The Opportunities of Artificial Intelligence for New Zealand Dairy Farmers

Report prepared for
DairyNZ

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Use of AI

This report was developed with the support of AI tools and incorporates AI-generated insights, which have been interpreted and validated by a Perrin Ag team member for accuracy and relevance.

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1 Executive Summary

Perrin Ag Consultants Ltd ("Perrin Ag") were engaged by DairyNZ to explore the opportunity for generative artificial intelligence (GenAI) for New Zealand dairy farmers.

This report provides a summary of the current GenAI adoption insights, including a catalogue of current and emerging use cases, and presents two pathways illustrating what a near-future, GenAI-enabled pasture-based dairy farm might look like.

Current adoption of GenAI amongst the dairy farming community appears to be low, with many farmers unaware of how GenAI can be used or the benefits it can provide. For farmers that are aware of the GenAI tools available, many have not yet engaged with it in a meaningful way. There is often concern around the accuracy of outputs, difficulty in seeing how GenAI can integrate within their existing systems or a feeling that their traditional methods are working adequately, and so their motivation to change is low.

In contrast, farmers that are engaging with GenAI are doing so in a variety of ways noting the ability to make better, more informed and faster decisions, reduce time spent on repetitive tasks, empower team knowledge and improve communication. Observed use cases could be placed into three categories; decision support (knowledge access, contextual reasoning, predictive modelling), task enhancement, and communication support. Decision support is by far the most common application of GenAI, with most uses focusing on either general knowledge access or contextual analysis. While most farmers acknowledged that GenAI responses are not always fully accurate, they valued the speed at which GenAI can provide information which in turn accelerates their decision-making efficiency. Areas of the farm business that are most frequently used in contextual analysis applications reflect those with high data availability (e.g., animal health, reproduction, and feed). This suggests that wider application of GenAI in the future will rely on increasing technology and data collection opportunities.

Novel use cases identified through this project include the creation of farm-tailored chatbots, large-language model (LLM)-powered digital twins, customised GenAI-driven breeding tools and the integration of farm or industry-specific data for tailored outputs. Diffusion of these currently advanced and novel applications is limited to the innovator and early adopter farmers who actively seek new opportunities, are willing to experiment and take risks, and can see potential early on. By contrast, use cases that have diffused beyond these groups of farmers are those that are more basic, but have proven value, including the use of GenAI to help draft documents, record or transcribe meetings, or perform basic question and answering (knowledge gathering).

Building on the adoption insights uncovered in the exploration phase of this project, a conservative and aspirational future pathway for GenAI adoption was developed considering limitations of the technology and the challenges of pasture-based dairy farming in New Zealand.

The conservative pathway illustrates a future where GenAI acts as a digital assistant/adviser supporting and accelerating farmer decision-making. Data integration remains a key limitation under this pathway and, as such, contextual understanding is limited to the data and information manually provided by the farmer. Accordingly, farmers interact with GenAI through standalone, and often customised, LLMs or through GenAI functionality embedded in web portals or software programmes that are easy to use, have high trust and provide seamless integration. Agentic capabilities are limited to low-level, rules-based tasks that remain firmly human-directed.

In contrast, the aspirational pathway illustrates a future where GenAI acts as an integrated digital partner operating within a connected technology and AI ecosystem. Data interoperability is no longer a constraint, enabling real-time data analysis, insights, contextual awareness, adaptive learning and more proactive decision-making. Mid-level agentic capabilities exist and can co-ordinate or adjust operations within farmer-defined boundaries and learn from outcomes to continuously refine future recommendations. A high level of on-farm technology and data capture devices maximises the value of GenAI.

These pathways align with how use cases may diffuse through the population in the near-term. GenAI adoption across the dairy farming population is currently low with diffusion of use cases to the mainstream farming population requiring proof of concept and ease of use. Looking ahead, achieving widespread diffusion of use cases, like real-time decision support and agentic workflows, will also depend on achieving farmer trust and having access to good on-farm data and technology infrastructure. In addition, while technically skilled farmers may be able to develop workarounds in the near team to achieve system interoperability, widespread adoption will require technology advancements and sector-wide progress in data integration.

Regardless of the specific pathway, limitations of GenAI, including an inability to replicate tacit knowledge and an inherent vulnerability to hallucinations and bias, is expected to firmly place the technology as a tool to support farmer judgement in the near future (3-5 years) as opposed to replacing decision-making. While there is expected to be a place for agentic capabilities, we suggest these will be limited to mid-level (Level 3-4) agency where the execution of workflows is constrained within human-set boundaries and goals. They will likely relate to tasks that are repetitive and/or can be guided by clear logic and available data.

As GenAI capability advances, the farmer's role is also expected to evolve. Maximising the value from GenAI tools will require time and experimentation. This might include refining prompts, reviewing and validating outputs, customising workflows and iteratively training GenAI to align with farmer goals and objectives. This will be particularly important for farmers developing customised solutions or integrating GenAI into more advanced, agentic applications.

DairyNZ is well positioned to play a leadership role in supporting and enabling farmers to explore GenAI and ultimately incorporate it successfully within their farming businesses. Key opportunities include providing or promoting practical training and guidance to build farmer capability and digital AI literacy, supporting farmers to become 'AI- ready' for future GenAI applications, and facilitating knowledge exchange through webinars, demonstration events, workshops and/or roadshows that showcase real farmer use cases. There is also scope for DairyNZ to evolve its own digital resources by exploring options to embed GenAI functionality in existing templates and spreadsheets or develop pre-built 'off-the-shelf' GenAI workflows to assist with certain activities (e.g., grazing management, feed budgeting, roster building).

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2 Terms of Reference

Perrin Ag Consultants Ltd ("Perrin Ag") were engaged by DairyNZ to explore the current opportunity that artificial intelligence (AI)-powered tools offer New Zealand dairy farmers. This includes developing a scenario(s) of how AI may be applied, and impact, pasture-based dairy farms in the near-term.

The project engagement was split into three key core areas:

i. **Definition:** define the scope of the project, with a focus on self-directed artificial intelligence.

ii. **Exploration:** develop a catalogue of current and emergent self-directed use cases of AI in New Zealand dairy farming through a review of available grey literature and insight from farmers and industry.

iii. **Ideation:** ideate a realistic, near-future scenario for the AI-enabled New Zealand pasture-based dairy farm.

The focus of the work was initially on "self-directed AI", referring to AI that farmers consciously choose to engage and interact with, as opposed to AI that is embedded in various technologies where the interaction with the AI occurs indirectly through the product.

It became evident through the course of this work, however, that the focus of self-directed AI could be further narrowed to generative AI (GenAI) and more specifically, large-language models (LLMs). This narrowed scope captures both the practical direction of self-directed AI use in farming and how self-directed AI is framed within the wider AI landscape.

Presentations to disseminate the work will be given by Perrin Ag at a DairyNZ Friday Curiosity session and at the 2025 Precision Dairy Farming Conference. Articles for the February 2026 Institute of Rural Professionals "Journal" and Inside Dairy magazine are also to be published, alongside a Talking Dairy podcast in January 2026.

3 Definition

The initial focus of the project was on "self-directed" artificial intelligence (AI) applications. This terminology referred to AI tools that farmers consciously choose to engage with, where the farmer initiates and controls the interaction and the AI provides outputs such as analysis, recommendations or decision support. Self-directed AI applications contrast with "product-embedded" AI which refers to AI functionalities that are built into products or systems and which operate as part of a product's internal logic. While these tools may also support decision-making, the farmer does not engage with the AI component directly. Instead, the interaction is with the product as-a-whole, and the AI's role is often passive.

Through discussions with industry and farmers it became evident that the use of self-directed AI was essentially limited to multimodal large-language models (LLMs), with OpenAI's 'ChatGPT' emerging as the predominant tool of choice amongst farmers. This appears consistent with other industries and personal applications of generative AI (GenAI), and with how self-directed AI is framed and discussed within industry lexicon.

For this reason, the focus of the project has shifted from "self-directed" AI to generative AI and, by inference, LLMs, given these are the most popular and commercially mature form of GenAI (Table 1, Figure 1).

GenAI and LLMs are considered to have a low barrier to adoption and high uptake potential. This is due to their relatively low cost, ease of trialling, and accessibility, particularly when compared to other available on-farm technology (with or without inbuilt AI) which may require upfront capital investment, high(er) ongoing costs and may be less easily reversed. As such, GenAI and LLMs are likely to feature prominently in near-future dairy farm systems and offer opportunities for farmers to engage with AI on their own terms as a supportive tool to enhance decision-making.

There is also potential for LLMs to exhibit agentic AI capabilities and move beyond simply providing outputs and recommendations to making decisions and taking action. There are currently examples of agentic AI in farming, but these tend to be found within rule-based automation technologies (e.g., drafting systems, variable rate irrigation) and are considered 'Level 1' within the five-level agentic AI classification (Bornet et al., 2025). Additionally, there are applications of GenAI involving natural language processing being used for repetitive tasks (e.g., GenAI-powered invoice processing) and which can be categorised as 'Level 2' on the agentic AI scale. In contrast, mid-high level agentic AI (Level 3 -5) applications, which exhibit increasing levels of autonomy and agency, remain an emerging area. They are, however, worth considering in this project (particularly Level 3-4) as they likely represent a natural evolution of GenAI and are expected to play an increasing role in future applications. Further detail on the agentic AI classification system is provided in Appendix 1.

Table 1: Definitions for key artificial intelligence terminology.

Term	Abbreviation	Definition
Artificial intelligence	AI	A machine-based system that can perform tasks that would typically require human intelligence, including making predictions, recommendations or decisions.
Generative AI	GenAI	Refers to any AI model capable of producing new content (e.g., text, imagery, video, code, audio) based on patterns learned from existing data.
Large-language model	LLM	A subset of generative AI models specifically trained on vast amounts of text data to understand, generate and interact using human language. Originally designed to work only with text, many LLMs are now evolving into multimodal models that can also handle images, audio and other data formats.
Agentic AI	-	An AI system that is capable of making decisions and executing goal-directed actions with varying degrees of human oversight. A further description of the five levels of agentic AI is provided in Appendix 1.

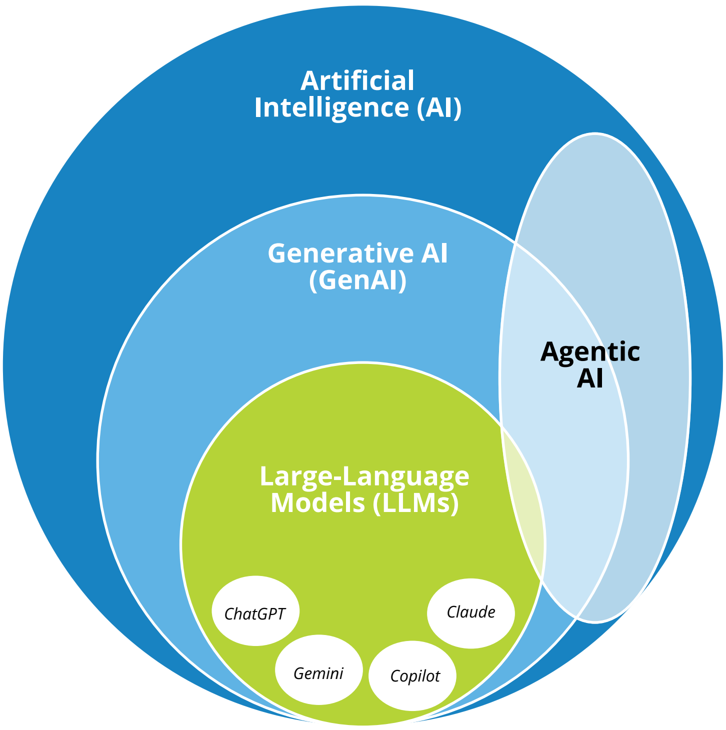

Figure 1: Relationship between AI, GenAI, LLMs and agentic AI.

4 Exploration

4.1 Method

To explore the use cases and opportunities for GenAI on dairy farms, a series of interviews and discussions with a diverse range of stakeholders across the AI and agricultural sectors were conducted. The engagement included ten dairy farmers, five subject matter experts in the AI domain, and five rural professionals/advisers. Additionally, a brainstorming session was held with DairyNZ to capture further insights and perspectives on how farmers may have already been engaging with GenAI and the potential future applications.

Interviews were relatively informal, held primarily via phone or Teams meeting, with some in-person conversations where possible. Most interviews were around 30 – 60 minutes in length, though in three of the farmer interviews where interest in GenAI was low, the interview time was shorter. The flexible interview approach allowed for in-depth exploration with those most engaged, while still allowing a broad cross-section of views to be captured. Interview insights were further supplemented by a review of grey literature including social media, industry and AI-focused articles which provided additional context into the rapidly evolving GenAI domain.

4.2 Adoption insights

Awareness of AI as a concept and the GenAI tools available (e.g., ChatGPT, Claude, Gemini, CoPilot) has increased rapidly in recent years; however, adoption amongst the farming community to date appears low. While the adoption of GenAI by farmers has not been overtly measured in this project, Rogers' (1962) diffusion of innovation model provides a useful framework for considering how different segments of the population are engaging with GenAI.

