IAgrE Student Awards

NOMINATION SUMMARY

IAgrE CNH Industrial Award

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Name of course studied:
BSc Honours Agriculture with Mechanisation

Period studied	**From:** 09/2021	**To:** 07/2025

Qualification gained: BSc Honours Agriculture with Mechanisation 2.1

Project Title:
The current uses, barriers to adoption, and the desired features of agricultural machinery telematics systems in the UK.

Details of material submitted with nomination: (Project/Exec Summary/DVDs etc)
Copy of project dissertation.
No confidentiality or NDA in place

Summary of George's thesis - (From George's thesis).

Introduction: Traditionally, data value and usage in agriculture has been minimal and rudimentary. Now data is perceived by many to be more valuable than oil (Uyar et al., 2024). Agricultural machinery telematics, a precision farming technology, uses telecommunication systems and sensor technologies to remotely monitor agricultural machinery. The recorded data can be used to optimise machinery usage, reduce downtime, and improve overall management of agricultural machinery (Goltyapin & Golubev, 2020). Telematics has been available for several years on self-propelled agricultural machinery. It is now available on a limited number of agricultural implements. Telematics technology supports the shift towards precision farming technologies, where data driven insights lead to smarter and more sustainable agricultural practices (Lowenberg-DeBoer & Erickson, 2019). This research aimed to understand current uses and future features required of agricultural machinery telematics systems, as well as determine the factors affecting and barriers preventing telematics use.

Methodology: An online questionnaire was distributed through Jisc Online Survey to UK agricultural machinery owners and operators, gathering quantitative and qualitative data. 200 valid questionnaire responses were received for analysis. Statistical testing was carried out using to understand interrelationships between differing variables.

Results: The study found that a significant majority (73%) of agricultural machinery owners and operators use telematics, with real-time data uses, such as remote monitoring, having the greatest level (>70%) uptake. Arable machinery operations, specifically seed drilling and fertiliser application, saw the greatest level of telematics use. Overall, respondents expressed satisfaction with current telematics systems (TS), but many desired greater integration with precision farming technologies, especially for wireless data transmission and data analysis.

The factors which had a significant association with agricultural machinery telematics use were occupation ($p<0.003$), agricultural enterprise size (ha), ($p<0.000$), number of self-propelled agricultural machinery ($p<0.000$), tractor kW ($p<0.000$) and the source/place of tractor purchase ($p<0.002$).

The most prominent barrier to telematics use was the financial cost. A lack of understanding of telematics technology and concerns regarding enterprise size were also a barrier, showing congruence with literature.

Conclusions: Overall respondents' perception of telematics is positive. However, telematics is just one precision farming technology. Precision farming technologies are noted to have the greatest impact on an agricultural production system when relevant technologies are used together. Telematics is no exception to this having the potential to create more resilient, robust and sustainable future agricultural production systems.

SIGNED BY PROPOSER: **David R White**	DATE SUBMITTED: **25/10/2025**

If you wish to provide any additional information to support this nomination please do so in a covering letter. When complete, return this form, together with the supporting documents, to

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The current uses, barriers to adoption, and the desired features of agricultural machinery telematics systems in the UK

by

George Andrew Elliott

being an Honours Research Project submitted in partial fulfilment of the requirements for the BSc (Honours) Degree in Agriculture with Mechanisation

2025

Student Declaration Form for Submission with Major Projects

Candidate's Name	George Andrew Elliott
Candidate's Number	18095500
Degree Programme	BSc (Hons) Agriculture with Mechanisation
Supervisor	David R White
Major Project Title	The current uses, barriers to adoption, and the desired features of agricultural machinery telematics systems in the UK
Word Count	9925
Confidential?	No

In submitting this Major Project I acknowledge that I understand the definition of, and penalties for, cheating, collusion and plagiarism set out in the assessment regulations. I also confirm that this work has not previously been submitted for assessment for an academic award, unless otherwise indicated

(Electronic) Signature of student: *G Elliott*

Date: 05/05/2025

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List of Abbreviations

AM	Agricultural Machinery
TS	Telematics Systems
PF	Precision Farming
PFT	Precision Farming Technology
VR	Variable Rate
VRT	Variable Rate Technology
SP	Self-Propelled
GNSS	Global Navigation Satellite System

The current uses, barriers to adoption, and the desired features of agricultural machinery telematics systems in the UK

G.A.Elliott, D.R.White
BSc (Hons) Agriculture with Mechanisation

Introduction: Traditionally, data value and usage in agriculture has been minimal and rudimentary. Now data is perceived by many to be more valuable than oil (Uyar *et al.,* 2024). Agricultural machinery telematics, a precision farming technology, uses telecommunication systems and sensor technologies to remotely monitor agricultural machinery. The recorded data can be used to optimise machinery usage, reduce downtime, and improve overall management of agricultural machinery (Goltyapin & Golubev, 2020). Telematics has been available for several years on self-propelled agricultural machinery. It is now available on a limited number of agricultural implements. Telematics technology supports the shift towards precision farming technologies, where data driven insights lead to smarter and more sustainable agricultural practices (Lowenberg-DeBoer & Erickson, 2019). This research aimed to understand current uses and future features required of agricultural machinery telematics systems, as well as determine the factors affecting and barriers preventing telematics use.

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Uyar, H., Karvelas, I., Rizou, S., & Fountas, S. (2024). Data value creation in agriculture: A review. *Computers and Electronics in Agriculture, 227*, 109602. 10.1016/j.compag.2024.109602

Chapter One: Introduction

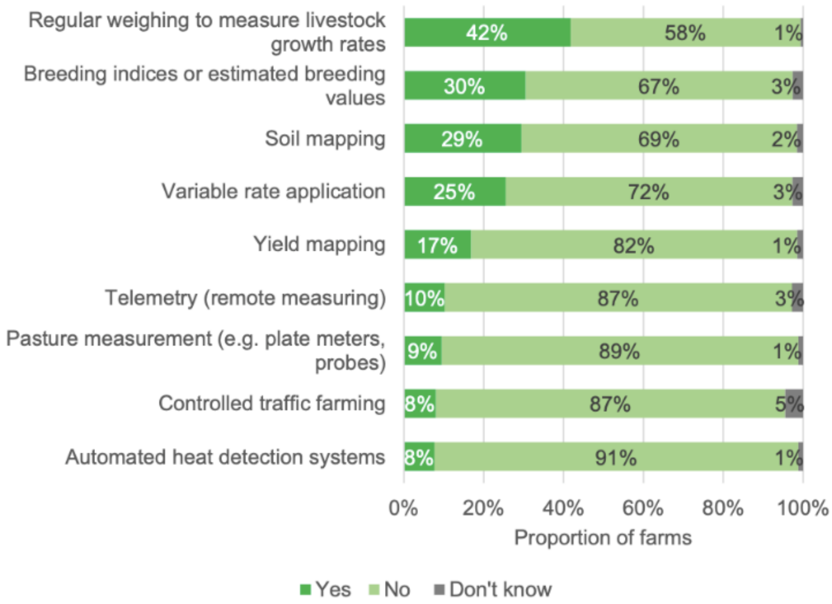
Traditionally, data value and usage in agriculture has been minimal and rudimentary, relying on observations and manual records (Mgendi, 2024). Now data is perceived by many to be more valuable than oil (Uyar *et al*., 2024). The advent of Agriculture 4.0, a term used to describe the current level of innovation, technology and software used in agriculture Connor Desai & Reimers, (2019); Rose & Chilvers, (2018), has agriculture evolve from a data scarce to a data rich industry (Uyar et al., 2024). In many instances, data is collected and stored with the expectation of deriving future value. However, the practicalities of deriving value from data remains a challenge (Kroupová *et al*., 2024; Tey & Brindal, 2022). Shahid & Sheikh, (2023) conclude without analysis, data is potential, not impact.

The demand for data is set to increase. By 2035, it is estimated a farm will produce more than four million data points each day (Lioutas *et al*., 2019). The onset of Agriculture 5.0 brings a new age of software technologies such as Artificial Intelligence (AI) believed capable of both analysing and deriving actionable insights from agricultural big data (Ahmad and Nabi, 2021; Shankarnarayan and Jahan, 2025; Holzinger *et al*., 2024; Uyar *et al.,* 2024).

Telematics is a telecommunication and information technology enabling remote monitoring, wireless transmission and storage of data and information (Miler et al., 2020). During the 1980s, the development of the internet and integration with Global Navigation Satellite Systems (GNSS) technology saw commercial use of telematics in the automotive industry for remote vehicle management, with systems sending data wirelessly from vehicles to a remote central computer system for monitoring and processing (Mikulski, 2016).

Agricultural machinery telematics, a precision farming technology (PFT), focused on the remote monitoring of agricultural machinery using wireless communication systems such as GNSS, and sensor technologies to gather, transmit and analyse agricultural machinery operational data (Anna & Jacek, 2015; Krzyżaniak & Kowalik, 2022). The recorded data has the potential to be used to optimise machinery by improving efficiency and productivity, reducing downtime, and improve the overall management of agricultural machinery (Mark and Griffin, 2016; Goltyapin and Golubev, 2020). Telematics technology supports the shift towards PF, where data driven insights lead to smarter and more sustainable agricultural practices (Lowenberg-DeBoer & Erickson, 2019).

The most recent survey into uptake of (PFT) by UK farmers was carried out by Defra in 2019 surveying 1,768 farmers. The survey results in figure 1 show 10 % of UK farmers use telematics (Defra, 2019). The low uptake is surprising as the survey also showed 78% of farmers stated their reason for using precession farming technology was improving efficiency and productivity (Defra, 2019).



(Source: Defra, 2020)

Figure 1. The uptake of precision farming practices by farmers in England

This study addresses a research gap identified through a critical literature review of agricultural machinery telematics. The aim of the study is to determine the current uses, the barriers to adoption, and the desired features of agricultural machinery telematics systems in the UK.

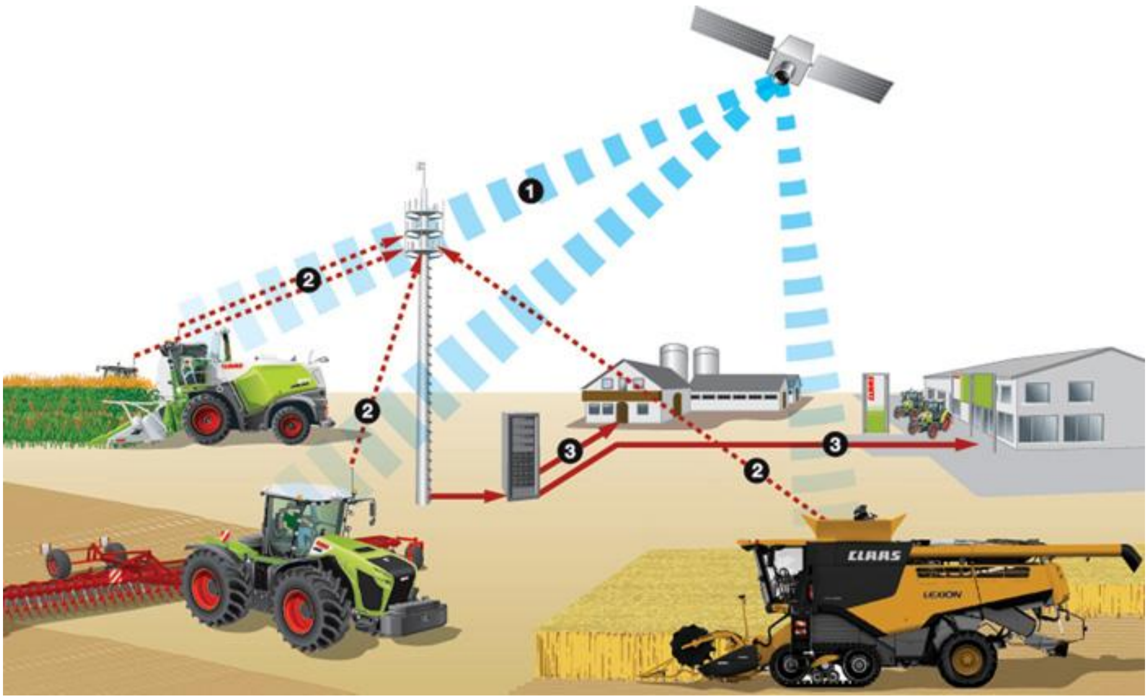
Statical tests were used to determine the significance of the factors affecting telematics use. The findings were compared to previous studies, on which conclusions and future recommendations are drawn.

Chapter Two: Literature Review

This literature review examines the applications of agricultural machinery telematics and the challenges surrounding use.

2.1 Introduction to Agricultural Machinery Telematics

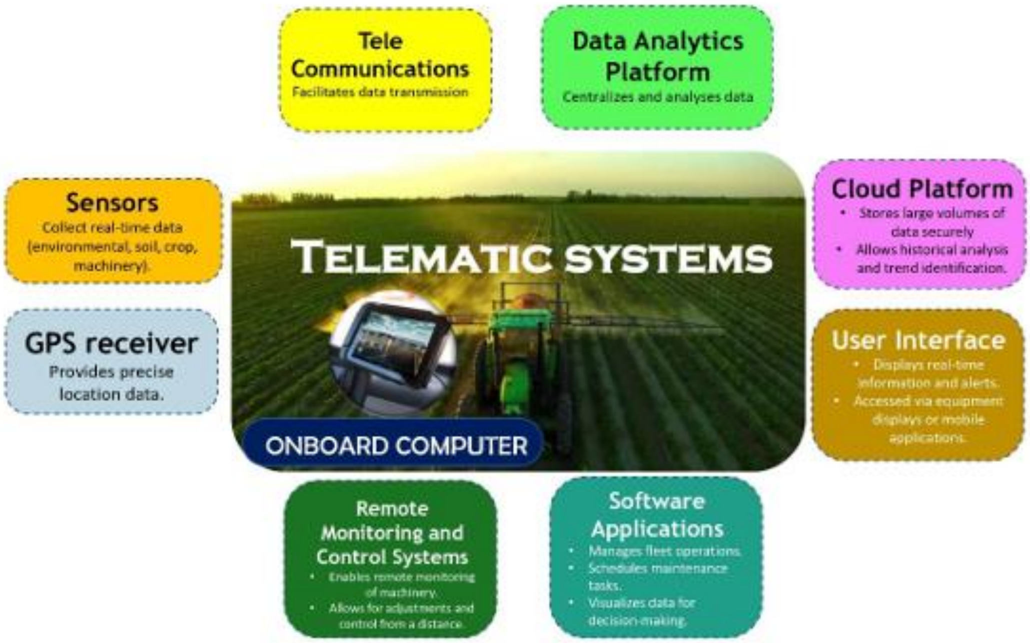
Currently all major agricultural machinery manufacturers provide a telematics system (TS) to remotely record and transmit data wirelessly from both self-propelled vehicles such as tractors and combine harvesters (CH) as well as agricultural implements such as seed drills and fertiliser spreaders (Mark & Griffin, 2016; Krzyżaniak & Kowalik, 2022). The way in which agricultural machinery data and information is captured, transmitted and stored is seen in figure 1, demonstrating how data recorded by agricultural machinery can be accessed remotely by both the agricultural machinery owner, supplying dealer and manufacturer. Although it may be considered useful for agricultural machinery data to be accessed by other individuals for uses such as remote diagnostics, Mark and Griffin, (2016) highlight the ownership of telematics data to be of concern. Further research is required to define the ownership of telematics data.



