Stakeholder-Driven Design for Collaborative Decision Support in New Zealand Agriculture

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This paper explores the experiences of New Zealand dairy farmers using data-driven applications for daily operations and associated decision-making. We analysed their engagement patterns, decision-making processes for various tasks, transitions between them, and the factors hindering their actions. Our findings indicate that farm managers rely on multiple apps for monitoring, which delays decisions and actions. They understand only task-specific data patterns and seek expert or peer guidance for complex decisions. We propose guidelines for designing collaborative, data-driven decision support systems for farms.

CCS Concepts: • **Human-centered design**; • **Human computer interaction (HCI)**; • **Empirical studies in HCI**;

Additional Key Words and Phrases: Agriculture data-driven application, Interviews, Collaborative decision support

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1 INTRODUCTION

The past decade has witnessed the rapid development and adoption of machines and smart technologies in the food industry, showcased by smart crop cultivation, livestock management, plant breeding, precision agricultural farming and agricultural robotics [23]. The incorporation of data-driven applications such as intelligent decision support systems [45], Internet of Things (IoT) and communication technologies has become increasingly important in optimising systems' productivity and sustainability [39]. In agriculture, data-driven applications enable farmers to make informed decisions that enhance animal welfare, increase efficiency, and reduce environmental impact. For example, IoT devices enable monitoring of vital parameters such as livestock conditions [24], while software platforms can optimise feed formulations based on nutritional data [20]. Despite the potential benefits of these technologies, farmers often face challenges in adopting and effectively utilising data-driven systems.

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This research explores the challenges New Zealand dairy farmers face using data-driven applications, aiming to develop effective decision support guidelines through semi-structured interviews and participant-led discussions. With the ever-growing global population, the demand for agricultural production and consumption is projected to rise by 60% by 2050, compared to 2005 levels [1]. According to the United Nations Food and Agriculture Organization (FAO), achieving sustainable agriculture heavily depends on managing accurate and timely information access and technical support [17]. Despite the proliferation of data-driven systems, there is limited understanding of how these technologies facilitate end-user decision-making and action mediation. Key aspects characterising their interaction with and adoption of these systems in work environments include perceived decreases in autonomy, negative impacts on user experience, and concerns about the quality of outputs or recommendations [47]. The effective utilisation of technological innovation is critical in addressing multifaceted agricultural problems such as climate change, resource limitations, market connectivity, agricultural extension services, and digital literacy [28].

Human-Computer Interaction (HCI) research has begun to explore the interplay between Artificial Intelligence (AI) systems and human-AI collaboration within the agricultural sector [11, 47]. However, there remains a gap in understanding how farm owners interact and collaborate with these data-driven systems. To our knowledge, no work has comprehensively analysed this interaction and collaboration. Such a study can concretely identify how these systems should be designed for the future of data-driven farming.

New Zealand dairy farmers face multiple decision-making challenges when using data-driven applications. Key issues include the lack of reliable techniques for monitoring and integrating information across various task-specific interfaces and the insufficiency of expert knowledge and context-specific information within these applications [3]. These challenges often result in delayed decision-making and increased operational costs. Current tools fail to blend seamlessly with farmers' operational workflows, necessitating the development of solutions that can integrate effectively with their day-to-day activities. To achieve this, it is necessary to observe how farm managers currently use data-driven tools for their work, access information, analyse on-farm observations, and seek technical guidance.

This study aims to bridge that gap by examining the experiences of New Zealand dairy farmers with data-driven applications in their daily operations. Using a combination of semi-structured interviews and participant-led discussions, we gathered insights into farmers' engagement patterns, decision-making processes, and the obstacles they encounter. By adopting a needfinding approach, which involves understanding users' needs through interviews [36] and observation [27], we aim to generate actionable design insights for the development of effective decision support tools. The data collected from these discussions provide guidelines for the interaction design of tools that support data-driven decision-making and enhance the operational efficiency of farm task management. These tools are envisioned to integrate seamlessly with existing workflows, provide contextual and expert information, and ultimately support the transition to more sustainable and efficient agricultural practices. Furthermore, as the aforementioned issues with decision support systems are common across numerous domains, the insights obtained in this study could contribute to solving these issues worldwide.

The primary motivation behind this research is to design data-driven collaborative decision support systems tailored to the needs of farmers, thereby enhancing their decision-making capabilities and operational efficiency. This research has made a number of contributions as follows:

(1) Conducted an empirical analysis of data applications and technologies used by farmers, covering both formalised and personalised approaches.

(2) Identified key challenges farmers face in integrating data into daily decision-making, including technical issues and lack of support.
(3) Recommended design implications for collaborative, data-driven decision support systems tailored to farmer's needs.