Rogers' model proposes that within any population there is a normal distribution in the ***willingness*** [our emphasis] of individuals within a population to adopt new technologies, ranging from innovators to laggards, based on their aversion to risk and propensity to adopt a specific innovation.

Figure 2 presents an adaptation of Roger's (1962) model that is overlaid with current use cases of GenAI within the dairy farmer population. It is based on findings from interviews with farmers and industry and shows how far various GenAI use cases have diffused through the farming population. Use cases positioned at the innovator or early adopter end remain confined largely to those segments, while those that have "crossed the chasm" (Moore, 1991) to the early majority have begun to spread into the mainstream farming population. Importantly, Figure 2 does not attempt to illustrate the rate of ***adoption*** of Gen AI which, like any emerging technology, currently appears to be low. Over time, as GenAI use cases mature and barriers to adoption reduce, the proportion of the population using GenAI will increase.

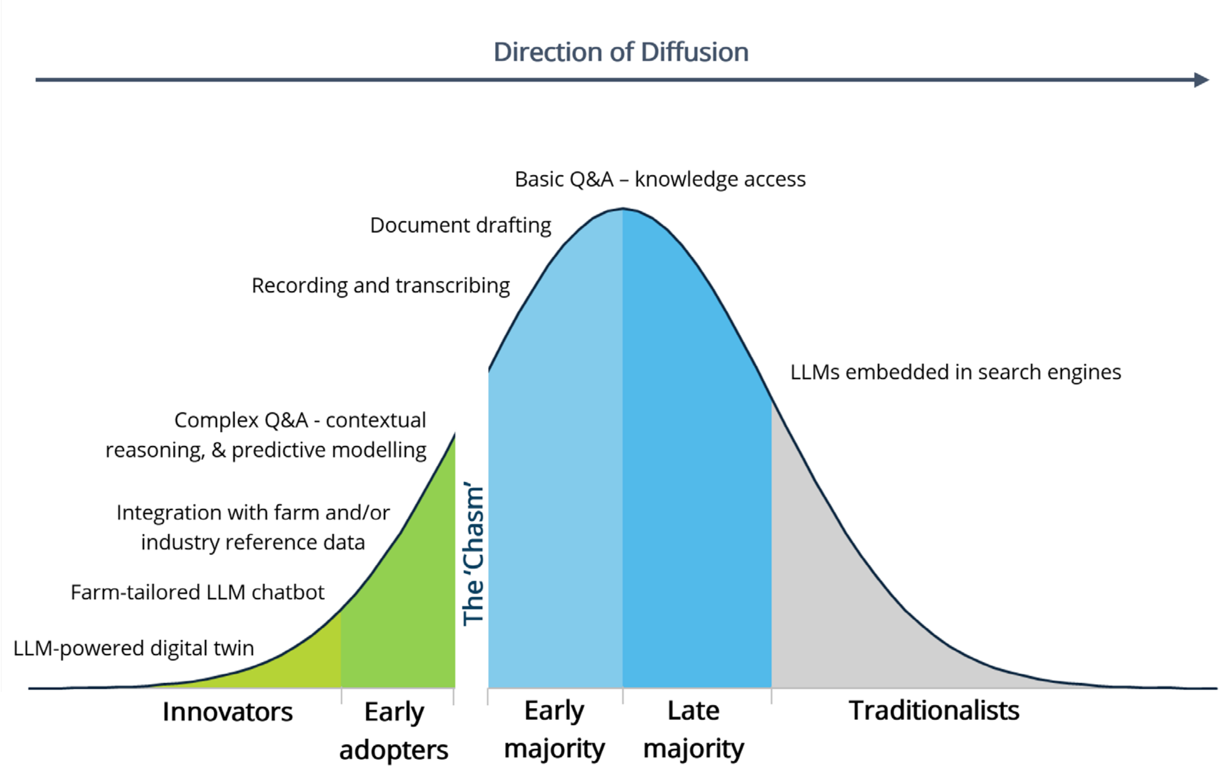

Figure 2: Stylistic representation of the estimated current diffusion of GenAI use cases amongst the New Zealand dairy farming population. Adapted from Rogers' (1962) adoption curve model based on the diffusion of innovation theory and Moore's (1991) 'chasm' concept.

A few innovator farmers were identified who were embracing AI and operating at the leading edge. These farmers have incorporated GenAI into daily operations and are actively building tailored GenAI-driven solutions to address challenges unique to their farm systems. This includes large-language model (LLM)-powered digital twins, farm chatbots and custom GenAI breeding tools.

In addition, early adopter farmers were identified who are beginning to embrace GenAI to support complex question and answering (Q&A), and to integrate their own farm data with the generic web-based information available to LLMs to create personalised farm-specific insights or recommendations. It seems the key distinction that separates the innovators from the early adopters is that the innovators have started building custom tools (e.g., custom GPTs or agents) while the early adopters are not yet doing so.

Albeit based on our limited sample, the number of farmers within the innovator and early adopter segments appears to be small, reflecting the typical adoption rate theory, where only a minor percentage of the population are willing to experiment with and invest (money and time) in new technologies.

The use cases that these groups are interacting with have not yet reached the mainstream farming population. This likely reflects a gap in adoption between the early adopters and early majority, often termed the 'chasm' in marketing literature (Moore, 1991). This concept appears to be relevant to GenAI adoption in dairy farming. While innovator and early adopter farmers are actively experimenting and integrating GenAI use cases into daily operations, the broader dairy farming population appears to be more cautious. Likely these farmers require greater proof of concept and confidence in their time investment to take the leap from basic functionality to routine use and integration with everyday farm activities. This suggests the barrier to adoption may not be as low as is often promoted.

Use cases that have crossed the chasm and reached the early majority include the use of LLMs for practical tasks such as drafting documents, recording and transcribing meeting minutes or basic Q&A. The use cases that this group engage with may overlap with the late majority; however, the adoption patterns of this group are more likely to reflect a higher level of willingness to experiment and integrate GenAI into regular activities. The late majority are likely to be more cautious, only adopting GenAI once it has proven to be successful and there is widespread adoption.

Finally, the traditionalists are either not interacting with GenAI at all or limiting their farming-related interactions to passive applications where GenAI is already built-in, such as Google searches powered by LLMs (e.g., Gemini).

There can be a range of reasons why farmers have not engaged or are slower to engage with GenAI. Some of the factors identified include:

- a lack of awareness or ability to see the practical benefits that the tools can provide;
- a feeling that their traditional methods are working adequately and, as such, the desire to change is low;
- concern around the reliability and accuracy of the outputs and how information might fit within their specific context;
- challenges with connectivity; and
- a lack of awareness of how to use the tools.

In contrast, the motivators for those embracing use of GenAI included:

- reducing mental workload;
- accelerating decision-making and access to information;
- reducing time spent on administrative or repetitive tasks and redirecting time to higher value activities;
- improving accuracy of technical or mathematical tasks (e.g., magnesium dose rates, pasture intake calculations);
- empowering team knowledge and collaboration;
- facilitating communication; and
- enabling the generation of new insights and informed decision-making through the integration and analysis of multiple data sources (e.g., cow wearables, sensors, farm policies and reference data).

The low-cost of these GenAI tools is likely to further support uptake and use.

The speed (six months or less) at which the innovator or early-adopter farmers have become advanced users of LLMs, such as ChatGPT, is impressive. There seems to be a relatively low-level of technological expertise required to engage in 'advanced' use cases (e.g., creating tailored farm chatbots), likely reflecting the natural language interface of the LLMs and the ability to quickly experiment and iterate. It suggests that with exposure to the possibilities of GenAI, and a desire to experiment, there is a strong opportunity for the slower adopters to move quickly from basic use cases to more advanced, tailored applications.

The purpose and positioning of GenAI on farms varied amongst the innovator and early adopter farmers. For one farm, the purpose of using GenAI was to minimise risk and support consistent implementation of farm policies between staff in a large multi-farm operation. In this example, the use of LLMs was grounded in a strong technical understanding of the desired system principles (e.g., accepted residual levels, pasture allocation). In contrast, other innovator farmers were using LLMs to tackle tasks they previously found difficult or time-consuming due to a lack of their own technical expertise – such as performing calculations, testing scenarios or interpreting data – often without concern about the precision of the output. While these use cases differed, they highlight the ability of LLMs to act as a 'cognitive exoskeleton' (Beatty, 2025), enhancing and extending human capabilities and serving different users in different ways.

Overall, while GenAI appears to still be an emerging innovation amongst the dairy farmer population, the range of existing use cases identified, particularly in the innovator and early adopter segments, provides insight into the future trajectory of GenAI to the mainstream farming population.

4.3 Existing use cases

Table 2 provides an overview of the current and emerging use cases for GenAI identified as part of this project. In every circumstance, LLMs were the only form of GenAI used, with ChatGPT being the most popular tool. While the number of farmers currently interacting with GenAI appears to be low, those that are using GenAI may be employing it in a multitude of ways. Rather than cataloguing the various interactions, existing use cases have been grouped by the purpose of the interaction:

- Decision support: Use of GenAI to assist decision-making through providing insights recommendations or calculations. We consider there to be three distinct sub-categories:
    - Knowledge access: GenAI primarily used to quickly access and synthesise generic and publicly available information.
      (e.g., summarising best-practice fertiliser strategies)
    - Contextual analysis: GenAI primarily used to analyse and interpret the farmers' own data (e.g., photos, spreadsheets, test results, kill sheets, wearable data) and turn it into actionable insights.
      (e.g., ChatGPT used to provide tailored fertiliser recommendation using farm soil test results)
    - Predictive reasoning: Use of GenAI to predict a future outcome, or model different scenarios and the consequent impact to the business.
      (e.g., future pasture growth predictions based on different fertiliser strategies)
- Task enhancement: Use of GenAI to increase efficiency of repetitive tasks, often administrative, reducing workload and increasing operational efficiency.
- Communication support: Use of GenAI to assist with team co-ordination, management and communication, facilitating work efficiency and collaboration.

Using LLMs for decision support appears to be the most common application for GenAI, with most of the interactions focused on either general knowledge access or contextual analysis. Some farmers reported using ChatGPT as a replacement for Google given its improved ability to quickly filter and synthesise information. This replacement of conventional search engines with GenAI aligns with thinking that the primary user of web-based information will increasingly be AI tools rather than humans. While most of the farmers accept that responses from GenAI may not be fully accurate, they value the quick responses and manage inaccuracies by 'sense-checking' the outputs.

Among the farmer interviewees, there was widespread use of LLMs to analyse farm-specific data and generate actionable insights or recommendations (contextual analysis). This ranged from uploading photos of stock for body condition scoring or weighing, to analysing kill sheets, to checking dietary imbalances, to interrogating MINDA and Halter animal datasets for reproductive insights (see Example Interactions, Table 2). Across the contextual analysis applications, LLMs were frequently used in the animal health, breeding, reproduction, and feed domains. This likely reflects the relative availability of data in these areas, such as animal software datasets, cow wearables data, and supplement composition data, which GenAI is then able to use and interpret.

While there were some examples of contextual analysis applications for financial, nutrient, equipment and machinery management, these use cases were less commonly noted. Notably, none of the farmers interviewed reported using GenAI for people management (e.g., rostering, health and safety or staff development). There were, however, examples of GenAI being used to improve team communication and these were categorised separately under 'communication support'.

Use of GenAI for predictive reasoning, as a sub-category of decision support, was less frequently reported but showed signs of becoming an emerging application. One advanced use case involved the creation of a 'digital twin' using ChatGPT. This LLM model could then be used to explore the impact of different scenarios (e.g., El Niño weather pattern versus a La Niña weather pattern) on the farm business. In more general applications, there were examples where GenAI was used initially for contextual analysis, such as feed budgeting, and then for predictive reasoning to query what might happen in a particular scenario if, for example, pasture growth rates dropped, or milk price reduced.

In the 'task enhancement' category, use cases tended to align with more established applications of LLMs, including writing assistance, meeting recording and transcription. There were a couple of more innovative applications identified including using GenAI to draft standard operating procedures (SOPs) and to semi-automate the drafting of a weekly structured Monday morning report. In the latter example, ChatGPT was being used by the farmer and could recognise the engagement such that a simple "It's Monday" prompt would initiate a set of questions prompting the information required (e.g., weather, production data) to complete the report.

The 'communication support' category also appeared to have few use cases. There was, however, one very innovative use case of a tailored 'farm chatbot' created by an operations manager in a multi-farm organisation. The chatbot was built as a custom GPT and configured to use farm policies for grazing and pasture management, and trusted third-party sources (e.g., DairyNZ, Fonterra, Federated Farmers contracts) for information such as animal health, calf rearing, milk grade information and employment queries. The purpose of the chatbot was to manage risk, ease mental workload on the manager and enable quicker support to farm staff given that queries often took a long time to move up the chain. The operations manager accepted there was potential risk in the GPT providing inaccurate results. However, this was managed by encouraging use of the tool for providing answers rather than making decisions (e.g., "what round length should I be on today based on the spring rotation plan?" rather than "help me build a spring rotation plan"), and caveating the use of the tool with staff to let them know responses may not always be accurate and to seek clarification if it doesn't sound right.

Table 2: Overview of the current and emerging use cases, including example interactions, for GenAI on dairy farms in New Zealand.