(Source Claas, no date given)

Figure 2. The flow of data in an agricultural machinery telematics system. 1. receiving location data via satellite; 2. transfer of data from machines to mobile network to server; 3. Data received and accessed remotely by agricultural machinery owner, supplying dealership and manufacturer.

Figure 3 below shows the hardware and software technologies and components that are incorporated to enable an agricultural machinery TS to function.



(Source: Prasanth, 2024)

Figure 3. The different technologies and software's used with an agricultural machinery telematics system.

Figure 3 demonstrates how agricultural machinery TS rely on multiple different technologies for telematics to function. This interdependency between technologies is a common theme of PF technologies. Griffin *et al*., (2017) discusses how PF technologies complement each other as data from one technology (e.g. yield monitors) can be used to enhance the effectiveness of another technology (e.g. variable rate input application).

2.2 Agricultural Machinery Telematics Uses

The information in table 1 demonstrates literature supporting the use and potential benefit of agricultural machinery telematics.

Table 1. Agricultural machinery telematics use

Telematics use	Description
Calculating agricultural machinery operating cost	Attributing machinery operating costs to individual agricultural machinery operations for specific businesses.
Understanding and calculating agricultural machinery productivity	Determining accurate work rates such as hectares per hour, fuel usage rate and idle time.
Understanding and calculating agricultural machinery efficiency	Improves task automation, machinery usage insights, and cost reduction.
Service and maintenance	Predictive maintenance, fix before fail. Proactive scheduling of maintenance minimising downtime.
Precision Farming	Wireless transmission of maps e.g. variable rate / yield.
Fleet Management	Tracking machinery in real-time, monitoring location, usage, and performance.
Data Driven Decision Making	Using telematics data to improve decision making accuracy.
Operational Efficiency	Improving task automation, machinery usage insights, and cost reduction.
Environmental Sustainability	Promotes sustainable practices through precise resource application and reduced emissions. Through data collection.

(Source: (Mark & Griffin, 2016; Krzyżaniak & Kowalik, 2022; Prasanth, 2024; Yeong *et al.*, 2024)

Whilst the literature in table 1 provides strong reasoning for the use of agricultural machinery telematics, Goltyapin and Golubev, (202), Krzyżaniak and Kowalik, (2022), Yeong, Panduru and Walsh, (2024), Prasanth (2024), Uddin, (2024) also highlight the potential challenges of using telematics including data analysis, data owners ship and data accuracy.

2.3 Calculating Agricultural Machinery Costs

In 2023, £2.3 billion of new agricultural machinery was sold in the UK, an 11% increase since 2021 (AEA, 2023). Given the substantial investment in agricultural machinery Krzyżaniak & Kowalik, (2022), Akram *et al.*, (2024) agree the importance for agricultural machinery owners to understand and be able to calculate ownership and operational costs. However current literature highlights that gross margin calculations of commodities such as wheat often rely on assumptions and not the specific contribution of individual machinery used due to the variability in machinery usage in crop establishment systems (Grains Research & Development Organisation, 2013; Redman, 2025). Farokhi and Pellegrina (2020) stress that assumption-based gross margins fail to reflect farming system variability, undermining precise financial planning. Cachia (2018) supports this, arguing that accurate and individual arable cropping margins cannot rely on assumptions due to varying machinery establishment systems affecting establishment costs. For example, the AHDB, (no date) estimates agricultural machinery accounts for 25–30% of wheat production costs yet this claim fails to incorporate individual farm machinery establishment systems. Godwin, (2014) findings exemplify these disparities, concluding direct drilling machinery establishment costs range from £45–50/ha compared to £160–200/ha for minimum cultivation. Although dated, this study remains relevant due to its focus on UK agricultural crop production. However, more recent research supports Godwin findings concluding machinery establishment systems affect establishment cost and overall crop gross margin

(Mohammadi, Rajabi, & Haghparast, 2024; Redman, 2025). Therefore, the AHDB, (no date given) claim of 25-30 % of wheat establishment cost being attributed to machinery is inaccurate and has little relevance for wheat growers to base gross margin calculations (Mohammadi, Rajabi, & Haghparast, 2024; Redman, 2025).

As literature is supportive of the need for accurate gross margin calculation based on individual establishment systems and that assumption based gross margins are inaccurate, this highlights the need to be able to capture individual agricultural machinery operating costs of individual establishment systems. For this individual data agricultural machinery TS may be used to record data such as fuel usage and work rate. This can be used to provide the data which is currently unavailable to calculate individual crop gross margins per hectare.

2.3.1 Evaluating the Impact of Machinery Size on Cost Efficiency

The size and working width of agricultural machinery has continued to increase (AEA, 2023). A reason to explain this trend is the belief of some agricultural machinery owners that machines with greater working widths improve productivity by increasing work rate per hour compared to smaller working width machines, in turn lowering production cost per hectare (Sangeetha & Baskar; Schimmelpfennig, 2018). Despite beliefs that larger machinery improves efficiency, between 2017 and 2023, wheat establishment costs have increased by £795 per hectare (AHDB, 2023). Future research should examine if there is positive correlation between the adoption of larger working width machinery and the reduction in operational costs. Future telematics systems may focus development on a predictive system to determine the effect of differing machinery parameters e.g. working width has on productivity. Future telematics systems able to do this would therefore enable more accurate gross margin calculations. Future systems may also include predictive modelling to assess the impact of new agricultural machinery working width has on productivity, efficiency, and operational costs before purchase.

2.4 Calculating Agricultural Machinery Productivity

Agricultural machinery productivity refers to the output or work rate achieved by a machine per unit of time, often measured in hectares per hour (Fuglie & Hitaj, 2019; Nilsen, 2000). Measuring productivity is crucial for identifying inefficiencies, enhancing sustainability, and optimising resource allocation (FAO, 2017). Research by Kryszak, Świerczyńska, and Staniszewski (2023) highlights the importance of productivity in devising cost-effective mechanisation strategies tailored to specific enterprises. To ensure effective decision-making and management planning, reliable and accurate data is paramount (FAO, 2017). Research indicates that productivity analysis using accurate data can enable tangible improvements and informed strategic decisions (Kryszak, Świerczyńska, and Staniszewski 2023).

For agricultural machinery not equipped with a TS or onboard computer to calculate work rate and productivity, individuals are required to use equations. See equation 1 below.

A= Effective traveling speed (kph)

B= Effective working width (m)

C= Agricultural machinery efficiency value (%)

D= Spot work rate (ha/hr)

E= Actual work rate (ha/hr)

Spot work rate formula: **D = A x B / 10**

Actual work rate formula: **E= A x B / 10 x C**

(Source: Nilsen and Luoma, 2000)

Equation 1. Calculation of agricultural machinery work rate

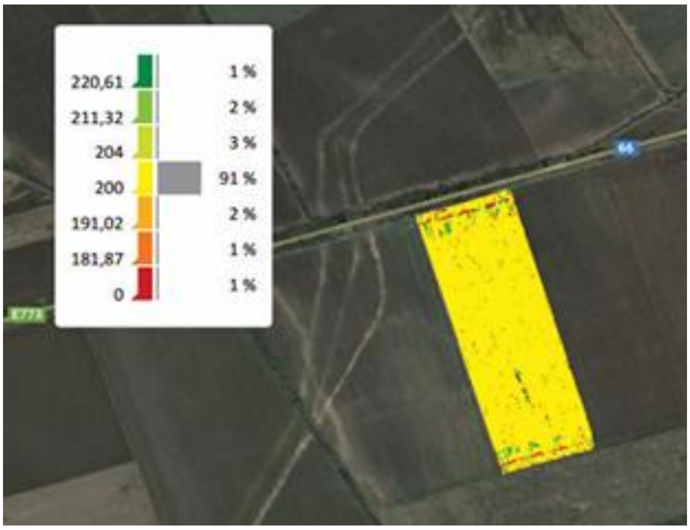
While effective for calculating spot work rate, equation 1, fails to represent the overall productivity of an agricultural machine due to relying on an efficiency assumption value. Agricultural machinery efficiency is defined as the ratio of effective operation time compared to total operation time (Fuglie & Hitaj, 2019). The distinction between productivity and efficiency lies in their focus. Productivity refers to machine output (e.g hectares/hour), whereas efficiency considers optimal use of time and resources (Rock, 2023). Calculating field efficiency provides a more accurate representation of a machine's performance, compared to spot work rates. Manual calculations rely on assumptions, such as estimated headland turning time and overlap factors (Nilsen & Luoma, 2000; Redman, 2025). The assumed efficiency figure ranges from 60% to 85%, depending on machine working widths and headland turning patterns (Kaminsky, 2024). Supporting evidence from Dusa, (2010) reveals that headland turning patterns can vary by 4.7 seconds between the fastest and slowest turns, amounting to a total time saving of 1 hour and 27 seconds. Additionally, turning patterns are influenced by factors including vehicle type (e.g., tractor, combine harvester), tractor configuration (e.g., conventional four-wheel, twin-track, articulated), implement mounting point (e.g., three-point linkage or drawbar), implement working width, and field shape and size (Bulgakov *et al*., 2019). The multitude of variables makes it impractical to calculate work rates based on estimated turning times. Therefor literature proves the limitations of Nilsen and Luoma, (2000) equation.

Kryszak, Świerczyńska, and Staniszewski, (2023) and FAO, (2017) emphasise, accurate machine-specific data is essential. This need has driven interest in agricultural machinery TS, which enable real-time capture, recording, and analysis of working parameters (Anna & Jacek, 2015). Further research is needed to evaluate whether agricultural machinery owners utilise telematics for productivity assessments and how these practices effect machine performance.

2.5 The Use of Telematics to Determine Agricultural Machinery Efficiency

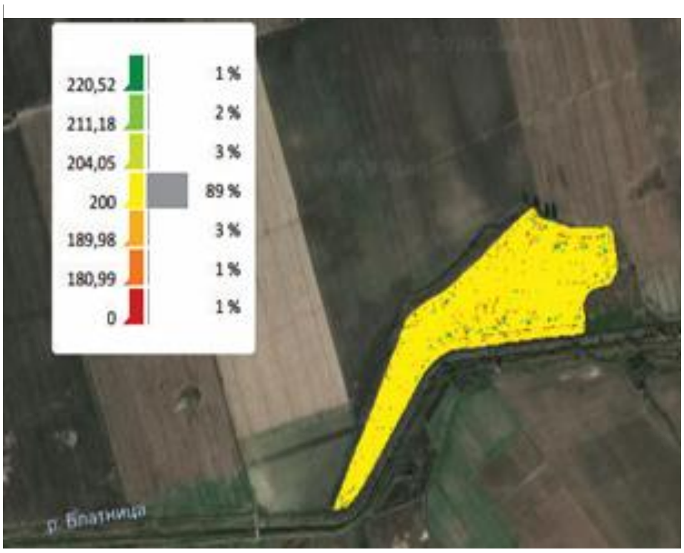
As discussed, determining efficiency of agricultural machinery is challenging due to difficulties capturing individual data of agricultural machinery. Previous research undertaken by Prasanth, Rathinavel and Jothiprakash (2024) concludes agricultural machinery TS can increase efficiency and productivity of agricultural machinery operations, providing savings in labour and production cost. However, the study provides no quantitative evidence to support this claim, therefore how great the impact of using telematics to determine efficiencies cannot be gauged.

To determine the effect field shape and size had on the efficiency of a tractor seed drilling, Tihanov and Hristova (2021) used the John Deere JDLink TS to record and analyse the tractors performance in two fields, designated as Field A and Field B shown in figure 4 and 5.



(Source: Tihanov and Hristova, 2021)

Figure 4. Field A



(Source: Tihanov and Hristova, 2021)

Figure 5. Field B

From the telematics data presented in table 2, the following conclusions were drawn:

Table 2. Telematics data

	Field A	Field B
Average fuel consumption l/h	Idel mode: 3.97 Work mode: 23.54	Idel mode: 4.37 Work mode: 26.66
Work rate ha/hr	3.81	3.05

(Source: Tihanov and Hristova, 2021)

From the telematics data in table 2, the following conclusions were drawn

1. **Impact of field shape and size:** Both fuel consumption and productivity were influenced by the shape and size of the fields.
2. **Operational inefficiency:** Field B required more turns and turning time compared to Field A, due to its shape. This explains why more the average fuel consumption was more for field B and the work rate (ha/hr) was less.

This study is valuable as it proves the success of a commercial TS. However, the study does not explore or propose strategies for how the inefficiency shown in the telematics data can be improved. Current agricultural TS focus on recording, transmitting, and analysing data without interpreting or providing actionable recommendations for improvement (Hundal et al., 2023). The responsibility for interpreting the data and making decisions remains with the individual user.

Similarly, Paraforos, Hübner, and Griepentrog (2018), like Tihanov and Hristova (2021), make use of historical commercial telematics data. Their findings shown in table 3, identify turning pattern T3 as the most efficient, reducing turn time by 15.78 seconds compared to T1.

Table 3. Number of turns and mean turn time for different headland turn patterns.

Turning pattern	Number of performed turns	Mean individual turn time (seconds)
T1	63	38.11
T2	60	27.08
T3	531	22.33
T4	302	23.51
T5	158	23.10
T6	90	25.26

(Source: Paraforos, Hübner, and Griepentrog 2018)

Over four years' worth of telematics data, T3 emerged as the most frequent turning pattern, as shown in table 4. If T1 had been used for all 531 headland turns, an additional 84 hours would have been required to carry out the same operation demonstrating the inefficiency of both time and additional engine hours.

Table 4.Comparison of total turn time for T1 & T3 turn patterns

Turning Pattern	Number of turns	Individual turn time (seconds)	Total turn time (hours)	Total hours difference
T1	531	38.11	202	84
T3	531	22.33	118	

(Source: Paraforos, Hübner, and Griepentrog 2018)

Hübner and Griepentrog (2018) identified turning pattern T3 as the most efficient, reducing turn times by 15.78 seconds compared to T1 and saving 84 hours of operational time across 531 headland turns. This shows the potential of historical telematics data in identifying inefficiencies otherwise undetectable. Inefficient practices, such as suboptimal turning patterns, increased fuel consumption and engine working hours, highlight the cost-saving potential of TS through more efficient operation of agricultural machinery.

Both Paraforos, Hübner, and Griepentrog (2018) and Tihanov and Hristova (2021) used statistical tests such as Kruskal–Wallis and Dunn-Šidák on analyse the telematics data. Although appropriate and proven statical testing methods for large data sets Jamil & Khanam (2024), the complexity of carrying out data analysis and statistical testing by the workforce of an agricultural enterprise presents challenges Hansson (2019). Ammar, Kheir & Manikas, (2022) research concludes agricultural businesses have data analysis skill gaps in their work force. Despite these challenges and skills shortage, Barnes *et al.,* (2019) survey of EU farmers opinions and adoption of PFT concluded 66% of farmers valued data-driven decision-making. Current TS have limited data analyses capabilities (Goltyapin & Golubev, 2020). It is clear from Barnes *et al.,* (2019) that there is a perceived value and demand by farmers for data driven decision making, however there is a barrier of analytics skills preventing agricultural machinery owners from being able to make use of telematics data. This may be a reason to explain the 8% uptake in telematics technology by British farmers (Defra, 2019).