2 RELATED WORK

Introduction to Data-Driven Agricultural Systems—Data-driven agriculture is still in its early stages, and accelerating its adoption could lead to significant changes for millions of people [7]. We define 'data-driven farming' as a system involving data from sensors, cameras, and IoT-enabled farm equipment, as well as data manually entered by farmers or imported from other online services (e.g., weather forecasts). In recent years increased investment in data-driven farming, combining hardware, software, and cloud computing, has ensured higher productivity and precise agriculture management. The industry standard practices in data-driven farming heavily rely on the use of advanced analytics, cloud-based data management systems, and real-time decision-making frameworks [53]. These systems can process large quantities of data and discern patterns not always noticeable to humans, improving decision-making and outcomes [47]. Modern agricultural systems are benefiting significantly from smart farming solutions that incorporate multi-disciplinary advancements, enabling informed and efficient decision-making processes in planting, tending and harvesting stages to maximise productivity and profitability [23]. The global applicability of these data-driven technologies is particularly significant in enhancing production and environmental sustainability within the agricultural sector, especially in dairy farming [32]. Precise management using these technologies can significantly enhance feed efficiency, milk production, and overall profitability while promoting sustainability.

Data Application and Integration Challenges—Effective data integration enables a deeper understanding of agricultural systems, facilitating knowledge that spans from micro-level field conditions to macro-level economic impacts. For instance, integrating sensor data on soil conditions with weather forecasts can help farmers make proactive decisions about irrigation and fertiliser application, optimising resource use and increasing yield efficiency. Moreover, by analyzing combined data from various phases of farming from sowing to harvest farmers can gain insights into the optimal times for planting and harvesting, which vary by crop type, regional climate, and market demand [12]. In the dairy industry, data allows advanced analytics and machine learning methods to detect different livestock diseases [43], estimate greenhouse gas emission [15], and predict yield [34]. While the advancement of data-driven technologies offers immense potential, current implementations often fall short in effectively integrating and utilising this data for operational decision-making across industries. In agriculture, this integration is critical, as it requires not only technical expertise but also a practical understanding of the agricultural environment that is unlikely to be fully automated soon [51]. Farmers often observe and interact with their environment, e.g., soil and livestock, using this data in everyday tasks integrated with various information management systems. Despite the entry of farm-level data into these systems, the collation of data points from several sources is frequently overlooked. Farmers face challenges in accessing and integrating data from multiple sources, particularly in coordinating data from different applications that are often updated independently [12].

AI and Intelligent Decision Support Systems—While AI holds promise for addressing the grand challenges of 21st-century agriculture, its capabilities must be made compatible with human input and behaviour in human-AI coalition [16]. Agricultural institutes and researchers focus on AI solutions based on three principles: adoption as a first principle in AI design, adaptability to changing environments and scales, and amplification of human skills and machine efficiency [16]. Despite efforts to develop intelligent decision support systems for agriculture, few systems have seen widespread adoption. Decision support systems aim to provide greater control through comprehensive, accurate data delivered in real-time and rendered as usable insights accessible anytime, anywhere through a single dashboard. While manual data collection is common, services often employ specific interfaces for several databases and recorded data. However, these systems frequently lack response accuracy and interoperability, overwhelming users who need to access and compare different information [41]. This situation forces users to consider the effort needed to synchronise input system availability with the level of accuracy provided.

Human Factors in Technology Adoption—Domain-specific intelligent systems aim to support users with varying levels of expertise simultaneously. However, factors such as prior domain knowledge and the ability to detect errors affect user trust, reliance, and confidence in these systems [33]. Understanding how digital tools interact with human operators in the farming environment is crucial. While human-like interactions may be beneficial in some scenarios, excessive perceived intelligence can hinder practical functionality when farmers need straightforward, background-functioning tools for quick decision-making [19]. Existing research often focuses on the design attributes, user interactions, and perceptions of smart solutions in smart farms but overlooks the role of humans in early technology development stages. It is particularly important to understand how these systems can facilitate collaboration and decision-making among users to access and utilise information effectively. The participant-led discussion we adopted provides insights into developing actionable and trusted technologies by capturing and understanding potential end users' needs, preferences, and perspectives.

3 METHODOLOGY

To understand how data-driven technologies integrate into farm practices, we conducted a field study focusing on mobile applications and decision support systems. Using semi-structured interviews, we examined farmers' daily tasks, data application incentives, and decision-making points to inform the design of interactive systems for better information access and decision-making. This research aims to support effective technology integration in farm management, facilitating the digitisation of dairy farms to keep pace with technological advancements. The study was part of the AgResearch Integral Design of Farm Digital Systems project and adhered to ethical protocols approved by the Anonymised University Human Research Ethics Committee.

3.1 Participants

Participants were recruited using a community networking approach, specifically employing snowball sampling. Initially, participants were identified and confirmed through direct calls, which then facilitated introductions to neighbouring farmers. This method ensured a representative sample of the dairy sector. The study involved seven participants (N = 7, 6 males, 1 female), organised into 3 dyads (P1 and P2; P3 and P4; P5 and P7) and one individual interview (P6). The mean age of the participants was 45.57 years (SD = 16.18). Participants held diverse roles within the dairy sector in South Island, New Zealand. The group included three share milkers, who were actively involved in the hands-on daily management of farming operations, and three farm owners (refer to Table 1). The written consent was obtained from all participants before the commencement of the study session.