Existing use case		Description	Example interaction(s)
Decision support *(Use of GenAI to assist decision-making through providing insights, recommendations or calculations. This can be achieved through combinations of accessing general knowledge, contextual analysis of the specific farm, and predictive reasoning)**			
Knowledge access	General Q&A	Use of GenAI to ask technical or operational questions providing access to a wide range of generic/publicly available (web-based) information. Both text and speech functionality used.	• *"How do I calculate the correct magnesium supplementation rate for my herd?"* • *"What is the typical utilisation of silage fed in the paddock?"* • *"What summer crop should I use?"* • *"What strategies can I use to improve communication on farm?"* • *"What type of drench should I use for my cows?"* • Weed identification using photos uploaded into GenAI tool. • Cow illness query using photo uploaded into GenAI tool. • Sense-checking information (e.g., calf milk additive rates). • Exploring alternative ways to complete tasks (e.g., drenching stock).
Contextual analysis	Pasture and feed	GenAI used to help farmers allocate pasture, balance feed and minerals, compare supplements, create spring rotation planners.	• Custom (and publicly available) GPT created to act as an AI-powered dairy consultant to primarily support feed and grazing decisions. Configured to provide tailored farm responses using farm data provided, specific industry sources (e.g., DairyNZ) and developer-authored system rules (e.g., pasture first approach). • Round length recommendations and grazing plans provided based on entered data including growth rates, stocking rate and feed available. • Diet recommendations provided based on nutritive quality of pasture and supplements available, and desired production level. • *"Create an annual feed budget using the provided farm and herd data and supplements available."*
	Animal health	GenAI used to support mineral supplementation, cow body condition scoring, weighing and kill sheet analysis.	• Mineral dosage rates provided based on photo of ingredients from mineral bag uploaded into AI tool. • Potential mineral deficiencies queried by providing AI with cow's diet. • Taking photos of a sample of cows in the paddock and uploading to ChatGPT to analyse BCS and track changes. • Weighing calves using ChatGPT based on provided age and uploaded side-on photo. • Analysing carcass weight, liveweight and dressing out percentage from multiple uploaded kill sheets.
	Reproduction	GenAI used to assist with analysing and interpreting data from various applications and/or cow wearables (via .csv files).	• Reproductive data from MINDA uploaded (as .csv files) and quickly interrogated. For example, "what is the conception rate of my 5-yr-old cows? How does that compare with my 3-yr-olds?" • Data from different products and information sources uploaded and interrogated alongside advisers. For example, Halter reproductive data and body condition score (BCS) data used to show impact of BCS on cycling rates.
	Breeding management	GenAI used to assist in creation of mating plans based on herd and/or cow specific traits and desired breeding goals.	• GenAI breeding tool developed that can create a tailored bull team based on published bull traits, individual cow records and farm breeding goals. • *"Design a sexed semen plan for my herd and identify the most appropriate cows to select."* • Side and rear photo of cow uploaded to ChatGPT to complete Traits Other than Production (TOP) scoring and summary based on New Zealand standards.
	Fertiliser planning and nutrient management	GenAI used to develop fertiliser recommendations.	• *"Create a fertiliser plan for my farm based on provided soil test results and targets."* • *"Should I apply nitrogen now and at what rate?"*
	Financial planning	GenAI used to benchmark performance, determine breakeven milk price, and support budgeting.	• Custom (and publicly available) GPT created to act as a 'financial assistant' for a range of functions including budgeting, scenario analysis, GST, tax planning, and benchmarking. Configured to provide tailored farm responses using farm data provided and specific industry sources (e.g., DairyNZ economic survey, Fonterra advance rates, IRD national average market values). • *"Help me create an annual budget for next season."* • *"How does my profitability compare with other farms in my region? Where could I improve?"* • *"Here is my expected income and expenses for the season. What is my breakeven milk price?"*
	Equipment and machinery	GenAI used to support operation, maintenance and repair of farm equipment and machinery.	• Tractor manual uploaded into GenAI tool allowing the farmer to question certain items. For example, "where are the grease points on my tractor? What does this fault code mean?" • Photo of a broken-down pump uploaded into GenAI to help troubleshoot issue.

Predictive reasoning	Scenario modelling	GenAI used to simulate alternative scenarios and "what-ifs" to help plan for varying conditions (e.g., weather patterns, milk price fluctuations).	• LLM-powered 'digital twin' of farm created using uploaded reference files and farm information to model impacts to system from different weather patterns (e.g., La Niña vs El Niño). • *"What happens if milk price drops to $7.00/kg MS?"* • *"What if August growth rates remain below 20 kg DM/ha/day?"*
Task enhancement *(use of GenAI to increase efficiency of repetitive tasks, often administrative, reducing workload and increasing operational efficiency)*			
Drafting documents and reporting		GenAI used to help draft and edit documents and support farm reporting.	• Generate standard operating procedures (SOPs) for various farm tasks. • Assist in writing documents or letters. • In-built GenAI in computer software used to help draft/edit email responses. • Support with drafting weekly/monthly farm reports and summarising key data.
Supporting administrative functions		GenAI used to speed up and/or automate administrative tasks.	• Using GenAI tools to record and transcribe meeting minutes.
Communication support *(use of GenAI to assist with team co-ordination, management and communication facilitating work efficiency and collaboration)*			

Farm 'chatbot'		Custom AI 'chatbot' created and tailored to an individual farm using reference files for which the GenAI considers when responding to queries. Often used in businesses with large/multiple farms to manage risk and increase farm staff access to knowledge in real-time.	• Custom chatbot created using farm-specific policy documents (e.g., farm-specific grazing policies, health & safety, RVM) and trusted industry data (e.g., DairyNZ animal health data, Fonterra supplier handbook) to support farm staff to access and query farm-specific information without having to contact owner or operations manager, for example:
			  • *"What round length should I be on today?"*
			  • *"I have a down cow and have tried everything, but she is still not getting up. What else can I try?"*
			  • *"We received a coliform grade. What do I need to check?"*
			  • *"Cow 354 has Strep. Uberis. Which mastitis drug do I need to use?*
			• Upload payslip and query why pay is different this fortnight.

Language translation		GenAI tool used to translate instructions or documents, as written text or audio, into primary language used by farm staff to improve communication.	• *"Translate these instructions for today's farm tasks into Filipino"* • *"Translate this SOP on how to put the plant wash through into Nepalese."*

**Decision support use cases allocated into sub-categories based on primary function (e.g., if the primary function is to interpret a farmers own data, this is categorised as contextual analysis. If it is mostly about pulling external information, this is categorised as knowledge access. If it is mostly about "what if", then it is categorised as predictive reasoning).*

5 Ideation

5.1 Introduction

The ideation phase of this project explores what a realistic, near-future AI-enabled pastoral dairy farm might look like, with a focus on GenAI applications. The ideation was developed by a group of Perrin Ag dairy farm specialists. It drew on insights and ideas developed throughout the project, including from those gathered through the exploration phase of the project. The ideation was developed around what were considered to be major “pain points” for New Zealand dairy farmers, key areas of decision making in a pastoral dairy farm basis, the key tasks within a “typical” day on a New Zealand dairy farm and considering the realistic application of GenAI within these domains.

Given the rapidly evolving nature of GenAI and uncertainties around future adoption, a scenario thinking approach was used to develop two plausible pathways that illustrate where and how GenAI could be incorporated within farming businesses in the near-term (3-5 years). While these pathways may deviate from actual adoption trends, they are designed to highlight realistic opportunities that GenAI could bring to the dairy sector. Consideration has been given to the current limitations of the technology and challenges of pasture-based dairy farming to help ground the thinking for the future pathways. The ideation process was both collaborative and iterative. Future use cases were discussed and refined before a final peer-review.

In addition to exploring these pathways, this section also provides a short summary on some practical tips and tricks for interacting with GenAI, potential key risks, and opportunities for DairyNZ to support farmer uptake and engagement.

5.2 Limitations of GenAI

GenAI presents significant opportunity for dairy farmers, whether that be in productivity gains, time savings, supporting an improved team culture, or allowing for greater work-life balance. As with most technology, there are limitations of GenAI. Understanding these limitations is essential in understanding how and where the technology may realistically be adopted in the near future.

5.2.1 Tacit and experiential knowledge

New Zealand’s pasture-based dairy farm systems are complex with many biophysical interrelationships. Furthermore, every farm system is unique regarding the farm’s physical characteristics, the systems operated, and the farmers that operate them. Farmers cope with the challenge of managing these variable farm systems through their tacit (experiential) knowledge built up over years of observing weather patterns, animals, pasture and land responses as opposed to learning from formal data.

In this regard, GenAI will always struggle in providing recommendations at a farm-specific level given this tacit knowledge is not accessible and is largely undigitised. Contextualising input information will help to improve the performance of GenAI, but for many farmers, being able to translate their nuanced, context-specific understanding into prompts that LLMs can interpret will be challenging. Given this limitation, GenAI is unlikely to replace farmer judgement in the near future but rather support decision-making.

5.2.2 Hallucination and bias

Large-language models are trained on vast amounts of text datasets, learning to predict the most likely next word or phrase based on patterns found in the training data. This training allows the LLM to generate responses that appear fluent and knowledgeable, but the LLM does not have genuine cognitive ability and cannot understand the content that is produced. As a result, LLMs are prone to hallucination - generating information that sounds plausible but is inaccurate, unsupported or fabricated. This problem can be compounded given LLMs often respond in a confident tone giving the user a false sense of security, especially if the farmers themselves have limited technical knowledge of the topic.

In addition, bias in GenAI models can arise from both the data they are trained on and the algorithms used to develop them. This can lead to outputs that are influenced by certain assumptions or perspectives that the model has been built on. For example, when used in a New Zealand dairy context, generic LLMs may reflect datasets that are more heavily weighted to overseas housed dairy systems which can make responses less relevant to the New Zealand pasture-based model.

The current presence of hallucinations and bias limits the extent to which LLMs can be relied upon for tasks where accuracy is critical. As farmers engage with GenAI and understand these technical limitations, use cases will likely lean towards decision-support as opposed to autonomous decision-making, particularly for tasks that require high levels of accuracy. Providing the LLM with context-specific information or trusted reference data can help reduce the incidence of errors and bias. Ultimately though, farmers (and other users) will need to critically assess outputs from GenAI and apply their own knowledge and judgement before acting. This is not untypical to the current situation where farmers must filter information from various sources – including from webpages, rural professionals, and others, before determining the best course of action.

5.2.3 Data interoperability

Most generic LLMs operate as standalone chat interfaces and do not easily integrate with farm management software, web portals or sensors. This limits the potential for GenAI to operate as a 'whole-of-farm' interface with outputs remaining relatively generic and based upon data provided directly by the farmer.

It is, however, theoretically possible (and there are some innovator farmers experimenting in this space) to create purpose-built interfaces (application programming interfaces; APIs) that allow an LLM to pull data from external systems or to create agents that can connect a GenAI model with another database. This is still an emerging area and the ability to achieve this interoperability is currently limited to those farmers that have the necessary technical skillset and the inherent permissions within third-party software and data sets for which access is required.

For those without the skillset or desire, integration in the near future is likely to be limited to direct provision of data (most likely as .csv or excel files) to an LLM model. For instance, downloading individual body condition score (BCS) data from MINDA or Herd-i and uploading into ChatGPT.

In the future, it is expected that there will be a greater prevalence of GenAI tools embedded within various farm management software and web portals and that can integrate data between various platforms. For example, MINDA integrating and sharing data with Halter for greater data analysis at the individual cow level.

5.2.4 Digital connectivity

While not a specific limitation of GenAI in itself, the challenge with digital connectivity on many rural farms should be acknowledged. In locations with poor connectivity, the use of GenAI can be significantly constrained. Accessing GenAI tools typically requires a reliable continuous broadband or mobile data connection. If this connectivity is not available, or is only available at the home office, then use of the tool will be limited.

This limitation is not just constrained to the interaction with a GenAI tool (e.g., an LLM like ChatGPT) on its own, but also in the ability to leverage the value of the tools through integration with other on-farm sensors, software and digital tools which may also be lacking on farms with poor connectivity.

It is noted that digital connectivity is improving, and more options are becoming available to connect farmers to the internet through satellite technology as opposed to relying on local infrastructure. It would be plausible to expect that within the mid-term (i.e., 5-10 years) challenges with internet connectivity will largely be resolved.

5.2.5 Farmer capability

Alongside digital connectivity, not all farmers will have the same level of comfort or confidence in using new technology such as GenAI. Farmers with lower confidence, typically those in the middle of the adoption curve ('the majority'), and who have a naturally lower willingness to experiment and change existing practices will be limited in their engagement with GenAI. Providing targeted support on how to use GenAI, in a rapidly evolving future, and demonstrable use cases will be key to reducing confidence and capability limitations.

Furthermore, as GenAI technology becomes increasingly a part of everyday farm systems and decision-making, the ability to effectively use and interact with GenAI will become more important. There is a growing risk that farmers who lack digital literacy or a willingness to engage with these tools may find themselves at a disadvantage to their peers. Supporting farmers to build confidence and, at least, basic digital AI literacy will therefore become essential to prevent capability gaps from widening across the industry.

5.3 Challenges of New Zealand's pasture-based dairy businesses

Pasture-based dairy farming in New Zealand faces several specific key challenges. Consideration of these key challenges provides insight into which aspects of the business GenAI is likely to be used in the near future, particularly when considering the mainstream farming population (early and late majority) who seek proven solutions to key pain points.