While it is clear existing agricultural machinery TS lack advanced data analytics capabilities, literature is supportive of the use of artificial intelligence (AI) and machine learning algorithms, being able to be incorporated into systems to analysis big agricultural data (Majumdar *et al*., 2017; Amini & Rahmani, 2023; Elbasi *et al*., 2024; Javaid *et al.,* 2023). To bridge the gap and provide a solution, future TS must prioritise useability by incorporating analytic systems such as AI and algorithms to address these gaps to provide analysed data.

2.5.1 The Sustainability of Using Telematics Data to Improve Productivity & Efficiency

Historically, landowners increased agricultural productivity by removing trees and hedgerows to create larger, more efficient fields for machinery (Baudry, Bunce & Burel, 2000). While it was perceived this improved efficiency, it came environmental costs. Current legislation prohibits such practices, classifying hedgerow and tree removal as actionable offenses (GOV.UK, 2025). Today landowners often repurpose low-productivity areas of fields into Sustainable Farming Incentive (SFI) schemes, removing land from food production (GOV.UK, 2024). Telematics data has become a tool in identifying these less productive zones due to perceived inefficiencies in these field areas (Danda, 2023).

However, repurposing land reduces overall field size, limiting potential productivity gains highlighted by (Tihanov and Hristova 2021). This creates a conflict between increasing agricultural machinery efficiency and adhering to environmental policies, challenging Prasanth, Rathinavel & Jothiprakash, (2024) claim that telematics data improves productivity. Further research is needed to determine whether telematics systems are being employed in this capacity and to evaluate their effectiveness in real-world agricultural machinery operations.

2.6 Agricultural Machinery Service and Maintenance

Agricultural machines have complex mechatronic structures, including physical components like gearboxes, engines, and brakes, as well as sensors and actuators controlled by an Engine Control Unit (ECU) (Safi *et al.,* 2018). A high-level diagnostic system is essential to facilitate communication between the ECU and CAN Bus, enabling effective data reporting for diagnostics (Taie, Diab, and ElHelw, 2012).

In the automotive industry, three main maintenance strategies are employed: predictive maintenance, reactive maintenance, and preventive maintenance recoding and transmitting data and information through a TS to the vehicles end use (Ruddle *et al*., 2013). Telematics has the potential to improve efficiency in agricultural machinery service scheduling and predictive mechanical and electrical component monitoring.

2.6.1 The Use of Agricultural Machinery Telematics for Service Scheduling

The timeliness and planning of the servicing of agricultural machinery is crucial to prevent loss of machine productivity (Ambo, 2024). Efficient servicing, timed to minimise operational disruption, is essential for machine reliability (Khodabakhshian, 2013). To quantify the importance of timely service scheduling Mayo *et al*., (2024) concludes an operating cost reduction up to 47% and productivity gains of up to 21% from timely maintenance.

Major tractor manufacturers provide remote service scheduling through TS, enabling collaborative monitoring of machine performance by service technicians and owners see Table 5.

Table 5. AGCO Connect telematics system tractor recorded data

Tractor model	Engine working hours	Next Inspection
Valtra T254 HiTech	2349	51 hrs
Valtra T172 Versu	1776	24 hrs

(Source: AGCO, no date given)

While beneficial in recording and providing a countdown as to when the next service is due to ensure servicing is completed on time, the systems fail to incorporate operational schedules. This therefore limits effectiveness of using TS to in minimise machine downtime. Mayo *et al*, (2024) emphasise the productivity gains achieved through timely maintenance scheduling; however current commercial telematics platforms do not consider machine usage patterns. As agricultural machinery uses vary with season and weather conditions (Tullberg, 2009).

Future TS could incorporate AI and predictive algorithms to analyse historical telematics data (Jiang *et al*., (2017), to determine when servicing should be carried out to avoid busy work periods, however, keep within service intervals. Further research is required to determine the effectiveness of predictive service scheduling applied in this way.

2.6.2 Accuracy of maintenance predictive algorithms

Algorithms have been developed to predict when maintenance is required. Shafi *et al.,* (2018) compared the accuracy of four remote data gathering predictive algorithms: Support Vector Machine (SVM), Decision Tree (DT), K-Nearest Neighbour (kNN), and Random Forest (RF) to test their accuracy compared to real time component failure.

The results in table 6 indicate that the Support Vector Machine (SVM) algorithm demonstrated the highest accuracy among all algorithms, with an average accuracy of 97%.

Table 6. Accuracy comparison of predictive algorithms

Vehicles System	**Decision Tree %**	**Support Vector Machine %**	**K-Nearest Neighbour %**	**Random Forrest %**
Ignition System	72.5	96.6	81.9	79.2
Fuel System	76.5	98.5	94.6	90.0
Exhaust System	78.5	98	89.9	88.6
Cooling System	78.5	96.6	94.6	89.3

(Source: Shafi *et al*., 2018)

The results suggests that predictive algorithms, when implemented correctly, can forecast component failures. However, the study uses a small dataset of 150 experiments in comparison a tractor produces 3.6 million data sets per 100 hrs of work (Götz et al., 2025). Therefore, the results of this study cannot be generalised and applied to wider agricultural machinery.

Similarly, Da Silva, Rodrigues de Sá, and Menegatti's (2019) investigation into predictive transmission failure of tractors. The study used PicoScope6 algorithm. The results yielded notable reductions in repair time (88%) and costs (93%), attributed to pre-emptive planning and resource allocation. However, the study's narrow focus on the clutch system of a specific tractor model raises concerns about the generalising of its findings. The study also fails to specify the frequency of data collection and provides no indication of the impact predictive maintenance has on machine lifespan and performance. For broader applicability, future research should expand its scope to encompass diverse types of agricultural machinery, specify data collection methodologies, conduct long-term studies, and perform comparative analyses with traditional maintenance methods.

2.7 The Accuracy of Telematics Data

Data accuracy is crucial in agriculture. Therefore, the data gathered by TS must be accurate, if calculations and decision-making is to be based on telematics data.

Savickas, Steponavičius, and Domeika, (2021) for their research used a telematics systems and data logger to calculate CO_2 emissions produced by a combine harvester. The authors reported discrepancies between the recorded telematics data and the actual field test data recorded by the data logger as shown in table 7.

Table 7. Comparison of recorded fuel consumption from telematics data and data loggers

Operating Mode	Fuel Consumption litres/year (Telematics Data)	Fuel Consumption litres/year (Field Testing)	Difference litres/year
Idle Mode	45	50	+5
Transport Mode	34	38	+4
Harvesting Mode	171	180	+9

(Source: Savickas, Steponavičius, and Domeika 2021)

The telematics data was taken from the Combine Harvesters Controller Area Network (CANBus) which took 10 readings per second. Although the authors did not specify the field-testing instrumentation system used, commonly agricultural data loggers take 100 readings per second (DEWESoft, no date given). The less frequent recordings taken by the CANBus compared with the data logger as well as CANBus data accuracy reported to be affected by environmental noise and conditions Boland *et al*., (2021); Parida *et al*., (2023), provides evidence to explain the discrepancies in the data recorded. Whilst it is acknowledged the less frequent recording of data by the CANBus may result in the data being considered less accurate, Marx *et al*., (2015) concludes telematics data is suitable for logistical and research purposes. Therefore, telematics data may be suitable for certain uses into agricultural machinery operation. Further research is however required to determine definitive accuracy for telematics data.

2.8 Identification of Research Gap

Existing literature highlights the role of telematics technology in recording and wirelessly transmitting agricultural machinery data. The literature emphasises the potential of telematics to improve agricultural machinery performance by providing insights into productivity, efficiency and inefficiencies, service and maintenance, financial costing, gross margin calculations, and machinery management. These insights, derived from telematics data, can lead to operational changes that positively impact both agricultural machinery operations and environmental sustainability.

While literature suggests historical and real-time telematics data can generate valuable insights, research lacks evidence to support this is the case for agricultural machinery owners. The 2019 Defra survey on PF uptake found that 8% of farmers used telematics. However, the survey did not investigate the uses, which sectors employed telematics, or the factors affecting telematics use.

There is a need to understand agricultural machinery telematics uses as well as issues surrounding use outside of academia. This study seeks to address the need for research that bridges the disconnect between theoretical potential and real-world usage of agricultural machinery telematics.

2.8.1 Research Aim

To determine the current uses, the barriers to adoption, and the desired features of agricultural machinery telematics systems in the UK.

2.8.2 Research Objectives

1.To understand the current uses and desired future features of agricultural machinery telematics systems.

2.To determine the factors affecting agricultural machinery telematics use.

3.To determine the barriers preventing agricultural machinery telematics use.

Chapter: Three Methodology

This chapter outlines the research methodology and data analysis techniques used to collect the data and information to address the research gap.

3.1 Research Philosophy

The research philosophy reflects pragmatism (see table 8) as the research question was the most important factor to determine the most appropriate positivist and interpretivist features.

Table 8. Research philosophies

	Research Approach	**Ontology**	**Axiology**	**Research Strategy**
Positivism	Deductive	Objective	Value free	Quantitative
Interpretivism	Inductive	Subjective	Biased	Quantitative
Pragmatism	Deductive / Inductive	Objective or Subjective	Value free / biased	Qualitative / Quantitative

(Source: Dudovskiy, 2016)

A quantitative and deductive approach helped test the research objectives in a narrow time frame by focusing on objective relationships between concepts or variables and drawing reliable conclusions from the data.

On the other hand, a qualitative and inductive approach allowed for broader generalisations to emerge from observed themes in the data. For this method an open mind approach with few preconceptions prevented bias.

3.2 Data collection

To gather the data and information required to achieve the research objectives, questionnaire was used to gather quantitative and qualitative primary data.

3.3 Rational for Questionnaire Use

A questionnaire was selected as the research method for gathering data due to the wide geographical reach, time efficiency, accessibility, and standardisation of questions (Testa & Simonson, 2017). These attributes aligned to ensure a suitable research methodology to meet the research objectives. The questionnaire allowed for electronic distribution to UK agricultural machinery owners and operators from all regions and sectors of the UK, ensuring broad participation. Although other research methods such as interviews could be considered appropriate for this study, Husband, (2020) concludes structured interviews are less effective at reaching wide audiences due to time and resource demands

Although online questionnaires allow time efficient distribution, Münnich *et al*., (2025) concludes a questionnaire containing irrelevant questions for respondents to answer decreases participation. Therefore, no matter the timeliness of distribution, the inclusion of irrelevant questions deters respondents from completing the questionnaire. Failure of respondents complete the questionnaire was prevented from being an issue as questions which were not relevant to respondents were not shown to them. Questions which were not relevant to respondents were determine by the previous answer give. The questionnaire design software allows this function to happen though coding of questions. This meant questions were kept to a minimum, resulting in a 10 minute completion time.

Standardising the questions and structure of the questionnaire enabled comparison and statistical analysis of responses (Joukes et al., 2018). This categorised data was valuable for addressing research objective one, which involved evaluating telematics uptake and identifying uses trends, highlighting uses of high and low adoption. This combination of practicality, comprehensive reach, and analytical rigor made a questionnaire an appropriate method of collecting the primary research required for this study Münnich *et al*., (2025).

3.4 Rational for Question Types

The questionnaire primarily consisted of closed questions. Limiting respondents to yes or no answers. Closed questions have a more time efficient responses rate, therefore reducing the response time by 22 – 55% (Connor Desai and Reimers, 2019). This is significant factor, as shorter questionnaires achieve higher response rates (Booker, Austin, and Balasubramanian, 2021).

Additionally, eight open-ended questions were included. This decision was made to address the limitation of closed questions, which restrict respondents being able to elaborate on their answers (Connor Desai and Reimers, 2019). Open ended questions enable in depth ideas and themes to emerge providing context to support the closed question answers (Pate, 2012). The objective of the open-ended questions was to delve deeper into the reasoning behind telematics usage and provide qualitative insights to add context to respondents' answers (Connor Desai and Reimers, 2019).

3.5 Rational Questionnaire Structure

The following discusses the reasoning behind the structure of the questionnaire.

Table 9. Reasoning behind questionnaire structure

Question	Reasoning
Section 1: About you Questions 2- 8	• Closed questions. • Categories were aligned with those used by Defra and the Farm Business Survey, allowing direct comparison with previous studies.
Section 2: Farm machinery and Tractors Questions 9 - 14	• Closed questions to determine the agricultural machinery used by respondents. • Categories for (kW) bands were aligned with those used by the Agricultural Engineers Association.
Section 3 Q19: Please give up to 3 reasons why you use telematics.	• Allowing unbiased response without being influenced by the other questions (Thau *et al.*, 2021).
Section 3 Q20: Please give up to 3 reasons why you do not use telematics.	• Research objective 3.
Section 4: Material Handlers Question 25 - 26	• Material handlers, uses can be specific to farming sectors, therefore, closed questions may limit a wide range of uses (Reis and Judd, 2014).
Sections 6, 7 & 8. Service and Maintenance Machine Efficiencies General telematics Use Questions 27 - 41	• Closed questions
Future Telematics Use Section 9 Questions 42 - 45	• Closed questions followed by open descriptive questions.

3.6 Questionnaire Piloting

A pilot questionnaire was undertaken by eight agricultural machinery owners and operators from differing agricultural enterprises. To test the effectiveness of the questionnaire on different respondent scenarios to ensure the questionnaire was accessible to all.

Review of the pilot questionnaire responses revealed all respondents understood the questionnaire and telematics technology was. However, feedback from the pilot respondents suggested some of the questions were the same but used different words. For example, respondents struggled to differentiate between efficiency and productivity. After reviewing a decision was made to split efficiency and general telematics use into separate sections to avoid confusion.

3.7 Time Scale

This questionnaire was opened on the 11th of February 2025 and closed 2nd April 2025. The timing of the questionnaire coincided with quieter winter months when agricultural machinery owners and operators are less busy.

3.8 Data Collection

The questionnaire was designed and distributed using Jisc Online Surveys software. Distribution was entirely electronic therefore no postal questionnaires were used. The questionnaire was distributed electronically to personal contacts in the agricultural industry such as farm managers and agricultural contracting business owners. Agricultural professional organisations such as the National Association of Agricultural Contractors also distributed the questionnaire to their members on the researcher’s behalf. Other distribution channels included targeted social media through Facebook agricultural groups such as “Farming Forum”, “Agricultural Machinery Operators”, and specialised agricultural machinery groups.

3.9 Sample Size

The minimum target sample size was 100 based upon a no justification approach to sample size due to the nature and purpose of the project (Islam & Aldaihani, 2022; Lakens, 2022). The minimum target was exceeded and a total of 200 valid responses were received.

A convenience sampling method was used due to the time and financial restraints to survey the entire population of UK agricultural machinery owners and operators.

3.10 Data Reliability, Validity and Generalisability

As discussed, closed questions were used. A drawback of using closed questions closed questions is they began with “Do you”. Hansen & Świderska (2024) report the use of this phrase may encourage respondents to answer the question in a way the respondent perceives the researcher may want them to answer. However, anonymity encouraged more honest answers and eliminating bias.

The data was collected from a diverse range of agricultural machinery owners and operators, varying in age, occupation, enterprise size, enterprise sector and regions of the UK. The diversity improved the reliability and validity of the research. However, despite the actual sample size being double the target size there was still a small sample size in comparison with the 462,100 individuals employed in agriculture (Defra, 2024). This therefore may limit the ability to generalise the findings, and conclusions as well as the overall magnitude of the study.

3.11 Quantitative Analysis of Data

The decision was taken to carry out statistical testing using Microsoft Excel. Although other software was available such as SPSS and Genstat, due to less familiarity with theses software’s, the decision was taken to use Microsoft Excel.

