# Obstacles and opportunities for automation in sheep and beef farming: a pilot study

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## Abstract
Automation of tasks on farm has had limited uptake in tools such as auto-weighing and auto-drafting. To develop an understanding of the range of digital tools and the potential to automate tasks in the sheep and beef industry, two pilot workshops with end-users were held in the North and South Islands of New Zealand. Current digital technology use on sheep and beef farms included 26 applications representing the categories of communications, administration, monitoring, automated tasks, decision support, prediction, and proof of placement. Obstacles included the amount of time required to either set up or support the technology once in operation. Interoperability and the transfer of information between applications and along the value chain were major obstacles to generating value from combining digital technologies. Automation of data flows along the value chain would provide a significant step forward in the uptake of digital technologies. Digital solutions to aid automation need to be interoperable, with data able to be passed between software solutions, and between users to reduce compliance time and increase accuracy of data handling. The technologies need to be appropriate to be adopted at scale in an automated way to capture labour-saving benefits. Automation solutions need to translate data into a decision-making form to allow easy interpretation and application of data.

**Keywords:** automation, farm tasks, information transfer, interoperability

## Introduction
Commercial scale red meat farming (sheep and beef) in New Zealand is characterised by large farms (approximately 700 ha average and 4,500 stock units), low labour inputs and low economic farm surpluses (1.85 FTE's and $130/ha; Beef + Lamb NZ 2023). Future aspirations of meeting environmental goals, increasing animal health and wellbeing, and improving people wellbeing, driven by public and consumer demand (Klerkx and Begemann 2020), may be met by the application of new digital technologies for precision farming (Shepherd et al. 2018).

Digital technologies, such as weighing scales or accounting and banking packages, have been available to farmers for some time. Technologies such as Farmax (Bryant et al. 2010) and FarmIQ (Isaac and White 2016) are extensions of digital approaches to assist in on-farm decision-making. Automation of tasks on farm has had some uptake in tools such as auto-weighing and auto-drafting (Dela Rue et al. 2019). However, greater opportunities may be available through Machine Learning (ML) (Mahmood et al. 2022) and application of Artificial Intelligence (AI) (Li and Hsu 2022).

In reviewing the literature for using digital technologies for automation in agriculture, an examination of 189 papers found that 52% of papers were related to monitoring technologies, 17% were related to task delivery, 12% were reviews, while applications for prediction and decision-making were approximately 7% each. Applications to communication, administration and proof of placement made up the remainder. Overall, 15% related to animals, 38% to plants, 7% to people, and 36% to land management (including plant biodiversity, water and soil management). The needs and progress of digital technology uptake in the New Zealand dairy industry has been tracked for several years (Jago et al. 2013; Edwards et al. 2015; Eastwood et al. 2016; Yang et al. 2020; Eastwood et al. 2022). However, little information regarding digital technology uptake (Casey et al. 2016) and potential future uses is available in the New Zealand red meat sector. To increase the rate of development and applicability of digital tools and to enable the acceleration of precision agriculture in the red meat sector, an understanding of the current technology use, obstacles to use and opportunities for development is required.

To understand the current state of uptake of digital technologies on sheep and beef farms, we asked farmers and agribusiness representatives about which digital technologies they currently use, their issues with current technologies, obstacles to future digital technology investments and the automation opportunities that they saw for their enterprises. This paper documents sheep

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and beef farm requirements and provides insight into technology requirements for successful applications and potential future commercialisation targets.

**Materials and Methods**

As a starting point we wanted to understand the obstacles and opportunities for automation on sheep and beef farms in New Zealand. This meant that we needed to investigate what digital technologies were in use, what issues had arisen with their use, and create a compendium of future potential opportunities. To do this we developed a workshop approach on the Technology Acceptance Model (Davis and Venkatash 2004), based on the theory of planned behaviour (Ajzen 1991). This approach enables the use of small groups to explore the future applications of a technology using an attitude to adoption approach which does not require quantification (Pierpaoli et al. 2013). The workshops were advertised through local school networks to include a wider community audience, acknowledging both the role of social factors in technology uptake (Duffy et al. 2021) and the requirement for digital technologies to be part of the greater value chain of agricultural production (Eastwood et al. 2023).

Two workshops were held with rural communities in May 2021 to investigate the role of automation on sheep and beef farms and their value chains. Each workshop was timetabled for 3 hours. This was a qualitative process where the audience was self-selecting. The approach was used to create an initial engagement with the sheep and beef industry to gauge the types of technology in use and the potential for automation. Therefore, the data collected is qualitative and indicative only. The workshop approach was approved by the AgResearch Human Ethics Committee.