5.3.1 Biological systems

Pasture-based farming operations are characterised by biological systems with complex interrelationships. These systems are inherently dynamic with pasture growth, grazing behaviour, and productivity all influenced by interacting factors such as climate, soil conditions, animal health, grazing and feed management. Successful management of these pasture-based systems require constant adaptation to seasonal and climatic variabilities, as well as to changing good practice and regulatory requirements.

Feedback loops within these biological systems offer farmers the ability to observe and refine management over time. For example, grazing decisions made today will affect immediate milk production and pasture regrowth which in turn affects future pasture availability and quality and, ultimately, animal performance. Some feedback loops are fast – appearing in just days, while others are slower, taking weeks, months or even seasons to fully unfold.

In biological, pasture-based systems, the timing of decisions is critical and can be the difference between a top-performing and an average operator. A delay in decision-making in one area can quickly flow through the system and impact on future outcomes. This is particularly evident in decisions around transition periods, such as deciding when to switch to once-a-day milking, dry cows off or alter the grazing rotation.

GenAI presents opportunity to support farmers in managing these complex biological systems by enabling timelier, or even real-time, data-driven decisions. GenAI also offers opportunity to test out a system under varying climatic or management scenarios using predictive modelling on a digital twin. This helps farmers anticipate the effects of different decisions before they are made rather than risk testing in real-life and waiting for feedback loops.

5.3.2 Labour

Labour is a key challenge of New Zealand's pasture-based dairy farms. The physical demands of farming, long working hours and rosters, rural isolation and limited progression pathways make it difficult to compete with urban-based employment and to attract and retain skilled staff. Seasonal fluctuations in workload further compound labour challenges and require flexible staffing arrangements and high levels of co-ordination. For smaller farms, the challenge of sourcing labour can be made more difficult where additional skilled labour might only be required for parts of the year rather than as full-time employment. In contrast, on larger farms, building a team with the skillset required to undertake the range of tasks required on pastoral farms (e.g., animal husbandry, pasture management, maintenance, machinery operation, data analysis and interpretation) can also be a challenge.

Increasingly, and often in response to these challenges, farms teams are made up of migrant workers and/or backpackers seeking short-term employment. This can also introduce additional challenges related to skill level, language barriers and requirement for ongoing training and supervision .

These labour constraints impact on productivity and efficiency, and challenge farmers who may not possess natural people management skills. Technology, such as GenAI, offer opportunities to support co-ordination of rosters and daily activities, facilitate communication, provide adaptive on-the-job training, and assist with recruitment activities, onboarding and professional development. Additionally, the use of migrant workers and backpackers could also become less problematic where there is higher level of technology and automation that mean tasks are less reliant on deep farm systems knowledge and experience. For example, real-time translation could eliminate language barriers for those who English is not their first language. Ultimately, GenAI presents opportunity to improve efficiency and create improved employment opportunities better able to compete with modern expectations for work-life balance.

5.3.3 Environment and animal welfare

New Zealand's pasture-based dairy systems face the challenge of reducing nitrogen loss to water and mitigating greenhouse gas emissions while remaining productive and profitable. In addition, there is growing scrutiny and pressure to improve animal wellbeing and increase biodiversity. Managing these issues is complex, given many mitigation options involve trade-offs between profitability, and environmental or animal welfare outcomes. For example, a mitigation that reduces nitrogen loss may increase greenhouse gas emissions, or one that promotes biodiversity may reduce profitability.

In some catchments, farms may already be nutrient-limited, putting constraints on farming intensity and activities (e.g., cropping, stocking rate). Looking ahead, farm environment and freshwater planning requirements are expected to increase bringing greater scrutiny to how certain activities or areas of the farm are managed.

GenAI offers potential to support farmers with addressing these challenges by applying a whole-farm lens to decision-making, considering effects of management options on profitability, animal wellbeing and environmental performance simultaneously. In addition, for farms operating under regulatory restrictions, GenAI offers opportunities to design systems that optimise profitability within a constrained system. Over time, GenAI tools integrated with real-time data could also flag environmental and animal welfare risks earlier and support a more proactive management approach.

5.3.4 Time pressures

Farmers tend to operate under significant time pressures that require balancing multiple competing demands across daily farm operations, administrative tasks, staff management, and personal or family commitments. The seasonality of contemporary pasture-based systems compounds these pressures, with busy periods such as calving and mating delaying or reducing time available for strategic planning or professional development. This delay can lead to reactive rather than proactive decision-making where short-term operational tasks take priority over longer-term strategic planning.

GenAI offers opportunities to help farmers free up time that can be used to focus on higher-value activities by streamlining information gathering, supporting automation of repetitive tasks and carrying out administrative functions. With mobile-friendly applications and voice-enabled tools, tasks that may have previously required being in the office can be carried out while on the go helping farmers to manage workloads more efficiently.

5.3.5 Information and cognitive overload

The rise in technology adoption on-farm (cow wearables/sensors, milk vat monitoring, water and effluent monitoring, weather stations, soil temperature probes and moisture meters, pasture monitoring software, in-shed milk meters and mastitis detection, walk-over weighing systems, farm management software) has resulted in large volumes of data being collected. This information, often spread across multiple portals and software programs, holds valuable insights but can quickly become overwhelming. Combined with the everyday time pressures of farming, the reality is the sheer volume and fragmentation of data can quickly lead to cognitive overload, decision fatigue and underutilisation of available data. In many cases, farmers revert to intuition because the interpretation and integration of data from multiple streams becomes too time-consuming.

There is an obvious opportunity here for GenAI to bridge this gap by synthesising information from multiple data streams and information sources into clear, actionable insights, and recommendations. Farmers could query their own farm data, as some are experimenting with now, using natural language interface. In addition, GenAI could accelerate the speed at which this is done and provide solutions embedded into existing software that farmers already know and use (e.g., MINDA) providing immediate trust. Through filtering and summarising information, GenAI can help reduce cognitive load and enable more confident, timely and informed decision-making. The caveat here is that bad data in will still equal bad data out. While GenAI will likely be able to autonomously structure data into the format it needs to work with, if the data is missing (e.g., unrecorded calving or health events) or inaccurate then the quality and reliability of outputs will be limited.

5.3.6 Maintaining returns on assets

Maintaining profitability and returns on assets is an ongoing challenge for New Zealand dairy farms. Farmers operate within a volatile commodity market where farmgate milk prices are largely outside of their control. Farmers must also contend with rising input costs, tightening environmental regulations and competition from alternate land uses (e.g., arable, horticulture, solar farming, carbon, and equine). Combined with typically high debt-loading, the reinvestment in technology, labour and farm improvements is constrained and often a balancing act between short-term financial viability and long-term sustainability.

GenAI offers potential to support farmers in this space by improving operational efficiency, identifying cost-saving opportunities, and more easily modelling financial impacts of management decisions or proposed capital purchases. There are also opportunities to strengthen financial planning through enhanced forecasting and risk analysis, including support for budgeting and hedging strategies. In doing so, GenAI could support farmers to maintain profitability and resilience in increasingly uncertain and complex operating environments.

5.4 Near-future positioning of GenAI

The preceding sections have outlined both the limitations of GenAI and the key challenges faced by New Zealand's pasture-based dairy farms. Together, these provide the foundation for understanding where and how GenAI is likely to be used in the near future. It has been noted from discussions with professionals working in the AI sector, and from early adopter and innovator farmers, that the potential opportunities for GenAI are seemingly endless. From a practical standpoint, however, it is unlikely that every technically possible use case will be adopted. Real-world uptake will depend on how well GenAI can align with farmers' existing systems, their trust and confidence in the technology, their level of awareness and capability, and the level of digital connectivity and interoperability able to be achieved.

Given current limitations, particularly with hallucination, bias and an inability to replicate tacit knowledge, it is expected that near-term adoption will focus on use cases that support rather than replace farmer decision-making. In practice, this will likely see GenAI being used to enhance data interpretation, streamline administrative processes, enable scenario modelling through natural-language interface, support communication and the co-ordination of people, resources and workflows, and act as a digital adviser supporting queries and helping with decision-making.

There will also be strong use cases for GenAI to be used for real-time data analysis, decision support and agentic capabilities. The ability for this to occur in the near-term will, however, depend on resolving challenges related to data interoperability and reducing hallucination and bias to levels that farmers consider acceptable.

In the next few years, farmers could be expected to continue to interact with standalone LLM interfaces (e.g., ChatGPT, Gemini, Claude) and also with GenAI applications that become available within existing farm management software, web pages and digital platforms. GenAI embedded into these platforms will provide the ability for fast, AI-driven insights that come from familiar and perhaps more trusted (relative to standalone, non-contextualised LLMs) interfaces. This embedded functionality is expected to appeal to the majority of farmers who want simple, reliable tools that integrate seamlessly and deliver clear benefits without requiring significant technical set-up.

The reality is that farmers will likely continue to have a desire to 'farm' and not spend hours sitting at a computer screen. It is therefore likely, that GenAI will be most valuable and used where it can be easily accessed and provide clear production, profitability or time-saving benefits without requiring significant screen time. More advanced, customised applications, such as those that might require custom-built data integration or multi-agent systems, are expected to remain limited to farmers with the necessary technical capability and desire to experiment (i.e., the innovator and early adopter farmers). Over time, some of these applications that provide proven solutions may evolve into 'off-the-shelf' GenAI workflow tools (e.g., feed budgeting, grazing planners) as service and technology providers adapt proven use cases into ready-to-use products for the wider industry.

To illustrate how GenAI adoption may unfold, Table 3 presents contrasting but plausible near-future pathways. This includes a conservative, perhaps more realistic, future reflecting a scenario where GenAI adoption progresses more cautiously and existing technical limitations remain. It reflects some of the edge-of-field use cases that innovator and early adopters may already be experimenting with and considers GenAI as a digital adviser/assistant . The second pathway reflects a more aspirational, innovation-driven future where GenAI is integrated across multiple aspects of farm management and assumes key limitations, particularly regarding data interoperability, have been resolved. In this pathway, GenAI acts as a digital partner/collaborator better enabled to support, and in some lower-risk cases, execute decision-making .

Agentic capabilities become more advanced in this aspirational pathway reaching mid-level status (Level 3-4) where they're able to plan, co-ordinate and execute multi-step tasks (see Appendix 1) and learn from previous decisions. While much of the technological limitations to GenAI are resolved in this pathway, inherent vulnerabilities relating to hallucinations, bias and an inability to replicate tacit knowledge mean than human oversight remains critical. Therefore, while agentic workflows are able to handle their own operational steps, they must still exist within human-set boundaries.

These two scenarios also represent pathways that might reflect different groups of the farming population. The first pathway aligns with the near future for the early and late majority group who prefer to wait for proven, reliable tools that integrate seamlessly within their existing systems and demonstrate clear benefits. The second pathway aligns with where we might expect the innovator and early adopter group to end up, who are more willing to experiment, take on risk and push the boundaries.

Table 3: Comparison of potential, near-term GenAI use cases for dairy farms under conservative (pathway 1) and aspirational (pathway 2) future pathways and considering the current challenges of these pasture-based systems.

Challenge		Current state	Pathway 1: Conservative future	Pathway 2: Aspirational future
		The present reality of most New Zealand dairy farms. Use of AI is minimal, and decision-making relies primarily on farmer intuition, observation and experience. While data is becoming increasingly available (e.g., AI-powered pasture management software, cow wearables, sensor technology), integration is limited, and data analysis is often manual and time-consuming. This results in low data utilisation and a largely reactive approach to decision-making. The level of supporting technology (e.g., automatic drafting gates, cow wearables, milk meters) varies widely.	GenAI acts as a digital assistant that supports and accelerates decision-making through insights and recommendations. Its contextual understanding of the farm is limited to the data and information manually provided by the farmer. Agentic capabilities are limited to low-level, rules-based tasks. Integration of data between systems is still a constraint. Accordingly, farmers interact with GenAI through standalone and often customised LLMs or through GenAI functionality embedded in web portals or software programmes. Off-the-shelf industry or commercial GenAI workflows are available for activities with clearly defined rules and goals and are used where they provide proven benefit. GenAI enhances efficiency and understanding but remains firmly human-directed.	GenAI acts as an integrated digital partner operating within a connected technology and AI ecosystem or central farm hub. High data integration enables real-time insights, stronger contextual understanding, adaptive learning, and proactive decision-making. Mid-level (see Appendix 1) agentic capabilities exist and can co-ordinate or adjust operations within farmer-defined boundaries and learn from outcomes to continuously refine future recommendations. A high level of on-farm technology and data capture devices maximises the value of GenAI.
Decision-making in biological systems		Farmer manually assesses paddocks, or uses pasture forecasting software, to determine grazing rotation based on experience.	Farmer uses GenAI functionality in pasture management software to model impacts to pasture covers from various decisions and uses results to decide on the best option to implement.	GenAI integrates with virtual fencing and manages the grazing round autonomously based on the weather forecast, current and predicted growth rates and historic patterns, pasture heading dates and upcoming activities (e.g., silage-making, cropping). Animal performance and pasture regrowth are monitored to inform and improve future decisions.
		Farmer splits herd into two mobs based on age to manage competition and improve performance of younger cows.	Farmer loads herd data (cow information, reproductive performance, herd test information and health history) into GenAI tool and requests recommendations on how to split the herd to optimise long-term cow performance.	GenAI connected to the central AI hub analyses farm and cow data and autonomously drafts cows to individual mobs to maximise performance. This includes consideration for cow hierarchy and social preferences, and those cows most suitable to grazing hill areas. Ongoing analysis of live data and connection to the autonomous drafting system allows for continuous optimisation of mobs throughout the season.
Labour	Staff co-ordination and rostering	Fortnightly roster, based on minimum daily staffing requirements, is created for the season using paper or spreadsheets. Adjustments for leave requests are reactive and manual.	GenAI is used to generate a staff roster. Staff availability and key farm tasks and labour requirement are uploaded to quickly produce an optimal roster that balances workload, farm requirements and staff time off for different times of the season. Updates for leave are still reactive and handled manually, but with assistance from GenAI.	Rostering evolves into dynamic daily work planning supported by a connected GenAI hub. GenAI integrates staff availability, skillsets and job lists to allocate tasks. Leave requests are made digitally and approved by the farm manager, based on GenAI recommendation. GenAI automatically updates the work plan, reallocates tasks and updates payroll records. Each team member receives updated daily schedules via mobile or desktop interface.
	Communication	After morning milking, the farm manager briefs the team on weekly jobs and writes the job list on the whiteboard, including setting up the irrigator. A Filipino employee begins setting up the irrigator but wasn't quite clear on the instructions and puts it in the wrong paddock. There was an issue with turning the irrigator on and the employee rings the farm manager to come out and help get it going.	A Filipino employee uses a voice-enabled LLM to translate the manager's instructions for setting up the irrigator in real-time. While out completing the job, the employee runs into a problem turning the irrigator on. They consult the farm-tailored chatbot which uses stored SOPs to suggest possible solutions. The employee resolves the issue and completes the job.	A Filipino employee receives a task to their phone from the central AI hub to set up the irrigator based on current soil moisture conditions and forecast weather. The instructions are automatically delivered in Filipino. An issue arises while setting the irrigator up, and the employee troubleshoots the problem verbally with the GenAI in their preferred language.