Statistical testing was conducted using the Chi-Squared goodness of fit test to evaluate the likelihood of an association between two categorical variables (Alberti, 2025). By assessing whether the observed frequencies significantly differ from the expected values Kottemann, (2017), it was possible to identify the factors that had a significant association with telematics use (Alberti, 2025).

3.12 Qualitative Analysis

Qualitative analysis of open-ended question was carried out using thematic analysis, coding responses using both inducive and deductive methods (Saldana, 2021). The most common themes and ideas were presented in tabular format with the frequency of each theme and idea presented. Tabular formats were preferred over alternatives such as word clouds due to their lack of scientific rigor, highlighted by Nowell *et al*., (2017). Tables were deemed the most effective for ensuring visual accessibility and facilitating ease of interpretation, thereby reducing ambiguity (Guest, MacQueen, and Namey 2011).

3.13 Ethical Considerations

Prior to both the pilot and actual questionnaire being launched the research was approved in accordance with the Harper Adams University Ethics process.

Before starting the questionnaire, participants were informed the questionnaire was anonymous, and their data would be securely stored until completion of the project. They could withdraw from the questionnaire at any time before completion. Participation indicated informed consent if respondents agreed with the information provided.

3.14 Limitation of Data Collection and Analysis

- The questionnaire was only able to complete online. Therefore, creating a bias towards individuals with internet access (Saunders *et al*., 2012; Dixon, 2024).
- The questionnaire contained closed questions beginning with the phrase “Do you”. Ryback, (2023) reports these types of questions can cause unintended bias, as the phrasing pushes respondents towards agreeing with the statement.

Chapter Four: Results

The questionnaire received 200 valid responses.

4.1 Participant Profile

A total of 200 UK agricultural machinery owners and operators responded to the questionnaire.

4.1.1 Occupation

The 200 respondents worked in a variety of occupations within agriculture. The majority 37% (74 respondents) were UK farmers.

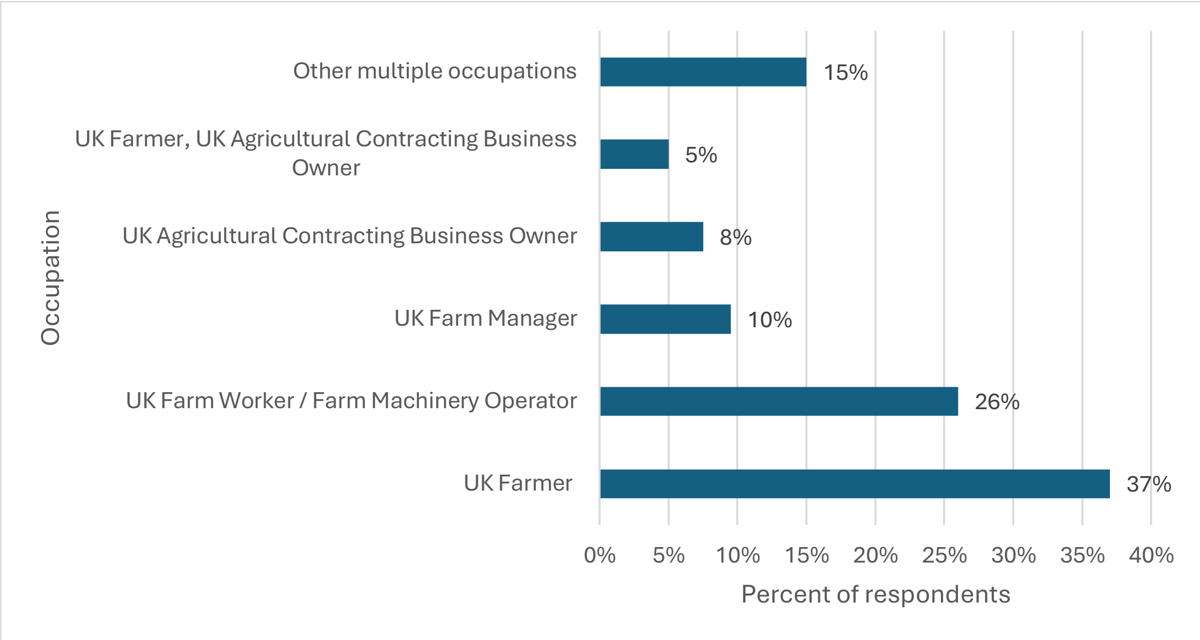


Figure 6. Respondents' occupation.

4.1.2 Agricultural Sector

Out of 200 respondents 136 (68%) worked in mixed agricultural sectors. Although sectors were original specified separately in the questionnaire see appendix 1 Question (Q) 4. The many different occupations dairy / beef cattle / arable and dairy / fresh produce / arable meant data has been grouped to allow affective analysis (McCarthy *et al.*, 2018). See appendix 2.

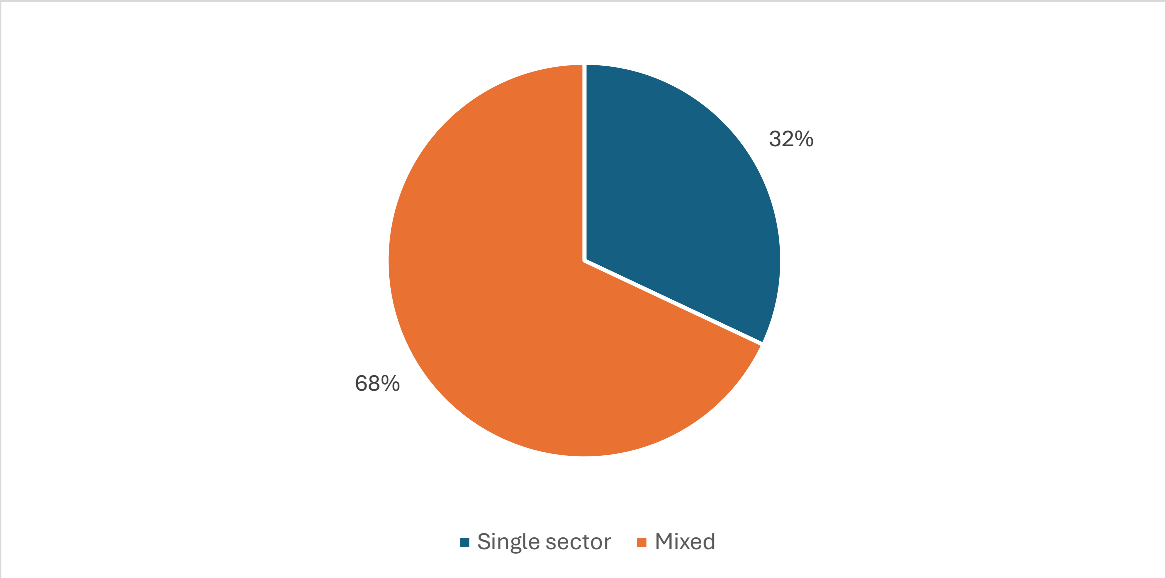


Figure 7. Proportion of respondents working in single and mixed agricultural sector

4.1.3 Agricultural Enterprise Size (ha)

Respondent either owned or worked on a variety of agricultural enterprise sizes. The most common agricultural enterprise size in which 61 (32%) of respondents either owned or worked on were 201 – 500ha enterprises. The majority (78%) either owned or worked on agricultural enterprise >200 ha.

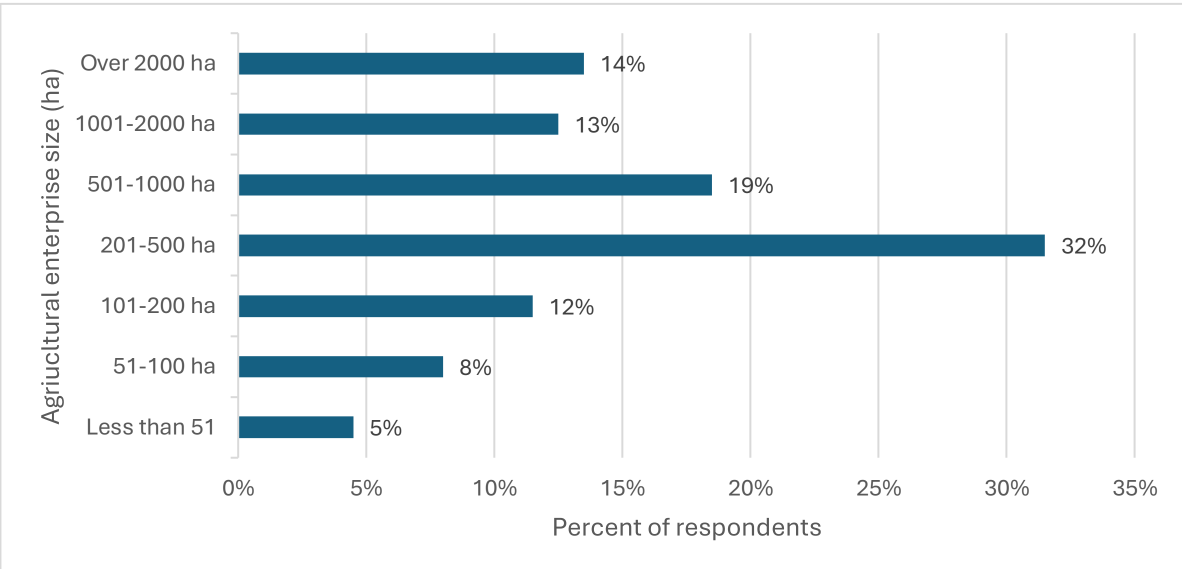


Figure 8. Distribution of agricultural enterprises by size (ha) and respondent percentage

4.1.4 Region of the UK

There were respondents from all regions of the UK. The highest percentage of respondents (46%) came from South West England (16%), East of England (15%), and East Midlands (15%). Regions with response rates <5 were grouped together.

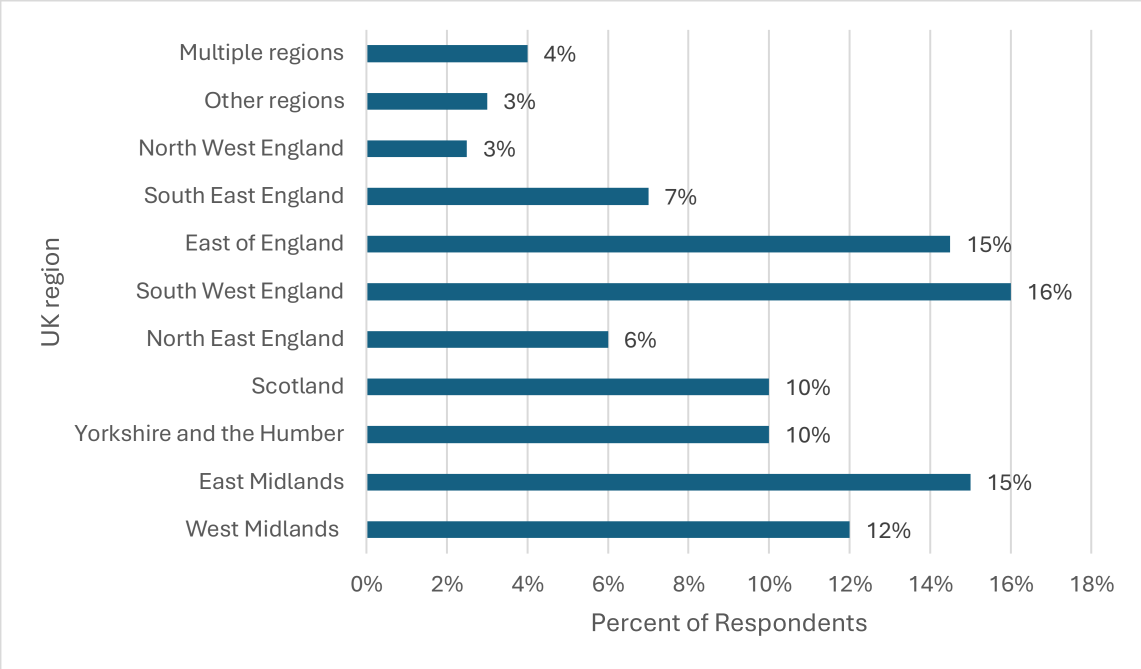


Figure 9. Regional distribution of respondents across the UK

4.1.5 Age

The largest age group is under 35, representing 51% of respondents. Other high reporting groups are aged 35–44 (20%) and 45–54 (19%). Meanwhile, ages 55–64 account for 8%, and the smallest group is 65 and over with 3% of respondents.

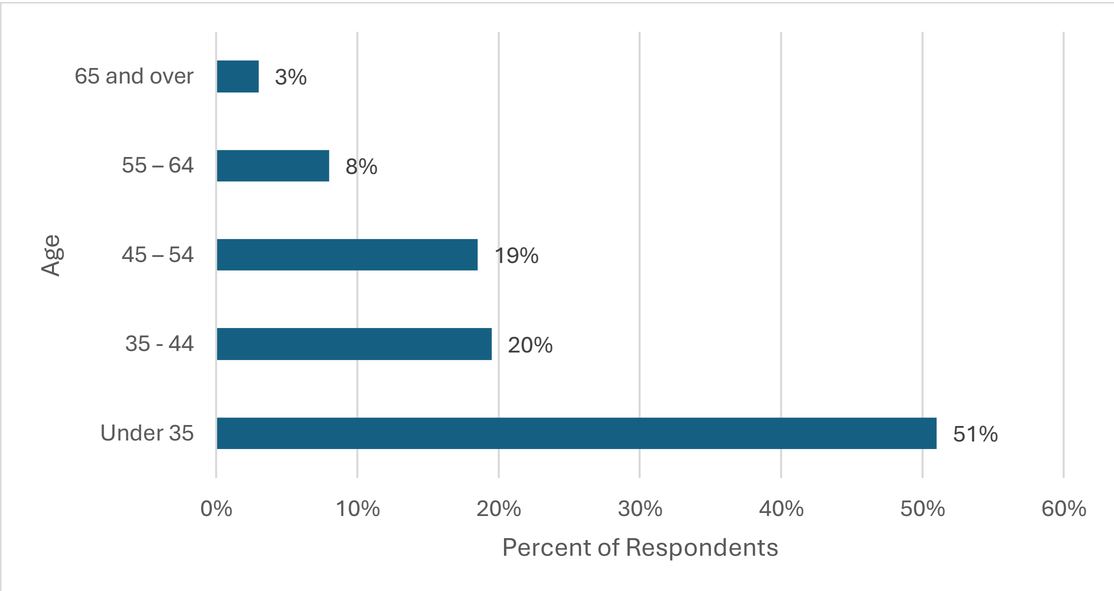


Figure 10. Age distribution of respondents

4.2 Agricultural Machinery Usage

The following presents respondent's agricultural machinery usage.

4.2.1 Self Propelled Agricultural Machinery

The majority, 95% of 200 respondents owned or operated mix self-propelled machinery types. The most popular combination of agricultural machinery was Tractor, Materials handler, Combine harvester, and Crop sprayer (30%). Moderate levels of usage are observed with 18% opting for Tractor / Materials handler and 15% favouring Tractor, Materials handler / Combine harvester. The least adopted was single machinery type of tractors (6%).