Twelve people attended the workshop in South Canterbury. This included 10 farmers and 2 agribusiness representatives. The audience was made up of nine men and three women who were mainly second and third generation farmers of the land. The predominant stock type was sheep, with beef support and some dairy grazing. Farm size ranged from 2000 ha hard hill to 300 ha irrigated flats. Most farms were dryland. All farms used contractors for shearing, hay and silage making, scanning and some yard work (hiring a local conveyer operator).

Ten people attended the second workshop in the King Country. These participants represented farming (four), and agribusiness (six), including stock sales and transport. Participants were predominantly women (eight). All but two of the women had off-farm jobs including teacher, transport/trucking, two x sale yards, and agribusiness.

The workshop began with an introduction and collection of background information to understand the diversity of the participants, on the basis that the diversity of participants would potentially influence the types of technology that they would require. Data collected included farm size, enterprise types, stock number, topography, use of irrigation, number of employees, and off-farm employment.

Current use of technology on-farm and through the value chain was collected using a white board session to list and discuss technologies already in use or previously used by the participants (including potential problems).

The creation of a set of farm tasks that may be suitable for automation was developed. This included organising farm tasks into daily, timetabled, seasonal or annual. This was then followed with a discussion of the information needed to complete the tasks, the transfer of information between parties and the potential for automation of the task itself. A list of potential opportunities was developed from this.

Finally, the barriers to implementation and the synergies that may be created by automation were listed and discussed.

An emergent process was applied by the research team to group data into processes, and then into categories of primary target. Processes included Communication, Administration, Monitoring, Prediction, Decision-making, Task Delivery, and Proof of placement/activity. Technologies were categorised into four groups including Animal, Plant, Land and People to differentiate the target of the technology within each group. Animal was used to identify those technologies that were directly related to animal health, welfare and productivity. Plant was used to identify those technologies used to identify and manage plants, both productive and weeds. The Land category included soils, biodiversity, water management and farm planning. The People category included technologies that were directly related to health and well-being or were used to reduce labour requirements. In this instance these technologies were sometimes aimed at measurement or task delivery in the other three categories.

## Results and Discussion

The range of digital technologies employed on sheep and beef farms covered many aspects of farming and some use was made of these technologies by all participants (Table 1). This high level of engagement has also been reported (Casey et al. 2016), both in farming and agribusiness segments. Both the communications and administration groups, with high use, reflected the universal nature of these technologies beyond farming. The groupings of prediction and task delivery had both relatively few technologies available and few users of those technologies.

Issues in the use of current technologies (Table

**Table 1** Current digital technologies used on sheep and beef farms identified by two workshop groups in the North and South Islands of New Zealand.

| Grouping | Number of technologies | Type | Use | Target category | Timeliness | Issues |
|---|---|---|---|---|---|---|
| **Communications** | Few | Cell phone, Radio Telephone | All | People | Operational | Coverage |
| **Administration** | Numerous | Banking, accounting, payroll, diary entry | All | People | Operational | Interoperability, data transfer |
| **Monitoring** | Numerous | Drone, weigh scales, EID, pasture meter, irrigation GPS, security cameras, water reserves/use, feed wagon scales, hyperspectral analysis | All | Animal, Feed, Land | Operational | Interoperability, data transfer, data interpretation, data handling, malfunction, retention |
| **Prediction** | Few | Farmax, pasture growth predictor | Some | Feed | Tactical | Cost, fit for purpose, calibration |
| **Decision** | Few | Farmax, feed budgeting, enterprise analysis | All | Animal, Feed | Tactical, Strategic | Cost, time for implementation, complexity, set-up time, maintenance time |
| **Task delivery** | Few | Auto-drafting, accounting, electric fence control, irrigation delivery | Some | Animal, People | Operational | Cost, reliability, variability |
| **Proof of placement/ activity** | Numerous | FarmIQ, irrigation GPS, Navibus herbicide GPS, TracMap, on-board GPS, Google Earth mapping | All | Animal, Feed, Land | Operational Strategic | Cost, fit for purpose, data transfer, data security, complexity, set-up time |

**Table 2** Obstacles to the implementation of digital technologies that provide automation solutions for sheep and beef farming and its value chains.

| Industry | Technical | Personal |
|---|---|---|
| Duplication of software/programmes | Physical problems with ear tags - loss, not reading, damaged | Generation – Dad won’t use it and he’s the one that could use it most. |
| No integration between programmes | Internet coverage | Perception of ability (self-efficacy, and lack of skills and knowledge) both of self and of the people supporting them |
| Overlapping information required but no way to replicate it between applications | Cell phone coverage | Overwhelmed with data – data not translated into something useful |
| IP – companies not wanting to share | | Need to ensure that human connections and communication are maintained or enhanced |
| Different platforms don’t talk to one another, but hold or need similar data | | |
| Range of products available e.g. mapping and tracking programmes – also needed for lots of things but don’t trade/swap data | | |

