short-term changing environment, especially the weather change." -A4
		"using the collar to know precisely when the animal is heated enables us to know the optimal hour in the day to perform artificial insemination, which improves the pregnancy success rates" - A2
	Adapt to the changing environment	"because of the unpredictability of the weather, we have to adapt quickly to prevent underfeeding or overfeeding.. using the information from PLF systems helps us adapt to the changing condition and coordinate the herds to feed just the right amount every day." - A5

Appendix 5: Information Generated from the System

Raw Data
<Cow123: x, y, z>
<Feeding: a kg>

Either manually checked or automatically captured by the PLF systems:

Animals:

- Weight
- Body Temperature
- Activities <ruminating, eating, mating, walking>
- Animal Health <Disease, vaccines>

Farming Activities:

- Feeding <how much fed, feed recipe>
- Breeding <when performed artificial insemination>
- Animal Health <How many vaccines given, health check>

Descriptive Information
<t, x: x over time>

Information can be created by non-PLF tools such as Excel presented in table or graphs:

- Historic records <animals, farming activities>

***Additional Information** that can only be generated by technologies embedded in the PLF systems:*

- Milk Quality <fat, protein, lactose, somatic cell count, conductivity>
- Precision - Heating Cycle

Calculated Des. Information
<A%, $>

Information can be calculated using non-PLF tools excel:

- Productivity
- Growth Rate
- Forecasting
- Return on Investments

[Can identify which cows generate highest values]

Additional Information that can be calculated more precisely using the information generated in the PLF systems:

- Breeding Worth
- Production Worth
- Lifetime Production Worth
- Lactation Worth

[Can identify which cows generate highest lifetime production worth]

Cause-Effect Information
<Cow123, A%, $>

Information can be generated by running regression models in non-PLF systems such as Excel:

- Relationship between feeding amount and productivity <if increasing amounts of feeding will increase the values>

Additional Information generated by PLF systems/DSS tools:

- Relationship among multiple factors <if increasing amounts of feeding will generate the highest return on investments>
- Decision Tree
- Neural Network

Suggested Actions

Suggested Actions:

- No suggested actions, farmers need to choose the actions to take based on the information

Additional Information generated by PLF systems/DSS tools:

- Feeding <when to feed, how much to feed, which feeding recipe gives the highest return on investments>
- Breeding <Optimal hour in the day to perform artificial insemination, when to dry off the cow, when to calve the cow>
- Animal Health <which cow to vaccinate>