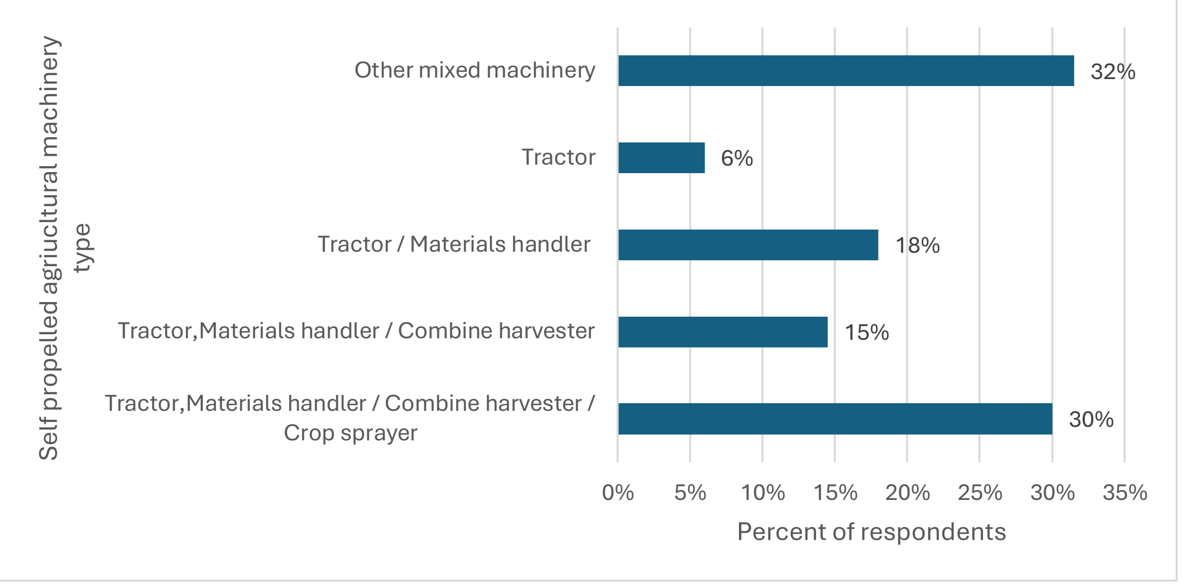


Figure 11.Respondents self-propelled agricultural machinery usage

4.2.2 Tractor Brand

Note: the following results relate specifically to the 197 respondents who either own or operate tractor(s).

The majority, 70% own or operate tractors from multiple brands.

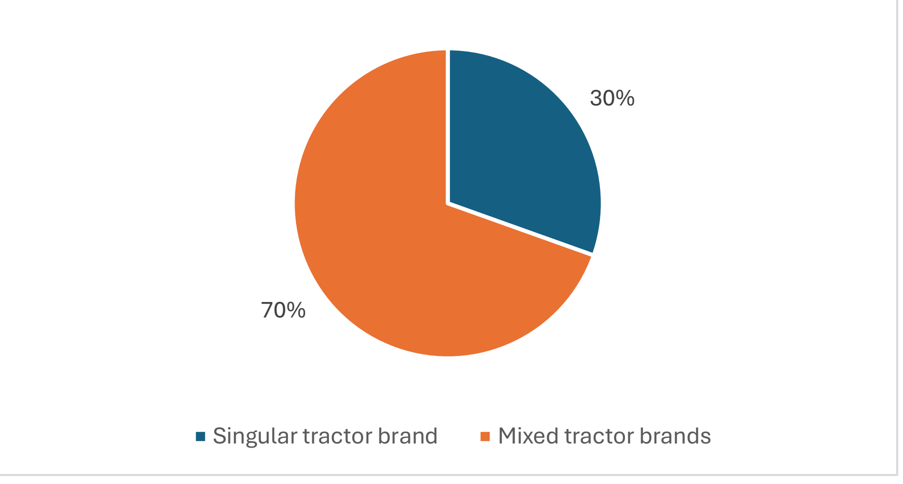


Figure 12. Distribution of singular and mixed tractor brands amongst respondents

4.2.3 Number of Tractors

Most respondents (56%) own or operate between 3-5 tractors. Smaller groups include respondents with 10 or more tractors (9%), and those with 6 or 7 tractors, 7%.

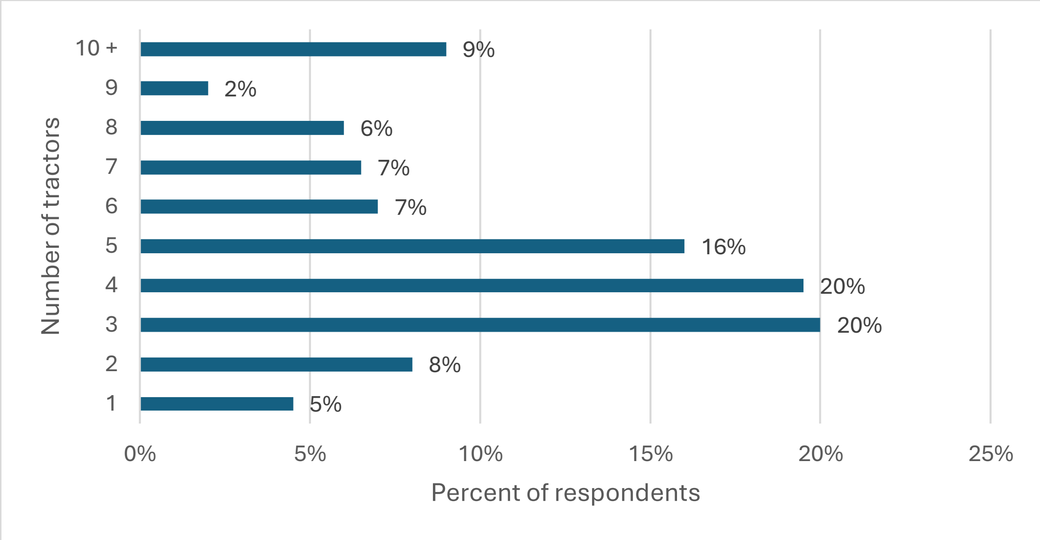


Figure 13. Percentage of tractors owned or operated by respondents

4.2.4 Tractor kW

Significant majority of respondents (75%) own or operate tractors >104kW. The most common tractor hp range is 201-204 hp (19%).

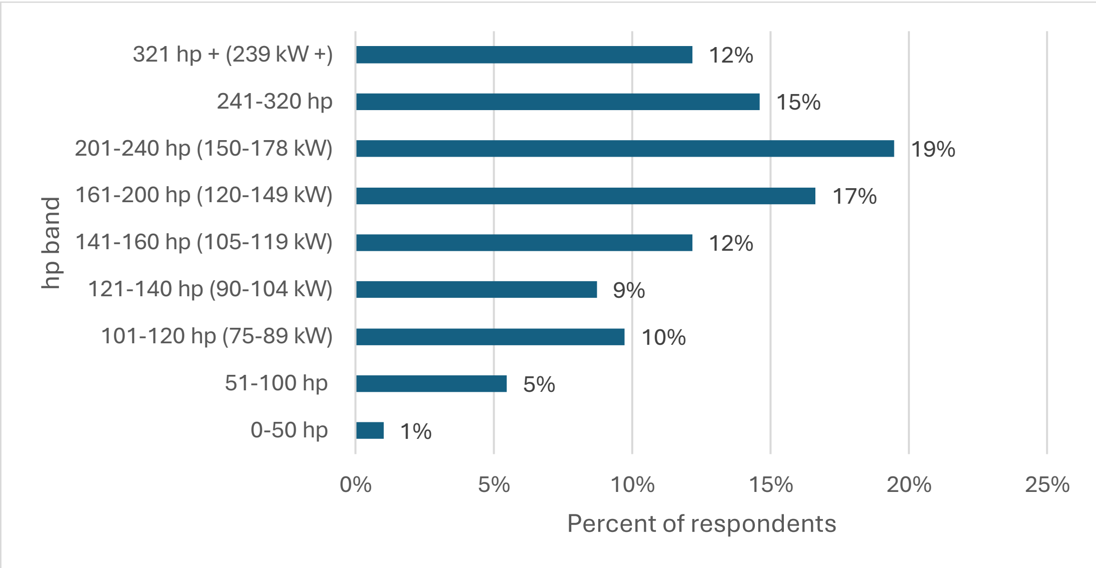


Figure 14. Distribution of respondents by tractor kW

4.2.5 Source of Tractor Purchase

Most respondents (62%) source their tractors from an official manufacturer dealership.

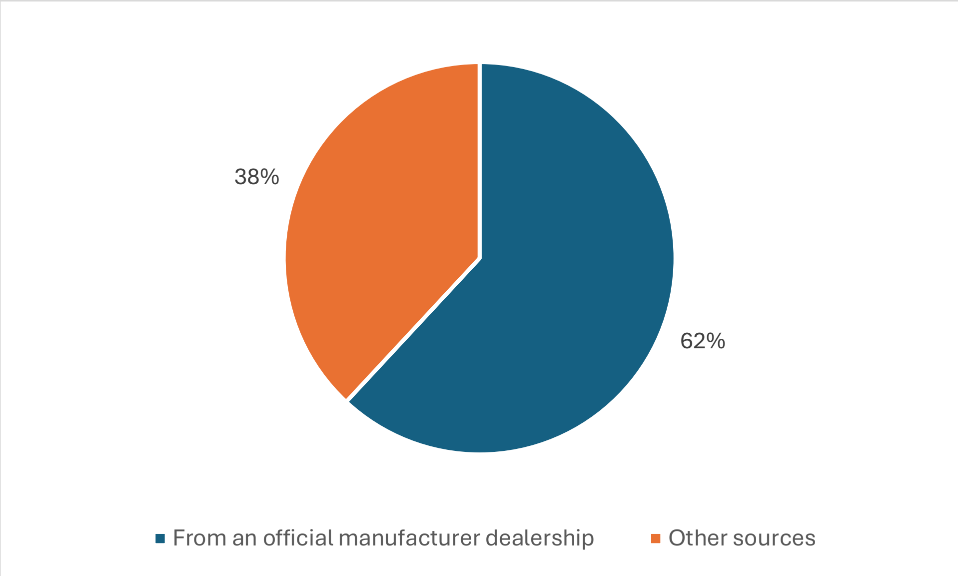


Figure 15. Sources of tractor purchases

4.3 Research Objective One

To understand the current uses and desired future features of agricultural machinery telematics systems.

The following results are of the 146 respondents that use agricultural machinery telematics.

4.3.1 Uptake of Agricultural Machinery Telematics

Out of 200 respondents a significant majority 146 (73%) use agricultural machinery telematics.

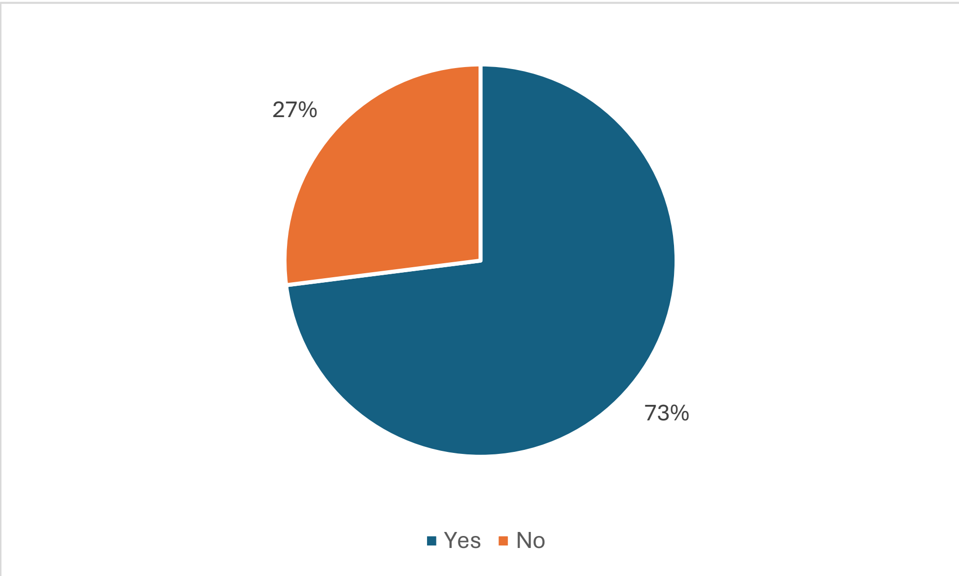


Figure 16. Percentage of respondents that use agricultural machinery telematics.

4.3.2 Agricultural Machinery Type Equipped with Telematics

Tractors where the highest reporting agricultural machinery type equipped with telematics (136 respondents). Following on combine harvester (83) was also a common machine equipped with telematics. Materials handler (49) and self-propelled sprayer (42) both had similar levels of uptake.

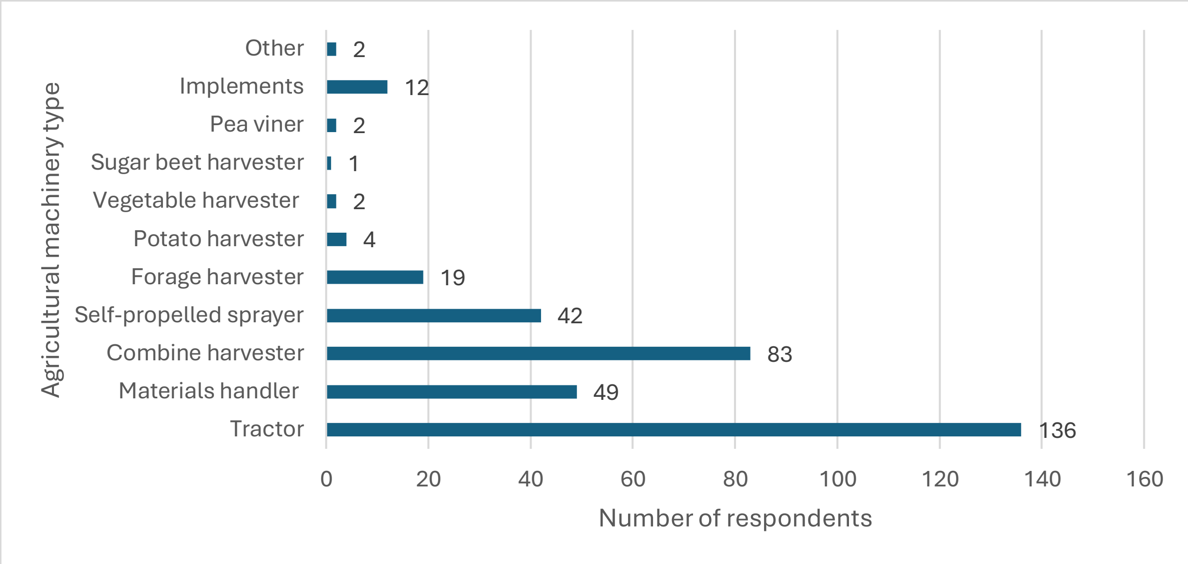


Figure 17. The agricultural machinery operated by respondents that is equipped with a telematics system.