3.2 Procedure

The study employed a mixed-methods approach, utilising dyadic interviews, participant-led discussions and one individual interview to gather insights. The dyadic interviews and participant-led discussions were conducted on dairy farms, while the individual interview was conducted via Zoom, each lasting for an hour.

Table 1. Demographic information of the participants

Participants	Gender	Age	Job Role	Herd Size
P1	Male	35	Sharemilker	700
P2	Male	37	Sharemilker	680
P3	Male	69	Owner	750
P4	Male	62	Owner	360
P5	Male	60	Owner	1,200
P6	Female	27	Sharemilker	500
P7	Male	29	Assistant manager	500

Initially, participants were briefed on the overarching goals of the research. The discussions began with a structured format but allowed for participants-led conversations towards the end to explore their perspectives in greater depth. Participants were involved at varying levels of digitisation, with most integrating multiple technologies into their daily processes, including data collection, organisation, and usage. Notably, one participant had developed a dairy system modelling tool for analysing past performance and predicting future outcomes.

During the participant-led discussions, we first identified key tasks and workflows in participants' day-to-day practices. We then created a journey map to capture their experiences with farm tasks and the technologies they use. We printed the journey map in a tabular format to gather and document participant insights across information needs and usage, decision-making processes, and interaction with services or people when performing key tasks. Participants were instructed to write their responses on Post-it notes and stick them to the corresponding columns (refer to samples in Figure 1). The discussions focused on how farmers access, interpret, and utilise information in their daily routines. We examined both traditional methods and digital tools to identify pain points, opportunities for improvement, and the impact on decision-making effectiveness and efficiency.

The semi-structured interview format served as a starting point for conversations on needfinding for data applications in farming practices. The rationale behind this method was to accommodate the diverse information needs and applications of the farmers. After describing the nature of the interview and obtaining consent, we began recording the conversation. We commenced with open-ended questions to encourage participants to think about their daily tasks and decisions. Refer to Table 2 for the complete list of interview questions. This approach allowed us to gather rich qualitative data, providing insights crucial for developing user-friendly, intuitive systems to support farmers' decision-making processes.

3.3 Analysis of Results

Familiarisation: The audio recordings were transcribed using the automated software TurboScribe [1]. It was assessed through a comprehensive manual review process to identify and rectify any transcription errors. This involved cross-referencing the transcripts with the original audio recordings, particularly focusing on areas where regional accents or dialects may have caused inaccuracies [13]. By doing so, we ensured that the final transcripts accurately reflected the participants' responses, thereby upholding the integrity of our qualitative data analysis.

Thematic Analysis: We analysed the results of the interviews using both inductive and deductive thematic analysis, following the process outlined by Braun and Clarke [4]. Initially, we defined categories of codes based on the structure of the transcribed interviews and discussions. This categorisation was guided by our working assumptions and additional

[1] https://turboscribe.ai

Table 2. Ten questions in the semi-structured interview.

Semi-Stuctured Interview Questions
1) Could you please walk us through a normal day on the farm in terms of your main tasks, actions, and interactions?
2) What are the decisions that you are making as you go through these tasks?
3) What tools or devices do you use or are you surrounded by as you make them?
4) What types of data or information do you have access to or use to inform these decisions?
5) How do you interpret the insights from mobile applications and other devices to inform your decisions?
6) Considering that various factors such as pasture growth, water levels, and soil moisture require continuous monitoring and action for irrigation and pasture management, how do you use this specific information to inform decisions about these interconnected tasks based on multiple data inputs?
7) In terms of decision-making, do you usually make decisions individually or collaboratively with staff and peers, or do you consult external experts or consultants? If so, when do these instances happen?
8) From your experience, what kind of information/data do you find most valuable?
9) To what extent do you use this data and access technologies about these factors on a daily basis?
10) Is there anything else you would like to share with us that would help us understand how you apply information technologies to support decision-making?