1) were similar to those that have been documented by others (Bahlo et al. 2019; Eastwood et al. 2021). Data issues were mentioned six times and included transfer, interpretation, handling, and security. Lack of interoperability, the ability to have different software or firmware interact, was a significant drawback. The time required to invest in learning new systems, and to maintain them and extract information was also identified as an issue. Technologies being fit-for-purpose, robust and appropriately calibrated to create reliable data with minimal variability was also a key problem. Cost of the technology was also identified as an issue, often in the context of not providing enough benefit to purchase or continue use of the technology

While digital technologies may have a range of deficiencies (Table 1), participants had the view that future versions of the technology would develop appropriate solutions, or that the application would go out of use. Obstacles to further automation and digitisation of the farming processes were identified as a different set of characteristics (Table 2). The first category identified was that of industry-wide issues. This included duplication of software which, while providing choice, also complicated the potential to integrate data sharing between applications. A further frustration was the inability to automatically transfer data collected for one application into another, when they required the same data. This issue of lack of interoperability has been identified as a major obstacle to the application of precision agriculture (Bahlo et al. 2019), as this exchange of data between applications and between entities is required to unlock the potential of ML and AI (Li and Hsu 2022; Mahmood et al. 2022). The area of intellectual property (IP) and the ownership of data was raised. Farmers were aware that the initial data was owned by themselves, but arrangements with technology providers restricted their ability to access raw data and potentially use it in other applications.

Technical issues were often seen as solvable by farmers, though internet and cell phone coverage were significant impediments. Recent launch of Starlink, (starlink.com) a competitive, high speed satellite service demonstrates the rapid development of solutions in these universal spaces. The retention of animal wearable technologies, especially ear tags, was a disincentive to use. Further to this, lack of retention was recognised as a serious flaw in data collection and interpretation. These issues are well recognised by industry (e.g. Eastwood et al. 2016) and the search for solutions is on-going.

Personal skills and attitudes were also identified as important obstacles to digital technology uptake. Generational issues were raised where tasks were done by past generations who were unfamiliar with digital technologies. However, this obstacle also extended to other demographics who may not be familiar with technology, had literacy issues or generally lacked self-efficacy in this realm. The role of personal factors in technology uptake cannot be underestimated. Duffy et al. (2021) highlighted the role of functions of the technology, such as usability, capability, learnability and difficulty, and added personal or user considerations such as familiarity, experience, and aptitude. Duffy et al. (2021) found that these can be compensated for by training, support, task-fit, surrounding norms and accessibility. The concept of too much data, or poor data distillation was also raised as an issue. This was mainly expressed as the data not being collated to the point of decision-making, or when data collected was interesting but not important. Finally, the need to maintain human-to-human contact, rather than digital-only interactions was seen as an obstacle to uptake

Using the groupings from Table 1, the two workshops produced a range of potential automation opportunities to aid people, animals, feed and land management targets (Table 3). This list of opportunities for improvement is similar to others that have been produced for sheep and beef farmers in New Zealand (Greer et al. 2015, Corner-Thomas et al. 2015). Many of the opportunities came with explanations of why automation would be useful, and generally reflected the main motivation of Perceived Usefulness identified in the Technology Acceptance Model (Pierpaoli et al. 2013).

Around sensitive times, such as lambing and calving, the benefit was early identification of critical animals to maximise the likelihood of successful intervention. The need to reduce disruption of the flock or herd, through human presence, was also noted. Increased effectiveness of labour around this time was identified and related to improved animal welfare outcomes. For example, the farmer would spend less time looking for potential birthing problems and more time working with animals which did have problems.

Reductions in yarding events to collect information such as liveweight were also linked to improved animal welfare outcomes such as reductions in potential pneumonia, reduced stress and early identification of other problems, such as internal parasite infection. Further to this were potential reductions in farm-related accidents, which are often related to animal handling events.

Reduced labour requirements for these physical activities were expected to be balanced by an increased requirement to scrutinise, collate and interpret the data, leading to changes in the types of skill that may be needed on-farm in the future. This then relates back to the obstacle (Table 2) of self-efficacy. However, the workshop participants also saw this as a benefit, requiring a change in the types of people employed and attractiveness of rural jobs within rural communities.