Labour	Recruitment	The farmer posts a digital advert to a job portal. Forty applications are reviewed, and the CVs are manually checked. Four applicants are shortlisted for referee checks and then an on-farm interview. The farmer selects the most suitable person based on their observations and offers the job.	The farmer uses GenAI to help write an engaging job advert which is subsequently posted to an online job portal. As applications are received, CVs are uploaded into the farm LLM which is asked to rank them on a scale of 1-10 based on their likely fit. The farmer requests interview questions for shortlisted candidates and later uploads the recorded interviews. The GenAI analyses responses and provides insights on likely fit, which the farmer considers alongside their own judgement before making the final offer	The farm's AI hub manages most of the recruitment process from drafting the job advert to onboarding. Drawing from farm policies, labour requirements and additional information provided by the farmer, GenAI drafts the advert and posts it across multiple digital platforms. As applications are received, they are automatically screened and ranked. The GenAI alerts the farmer to the shortlisted applicants and provides relevant, individualised questions to ask each candidate. Once the chosen applicant is selected, GenAI handles much of the onboarding including sending through the required documentation and personalised training plan.
	Team upskilling	An employee, new to the industry, is sent on a formal course comprising classroom sessions and written assessment to learn about calf rearing. This is reinforced through on-the-job training with a more experienced team member to learn the farm-specific systems.	The farmer uploads their calf-rearing SOP into a GenAI tool which converts it into a step-by-step narrated video specific to the farm. Content is reviewed and approved by the farm manager before being shared with staff for onboarding and refresher training.	When the farm revises their calf rearing protocol, the GenAI automatically revises the associated training material and sends a notification to staff through the AI ecosystem. The format is adapted to the needs of each employee including a short visual summary for one member, an audio walkthrough for another, and a narrated video in French for a fixed-term employee. The system is linked to staff training plans and automatically suggests or creates modules linked to identified skills gaps.
System optimisation		A farmer works with a consultant to identify different scenarios that will optimise their farm system within their resource constraints and nutrient limitations. The process is time-consuming, and outputs are manually compared. Performance of the new system is reviewed annually following implementation.	The farmer engages with a GenAI assistant that already holds key information about the farm system. After providing goals and constraints in natural language the GenAI synthesises relevant data and produces three scenario options that balance profitability and environmental performance. The farmer reviews the options alongside their consultant and selects the preferred system. Annual reviews are completed.	The connected GenAI hub integrates with scientific modelling tools, such as Overseer and Farmax, using historic and real-time farm data. Various system optimisation scenarios are run and the GenAI recommends the scenario that best balances farm profitability, environmental performance and the farmers goals. Following implementation supported by their consultant, real-time modelling tracks outcomes against the plan and suggests any adjustments over the season as required to maintain outcomes.
Environment/ animal wellbeing		The farmer uses soil maps to identify high-risk areas within paddocks for nitrogen loss and integrates this knowledge with virtual fencing capability. In wet weather, the farmer manually adjusts breaks to exclude stock from these areas to minimise nitrogen loss.	The farmer uses GenAI to combine soil maps, past GPS fertiliser spreading records, and effluent application records to generate a heat map showing areas of higher nutrient-loss risk. The map helps guide farmer decisions on fertiliser and effluent application and grazing management to enable greater nutrient utilisation and reduced nutrient loss.	GenAI continuously analyses nutrient application data (fertiliser and effluent records) and calibrates against pasture growth measurements taken at the square meter level. This creates a live, sub-paddock scale map of nutrient response allowing the farmer to identify areas where uptake of nutrients by pasture is minimal and risk of nutrient loss is high. From the nutrient response map, a variable rate application map is created that enables precise, sub-paddock scale nutrient application that maximises uptake and minimises loss.
		Cow health is monitored by the farmer through direct observation or alerts from cow wearables. When abnormal behaviour is noticed, the farmer investigates.	The farmer exports wearable and GPS data into the farm's LLM to identify behaviour patterns and possible cow comfort or wellbeing risks. The system analyses activity and highlights that cows grazing in one paddock consistently spend less time feeding and more time standing. It suggests reviewing shade, water access or pasture quality. The farmer investigates, decides to re-grass the paddock and observes for any change.	Through continuous analysis of data, the GenAI detects a pattern from wearable data and GPS technology that cow comfort and behaviour is sub-optimal in a certain area of the farm. It alerts the farmer and suggests checking pasture species, eczema spore counts, and shade availability. The farmer reviews, implements a change and GenAI tracks the changes to refine future recommendations.

Time management	After milking, the farmer catches up on outstanding administration jobs. The weekly farm report is manually prepared and sent to the consultant, feed contracts are checked, an application for a bank green loan is filled out and a new SOP is developed. Accounting software has automatically coded invoices and an in-email GenAI tool has summarised emails, but overall, most of the work is done manually taking several hours each week.	While mowing a paddock, the farmer uses hands-free voice interaction with their farm GenAI assistant to update the weekly report, check new emails, send replies, and start development of a new SOP. Back at the office the prepared farm report is sent off to the consultant, feed contracts and invoices for approval are still manually checked, and the bank green loan application is filed out with drafting assistance from GenAI.	While mowing a paddock, the farmer receives an alert on their phone to approve the monthly invoices. At the same time, the farmer checks in with the central GenAI hub on other admin tasks. The system confirms that the farm report, generated from real-time production and system data, has been automatically shared with the consultant. Feed contracts have been reviewed, and the next delivery as part of the feed budget ordered. The GenAI has also pre-filled the green loan application form ready for review and approval. With most repetitive admin tasks handled, the farmer can redirect time to higher value activities.
Data analysis and cognitive overload	The farmer logs into multiple platforms including the production portal, cow wearable dashboard, and herd management software. With dozens of alerts and graphs to interpret, it's difficult to see the bigger picture, so decisions are made quickly using intuition. The farmer often feels overwhelmed by the amount of information and tends to focus only on the most urgent issues.	The farmer uploads .csv files from their production portal, cow wearable dashboard, and herd management software to their GenAI assistant. Within minutes, and on request, the GenAI has provided insights and a summary highlighting reproductive and production trends. The farmer reviews the finding and decides to make a change to their mating strategy.	The central GenAI hub continuously analyses live data from sensors, wearables and software platforms. In preparation for next season's mating, the farmer asks what areas they should focus on to improve reproductive performance, and the system provides a clear, spoken summary for the farmer to implement. Just prior to mating start date, the central AI hub flags a developing pattern of a lower cycling rate in one herd. It recommends adjusting feed levels to this group, notifies the farmer, who subsequently approves and the adjustment is implemented. Data is now synthesised automatically and decisions are proactive.
Financial resilience	An annual budget is prepared using last year's figures and the current milk price forecast. Reforecasts are only made in response to major changes (usually milk price) and limited 'what-if' analysis is undertaken. With no significant hedging in place , any drop in milk price or rise in feed costs directly affects cashflow. Financial focus remains on the current season rather than building for long-term resilience.	The farmer uses an 'off-the-shelf' GenAI workflow to create the annual budget. Inbuilt functionality allows the tool to use current market data and test multiple 'what-if' scenarios. Several pressure points are identified and trusted mitigations including cost-saving strategies and potential hedging strategies to protect margins are suggested. The farmer adopts a hedging strategy, reviews the plan with their accountant and uses the workflow throughout the year to track actuals against budget and reforecast as required.	The central GenAI hub builds and maintains a rolling multi-year budget using live farm data and market forecasts. It develops a hedging strategy based on the farmers financial position and risk tolerance. As global markets changes, the system automatically reforecasts cashflow and notifies the farmer of potential impacts to profitability. It recommends operational changes to preserve margins when market conditions are dropping. Conversely, when conditions are favourable, it suggests strategies to capitalise.

5.4.1 'Day-in-the-life' example: aspirational future

To complement the pathways described in Table 3, and by way of example, this section provides a 'day-in-the-life' of the aspirational AI usage pathway to help illustrate how GenAI might operate within a near-future, pasture-based dairy system.

In this aspirational near-future, GenAI is deeply embedded across the farm business acting as a 'digital AI partner'.

Farm policies, resources, constraints and goals have been provided by the farmer to enable the AI to have a comprehensive understanding of the farm business and operations. The challenges of data interoperability have largely been resolved enabling GenAI to not only integrate data streams but also synthesise and analyse data in real-time and co-ordinate actions through connected systems. The integration opens up opportunity for higher-level agentic capabilities and creates a new GenAI 'ecosystem' that is always running in the background and available at any time to support farm operations, decision-making and co-ordination. Moreover, the GenAI ecosystem anticipates needs and continuously learns about the farm business updating its digital model of the farm.

In this pathway, agentic capabilities pull data from various systems and platforms, anticipates needs, initiates routine actions and co-ordinates people, resources or certain tasks while keeping the farmer informed. Interaction occurs naturally through desktop, mobile and voice interfaces and extends beyond just the farm owner/manager to team members and consultants, each with role-based access.

The farmer continues to shape the GenAI's learning and functionality, spending short sessions each month refining prompts, reviewing outputs, and experimenting with new integrations. Over time, this iterative training enables the GenAI ecosystem to become an intelligent, trusted partner, providing insights and recommendations while freeing up time on routine administrative functions to focus on tactical and long-term strategic goals.

5:00 AM – The day begins
While the cows are making their way to the cowshed using virtual herding technology, the farmer starts the day with a summary review from their tailored GenAI dashboard. This uses data pulled from sensors around the farm and digital platforms to provide key metrics and real-time updates on production, cow health, pasture and feed, environmental factors and staff availability. On this particular morning, the system informs the farmer of the day's activities, staff rostered on and highlights potential issues including cow 236 which is scheduled to be drafted based on her unusual gait movement and a change in the weather forecast – heavy rain is expected overnight.

5:30 AM – Milking, animal health and grazing plan
While the cows are being milked, GenAI notices that cow 42 has entered the milking shed significantly out of her usual order – a large behaviour change for this specific cow and indicative of a potential shift in her mental wellbeing. Subsequently, GenAI connects with the drafting gate to draft her out for the farmer to look out. On inspection, the farmer sees she has slipped. Using voice, the farmer lets the GenAI know. The health event is logged in MINDA and GenAI uses this information as part of its continuous learning.

Near the end of milking, GenAI is also used to support decision-making on which cows are ready to leave the colostrum mob. Using data from milk meters and wearable health data, the farmer is notified that four cows no longer have subclinical mastitis, and health and rumination levels have returned to normal levels. The GenAI suggests they are ready to be transitioned into the milking herd, provided milk appearance passes a visual colostrum check.

Through integration with the drafting system and staff work schedule, the GenAI hub has also drafted cow 236 for treatment and allocated the task to one of the farm's employees

The employee checks the lame cow but is unsure of the required treatment pathway. A photo of the affected hoof is loaded into the AI ecosystem which promptly lets the employee know by voice interface that white line disease is the most likely cause and suggests a treatment plan. In the background, the central AI hub checks its training resources, noting a gap in lame cow training. A new, adaptive module is created and sent to the farmer for review.

While the farm staff have been attending to animal treatments and washing down the shed, aided by the automatic plant and yard wash, the farmer has headed to the central GenAI hub in the shed office. The system has provided a snapshot of herd production and reconciled this against pasture intake, calculated using AI-driven pasture management software, from the last grazing event.