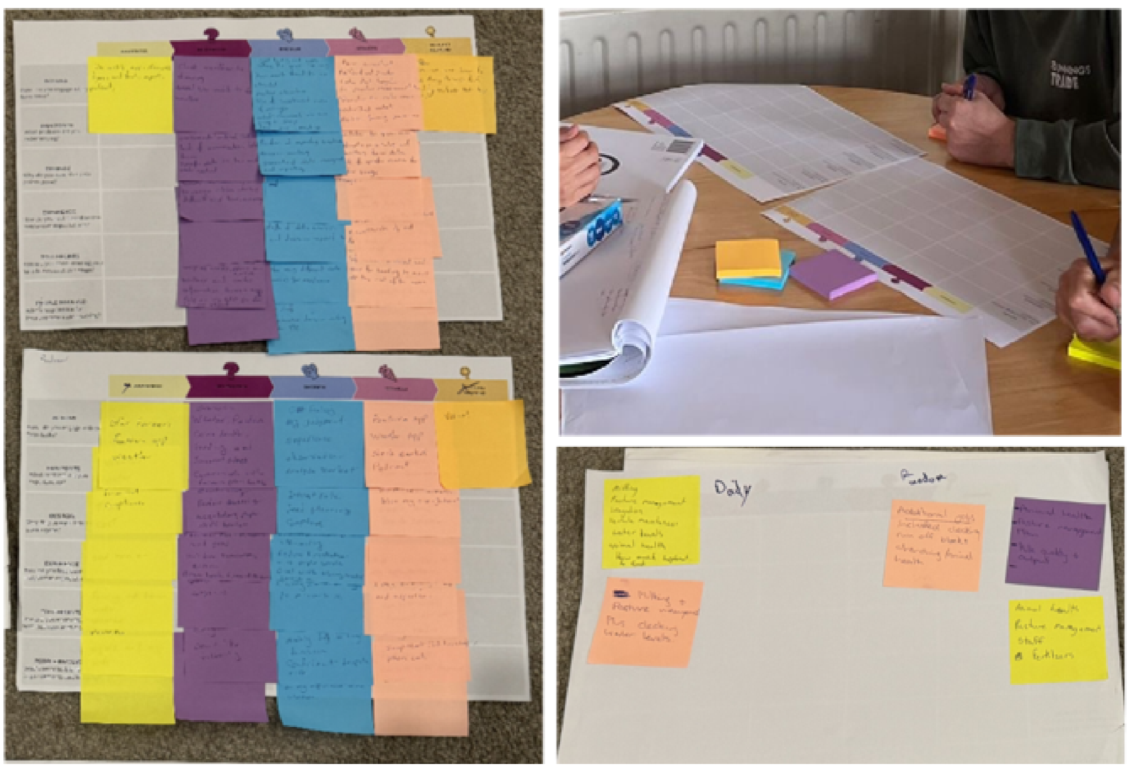

Fig. 1. Example of journey maps, post-it and sketches generated during the workshop

information related to the research goals and questions. We synchronized the transcripts using NVivo [50], which enabled the visual mapping of relevant data and identified themes and relationships within the data. This approach facilitated anticipatory data condensation by providing clear visual reference points within the transcripts.

Mapping and Interpreting: Within each category, we annotated subcategories of codes inductively by identifying the variations in responses from each interviewee and grouping them into broader, meaningful themes. To ensure reliability, the interviewer and another researcher independently coded the interviews. They then discussed reconciling any differences in the codes and refining them as needed. After this initial coding, they re-coded all the interviews, discussing and incorporating any new emerging codes. The codes were designed to be all-inclusive, covering all aspects of the responses, and mutually exclusive, ensuring that each response could fall into one subcategory within the same category.

To enhance the reliability and validity of our findings, we employed triangulation. Specifically, we cross-verified the findings from interviews and discussions. This method provided a consistent understanding of the topic and facilitated the identification of various data levels and their mutual contributions [21].

4 FINDINGS

This section presents the key findings from our study on the operational use of data-driven applications by New Zealand dairy farmers. The findings are organised into two primary themes: operational decision-making and data-driven decision-making challenges. Each theme is further divided into sub-sections to provide a detailed analysis of the farmers' experiences and challenges.

4.1 Operational Decision-Making

Our analysis revealed three distinct stages in the operational decision-making process: preparation and planning, implementation, and review and adjustment. We examine how participants integrate data applications and personal expertise across these stages.

Preparation and Planning—During the preparation and planning phase, participants exhibited a synergistic integration of data applications and personal expertise. The utilisation of weather forecasting applications and engagement with expert groups such as DairyNZ was prominent.

Implementation—In the implementation phase, participants detailed how they applied their plans by closely monitoring various factors such as pasture types and adjusting operational activities such as grazing schedules. They illustrated the reliance on real-time data, using mobile applications to directly input actions such as fertiliser applications, thereby streamlining end-of-year reporting processes and compliance.

Review and Adjustment—The review and adjustment phase involved the assessment of outcomes and the strategic refinement of operations. This was done using a comprehensive review and analysis of data provided by farm consultants and digital tools like decision support systems.

Most participants relied on various software applications in making informed decisions. However, they pointed out the challenge of managing detailed data, which can be time-consuming. Participants highlighted the critical role of technology in operational efficiency and the need for systems that can synthesise and streamline data analysis to support more efficient decision-making.

For instance, several participants emphasised the time spent on data collection, suggesting that continuous review is integral to their operational strategy. Participants with extensive experience and a more strategic viewpoint still see the benefit of an advisor or farm consultant who could synthesise and analyse data to inform decision-making.