**Table 3** Opportunities to automate processes on sheep and beef farms

| | Category | | | | | | |
|---|---|---|---|---|---|---|---|
| **Grouping** | **Communications** | **Administration** | **Monitoring** | **Prediction** | **Decision** | **Task delivery** | **Proof of placement/activity** |
| **People** | Maintaining human contact and making sure that communication occurs | Task assignment tool for infrequent tasks | Tracking humans – time and motion, safety, warning of no-go zones etc. | | | | |
| **Animals** | | | Pasture loading measurement of sheep internal parasites | Pasture loading prediction of sheep internal parasites | Use of animal history and weight to provide alerts when change is greater than cohort | Animal handling potentially in situ and remotely | |
| | | | Faecal loading measurement of sheep internal parasites | Faecal loading prediction of sheep internal parasites | Identifying animal health status (e.g. flystrike) to target mobs/individuals for treatment | Weighing and dosing accurately | |
| | | | Remote/autonomous measurement of liveweight and body condition | Prediction of ewe lactation output, lambs potential performance | Monitoring calving time (esp. heifers) to detect process and manage interventions | Remote sensing of BCS and pregnancy, potentially non-contact | |
| | | | Remote sensing of animal health and welfare (e.g. drones to detect flystrike) | Predict outcomes from pasture, ewe body condition and animal requirement when continuously grazed | Monitoring the lambing process as above | | |
| | | | Facial eczema spore counting | Using feeding behaviour and temperature variation to predict potential disease and target intervention. | Detecting animal behaviour to understand well-being and health. | | |
| | | | | Predict animal performance from pasture measurements | | | |
| **Feed** | | | Detection of invertebrate pests (e.g. black beetle, cutworm, army worm, crickets) | Predict insect outbreaks | Allocation of feed/pasture to appropriate stock class (beyond the lactation period) | Drones to deliver specific nutrients to specific sites | |
| | | | Detection of vertebrate pests (e.g. opossums, goats' pigs) | Stocking rate predictions for periods of continuous grazing | Make decisions about the management of pasture, based on pasture measurements | Virtual fencing in hill country | |
| | | | Crop monitoring – fertiliser needs, pests in real time | | | | |
| **Land Management** | | Reporting for Regulation | Metrics of state (e.g. update of water quality measurements automatically) | | | | Proof of action – e.g. photos (with GPS and time stamps) to identify improvements |
| | | Document store for Farm Planning | Hyperspectral development for ecosystem measurements | | | | |
| | | Reminder system for Farm Planning actions | | | | | |

Opportunities were often stated as a monitoring exercise at first and then developed into a decision-making process. Prediction technologies were similar except that the timeframe for delivery of the decision may be longer. There was a merging of monitoring with prediction, acknowledging that prediction may be required when attributes, such as lactational output, are currently not able to be measured directly at farm scale. For example, one opportunity was to measure feeding behaviour and body temperature variation to then predict potential disease and then be able to target interventions at an individual animal scale. This chain combined monitoring with prediction and finally a decision-making process. The workshop participants were very aware that just monitoring alone was not useful, reflecting their identification of obstacles such as lack of fitness for purpose, the overwhelming nature of unanalysed data, and the need to automate the process all the way to the decision-making point. Communication technologies were often stated as maintaining human contact, and as a health and safety option, making sure people were safe in their work.

Many of the solutions and opportunities that were identified already have some technologies or investigation associated with them. Often, however, they are related to dairy cow farming rather than sheep and beef. For example, walk-over weighing and automated body condition scoring (Brown et al. 2015) have been commercial in the dairy industry for some time. However, issues such as timeliness, coat depth (and wool cover) and inconsistency in colour recognition prevent application of those solutions to red meat farming at scale. Even remote sensing of pastures (e.g. Edirisinghe et al. 2012; French et al. 2015; Milsom et al. 2019) have significant issues of cloud cover, saturation, shading and sun angle when transferred to red meat enterprises, especially in variable terrain (Dymond et al. 2006), and these issues remain unresolved. Technologies that match lambs to their mothers (Morris et al. 2011), record grazing behaviour (Werner et al. 2018), and predict and monitor parturition (Neethirajan 2017) are all available. While technically feasible, the deployment of these technologies, and the automation of monitoring and response to these technologies at the scale of red meat farms is not a viable or cost-effective solution yet.

## Conclusions

Farmers and the wider agricultural community exhibited an interest in applying digital technologies and opportunities for automation. However, digital solutions to aid automation need to be interoperable, with data able to be passed between software solutions, and between users to reduce compliance time and increase accuracy of data handling. Technological issues such as connectivity and interoperability were highlighted. The technologies need to be appropriate to be adopted at scale in an automated way to capture labour-saving benefits. Automation solutions need to translate data into a decision-making form to allow easy interpretation and application of data.

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