4.3.3 Telematics System Brand Uptake

John deere JDLINK telematics brand had the greatest uptake (88). Self-propelled agricultural machinery TS such as JCB LiveLink had the greatest. Agricultural implement TS such as Horsch Connect and Keverneland Sync had the least uptake

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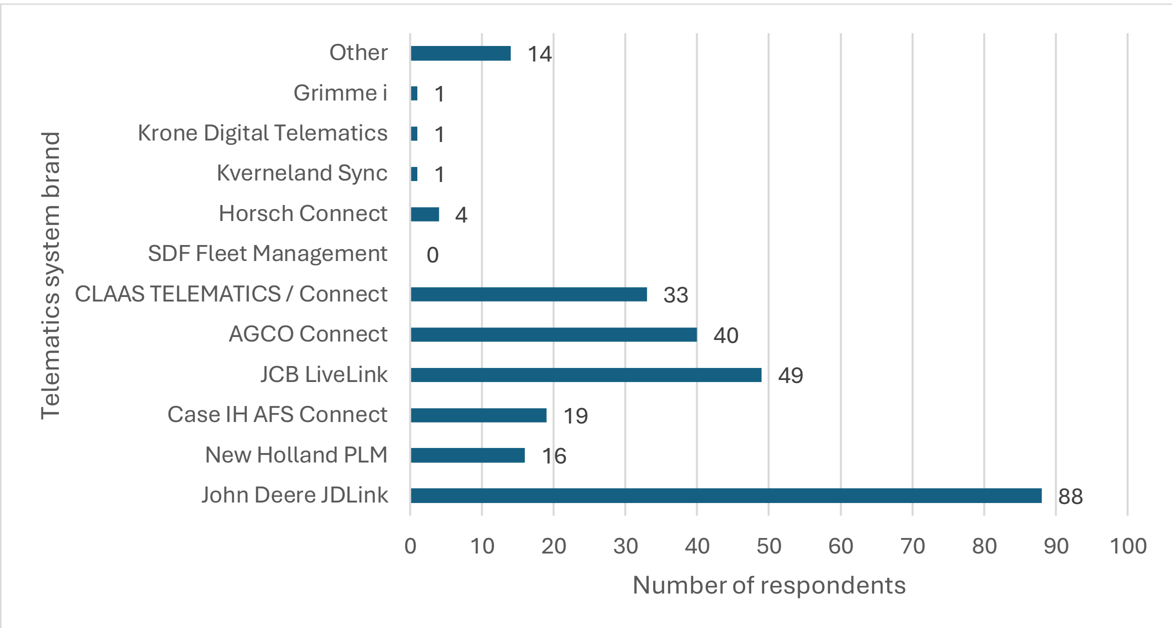

Figure 18. Uptake of agricultural machinery telematics system brands

4.3.4 Agricultural Machinery Operations Utilising Telematics

There are two patterns emerging of telematics use. Arable machinery operations such as seed drilling (104), fertiliser application (102) and cultivation (81) have the greatest level of telematics use. Livestock/Grassland machinery operations such as rear discharge spreading (32) and silage mowing (30) had more moderate levels of use. Potato / Fresh Produce machinery operation has the least use. There may be overlap between arable and livestock machinery uses, such as in fertiliser application and rear discharge spreading.

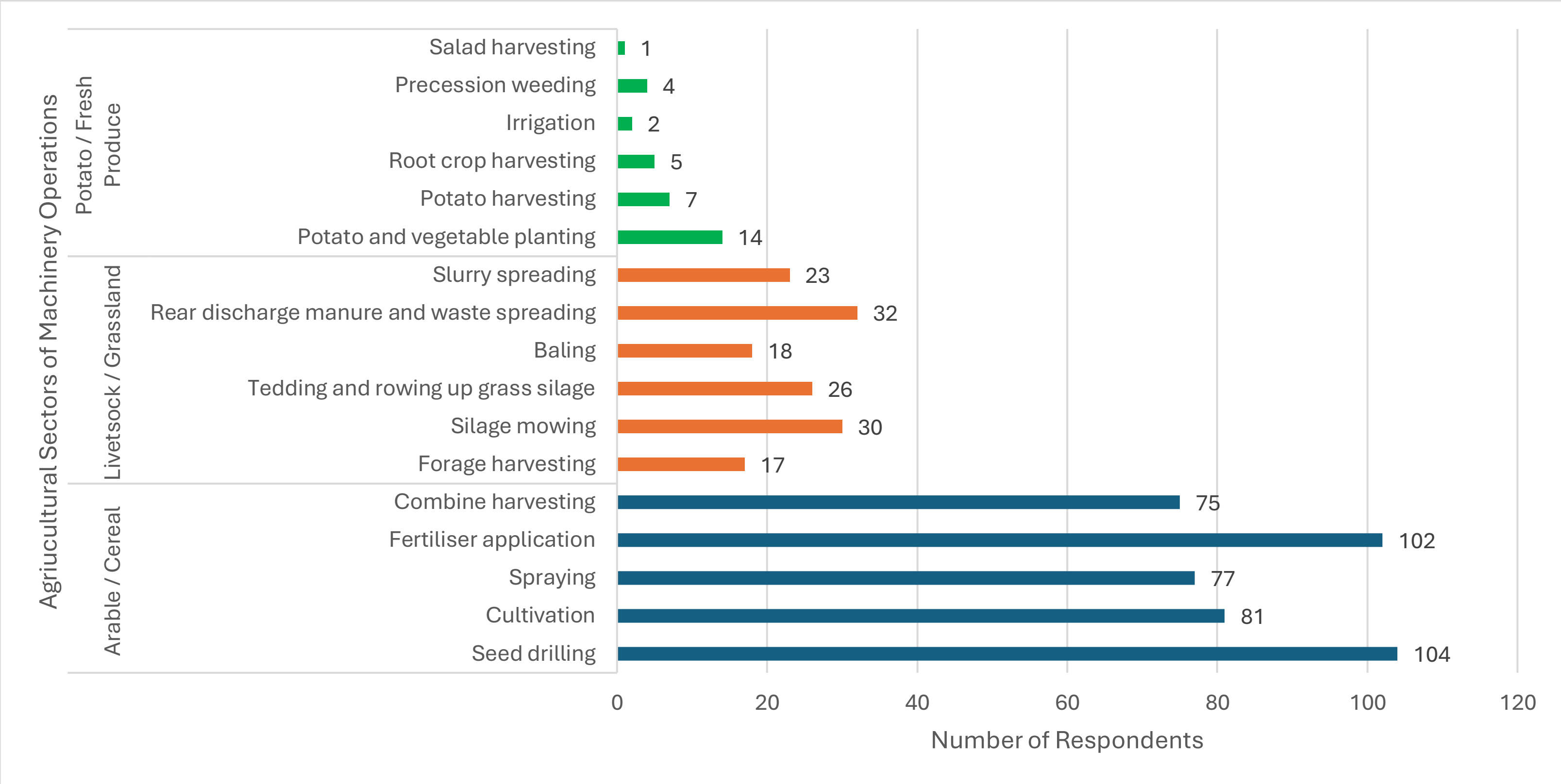

Figure 19. Adoption rates of various agricultural machinery operations using telematics

4.3.5 The Uses of Agricultural Machinery Telematics

A significant majority (uptake >70%) use telematics for remote diagnostics (75%), service scheduling (70%) and machine loaction (77%)

A significant majority also use telematics to aid agricultural machinery efficiency, day to day operation and management (71%) and remote monitoring of working parameters (77%). Overall (68%) believed the use of telematics has improved the efficiency of agricultural machinery operations.

Most respondents (>50%) use telematics to aid cost calculation (69%), monitoring and recording yield data (69%) and for contractors to provide customers with record telematics data (59%).

Most respondents (63%) do not use telematics for material handler operations. The minority that does (22%) use material handler telematics for service and maintenance, remote diagnostics and fuel efficiency.

Table 10. Comparison of percentage uptake of agricultural machinery telematics uses.

Area of Use	Specific Use	Yes %	No %	Majority Use
Materials Handler	Respondents using materials handler telematics	22	63	No
	Uses	Service & maintenance, remonte diagnostics, fuel efficiency.		
Harvesting Machinery	Controlling one machine from another	11	89	No
	Monitoring and recording yield data	69	43	Yes
Service and Maintenance	Remote diagnostics	75	25	Yes
	Service scheduling	70	30	Yes
Agricultural Machinery Efficiency	Data to day operation and management	71	29	Yes
	Remote monitoring for working parameters e.g. fuel usage rate	77	23	Yes
	Has telematics improved efficiency	68	32	Yes
General Telematics Use	Locating machines	75	25	Yes
	Aiding cost calculation	69	31	Yes
Agricultural Contractors	Providing customers with recorded data	59	41	Yes

4.3.6 Comparison of Real Time and Historical Data Uses

Real-time telematics uses such as remote monitoring and remote diagnostics have the greatest percentage uptake, with a significant majority of respondents (>70%) using telematics for real time data uses. Historical telematics data uses such as data to aid cost calculation and comparing machine performance has majority use (>50%). The minority (47%) use previous telematics data to inform future decision making

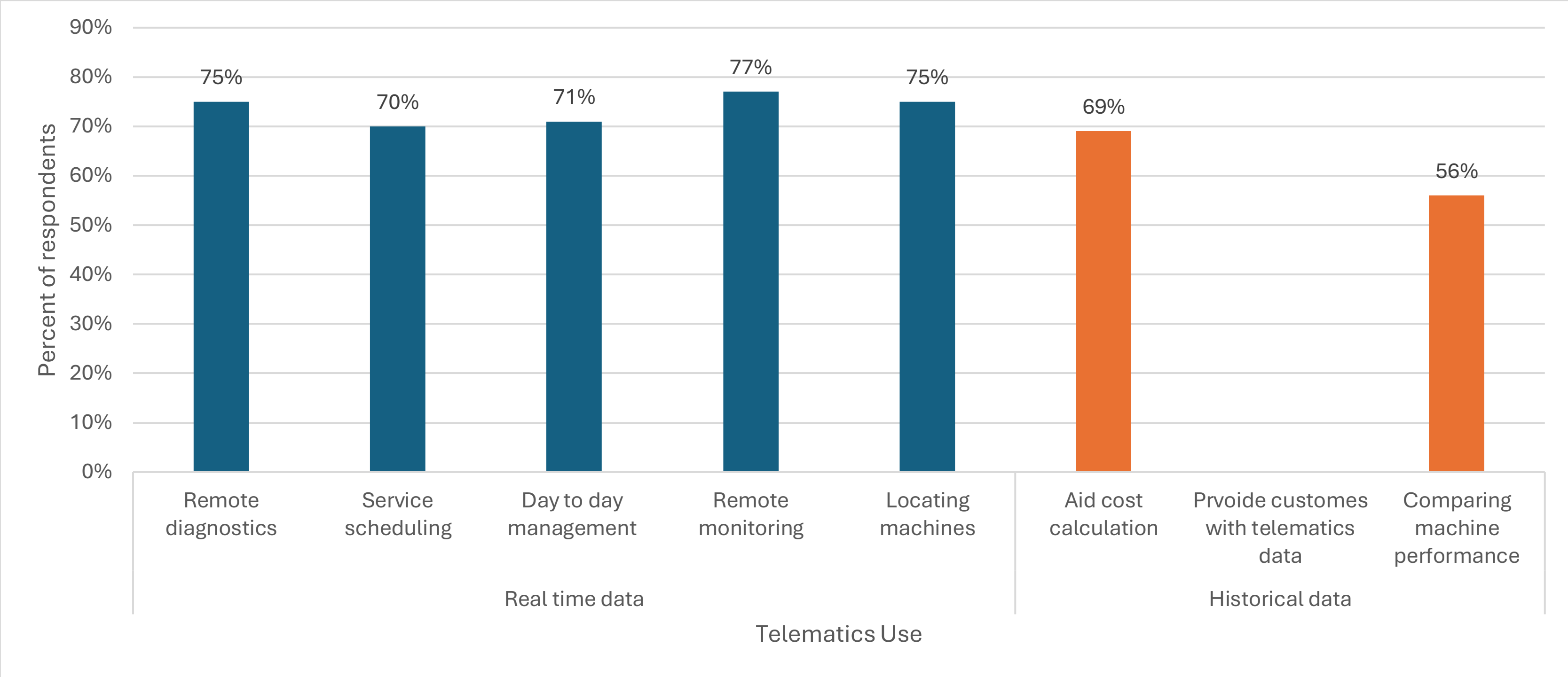

Figure 20. Comparison of uptake for historical and real time telematics data use

4.3.7 Future Features of Agricultural Machinery Telematics Systems

The following section outlines the findings from the thematic analysis of respondents' responses on future features of agricultural machinery TS. See appendix 4 for complete table of thematic analysis.

The most common theme expressed was no improvement need on current TS. Noting current systems fulfil their requirements. Precision farming advancements was a common theme, wireless data transfer and improved mapping capabilities. Improved integration though better connectivity and compatibility with other technologies was also identified. Also, a common theme was greater in-depth analysis focused on advanced diagnostics, AI decision making. Least common theme service and maintenance.

Table 11. Thematic analysis results from questions 47 - common themes for future agricultural machinery telematics systems

Theme	**No Improvement**	**Precision Farming**	**Improved Integration**	**Greater Data analysis**	**Service and Maintenance**
Count Frequency	38	32	17	13	7
	Little improvement Systems do all that is required JDLink has everything we need	Soil maps Topography & compaction maps NDVI maps Software matching up yield / soil maps	Talk to each other easier Improved integration Link multiple systems	In depth diagnostics More data analysis AI decision making	Service data Greater diagnostics Dealers to consult telematics

4.4 Research Objective Two

To determine the factors affecting agricultural machinery telematics use.

The following Chi Squared test results had a significant association ($p<0.05$) with agricultural machinery telematics use.

See appendix 4 and 5 for all Chi Squared test results and calculation output.

Were appropriate, from the primary Chi Squared tests where 20% or more of the expected values were below five, resulting in an invalid test. See appendix 6 & 7. The data was grouped to resolve this issue (Chimitova & Lemeshko, 2017).

Table 12. The factors with a significant association (p<0.05) with telematics use

Factor	Chi Square value	Critical Value	Degrees of Freedom	p value
Occupation	18.000	11.070	5	<0.003
Agricultural enterprise size (ha)	36.601	12.592	6	<0.000
Self-propelled agricultural machinery	27.823	9.488	4	<0.000
Tractor (kW)	98.047	15.507	8	<0.000
Tractor source of purchase	9.646	11.070	1	<0.002

4.4.1 Further Analysis of the Factors with a Significant Association with Telematics,

The following results present further analysis of the significant factors, to determine which category within each factor had the greatest association with telematics use.

Due to the small sample sizes for certain categories, wider confidence intervals are observed. These results should be interpreted with caution as they may not be statistically reliable (Thiele & Hirschfeld, 2023).

Table 13. The effect different occupations had on percentage of respondents using telematics.

		Actual Number of Respondents		
Occupation Category	% of Respondents Using Telematics	Yes	No	Total
UK Farmer	58%	43	31	74
UK Farm Worker / Farm Machinery Operator	85%	44	8	52
UK Farm Manager	89%	17	2	19
UK Agricultural Contracting Business Owner	60%	9	6	15
UK Farmer / UK Agricultural Contracting Business Owner	90%	9	1	10
Other multiple occupations	80%	24	6	30

Conclusion: UK Farmer, UK Agricultural Contracting Business Owner, a dual occupation, has the greatest association with telematics use (90%).

Table 14. The effect different agricultural enterprise sizes had on percentage of respondents using telematics.

Agricultural enterprise size (ha) Occupation Category	% of Respondents Using Telematics	Actual Number of Respondents		
		Yes	No	Total
Less than 51	33%	3	6	9
51-100 ha	44%	7	9	16
101-200 ha	48%	11	12	23
201-500 ha	70%	44	19	63
501-1000 ha	89%	33	4	37
1001-2000 ha	92%	23	2	25
Over 2000 ha	93%	25	2	27

Conclusion: Telematics usage increases with agricultural enterprise size.