They highlighted the consultant as an expert who adds another dimension to the review phase, offering wisdom and helping farmers examine data to make better decisions. This underscores the crucial role of consultants in providing data analysis and interpreting it in a way that leads to actionable insights for farmers.

Across all stages, there is an evident blend of relying on applications and decision support software for data gathering and analysis, with a strong emphasis on personal judgement and experience to inform decisions. Each participant highlighted the importance of balancing technology with hands-on expertise and context-specific information in the field. This demonstrates that while digital tools are invaluable, the human element remains irreplaceable in farm information management practices and decision-making.

4.1.1 Hand-on Management and Personal Accountability in Data-driven Decision-making. Participants (P1, P2, P3, P4, and P5) use data and decision-support systems for various tasks on their farm, with water management and livestock tracking being the prominent tasks. However, they retain primary decision-making responsibilities. For instance, P2 emphasised that:

> *"I've got staff who don't have access to data but I communicate directly with them. Ultimately, I'm the person in charge so I decide when the water's going on. That's my responsibility to Environmental Southland. I don't rely on others. If something goes wrong it comes back to me."*

This highlights a hands-on approach and the importance of personal accountability. Participants manage crucial decisions and prefer direct communication rather than relying solely on technology to disseminate information. This underscores the value of human oversight and control in managing farm operations. While technology plays a critical role in farming, it does not entirely replace the human understanding, personal accountability, and experience-based knowledge that humans provide.

4.1.2 Integration of Technology with Hands-on Experience. Participants (P1, P2, P3, P4, and P5) indicated the seamless integration of digital tools with farmers' hands-on experience is the most effective method. These data-driven tools provide data and enhance, rather than replace, traditional farming methods. For instance, P1 emphasised:

> *"There are 40 years of experience and we are actually on the ground, doing the day-to-day job, looking at the cows, milking the cows every day. So, probably we are not normal dairy scenario and that's why we are getting good results in that. Information is a complement to your judgment. Your gut should come first because they're always fighting fires on the farm."*

4.1.3 Integrating Expert Insights. We identified that farmers value feedback mechanisms, particularly in the form of expert feedback and technological insights. They pointed out the importance of soliciting expert consultations to offer options and ideas based on data comparisons and agricultural best practices to enhance different aspects of their farm operations effectively. In terms of technology used for feedback, they employ various tools such as FARMAX [5], Farm Minder [30], Fonterra tools and services [10], Levno app [22], electronic identification tags and weather apps such as MetService [29], which essentially serve as feedback loop, providing data that inform their decision-making processes. These technologies allow them to adjust operations based on monitoring farm activities, tracking and managing cows, and environmental conditions.

Additionally, participants with both technical and non-technical backgrounds expressed a need for more effective collaboration and communication tools with external experts and farm advisors. For instance, they mostly rely on external information and advisors from platforms like Fonterra and DairyNZ. A design that integrates this external expert advice directly with their on-farm data, enabling them to make better-informed decisions based on a combination of real-time data and expert recommendations, is highly sought after for future agricultural advisories [38].

For instance, if predicted weather changes could critically affect soil moisture levels, the system could automatically suggest adjustments to irrigation schedules. This involves exploring advanced features, understanding the nuances of applications' outputs, and finding their methods to achieve the best outcomes. For instance, P2, a dairy farm share-milker, reflected:

> *"Technology has been crucial for farm management for a while now, but with the latest systems, we can do a lot more. For example, we use soil moisture telemetry to make informed irrigation decisions. The real trick is getting to know how these systems give feedback and what it means practically. I regularly check our soil moisture levels through an app on my phone, and it shows me not just numbers but trends. Understanding these trends and interpreting what they mean for the next day's or week's weather and soil moisture conditions help us use water more efficiently and effectively."*

Participants value technology for its data and efficiencies but rely on human expertise for comprehensive decision-making, especially in complex and critical situations. They highlighted the importance of consultants as a way to better integrate human cognitive and professional skills with digital enhancements to optimise outcomes. This underscores the importance of human judgment, experience, and strategic insights working together to achieve superior outcomes in the collaborative work environment. This reliance is often due to the limitations of technology in handling exceptions, providing context-specific advice, and integrating diverse types of data into actionable insights. Thus, the design of future user interfaces' feedback mechanisms could be enhanced in multiple ways:

(1) Improved accessibility;
(2) Providing customisable input channels for users to input specific data points easily;
(3) Integration of data analytics and recommendations similar to those given by human farm consultants;
(4) Offering a real-time feedback loop, such as alarming users to immediate issues or opportunities.

4.2 Data-driven Decision-Making Challenges

This section examines the current practices and tools used to inform data-driven decisions. Most participants employed general-purpose mobile applications, such as weather and performance-tracking apps, to access up-to-date production and quality information. They used this data to complement their hands-on experience, analysing patterns by comparing historical data with current conditions based on their observations.