Based on declining growths rates, predictive modelling recommends extending the round length and adding silage into the diet to maintain production and protect grazing residuals. A change in the paddock selection for the nights grazing has been implemented based on this paddock having the propensity to pug under wet weather.

7:30 AM – Team briefing
Before heading home for breakfast, the team gather in the office for the weekly briefing. Rather than focusing on the week's tasks ahead (as these are largely handled by the GenAI), the focus is on strengthening team connection and culture, including checking in on team wellbeing and sharing goals and achievements during the week. Any upcoming changes are also discussed.

Staff are able to share their feedback on what's working well and what isn't including suggestions on how the GenAI system could be improved. During this particular meeting, an employee noted the grazing planner didn't account for shelter availability when selecting yesterday's paddock resulting in the cows being exposed to strong winds. This observation was noted by the farmer for AI training. In addition, a new health and safety (H&S) risk that was added into the digital register yesterday is reviewed, along with a new H&S concern flagged by the AI system about a section of track that may become slippery with the expected rain.

9:00 AM – Feed budgeting
The farmer is concerned pasture growth rates will be lower than normal over the next month and opens the AI ecosystem. Through natural language interface, the farmer runs various scenario models on pasture growth rates and the resulting impact to covers and milk production. The farmer notes that there is sufficient silage on-hand to fill a short-term feed deficit but may need to apply additional nitrogen if growth rates fall 20% below budgeted. The farmer checks with the GenAI system if their nutrient allowance will allow an additional round of nitrogen and asks the system to schedule a notification to apply nitrogen if the low pasture growth pathway is looking likely.

10:00 AM – Consultant visit
The farm consultant arrives on-farm already aware of the current farm position given their access to specific areas of the digital AI ecosystem. The discussion on operational and tactical decisions is brief given this is largely handled by the GenAI and quickly moves into strategic planning focusing on succession Together, with the AI, they explore different ownership and transition scenarios modelled against future profitability, labour requirements, and lifestyle goals. As they discuss options, the AI updates projections in real time and highlights the implications of each approach. By the end of the session, a draft succession roadmap outlining the next steps is generated and shared automatically.

1:00 PM – Administrative tasks
After receiving an alert earlier in the day that invoices have been coded ready for approval and payment, the farmer heads to the office. After a quick review, adjusting the coding on just a couple of new expenses the AI hasn't encountered before, payment is approved.

While at the office, the farmer asks how cashflow is tracking against budget, the GenAI reports the farm is tracking slightly above budget given the tight expense control by the farmer and increased milk income supported by the hedging strategy GenAI helped design earlier in the season. Through analysing market trends, GenAI has, however, noted that phosphate prices are expected to rise at a higher rate than expected and suggests applying the bulk of the capital fertiliser in the spring rather than waiting until autumn.

The farmer then switches to preparing winter grazing audit documents for their milk company incentive scheme. The process only takes a few minutes as the plan has already been pre-filled by GenAI suggesting the most suitable paddocks based on those that would benefit from renewal (using pasture growth data) and have the lowest environmental risk. A tailored plan for the grazing management of each paddock has also been provided.

Finally, while still at the computer, the farmer decides to check the lame cow training module the AI created earlier. On approval, the module is added into the relevant team members job tasks. Upon completion, this will be logged in their competency registers.

2:00 PM – GenAI training
Before heading back on farm, the farmer dedicates 30 minutes to "training the trainer." Through desktop interface, they review the AI's decision logs and annotate cases where human judgement overrode automation — for instance, a paddock held back despite the AI's grazing suggestion.

The farmer also follows up on the staff member observation regarding GenAI's consideration for shelter availability when making grazing decisions. Checking the systems reasoning log, the farmer sees that shelter availability (based on previous drone surveys) has been given low priority. Using voice command, the farmer asks the GenAI to elevate the priority of shelter availability during adverse weather.

These insights and updates are fed into the GenAI's adaptive learning loop, improving the model's understanding of the farm's unique conditions and the farmer's preferences.

3:00 PM – Farm drive
While the cows are being milked, the farmer goes for a drive around the farm. Using voice-enabled interface, the farmer notes a broken post and a fallen tree to be cleaned up. These are immediately added to the job list, along with the required PPE and materials to complete the job, for allocating amongst the team.

Driving past a steep hillside and small wetland, the farmer talks to the AI about retiring these areas from grazing. The system discusses the benefits and costs, considers species selection and design, and notes funding opportunities through regional programmes.

4:00 PM – End of day
Before heading home for the day, the farmer heads to the milking shed to check in with the team and the GenAI hub. A summary of the day's performance, including herd health updates, grazing plan and task completions, is available along with a high-level overview of the week's plan ahead. The farmer goes home feeling confident that everything is in hand.

5.5 Near-future diffusion of GenAI

The GenAI diffusion curve presented earlier (Figure 2) has been updated to provide a visual representation of the predicted near-term future uptake of GenAI across the dairy farming population (Figure 3). It is based on the key characteristics of the conservative and aspirational pathways and aligns these with the adopter categories to illustrate how far different use cases are expected to diffuse through the population in the near-term.

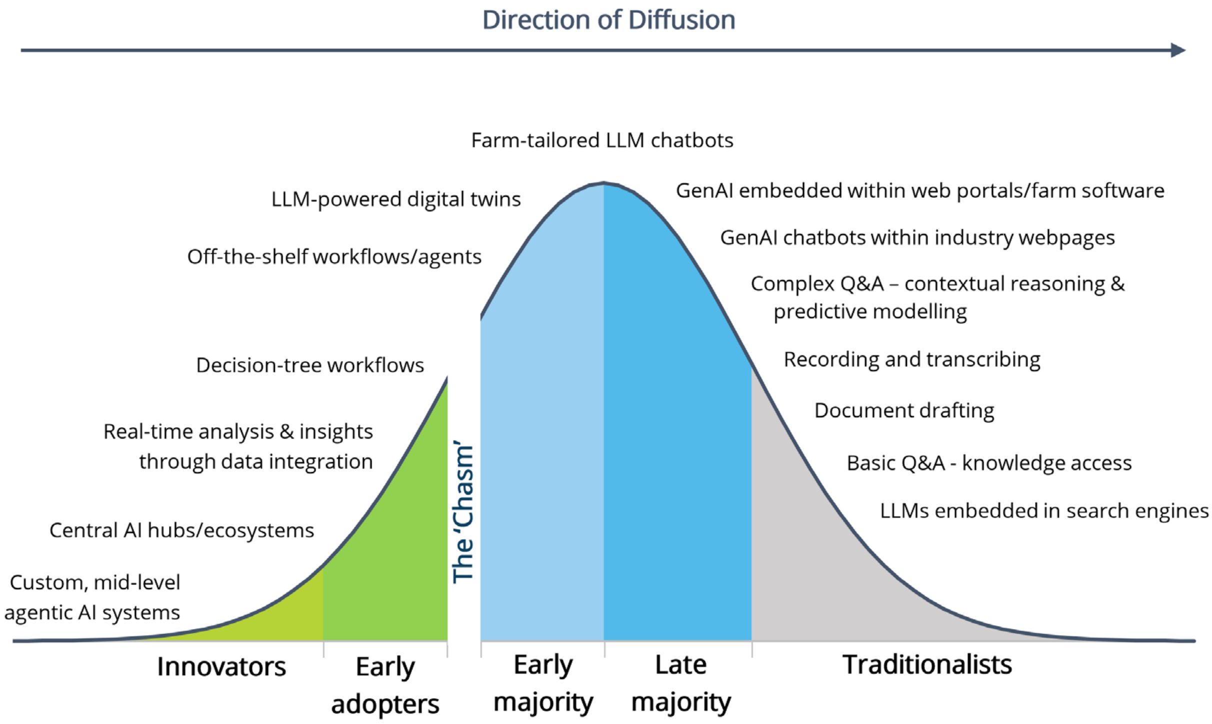

Figure 3: Stylistic representation of the predicted near-future diffusion of GenAI use cases across the dairy farming population. Adapted from Rogers' (1962) adoption curve model based on the diffusion of innovation theory and Moore's (1991) 'chasm' concept.

The GenAI use cases that remain in the innovator and early adopter groups and are unlikely to cross the chasm in the near future are those that are tightly integrated with existing farm technologies, forming real-time, data-enabled systems that optimise farm management. Farm operators in these groups have a high degree of trust in GenAI to make sound decisions and are comfortable delegating selected workflows to mid-level agentic AI systems. These include workflows that are deemed low risk due to their repetitive nature (e.g., rostering, inventory stocktake and ordering) and/or ability to be guided by clear logic and available data (e.g., autonomous grazing management, feed allocation optimisation). While these uses offer tangible efficiency and management benefit, their wider diffusion is constrained by limitations in system interoperability, the availability of data and on-farm automation technology, and the trust required for AI decision-making (particularly in agentic workflows).

In contrast, use cases that have crossed the chasm and reached the early and late majority are those that are expected to have demonstrated proven value in timesaving or performance benefits. These include farm-tailored chatbots for improved communication, knowledge access and decision support, and LLM-powered digital twins for predictive modelling. Other, more novel use cases, such as GenAI functionality embedded within software programmes are also expected to reach mainstream status quickly given their expected ease of use, ability to access relevant farm information, and high-trust level that allow them to be seamlessly integrated within standard farm operations.

An increasing amount of use cases are also expected to have reached the laggards. This includes document drafting and use of LLMs for basic Q&A where the functionality has become embedded or the interaction has become largely passive and part of everyday function.

5.6 Risks

GenAI offers a plethora of new opportunities for pasture-based dairy farming but there are risks that need to be considered and that should inform use of the technology.

The largest risk relates to an over-reliance of GenAI resulting in the loss of human judgement, particularly in areas where GenAI performs worse than the human. As the capability of GenAI systems increase, there may be a temptation to defer to GenAI more frequently or take outputs at face-value especially if it is an area where the farmer lacks specific knowledge. This can lead to negative consequences given GenAI is inherently a predictive model, not a cognitive model. While GenAI is expected to improve with time, it will inevitably be unable to eliminate all errors particularly if data used for decision-making is incomplete, the training model is based on biased or irrelevant information, or the specific farm conditions differ from the tool's assumptions.

Critical thinking and human oversight therefore remain critical where GenAI is to be used to support or make decisions. This is particularly the case in farming, where the biological nature of dairy systems means the context is constantly changing. Where GenAI is to be used in agentic workflows, there remains a critical need for human-defined goal setting and boundaries, along with the ability to monitor and review decision steps for alignment against business objectives and tacit knowledge.

Beyond technical risks, there are also ethical considerations aligned with the use of GenAI. Over-delegation of decision-making to GenAI could erode the sense of agency and satisfaction that comes from hands-on farm management and problem-solving. If GenAI handles all or too greater a degree of decision-making, there is a risk that farmers may lose the enjoyment of farming and making and owning their decisions. This could have broader implications for farmer wellbeing and motivation.

Data security and privacy is another key risk that farmers should consider when engaging with GenAI. Free-access GenAI tools, such as LLMs, tend to have lighter controls on how data is handled, stored and used compared to paid models. Information and data entered into public LLMs, for example, might be used to improve and train the model and, without safeguards, may result in confidential data (e.g., financial performance, staff contracts) being exposed. In agentic use cases requiring high levels of data to be effective, the risk of data security becomes more pronounced. In these scenarios, farmers should be questioning how their data is stored and managed, who has access to it, and what safety protocols, including secure authentication and data encryption, are in place.

5.7 Tips and tricks

Through the course of this work, insights were gained on different strategies that can be used to improve the effectiveness of GenAI. A brief summary of a few key concepts is provided here.

5.7.1 Prompt engineering

Effective prompt engineering is the art of formulating questions or instructions in the right way to improve the accuracy and relevance of the GenAI response. In general, specificity of prompts with clear, detailed instructions will drive more precise outputs while vague questions will result in generic responses.

A basic prompt structure should include:

- the context – *background information to help the tool understand the situation.*
- the specific question – *what you want the tool to do.*
- the desired output format (tone and structure) – *tone, structure, and format.*
- any constraints – *this could be specific (e.g., word limits) or broader constraints (e.g., staff availability in a rostering situation).*

Instructing the LLM to act as a prompt engineer before running a query is another effective way to create the prompt. Through this approach, the tool will assist in first drafting and then refining the prompt until it is ready to execute. Checking for any blind spots or if the tool appropriately understands the request, simply by asking, can be another effective way of improving responses.

Depending on the task, another way to improve the GenAI responses is to use an example as part of the prompt (termed "few-shot prompting") rather than providing long instructions. The LLM can then follow the structure of that example and provide a consistent response. In addition, getting the LLM to "think step-by-step" is another way to improve outputs. The prompt can be structured to allow the LLM to build up to the final answer by working through the problem step-by-step.

5.7.2 Contextualising inputs

GenAI responds to questions based on its training data and any information the user provides. To help generate a response that is relevant to the specific situation, providing as much of the necessary context as possible will help to reduce the chance of training data bias or hallucination.

Context can be incorporated through:

- the inclusion of key background information in the prompt.
- uploading relevant information to the tool, for example as images, documents or datasets.
- creating tailored LLMs constrained or weighted to defined datasets, reference documents or web pages.