Table 15. The effect different self-propelled agricultural machinery had on percentage of respondents using telematics.

Self-Propelled Agricultural Machinery Occupation Category	% of Respondents Using Telematics	Actual Number of Respondents		
		Yes	No	Total
Tractor, Materials handler, Combine harvester, Crop sprayer	87%	52	8	60
Tractor, Materials handler, Combine harvester	59%	17	12	29
Tractor, Materials handler	56%	20	16	36
Tractor	33%	4	8	12
Other mixed machinery	84%	53	10	63

Conclusion: Tractor, Materials handler, Combine harvester, Crop sprayer has the strongest association with telematics use. It can also be inferred from the data as the number of self-propelled agricultural machinery owned or operated increases as does telematics use.

Table 16. The effect different tractor horsepower had on percentage of respondents using telematics

Tractor kW Occupation Category	% of Respondents Using Telematics	Actual Number of Respondents		
		Yes	No	Total
0-50 hp (0-37 kW)	80%	4	1	5
51-100 hp (38-74 kW)	41%	11	16	27
101-120 hp (75-89 kW)	42%	20	28	48
121-140 hp (90-104 kW)	60%	26	17	43
141-160 hp (105-119 kW)	73%	44	16	60
161-200 hp (120-149 kW)	79%	65	17	82
201-240 hp (150-178 kW)	85%	82	14	96
241-320 hp (179-238 kW)	93%	67	5	72
321 hp + (239 kW +)	97%	58	2	60

Conclusion: With the exception of 0-50 hp tractors, as tractor hp increases as does telematics use. The reason for this is due to the low denominator of total respondents for 0-50 hp.

Table 17. The effect of the place of tractor purchase had on percentage of respondents using telematics.

Source of Tractor Purchase	% of Respondents Using Telematics	Actual Number of Respondents		
		Yes	No	Total
From an official manufacturer dealership	80%	98	24	122
Other sources	60%	45	30	75

Conclusion: Tractors purchased from an official manufacturer dealership (80%) has the strongest association with telematics use.

Overall it can be inferred from the factors with a significant association with telematics use that a dual occupation UK Farmer / UK Agricultural Contractor, with an agricultural enterprise over 2000 ha, using multiple agricultural machinery, specifically, Tractor, Materials handler, Combine harvester, Crop sprayer, using 249 kW + tractors, purchased from an official manufacturer dealership, have the greatest significant association with agricultural machinery telematics use.

4.5 Research Objective Three

To determine the factors affecting agricultural machinery telematics use.

The following results are taken from the 54 respondents who do not use agricultural machinery telematics.

Out of 54 respondents the majority (65%) do not own or use agricultural machinery that is equipped with a TS. 11% own or use agricultural machinery equipped with telematics but do not use it. 11% are unsure whether their agricultural machinery has a TS.

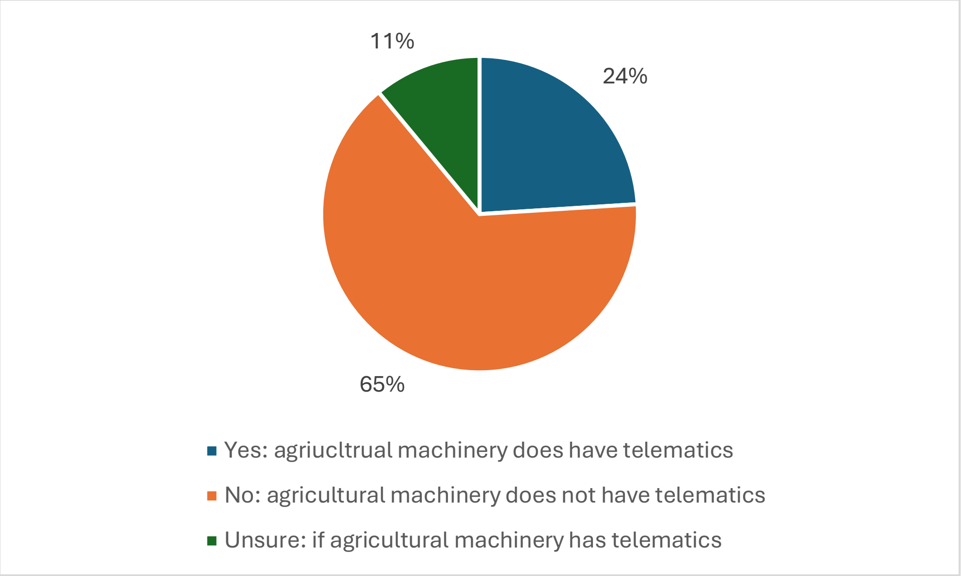

Figure 21. Breakdown of respondents not using telematics showing whether their agricultural machinery is equipped with a telematics system

4.5.1 Respondents Responses to Barriers Preventing Telematics Use

Financial cost are the most common reasons respondents do not use telematics. Also, lack of understanding, dealer did not show us, farm size and ageing machinery of enterprise were also common themes. See appendix 8 for full responses.

Table 18. Thematic analysis results of why respondents do not use telematics

Common Themes / Ideas	**Financial Cost**	**Do Not Understand Telematics**	**Farm Size**	**Ageing Machinery**	**Contractors**
Count Frequency	17	13	12	10	4
	Too costly Expensive Additional cost	Not sure of benefits Need to know more about Dealer never shown us how to use it	Ring fenced farm Small farm	Tractor to old Tractor not modern Machine age	Use contractors Contractors for arable Field work use contractors

Chapter Five: Discussion

The discussion section has been broken down into four sections, discussing the three research objectives as well as the demographic profile of respondents (Newbrook, 2020; Olivant, 2020).

5.1 Respondent Profile

The majority (51%) of respondents were aged under 35. However, the age profile is skewed, as shown in table 20. Data from Defra, (2024) UK agricultural workforce statistics show as age increases so does the percentage of people employed in agriculture, whereas the data gathered from this research shows the opposite.

Table 19. Comparison of Age distribution between Defra 2024 survey results and actual questionnaire results.

	Defra %	Actual %
Under 35	5	51
35-44	10	20
45-54	16	19
55-64	30	8
65 and over	38	3

(Defra, 2024)

The difference in age profile between the two studies may be attributed to the questionnaire being accessible only to those with internet access. Furthermore, the questionnaire was predominantly promoted via targeted social media platforms. This resulted in an unintended bias to respondents with access to the internet Saunders, (2012) as well as those who use social media, of which the majority are under the age of 35 (Dixon, 2024). The age profile is however aligned to that of that of Pickthall & Trivett (2017) and Boothby & White (2021) as well as more recently (Masi et al., 2023) who undertook similar studies using a questionnaire to gather data on PF uses and uptake. Furthermore, rural youth are recognised as being more engaged in broader agricultural industry research, demonstrating a notable interest in PF (Leavy and Smith, 2010; Gardezi *et al*., 2022). The combination of an online questionnaire focusing on a PF technology provided an ideal platform and subject matter, which appealed to the younger generation of agricultural machinery owners and operators and encouraged their participation.

5.2 Research Objective One

To understand the current uses and desired future features of agricultural machinery telematics systems.

The results showed a significant majority (73%) use agricultural machinery telematics. The research findings show a significant majority (>70%) use telematics for remote machine locating, service scheduling, and remote diagnostics. These uses align with the previous research of Anna and Jacek (2015), Krzyżaniak and Kowalik (2022), Prasanth (2024), and Yeong *et al*., (2024), who identified these uses as benefiting to agricultural machinery users.

5.2.1 Arable and Grassland Agricultural Machinery Operations

The results highlight the varying levels of uptake of agricultural machinery operations that utilise telematics. Arable machinery operations have greater uptake of telematics use compared to livestock/grassland machinery operations. This trend aligns with broader previous research findings, concluding agricultural machinery PF technologies have greater uptake of use for arable machinery operations than livestock grassland based (Griffin, Terry W., Shockley and Mark, 2018; Monteiro, Santos and Gonçalves, 2021).

Arable machinery operations, specifically seed drilling and fertiliser application exhibit the highest levels of uptake. Reasoning for this may lie in the established use (20 years) of variable rate (VR) application of inputs such as seeds and fertiliser (Rutto and Arnall, 2009). For variable rate applications to take place telematics systems are used to transfer maps between farm office and agricultural machine (Mark & Griffin, 2016) as well as record previous cropping yield data which has influence on VR maps. Furthermore, established of VR has resulted in incorporation of VR technology as standard on agricultural machinery, commonly seed drills and fertiliser applicators (Sharma *et al*., 2025). The long period of established use, combined with the integration of VR technology into agricultural machinery as standard, provides reasoning for the greatest level of telematics use for the arable machinery operations.

5.2.2 Real Time and Historical Telematic Data Uses

Further analysis of the results shows there are two types of telematics data uses. Real time such as remote monitoring and historical such as comparing the performance of agricultural machinery. Real time has a significant majority (>70%) use whereas historical data has a majority use (>50%). In contrast the academic studies reviewed in the literature review by Paraforos, Hübner, and Griepentrog, (2018), Tihanov and Hristova, (2021), Campos-Ferreira *et al*., (2023) all utilise historical telematics data. Reasoning to explain this difference may be due to historical telematics data requiring additional analysis to generate meaningful insight Kelly *et al*., (2022). Data analysis was carried out on all the telematics data used in the research studies. Furthermore, agricultural enterprises face a shortage of data analytics skills in their workforce (Barnes *et al*., 2019). In contrast, professional researchers possess both the expertise and appropriate analytics tools (Medina-Rivera, Castro-Gonzáles, and Vega Vilca, 2017). This skills gap in agricultural enterprises explains the limited use of historical telematics data. Given this, manufacturers should incorporate data analytic technologies such as AI, which are suitable for analysing large data sets Javaid *et al*., (2023). Thus, future studies may wish to explore the effectiveness and accuracy of employing data analytic technologies for machinery telematics data.

5.2.3 Agricultural Machinery Type

The results show a significant majority (77%) use telematics to monitor self-propelled agricultural machinery such as tractors and harvesters. This aligns with the uptake of TS brand, with greatest uptake being self-propelled agricultural machinery brands such as JDLink. In contrast 3% of respondents use agricultural implement TS such as Kverneland Sync. The low uptake of implement TS may be due only being commercially available for the past five years in comparison with tractor telematics systems which been commercially available since 2007 (Goltyapin & Golubev, 2020). These factors provide reasoning for the greatest uptake level of uptake being for SP agricultural machinery.

5.2.4 Future Features of Agricultural Machinery Telematics Systems.

Overall, the most common theme regarding future features of TS was that no improvement on existing commercial telematics systems was required. The thematic analysis also shows common recurring themes are for greater incorporation of PFT, particularly those related to soil mapping. Additionally, there is emphasis on the need for improve integration between telematics platforms and non-agricultural machinery technologies such as NDVI. This indicates that current TS have a limiting factor in poor integration between non-agricultural machinery technology preventing the integration of PFT.

Future telematics systems may need to include these discussed features as commercial development is taking place focusing on smart precision agricultural implements (Zawada *et al*., 2021). For example, development is taking for cultivators to automatically adjusting working depending on soil compaction levels (Zawada *et al*., 2021). This system relies on telematics to capture, transmit and store soil compaction map data, highlighting the importance of digital connectivity in agricultural implements. The future uptake in use of agricultural machinery telematics may me greatest for agricultural implements rather than

SP machinery. To support this evolution, developers of agricultural telematics software should enhance compatibility with PFT.

5.3 Research Objective Two

To determine the factors affecting agricultural machinery telematics use.

Although there is no previous research investigating the factors affecting agricultural machinery telematics use. There has been considerable previous research examining the factors affecting PFT use (Pickthall and Trivett (2017), Boothby & White, 2021; Hennessy *et al*., 2016; Lowenberg-DeBoer & Erickson, 2019; Kernecker *et al.,* 2019; Tey & Brindal, 2012; Townsend & Noble, 2022).

5.3.1 Occupation

Respondents who were both UK farmers agricultural contractors showed the strongest significant association ($p<0.003$) with agricultural machinery telematics use. This result is unsurprising, as telematics technology is essential for agricultural contractors whose businesses rely on managing multiple agricultural machines to carry out contracting work, often spanning entire counties or multiple regions (Nye, 2020). Consequently, the significant majority (77%) use of telematics for remote monitoring of agricultural machinery aligns with the use of telematics by agricultural contractors.

Blasch *et al*, (2022) similarly concluded that the adoption of PFT is linked to farmers who own their farms, as they have greater direct control and decision-making power. This finding correlates with the significant association between UK farmers and telematics use, as farmers who own their businesses act as the primary decision-makers (Edwards-Jones, 2006; Hayden *et al*., 2021).

In conclusion, the strong association between telematics use and the dual occupation of UK farmers and agricultural contractors is expected. These individuals are responsible for ensuring machinery profitability while simultaneously making decisions regarding telematics adoption. Additionally, TS serve a dual purpose, meeting the operational needs of both enterprises.

5.3.2 Agricultural Enterprise Size (ha)

A significant association ($p<0.000$) between agricultural enterprise size and agricultural machinery telematics use was observed, with results showing that telematics adoption increased alongside enterprise size. Similarly, Pickthall and Trivett, (2017) identified agricultural enterprise size had a 99.9% significant association with PFT use. More recently Wang *et al*, (2023) concluded the same trend, reporting ($p<0.001$). The academic research discussed is also supported by the most recent Defra UK agricultural survey report concluding the largest farms, those employing five or more full-time employees, had the highest uptake (38%) of PFT (Defra, 2024). Kernecker *et al*., (2019) attribute the greater levels of adoption to larger agricultural enterprises due to their stronger financial position than smaller farms. Bronson, (2018) and Rose & Chilvers, (2018) support this reasoning, noting that the costly initial investment required for PFT favours larger farms.

Further discussion as to why telematics use has the greatest association with larger agricultural enterprises may be attributed to its relative newness as a PFT (Rutto & Arnall, 2009). Hennessy *et al,* (2016) discuss the top-down adoption model of PFT, whereby PFT use trickles down from the largest to smallest farm, however, Hennessy et al. (2016) reports this adoption strategy creates a digital divide between large and small farms. This divide stems from the perception that PFT suites larger agricultural enterprises. Defra, (2024) defines the average UK farm size as 82 ha, an enterprise size only 8% of respondents to this study were placed. Thus, the low adoption of telematics by small and medium sized enterprises may be attributed to the trickle down of the technology and the low pace of PFT adoption (Pickthall & Trivett, 2017) means telematics is yet to have widespread adoption by these farm types.

5.3.3 Self-Propelled Agricultural Machinery and Tractor kW

It is not surprising there is a strong association ($p<0.000$) between the number of SP agricultural machinery used and telematics use. As well as a significant association ($p<0.000$) between tractor kW and telematics use. Garzón, (2020) reports a as farm size increases as does tractor kW and number machines used. The benefits of agricultural machinery fleet management through telematics as discussed by Mark & Griffin, (2016); Goltyapin and Golubev, (2020) aligns with these two results as the association with telematics use increased with the as the number of individual agricultural machinery used.