Several challenges were identified regarding these systems. Participants highlighted issues including complexity, disparate data sources, and reliance on expertise to solve complex problems. To address these challenges, they employed strategies such as integrating technology with practical experience, balancing technology use with expert consultation, and using accessible and practical data sources.

As depicted in Figure 2, users employed multiple applications to gather information that facilitates enhanced decision-making. However, they often found themselves overwhelmed by the volume of data and the complexity of deriving decisions from interconnected data points. Despite this, there is a clear demand for greater transparency and expert insight to validate their decisions. Interaction with peers and consultations with experts, which provide additional information, are crucial in this process. The availability of such supplementary information is contingent upon the accessibility of experts and peers, as illustrated by the dotted lines in Figure 2. When experts or peers are not available, users are compelled to rely solely on their own knowledge and the information derived independently.

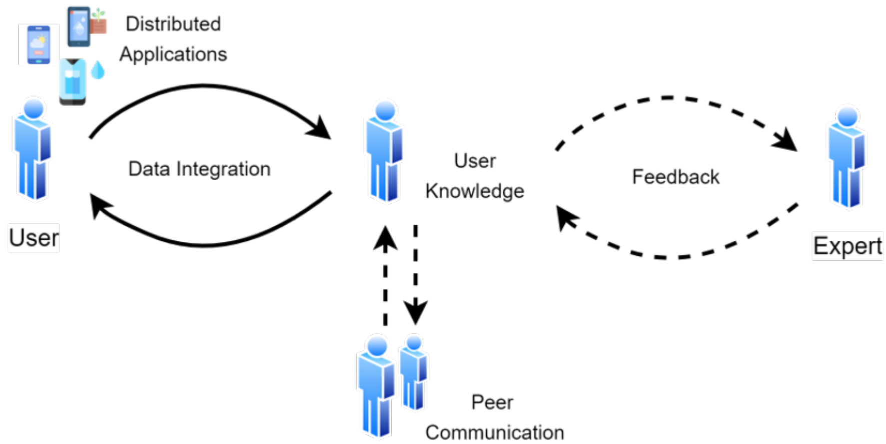

Fig. 2. Users' challenges in utilising data applications and decision-making in the field.

4.2.1 Large Amount of Data Sources. Participants observed a significant increase in data resources related to digital tools for their farming operations, ranging from weather forecasting apps to applications such as the Fonterra app, which provides specific details about their milk production, quality, and compositions. Some participants noted that these resources offer technical knowledge and insights into their operations, enhancing their understanding of the data and maintaining their competitiveness within the industry. For example, P4, a farm owner and consultant, noted:

> *"I gather information from several tools such as different weather forecasting apps, decision support systems and industry knowledge through direct communication with other farmers."*

4.2.2 Distributed Information Resources. We also discovered a noticeable challenge in collating various data points from several sources. Most farmers face difficulties when accessing and integrating data from multiple sources due to the complexity of coordinating data from different applications that are often updated independently. This leads to inconsistencies in data accuracy and timeliness, complicating decision-making. For example, P6 shared:

> *"I must navigate multiple applications to access critical farming data. Each app dedicated to monitoring different aspects such as water level, weather conditions, and soil moisture operates independently, requiring one to open and review each one separately. This process complicates the task of gathering comprehensive data but also adds complexity to make informed choices about irrigation and other farm operations."*

4.2.3 Effective communication and coordination for sharing and receiving data. Participants emphasised the importance of effective communication and coordination for managing farm operations. They use multiple digital tools for daily tasks but face challenges with integrating diverse data sources. Trust and reliability in these tools are crucial for supporting decision-making processes. Participants also highlighted the need for tools that provide actionable insights tailored to their specific environmental conditions and operational practices. Seeking peer or expert guidance for complex decision-making is a common practice, underscoring the importance of human expertise in conjunction with digital tools.

One participant, P2, showed that an application such as Resolution Farming can be especially beneficial for real-time data capture, integration with daily operations, task assignment and management. They demonstrated that such an interface allows them to communicate essential data and decisions to their staff, enhancing coordination, information transparency and accessibility, and compliance with regulatory requirements. Participants integrate digital platforms that have the potential to enhance the livestock management system by facilitating connections among system actors, improving coordination, and enabling data-driven transactions, ultimately supporting more efficient and effective farm management.

4.3 Technological Adoption and Integration Challenges

4.3.1 Participant Opinions on Voice-Activated Applications. In the final part of the interview, we asked all participants two questions about their opinions on voice-activated applications and the potential utilisation of generative AI technologies in future farm decision support systems:

(1) "Would you talk to the applications to input data or get recommendations in spoken language?"
(2) "Do you think if you have one system that could make sense of all data, for example, provide calculations of how much fertiliser should go into the land or connect you with consultants could help with managing your tasks?"