5.7.3 Experiment

For those yet to engage with GenAI, an effective entry point is through practical experimentation. Beginning with small, low-risk tasks allows a user to build familiarity and confidence in how GenAI operates. For example, using GenAI for knowledge access or document drafting. Downloading a LLM app onto a mobile phone to use in place of conventional search engine queries is a good way to quickly access and involve GenAI in everyday use, as is interacting with GenAI using voice-enabled functionality.

With time and use, users develop an understanding of how GenAI works, what it is good at, what is not good at and how to best engage with it. This experiential learning supports the ability of users to engage GenAI in more complex tasks, such as contextual reasoning, predictive modelling and development of customised agents or tailored chatbots, while having a solid understanding of its limitations.

5.7.4 Data safety and privacy

Where data security and privacy are a concern, paid subscription models generally offer greater protection than free-access alternatives which allow data to be reused for future model development. However, while paid versions typically provide stronger default privacy and security controls, the specific data protections and security measures may still need to be configured or selected with the platform's setting's to ensure they align with individual needs.

5.8 Opportunities for DairyNZ

DairyNZ is well-placed to support farmers in building their digital AI literacy skills and to responsibly integrate GenAI within their farm systems. Key opportunities include:

- Building farmer awareness and understanding of AI
  Uncertainty about what AI is and how it works will be a barrier for some farmers in experimenting with and using GenAI tools. Overcoming this barrier could be achieved through developing clear, non-technical resources explaining what AI and GenAI is, how it works and where it could add value on-farm. While the technology is evolving rapidly, farmers will still benefit from basic guidance to begin their journey and equip them as the technology improves.

- Demonstrating practical use cases
  Farmers often gain the greatest understanding from seeing practices/technology in action as opposed to just reading or hearing about them. Hosting demonstration events, workshops or an 'AI roadshow' to showcase real-world examples and enable peer-peer learning could be an effective way of speeding up farmer awareness and engagement with GenAI.

- Strengthening farmer capability and digital literacy
  Building digital literacy and capability to use GenAI will be essential in enabling farmers to maximise its value on farm, particularly for interpreting recommendations and creating customised tools tailored to individual systems. This could be achieved through providing or promoting access to practical training opportunities that help farmers learn how to use GenAI confidently and safely. This might include providing a list of existing courses available or provider options, hosting webinars with AI experts, or creating/promoting guidance on how to use GenAI effectively, including 'tips and tricks' on how to interpret outputs and maximise value, 'risks and pitfalls' to look out for, and the type of information that should be provided and the process followed to create tailored tools.

- Supporting farms to become 'AI-ready'
  As we head into the future, staying competitive and maximising value from GenAI will require having access to good quality, complete and accurate datasets. This will require an increase in adoption of on-farm technology and/or an improvement in the amount and accuracy of data recorded. There is a role here for DairyNZ (and the wider industry) to promote good record-keeping through linking to the types of tasks that GenAI could support if the data was available, and in providing guidance or evaluation on available technology options.

- Evolving DairyNZ resources
  There is an opportunity for DairyNZ to step into the GenAI space and assist farmers with improving the efficiency of certain tasks. This could be through exploring opportunity to embed GenAI functionality into DairyNZ templates and spreadsheets (e.g., diet checker, budget templates, advanced spring rotation planer) or providing 'off-the-shelf' GenAI workflows for certain activities (e.g., grazing management planner, winter feed budgeter, staff roster builder).

6 Conclusion

GenAI offers substantive benefit to dairy farmers in New Zealand. Those engaging with GenAI now are noting the ability to make better, more informed and faster decisions, reduce time spent on repetitive tasks, empower team knowledge and improve communication. Ultimately, this is allowing farmers to reduce cognitive burden, redirect time to higher-value tasks and improve performance. Current use cases are varied and can be categorised as decision-support (knowledge access, contextual reasoning and predictive modelling), task enhancement or communication support.

Despite these benefits, adoption remains low and is heavily weighted to the innovator and early adopter segment groups with diffusion into the mainstream farming population limited. Innovators and early adopters are experimenting with more [currently] advanced and tailored applications, but proof of concept and ease of use are key barriers creating a "chasm" that limits further diffusion to the mainstream population.

Looking ahead, the ongoing evolution of GenAI is expected to open new possibilities for future applications (e.g., real-time decision support, agentic workflows). Crossing the chasm and achieving widespread diffusion of these use cases in the near-future will require resolving additional challenges relating to farmer trust (particularly for agentic workflows), and accessibility to good on-farm data and technology infrastructure.

Although there are hurdles to overcome, achieving real-time, data-enabled decision-making offers transformative value to pasture-based farm systems. Decision-making informed by live data addresses one of the most challenging aspects of pasture-based dairy farming – the complex and dynamic nature of a biological system which makes sound and timely decision-making tough. Achieving this state of real-time, data-enabled decision-making relies on several key enablers. These include having access to sufficient, high-quality data points that enable strong contextual awareness, access to sufficient automation technology for which the GenAI or farmer can act on, and effective interoperability between digital systems. While technically skilled farmers may be able to develop workarounds in the near-term to achieve system interoperability, widespread adoption will require technology advancements and sector-wide progress in data integration.

If effective system interoperability or data integration cannot be achieved, then near-future use cases are likely to centre more heavily on GenAI functionality embedded within web portals or farm management software. Such applications of GenAI offer strong potential for widespread diffusion through the dairy farming population as they are more likely to be trusted, be easier to use, and be able to seamlessly integrate within existing farm activities, relative to standalone LLMs.

Additionally, limitations of GenAI, including an inability to replicate tacit knowledge and an inherent vulnerability to hallucinations and bias, is expected to firmly place the technology as a tool to support farmer judgement in the near future (3-5 years) as opposed to replacing decision-making. While there is expected to be a place for agentic capabilities, these will be limited to mid-level (Level 3-4) agency where the execution of overall workflows is constrained within human-set boundaries and goals. They will likely relate to tasks that are repetitive and/or can be guided by clear logic and available data.

As GenAI capability advances, the farmer's role is also expected to evolve. Maximising the value from GenAI tools will require time and experimentation. This might include refining prompts, reviewing and validating outputs, customising workflows and iteratively training GenAI to align with farmer goals and objectives. This will be particularly important for farmers developing customised solutions or integrating GenAI into more advanced, agentic applications.

DairyNZ is well positioned to play a leadership role in supporting and enabling farmers to explore GenAI and ultimately incorporate it successfully within their farming businesses. Key opportunities include providing or promoting practical training and guidance to build farmer capability and digital AI literacy, supporting farmers to become 'AI-ready' for future GenAI applications, and facilitating knowledge exchange through webinars, demonstration events, workshops and/or roadshows that showcase real farmer use cases. There is also scope for DairyNZ to evolve its own digital resources by exploring options to embed GenAI functionality in existing templates and spreadsheets or develop pre-built 'off-the-shelf' GenAI workflows to assist with certain activities (e.g., grazing management, feed budgeting, roster building).

7 References

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8 Appendices

8.1 **Appendix 1:** Agentic AI classification system.

Table 4: Description of the varying levels of agentic AI including examples relevant to dairy farming. Adapted from Bornet *et al*. (2025).

Level	Description	Best used for	Limitations	Example(s)
Level 0: **Manual operations**	Humans perform all tasks and decision-making relying on experience and observation. Technology plays limited or no active role in decision-making. Represents traditional workplaces that use basic digital tools like spreadsheets and email but processing is largely manual.	Contexts requiring human judgement, creativity and emotional intelligence.	Ability to utilise data is constrained by human capability and capacity.	• Manual coding of invoices in accounting systems. • Animal drafting by visual observation and manual gate operation.
Level 1: **Rule-based automation**	Basic automation that follows fixed rules and predefined steps (e.g., decision trees, "if-then" logic). Processes are standardised and cannot adapt or learn.	Repetitive, high-volume tasks with clear business rules.	Can face challenges when encountering exceptions or scenarios outside their programmed parameters.	• Automatic drafting systems that separate cows for mating based on preset rules (e.g., if cow in heat, draft to pen 1). • Variable rate irrigation systems applying fixed volume based on rule-based soil or zone thresholds.
Level 2: **Intelligent process automation**	Combine traditional automation with cognitive abilities including natural language processing, machine learning and computer vision. Ability to process semi-structured data, recognise patterns, and make basic decisions within set boundaries. These systems exhibit some ability for reflection through performance monitoring and basic feedback loops.	Data-driven tasks requiring pattern detection, prediction or adaptive decision-support. Ideal for streamlining operational efficiency and improving consistency without needing full autonomy.	Integration challenges limit ability to utilise data in different systems. Limited contextual reasoning and adaptability beyond training scenarios.	• GenAI invoice processor that interprets invoices and automatically codes. Accuracy is improved over time learning from past decisions. • AI-powered animal health systems that interpret wearable data and flag sick cows. Alert thresholds adjust over time as data patterns evolve.

Level 3: **Agentic workflows**	Represents the emergence of true AI agents – systems that can use tools like APIs to execute multi-step tasks, and for the first time, autonomously plan, co-ordinate and execute a workflow within human-set boundaries	Complex, multi-step workflows where data interpretation, planning, and co-ordination are required. Suited to environments where humans set strategic goals, and AI agents handle the operational steps needed to achieve them.	Can make errors, may struggle with tasks requiring deep domain expertise and requires careful monitoring to ensure alignment with business goals and objectives. Integration across data systems still pose a challenge.	• AI-powered grazing co-ordinator that pulls satellite imagery, soil sensor data, weather projections and herd information to autonomously plan and execute grazing rotations that link with virtual herding technology. • AI-powered maintenance scheduler that monitors machinery and automatically orders parts or books services when predictive models flag upcoming maintenance requirements.
Level 4: **Semi-autonomous systems**	Systems approaching true autonomy that have the capability to set their own sub-goals, learn from experience and adapt strategies over time. They co-ordinate across workflows and refine actions through continuous feedback.	Highly complex environments with multiple workflows where adaptive decision-making and strategic optimisation are needed across time and systems.	Still largely experimental. Reliant on data integration, monitoring and ethical considerations.	• A digital farm consultant that learns from historical farm data and market signals to autonomously recommend and execute seasonal strategies. • An AI-powered labour co-ordinator that learns from past work patterns and reassigns tasks based on resource availability and predicted workloads.
Level 5: **Fully autonomous agents**	Fully autonomous and agentic systems that can operate independently across integrated systems. The AI exhibits full environmental awareness, independent goal formulation, advanced reasoning and self-improvement through continuous learning. Beyond governance, there is minimal human input.	Large-scale, integrated operations requiring full autonomy, long-term optimisation, and real-time adaptation.	Currently remain largely theoretical. The challenges move beyond just technical capabilities to fundamental questions about accountability, control and the role of human judgement in complex decisions.	• A fully autonomous farm management system that operates the entire farm (e.g., scheduling milking, managing and purchasing feed, hedging milk contracts, coordinating staff and resources) and is optimised for long-term profitability and sustainability. • A connected AI farm cooperative, where multiple autonomous farms share data and self-organise resource use and market strategies.

8.2 **Appendix 2:** Raw data – commentary and insights from farmer and industry discussions.

Industry insights

AI experts and developers

- Farmer education on AI is currently low but increasing quickly.
- Three groups of farmers in terms of AI use:
  - Those that don't even want to have a conversation about AI.
  - Those that are really advanced and innovative.
  - Those in the middle – probably using just ChatGPT. It has the right price point, easy to use.
- Biggest constraint for AI adoption and use is connectivity. Once farmers have connectivity anywhere on farm, huge changes will be seen.
- Data is also a challenge for AI systems – both the availability of sufficient on-farm data and research data.
- Data integration has always been a challenge. AI will accelerate problem-solving solutions including autonomous data labelling. Will no longer be about standardising data.
- Farmers are not IT people; information needs to be available as information not data. A limited portion who have a 'data hobby' but for the most part, if data is not synthesised and turned into insights, it will not be used.
- Agents are very good at doing narrow, focused tasks. Not good at big, complex tasks.
- Agentic AI currently is not stable. Troublesome to make and hallucinates. Often does not explain rationale and becomes a 'black box' creating ethical and security issues. Decision-tree logic presents a stronger path, is more accurate, maintains human oversight and can escalate a problem when it arises.
- 'Digital advisers' can be built on decision-trees and rented out to solve certain activities.
- Paid models will give much better data security/privacy.
- AI models are never 100% accurate. Create bias and hallucination.
- Anything you can do manually – you can do with AI. Opportunities for use cases are endless.
- Quick wins for farmers will cone in off-the-shelf products, more strategic, high-value pieces will come in custom-builds.
- Farmers are 'users' of things.
- Small language models likely to be useful. These can exclude non-relevant data and have limited boundaries (though still based on large-language models). Can be adapted to a specific context and grow over time. Useful for farms with fluctuating staff where institutional knowledge is valuable, but managers don't have time to talk all day.
- Voice solutions likely to be grasped quickly by farmers.
- LLM outputs will always need to be sense-checked but this is no different to human-beings now who also can make up information or give incorrect advice.
- Need to train farmers on how to use information. For instance, creating successful prompts and knowing what to use for different questions.
- NZ market is too small (limited by scale and cost) for deep AI innovations. Creating alliances across countries and companies would unlock scale and greater innovation.