All participants responded positively to the first question, indicating a willingness to adopt voice and video-activated features to input data, call staffs staff and connect with external parties. Notably, P2, the most favourable participant in voice-activated applications, cited an example of an existing app that he uses and works with his existing workflow:

> *"I use voice commands and video tasks extensively. For example, if a staff member needs to fix a leaking trough in the paddock and isn't sure about the reassembly, I can create a step-by-step instructional video. This method not only clarifies the task but ensures accurate completion. We subscribe to a service that facilitates these communications for 3, 000annually, witha1,500 sign-up fee and a $1,000 yearly subscription. It's a new tool for us, and we're still exploring its full functionality, but I believe it's worthwhile."*

4.3.2 Desire for Integrated Data Platforms. In response to the second question, 6 out of 7 participants answered positively that they would use the one platform that could store the data collected from different sources and provide streamlined information to aid their operational decision-making and improve information accessibility. For instance, P2 expressed his interest and highlighted farmers' context-specific information and recommendation needs:

> *"Interesting, yeah, yeah, yeah, interesting. I mean, often I've said it would be great to have one platform where all this data is collected, and we go to there. The person who comes up with that will be very rich. Like, honestly, like, if, you know, I mean, every farm's different. If you go further that way, less irrigation, so information about freshwater irrigation onto land, not applicable, you know."*

However, one participant, P4, expressed unwillingness and cited the following reasons for their negative opinion: 1) implementation challenges and 2) specialization and efficiency of individual apps. P4, a farm owner and a certified farm advisor, stated:

> *"Individual apps are actually better than and move faster than the program that's trying to consolidate everything. Yeah. Yeah, in terms of a decision support tool."*

4.3.3 Balancing Optimism and Challenges in Data Applications. Our participants expressed a blend of optimism and discouragement regarding data applications and decision-support systems in New Zealand's primary sector. This sentiment is present throughout the process of using and accessing information and digital tools, and yet users consistently demonstrate active agency to overcome challenges encountered in the process. They expressed their desire to use systems that support fine-grained access control. For instance, tools should allow users to precisely specify how much water is needed to optimise soil moisture levels. Additionally, participants often rely on external information and advisors from platforms like Fonterra and DairyNZ. A design that integrates this external expert advice directly with their on-farm data would enable farmers to make better-informed decisions based on a combination of real-time data and expert recommendations. This integration is highly sought after for future agricultural advisories [38].

5 DISCUSSION

This study offers valuable insights into New Zealand dairy farmers' perceptions of future data-driven decision-making systems in high-uncertainty contexts. Based on these findings, we discuss future directions and provide design suggestions to enhance integration into commercial farm data practices.

For effective integration of data-driven decision support systems, designers must understand users' needs—including demographics, environmental behaviour, farming tasks involving data and decision-making, and the creation of seamless, natural interfaces. Our study highlights that farmers combine data-driven applications with personal expertise across the preparation, implementation, and review stages. However, they face challenges like managing large amounts of data from various sources, integrating distributed information, and ensuring effective communication. While participants show interest in voice-activated applications and integrated data platforms, they express concerns about implementation challenges and the need for specialized tools and support. To assist designers in creating systems that seamlessly integrate into existing workflows, we discuss current tasks and potential design implications.

5.1 Operational Decision-Making and Integration of Technology

We found that farmers utilise a three-stage decision-making process, integrating data applications with personal expertise. This aligns with findings from Eastwood et al. (2019) [9], who noted the importance of combining the experiential knowledge of farmers to provide decision options. Intelligent technologies such as IoT-based recommender systems are designed to provide personalised and context-aware recommendations to farmers. These systems use advancements in sensor technologies, data analytics, and machine learning algorithms to collect and analyse data from various sensors such as soil moisture sensors, weather sensors, and water level sensors to support decision-making about pasture growth forecasts and milk production [18].

Farmers maintain primary decision-making responsibilities despite using data and decision-support systems for effective farm management. Similarly, Rose et al. (2018) [42] found that farmers value personal control in decision-making processes. Future research and policy development should focus on creating robust regulatory frameworks that address the complexities of accountability in AI-driven farming systems. These guidelines would aim to protect the interests of farmers, consumers, and other stakeholders as the agricultural sector increasingly adopts advanced technologies [18].

Immersive technologies such as Augmented Reality (AR) and Virtual Reality (VR) could enhance hands-on farm management by overlaying data onto physical spaces and allowing risk-free simulation of decisions [14]. Integration with IoT and AI could further create intelligent, context-aware experiences for farm operations, while AR-enabled remote assistance could provide real-time guidance for decision-making [35, 37].

5.2 Expert Insight and Data Integration Challenges

Farmers value feedback mechanisms, particularly in the form of expert feedback through farm advisors and technological insights provided in tabular and visualisation formats. While users employ data applications and decision-support systems, the advisors' role is to act as a sense-maker and human verification of such systems. The human expert in the loop enables farmers to derive greater value from data-driven smart farming [8]. This interaction creates trust between users and technological solutions, as humans are adapted to interact with and trust experts. However, consultation with human advisors requires time and effort to input individual farm data and analyse it to provide recommendations, and their availability is limited.

Technological designs should consider these user attributes when developing information and decision support systems. Recent advancements in HCI technologies, including conversational agents [44, 55] coupled with the next generation of multimodal large language models (LLMs), have captured the attention of agricultural technology developers [25]. LLM-powered conversational agents and virtual platforms could facilitate virtual consultations with experts, similar to those in healthcare. Given their human-like conversational capabilities and advanced reasoning and decision-making capabilities, these AI agents can provide tailored recommendations based on farm-specific data [40]. However, there are often ethical, social and responsibility problems in developing and deploying LLM models [54, 56]. Additionally, these models can exhibit biases and hallucinations, generating outputs that seem reasonable but are actually flawed, which poses significant risks in agricultural applications [6]. Therefore, it's imperative to design systems that can detect and mitigate these issues to ensure the reliable and ethical use of large models in agriculture.

5.3 Large Amount of Data Sources and Distributed Information Resources

We found two main challenges in farm data application practices: managing a large number of data applications to inform decision-making, also reported by [12] and integrating data from independent sources, such as weather factors (e.g., temperature, rainfall, wind) and farm-specific information (e.g., soil moisture, grazing patterns, and water level data). These sources offer insights into important operational tasks such as animal health planning, irrigation management, and deciding fertiliser applications. However, data integration from multiple sources is a common challenge in many domains, including agriculture [52].

Farmers expressed interest in a unified platform for storing and analysing data from various sources (See Section 4.3.2). The integration of data in multiple forms and formats is a complex problem in many domains. The recent integration of multimodal LLM capable of processing textual, visual, and video inputs, analysis and output within web platforms offers more effective and deeper insights for reasoning multiple data sources [49].

5.4 Effective Communication and Voice-Activated Applications

Farmers need to access insights from data applications to facilitate decision-making and communication. A user interface that facilitates community-driven data access and interaction among system actors has proven effective in enhancing interoperability and accessibility [2].

Farmers were willing to adopt voice and video-activated technologies for interacting with information. One notable modern technology is the use of voice-activated personal assistants in everyday routines. A popular example is the OpenAI GPT4o, which offers multimodal capabilities in processing and understanding voice and video feeds, advanced conversational abilities and an integrated user interaction model [26, 48].

5.5 Balancing Optimism and Challenges in Data Applications

Reflecting on recent research about the adoption of digital tools in agriculture [12, 31, 46], we observed a mix of sentiments towards data applications and technologies. While many appreciate the potential of data-driven technologies to enhance decision-making accuracy and optimise sustainable production, others find these solutions complex and not economically viable. The perceived value of digital solutions varies significantly based on specific task requirements and farmers' technological familiarity. For instance, real-time monitoring tasks like irrigation management demand more sophisticated digital tools compared to routine data collection activities such as daily milk recording. Moreover, experienced farmers tend to be more critical of digital tools' limitations than their less experienced counterparts.

Our findings underscore the multifaceted nature of farmers' perspectives, highlighting the need for further research into key factors influencing technology adoption across diverse farming contexts. This understanding is crucial for designing digital solutions that effectively address the nuanced needs of different agricultural settings.

6 CONCLUSION AND FUTURE WORK

This research aimed to understand the integration and utility of data-driven applications in operational decision-making among New Zealand dairy farmers. The findings highlight current challenges and practices within this sector, providing a foundation for future decision support system enhancements. We identified key areas where design improvements are necessary to support farmers more effectively. These include the integration of diverse data sources into a unified platform, enhancing user interfaces for information accessibility and providing technical support for daily operations. We have also proposed specific solutions that address the challenges identified in our research.

Building on our findings, future research should focus on enhancing human-AI interaction in agricultural settings by developing intuitive, user-centered systems that align with farmers' workflows and expertise. This includes exploring the integration of advanced AI technologies such as voice-activated assistants and conversational agents powered by LLMs to facilitate natural and efficient communication between farmers and AI systems. Investigating how these technologies can augment farmers' experiential knowledge while addressing challenges like data integration, biases, and hallucinations is crucial. By involving farmers in the co-design process, we can create AI-driven decision-making tools that are not only technologically advanced but also ethically responsible, culturally sensitive, and tailored to the specific needs of the agricultural community.

Looking ahead, we plan to continue this research by developing an agentic workflow to be used as an information source or as a decision support system if influencing users' decision-making process. Based on the guidelines proposed, the system will feature multimodal interaction capabilities that leverage the strength of the most recent LLMs (e., GPT4o). This prototype will be tested and refined through iterative feedback sessions with farmers to ensure it effectively addresses the identified challenges and meets the specific needs of users in their working environments.

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