Rural advisers

- AI has the power to connect and bring to life on-farm data to 'show' rather than 'tell' farmers (e.g., using Herd-i BCS and Halter reproductive data to show low BCS cows are slower to cycle). Provides the ability to make the data understandable and lead to action on-farm.
- ChatGPT (or other tools) will be quicker at basic farm math (e.g., mag calculations) and never get it wrong.
- Opportunity for farmers to use ChatGPT for conversing using audio as opposed to text (e.g., while farmers are driving around the farm pondering a question). You can talk to it like you're having a conversation with a person.
- Ways to improve AI outputs/increase 'safety'
    - Prompt engineering
    - Paid subscriptions
    - Custom GPTs using trusted reference files
- Start small with AI, asking basic technical questions and getting comfortable with it. As you become more comfortable, can increase complexity and guardrails can go up. Key is to make a start. Start asking questions.
- Combination of AI tools and real-time data (e.g., wearables) can provide valuable data insights. There is an opportunity with AI to put people in a position to make changes by turning data into insights. Farmer adoption of AI and adviser expertise, however, remain as key challenges.
- Many farmers with wearables aren't fully leveraging the data or changing practices.
- Outdated tools and spreadsheets are still prevalent among farm advisers.
- There is a need for upskilling both farmers and advisers in data interpretation.
- Possibility of reaching some of the estimated two thirds of farmers currently not using farm advisers through AI-enhanced services.
- Can be used to support post-visit tasks:
- For example, takes notes during visit, take a screenshot and upload to ChatGPT which in turn writes the report. Report is checked, edits made as required with certain points fleshed out.

DairyNZ brainstorming session

- Farmers more likely to adopt AI that assists by suggesting and prioritising actions rather than fully autonomous systems, as the latter may be intimidating or less trusted. High integration with low autonomy is perhaps the preferred approach.
- Assisted decision-making is the logical, first step and likely natural progression for many farmers. Established and well-proven.
- AI chatbots can hallucinate and provide agreeable but potentially inaccurate responses. The quality of AI output depends on the data sources and tools used. We need to balance source credibility and consider relevance of institutional knowledge held in grey literature.
- Concern that farmers might accept AI outputs without scrutiny, potentially replacing expert knowledge and ignoring legal caveats such as financial advice disclaimers.
- AI will struggle with the complexities of pastoral farming and requires contextualising information to an individual farm to be effective.
- Credibility of 'answers' could be improved if users question what other information should be provided to give an informed answer.
- Pastoral farming has complexities that AI may struggle to be informed about at times. Providing farm-specific content is a natural barrier for AI.
- Opportunities to use AI to bridge the gap caused by a shortage of skilled people and reduce human error especially for less experienced farmers/farm staff.

- Quality received will depend on what tools are used (e.g., free tools vs purchased products).
- A current challenge is the limited availability of skilled individuals. AI could help address this gap (e.g., by supporting timely pasture management or animal health decisions). While experienced farmers can do this on instinct, exploring ways in which AI can replicate or support these abilities could be an area for further investigation.
- Human error – we have average and below average farmers/reps. Even if AI is not 100% right, is 95% right still better than the average decision? Are we using AI for the top 5% or as a tool to drag bottom 25% up? (e.g., we put wearables on to detect heat. Not to be 100% accurate, but to be as good as the best person).
- Current use cases of generative AI:
    - Translation. Use of AI to translate data into language used amongst farm team (e.g., Filipino).
    - DIY repairs (e.g., Taking picture of a broken-down pump – AI able to identify potential issues that could be drilled into to solve the problem).
    - Note taking. Recording minutes on farm
    - Fertiliser plans. Taking soil test info and feeding into ChatGPT. Farmer got complete recipe for a fertiliser plan. Peer-reviewed by consultant and thought was very good. Opportunity for farmers to go direct and shop around. Could also be very dangerous if no one is checking.
    - Putting manuals into AI (e.g., tractor manual) and then asking for information about certain items.
    - Breeding plans. Farmer developed an AI bot to create breeding plans. Feed in the bull traits and herd information and the AI can create a bull team based on the traits wanted for a particular cow/herd.
- Future use cases of generative AI:
    - Financial applications. Linking production, interest rates, OD etc together to provide ongoing interpretation of financial data.
    - Investment analysis. Analysing land use options, forecasting.
    - Asset management. Do I replace my JD6100 tractor or push on for another year. Make more educated asset management decisions.
    - Inventory management.
    - Managing/scheduling maintenance.
    - Disease predictions
    - Animal welfare metrics
    - People management. Support better communication amongst team
    - Farm CoPilot/Planner (e.g., Here's the things to do today and my suggestions on how to order the day)
    - Data integrator. Data integration is a challenge. Can AI help with this and be the integrator between software?
    - Reports/podcasts. Using different inputs and AI to feedback reporting to farmer in a more digestible manner. Near-future solution.
    - Connecting productions systems together (e.g., production, supplements, pasture and milk).
    - "Intelligent control systems" – AI takes data from various inputs to make decisions about the system (e.g., in-shed feed allocation using various animal metrics)

Farmer insights

Owner-operator, Waikato

- Uses ChatGPT for information gathering. Gives fast decisions. Access to quick information.
    - Could use Google, but then I'd have to find (for example) the DCAD formula and then do the calculation myself. ChatGPT can do the whole lot for me and much faster and I can run 'what if' scenarios.
- Using predominantly for feeding decisions:
    - Balancing diet – e.g., consider typical spring grass nutritive value, feeding X amount of pasture, want to produce X amount of milk, have these supplements available – how much should I feed, what minerals do I need to add?
    - Next step – take pasture samples and upload
    - Can take photos of ingredients from mineral bags and directly upload into GPT
- Also uploading breeding profiles to match bulls and cows. Matching BVs for the traits we want to breed. Can see real value in using it more for breeding- e.g., making sexed semen decisions.
- Have used ChatGPT with vets. Uploaded data into it and then interrogated data. For example, what is the conception rate for 5-yr olds versus 6-yr olds. Can filter and spit out information really quick.
- Currently using free version – limits me to only uploading two files at a time. Testing it out to see if I can use it enough to make it worth paying for. But is great being able to upload information.
- Can see AI being of real-value particularly for larger farms with staff – creating a "hub" of information. Similar to construction industry – every person has access to information instantly.
- Have thought about using ChatGPT to BCS cows using DairyNZ reference files. Professionals do all the training and that is fine. I could probably get within 80%. But for staff who don't have the knowledge/completed the training it would make it easier for them.

Owner-operator, Waikato

- Using ChatGPT to:
    - BCS cows within +/- 0.25 accuracy
    - Create a digital twin – modelling El Niño/La Niña, other farm scenarios
    - Creating APIs to link to other data (e.g., MetService)
    - Make pasture management and grazing decisions (maths/formulas not my strong point)
    - Select and match sires
    - PCBS DairyEdge, FinancialEdge – pasture and financial management
- The opportunities for AI are endless – it's not what you can do, but what you want to do. Uptake of AI will be dependent on individual farmer attitude and desire to change. Not everyone wants data or wants to analyse data. Expect increase in AI familiarity and use with generational change.
- AI provides significant opportunity to support farmers to make better decisions or do 'maths' quicker and easier (important for farmers who are time-pressured and need to make quick decisions, and sound decisions).
- Integration with real-time data sensors will unlock the power of AI – turn generalised information into tailored, farm-specific information and advice.

Operations manager, Waikato

- Created a GPT chatbot based on farm policies and key reference files (e.g., DairyNZ, FedFarmers contracts, Fonterra handbook) noting information to use and not to use (e.g., reference DairyNZ calf rearing, animal health, SCC data but for pasture management, supplement and grass reference farm policy)
- $400 monthly subscription
- Whole team has link to the GPT model on their phones. Can ask questions e.g.,:
  - How much mag to dust?
  - Have a down cow, tried everything, still not getting up what else can I do?
  - Why is my pay different this week? (staff can load timesheets, payslips)
  - Why have I got a coli grade – what do I need to check?
- Want to get to the point where each farm RVM is loaded into the model so the GPT knows what drug to recommend for a given time and farm.
- Large farming operation (4,500 cows) by the time technical questions get to me, it's too late.
- Use of the chatbot eases the mental workload on the whole team
- Have caveated the model with the team – if the GPT answer doesn't sound right then they should ask. However, this doesn't typically happen (that he's aware of) unless its pulling US/UK data. Team aren't using it for grazing decisions, more for basic technical questions.
- Actively promotes the use of the tool amongst the team. Some use it, some don't (probably because they don't need to). Unsure how often it is actually utilised – don't monitor it.
- Every farm has Halter. We work on m^2/cow so not asking technical grazing questions, but the model will tell them what m^2 or round length to be on at a given time.
- Farm policy is very rules focused. Farms must follow spring rotation plan.
- Keep the GPT out of making decisions (it can be easy to mislead the AI), more for quickly providing answers.
- Would like to get to a point where we can have a dashboard with AI monitoring of key KPIs. For example:
  - Water use/cow
  - Cowshed on/off time
  - Production
- Actively uses ChatGPT within the business as well:
  - GPT window always open on computer
  - Uses it to write documents, letters, draft emails, complete admin tasks
  - Every week send out a Monday morning report. The GPT now recognises it's Monday and prompts the data needed to go into the report (e.g., production, weather, weekly policy item from manual)
  - Tool to make life easier using my IP
  - Always review and humanise outputs from the model
  - Significant time saving (20 hrs/week)
  - To make the time saving, there was only a very minimal (negligible) period where it added time to the week in setup
  - It is like the EA they've never been able to hire
  - Now starting to use AI to code in Xero – expect accountants and lawyers to be out of job in 10-15 yrs
  - Starting to play around with operator function (agentic) of ChatGPT

- Overall comments:
  - Don't let AI make decisions for you, but useful in giving context to others
  - It can't be your farm consultant, but can be a good aid
  - Powerful tool for freeing up time
  - Farm owners time is high-value that can be put to use in other aspects to improve farm performance/productivity
  - Expect average and above farmers could set up a similar chatbot but below probably not below average. Requires someone that has good technical knowledge of their farm system and can type on a computer. Those that work on gut instinct/ not technological probably won't be able to take advantage of it.
  - Not necessarily a generational thing either, some of my 50-60 yr old staff fairly advanced with tech, likewise some younger farmers don't want a bar of it
  - Can see a future where every individual farm has its own AI ecosystem (e.g., walk into the office and the AI is telling you its 1 Sept, time to put your fert orders through, or a staff member can walk in and ask whose day off it is tomorrow).
- Started using AI seriously in Feb/Mar now pretty advanced.

Owner-operator, Taranaki

- Started using ChatGPT for personal use initially (plan trip around Europe), now using it for a range of farm tasks.
- Traits Other Than Production (TOP) scoring cows:
  - Upload side and rear photo of cow and ask it to analyse TOP to New Zealand standards and write a short blurb about each cow.
  - Takes subjectivity out of scoring.
  - Reasonably accurate so far but haven't tested on a bad cow yet.
- Weighing calves:
  - Upload side on photo of the calf and provide its age.
  - Seems to be more accurate than belly strap, not as good as actual weighing which we still do anyway.
- Analyse kill sheet data:
  - Recently uploaded the last 15 kill sheets and analysed carcass weight, liveweight, dressing out percentage which it calculated itself. Would have taken hours to do that if I had to do it manually.
- Sense-checking
  - Nutritionist recommended apple cider vinegar and nutmeg as additives to milk fed to calves.
  - Calves ended up scouring really bad so used ChatGPT to check rates – apparently need to be very careful with nutmeg dosage rates – can cause blindness and is like a narcotic.
- Use it to write letters, draft summaries. Still need to fact check the output.
- Have used it to see if it can give me alternative ideas/options. For example, we drench animals which is quite hard, physical work. I was seeing if there were any other ways or products that could make the job easier. For example, there might be a product on Temu that I could purchase.
- I wouldn't use it for bull selection. That's something I enjoy doing (pedigree Holstein-Friesian herd), and also concerned that if we use AI to do that we could end up narrowing the genetic pool.
- Essentially use ChatGPT as first point of call rather than Google.

- Sometimes use Gemini if I'm on my phone (Samsung). It's easy to do a one-press on side the side button and can then use Gemini handsfree if I have my gloves on for example. Otherwise, use ChatGPT on phone or computer.
- Future opportunities:
    - One of the industry's challenges is that we don't have enough good data. This could be a way to build up a good database quickly and easily.
    - I have a herd manager completing their Level 4 production manager certificate. He was really struggling with it so I bought the Farm4Life pack. He's now much more engaged and learning a lot better. AI also has the opportunity to make different learning methods available.
    - Opportunity to integrate data sources better. No longer governed by single data sources.
    - Would love to be able to put my grazing plan in and production and for it to give me kg MS/paddock. Could sit down and do it manually in excel but that would be painstaking.
- Have other tech on-farm – AIMER, Smaxtec boluses, DairySmart mastitis detector, Trello
- Don't currently use the paid subscription version ("I'm too tight"). If I get to the maximum question limit will just wait until the next day. Eventually, I probably will pay for it. Not worried about data security – who cares about pasture covers or cow 52's herd test data? Wouldn't put my banking data in, however.
- Do need to be careful about data coming out – only as good as the reference source it uses.