5.3.4 Source of Tractor Purchase

The source of tractor purchase has a significant association ($p<0.002$) with telematics use. Tractors purchased from official manufacturer dealerships show the strongest association with telematics usage. Although the questionnaire did not determine the age of respondents' tractors. Tractors sold by an official manufacturer dealership are typically new or still within manufacturer's warranty (Durczak *et al*., 2020). The age of the tractor is relevant as the newer the tractor the greater the likelihood of being fitted with a GNSS (Durczak *et al*., 2020; Ruiz-Garcia and Sanchez-Guerrero, 2022). The inclusion of a GNSS system as a standard feature maybe perceived that purchasers are getting GNSS system at no additional cost, as often the GNSS licence fee is included in the purchase price (Durczak *et al*., 2020). A GNSS is a gateway to the use of telematics as a GNSS system is required to enable telematics due to the requirement of satellite connection. The use of a GNSS system is therefore a key requirement to telematics use and due to the greater likelihood of a tractor having a GNSS system through the purchase of a tractor from an official manufacture dealership therefore increase the likelihood of telematics use.

5.4 Research Objective 3

To determine the barriers preventing agricultural machinery telematics use.

Thematic analysis of the 54 respondents who did not use telematics identified the financial cost of a TS as the most common reason for non-adoption. Pickthall and Trivett (2017) and Boothby and White (2021), similarly found that financial cost was the most significant barrier to the adoption of PFT's. More recently, Wang, Jin, and Sieverding (2023) also reported financial cost ($p<0.001$) had a significant association with PFT uses.

It is notable that the majority (65%) of the 54 respondents who do not use telematics either own or operate agricultural machinery that is not equipped with telematics. Consequently, the primary barrier to telematics adoption is the absence of TS in their current machinery. Results from the thematic analysis highlight the age of agricultural machinery as a common barrier, suggesting that the machinery used is too outdated to have been originally equipped with GNSS systems. Alternatively, the machinery may have been purchased without a GNSS system to save cost.

The implication of owning agricultural machinery without a TS is the machine would require the retro fitment of a GNSS system, or the purchasing of newer machine equipped with GNSS. Both options involve significant initial financial investment. Therefore, providing reasoning as to why financial cost was the most common barrier to telematics use.

Previous research concludes data ownership is a common barrier preventing both telematics as well as the wider use of PFT's (Mark and Griffin, 2016; Uddin, 2024). The results of this research however do not report any themes suggesting data ownership is a barrier to telematics use. The reasoning for this may be aligned with the age demographic of respondents as 30% were over 44 years of age. Armantier *et al.,* (2024) concluded as age increases, so do data ownership and privacy concerns, along with unwillingness to share data. The most reluctant age group to share data is those aged over 65 (ONS, 2025). Given the age demographic of respondents, it may be inferred that data ownership and privacy concerns were less of a barrier for the respondents of this study, as 70% were aged under 44 for whom data ownership is less concerning.

Chapter Six: Conclusion, Limitations and Recommendations for Future Work

Research aim: To determine the current uses, the barriers to adoption, and the desired features of agricultural machinery telematics systems in the UK.

6.1 Conclusions

73% of agricultural machinery owners and operators use agricultural machinery telematics. The greatest level of uptake was real time data uses such as remote monitoring. The agricultural machinery operations which used telematics the most was seed drilling and fertiliser application.

Overall respondents are satisfied with current agricultural machinery TS and believe they require no improvement. The results also suggest greater integration of more PFT specifically those which use telematics to transfer data. Although some TS have the capability for wireless transmission of data, there were several respondents who still require this.

Research findings showed that occupation ($p<0.003$), agricultural enterprise size (ha) ($p<0.000$), number of self-propelled agricultural machinery operated ($p<0.000$), tractor kW ($p<0.000$) and source of tractor purchase ($p<0.002$) were factors which had a significant association with telematics use. Dual occupation, farmers and agricultural contractors had the greatest association with telematics use. The larger the agricultural enterprise (ha) as well as the greater number of self-propelled agricultural machinery and higher kW tractors owned or operated also increased the association with telematics use. Tractors purchased from an official manufacturer dealership also had the greatest association with telematics use.

The barriers preventing agricultural machinery telematics use align with those preventing the use of general PFT in congruence with previous studies. Financial cost is the most prominent barrier to telematics use by those respondents who do not own agricultural machinery currently fitted with telematics. Respondents also commonly felt they did not understand telematics technology, therefore preventing use. The research also concluded agricultural enterprise size is a barrier.

Overall respondents' perception of telematics is positive. However, telematics is just one PFT. PFT's are noted to have the greatest positive impact on an agricultural production system when relevant technologies are used together. Telematics is no exception to this having the potential to create more resilient, robust and sustainable future agricultural production systems.

6.1.1 Limitations and Recommendations for Future Work

It is recommended that this research be replicated with a greater financial budget and extended timeframe. Distributing the questionnaire both online and via postal copy would improve accessibility, therefore resulting in a more representative sample of the actual UK agricultural workforce and potentially more conclusive findings. An extended timeframe would also allow for the inclusion of case studies. These would provide quantitative data and tangible evidence to support respondents claims of how telematics has impacted their agricultural machinery operations.

For certain questions respondents could select multiple answers. As a result, it was difficult to determine the main sector of agriculture respondents worked in. For example, respondents who selected multiple occupations meant it was unclear which was their primary occupation. For future research, questions should be structured to first ask respondents about their main agricultural sector, followed by any additional sectors. This approach would improve the accuracy of aligning agricultural machinery uses with specific agricultural sectors.

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Appendices

Appendix 1. Electronically distributed questionnaire

Welcome Page

This questionnaire forms part of an Honours Research Project being undertaken by George Elliott, a final year BSc (Hons) Agriculture with Mechanisation student at Harper Adams University. The purpose of this questionnaire is to gather information from UK agricultural machinery owners and operators.

Honours Research Project Title: An investigation into the current and future uses of agricultural machinery telematics in UK agriculture.

What is agricultural telematics? It is the remote monitoring of agricultural machinery using wireless communication systems such as Global Navigational Satellite Systems (GNSS), for example GPS, and sensor technologies to gather, transmit and analyse farm machinery operational data. Telematics is available from many tractor and agricultural machinery manufactures under brand names such as:

- John Deere JDLink
- JCB LiveLink
- Case IH AFS Connect
- AGCO Connect

Participation:

Participants of the questionnaire must be 18 years of age or older and either own or operate agricultural machinery. Participation is voluntary and anonymous, and participants may withdraw at any time before submitting the questionnaire.

Questions: Some questions may not apply to you, and the questionnaire will guide you based on your responses. It will take approximately 5 to 10 minutes to complete.

Data Protection: The project has been reviewed and approved in accordance with the Harper Adams University Ethics process. Data gathered from the project will be stored until May 2025.

If you have any questions or would like to know more about this study, you can contact George at 18095500@live.harper.ac.uk or David R White the Honours Research Project Supervisor and Senior Lecturer in Engineering at Harper Adams University at drwhite@harper-adams.ac.uk.

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Thank you for your participation in this questionnaire.

1. I agree with statements above and am happy to proceed with the questionnaire.

- Agree
- Disagree

Section 1: About You

2. What is your occupation? Please select the box(s) that best apply to you.

- UK Farmer (owned or tenanted farm)
- UK Farm Manager
- UK Agricultural Contracting Business Owner UK Agribusiness (business involved in a variety of enterprises all within the agricultural sector
- UK Farm Worker / Farm Machinery Operator
- Other

3. If selected other, please state your occupation.

4. Which sector(s) of agriculture is your business involved in? Please select the box(s) that best apply to you

- Cereals
- Fresh produce
- Potatoes
- Dairy
- Beef cattle
- Sheep
- Pigs
- Poultry
- Other

5. If selected other, please state the agricultural sector.

6. What is the size of your farm, farming enterprise or contracting area? (Hectares)

- Less than 5 ha
- 5-20 ha
- 21-50 ha
- 51-100 ha
- 101-200 ha
- 201-500 ha
- 501-1000 ha
- 1001-2000 ha
- Over 2000 ha

7. Which region(s) of the of the United Kingdom is your farm, farming enterprise or contracting area located in? Please select the box(s) that best apply to you. Scotland Wales

- Scotland
- Wales
- Northern Ireland
- North West England
- Yorkshire and the Humber
- East Midlands
- North East England
- West Midlands
- East of England
- Greater London
- South East England
- South West England

8. What is your age?

- Under 35
- 35 - 44
- 45 – 54
- 55 – 64
- 65 and over
- Prefer not to say

Section 2: Agricultural Machinery and Tractors

The following questions are about your agricultural machinery and tractor(s).

9. What self-propelled agricultural machinery do you own or operate? Please select the box(s) that best apply to you.

- Tractor
- Materials handler (telehandler, wheeled loading shovel, etc)
- Combine harvester
- Crop sprayer
- Forage harvester
- Potato harvester
- Vegetable harvester (carrots, parsnips, onions etc)
- Pea viner
- Sugar beet harvester
- Other

10. Please state the other self-propelled agricultural machinery you own or operate

Only respondents that select "Tractor" answer

11. Which brand of tractor(s) do you own or operate? Please select the box(s) that best apply to you.

- John Deere
- JCB
- Case IH
- New Holland
- Fendt
- Massey Ferguson
- Valtra
- Challenger
- CLAAS
- Kubota
- Same - Deutz Fahr
- McCormick
- Landini
- Other

Only respondents that select "Other" answer

12. Please state the brand.

Only respondents that select "Tractor" answer

13.Please select the number of tractors you actively use in your farming enterprise. Please exclude any tractors that are rarely used or retired.

- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- 10 +

Only respondents that select "Tractor" answer

14. What horsepower are your tractors? Please select the box(s) that best apply to you. 0-50 hp (0-37 kW)

- 51-100 hp (38-74 kW)
- 101-120 hp (75-89 kW)
- 121-140 hp (90-104 kW)
- 141-160 hp (105-119 kW)
- 161-200 hp (120-149 kW)
- 201-240 hp (150-178 kW)
- 241-320 hp (179-238 kW)
- 321 hp + (239 kW +)

Only respondents that select "Tractor" answer

15. Where do you typically source your tractors? Please select the box(s) that best apply to you. From an official manufacturer dealership (e.g. Farols, Chandlers, Russels, etc)

- From an independent farm machinery dealer (e.g. Parris Tractors, GM Stephenson, etc)
- From a tractor hire company (e.g. SW Hire, Tractor Hire UK, etc)
- From a farm machinery auction (e.g. Cheffins, Brown & Co, etc)
- From a private seller
- Other

Only respondents that select "Other" answer

16. Please state the source.

Section 3: Agricultural Machinery Telematics Usage

17 Do you use and agricultural machinery telematics system?

- Yes
- No

Only "No" I don't use respondents answer

18. Do you use and agricultural machinery telematics system?

- Yes
- No

Only "No" respondents answer

19. Please give up to 3 reasons why you use telematics.

Only "Yes" I use telematics respondents answer

19. Please give up to 3 reasons why you use telematics.

Only "No" I don't use telematics respondents answer

20. Please give up to 3 reasons why you do not use telematics.

Only "Yes" I use telematics respondents answer

21. Please select from the list below the agricultural machinery you use that is equipped with a telematics system.

- Tractor
- Materials handler (telehandler, wheeled loading shovel etc)
- Combine harvester
- Self-propelled sprayer Forage harvester
- Potato harvester
- Vegetable harvester (carrots, parsnips, onions, etc)
- Sugar beet harvester
- Pea viner
- Implements (balers, seed drills, mowers etc)
- Other

Only “Other” respondents answer

22. Please state the other agricultural machinery you use that is equipped with a telematics system.

Only “Yes” I use telematics respondents answer

23. Which telematics systems do you use? From the options below please select the box(s) that best apply to you.

- John Deere JDLink
- New Holland PLM
- Case IH AFS Connect
- JCB LiveLink
- AGCO Connect (Fendt, Massey Ferguson & Valtra)
- CLAAS TELEMATICS / Connect
- SDF Fleet Management
- Horsch Connect Kverneland Sync
- Krone Digital Telematics
- Grimme i
- Other

Only “Other” respondents answer

22. Please state the name of the telematics system.

Only “Yes” I use agricultural machinery telematics respondents answer

25. Do you use telematics to help carry out any of the following agricultural machinery operations?

- Seed drilling Potato and vegetable planting
- Cultivation
- Spraying
- Fertiliser application
- Combine harvesting
- Potato harvesting
- Root crop harvesting (e.g. carrots, parsnips, onions, etc)
- Forage harvesting
- Materials handler operations
- Road haulage (e.g. grain and silage transportation)
- Silage mowing
- Tedding and rowing up grass silage
- Baling
- Rear discharge manure and waste spreading
- Slurry spreading
- Irrigation
- Precession weeding
- Salad harvesting
- Other
- Do not use telematics to help carry out agricultural machinery operations

Only “Other” respondents answer

26. Please state the agricultural machinery operation.

Only “Yes” I use telematics respondents answer

Material Handlers

27. Do you use the telematics system on your materials handler?

- Yes
- No
- Do not own or operate a materials handler

Only “Yes” I use telematics respondents answer

28. Please state what you use your materials handler telematics system for?

Only “Yes” I use telematics respondents answer

Harvesting Machinery

29. Do you control one machine from another? (e.g. controlling a tractor and trailer from a combine harvester while unloading grain)

- Yes
- No
- I do not operate harvesting machinery

Only “Yes” or “No” I operate harvesting machinery respondents answer

Harvesting Machinery

30. Do you use telematics to monitor and record yield data from harvesting machinery?

- Yes
- No

Only “Yes” I use agricultural machinery telematics respondents answer

Service and Maintenance

31. Do you carry out remote diagnostics of your agricultural machinery through a telematics system?

- Yes
- No

Only “Yes” I use agricultural machinery telematics respondents answer

Service and Maintenance

32. Do you plan servicing schedules using telematics data to minimise downtime? (e.g. Machinery in use times, remotely checking service intervals, etc)

- Yes
- No

Only “Yes” I use telematics respondents answer

Agricultural Machinery Efficiencies

33. Do you use real time telematics data to aid in the day-to-day operation and management of your agricultural machinery?

- Yes
- No

Only “Yes” I use telematics respondents answer

34. Do you use telematics to remotely monitor agricultural machinery working parameters? (e.g. fuel usage, wheel slip, engine speed, etc)

- Yes
- No

Only “Yes” I use telematics respondents answer

35. Do you use telematics data to compare the performance of your agricultural machinery against your own or others' agricultural machinery? (e.g. hectares worked, combine harvester grain losses, etc)

- Yes
- No

Only “Yes” I use telematics respondents answer

36. Has the use of telematics improved the efficiency of your agricultural machinery operations?

- Yes
- No

Only “Yes” telematics has improved efficiency respondents answer

37. Please explain how.

Only "Yes" I use telematics respondents answer

General Telematics Use

38. Do you use telematics to locate agricultural machinery?

- Yes
- No

Only "Yes" I use telematics respondents answer

39. If you undertake agricultural contracting work, do you provide customers with recorded telematics data of the work you carry out? (e.g. total area worked, fuel usage, tonnes harvested, etc)

- Yes
- No
- Do not undertake agricultural contracting work

Only "Yes" I use telematics respondents answer

40. Do you use telematics data to aid cost calculations for agricultural machinery operations? (e.g. fuel usage, time taken to complete, seed used, etc)

- Yes
- No

Only "Yes" I use telematics respondents answer

41. Do you use telematics for anything else not previously mentioned in this questionnaire?

- Yes
- No

Only "Yes" I use telematics for things not mentioned in this questionnaire respondents answer

42. Please describe what it is you use telematics for.

Only “No” I do not use telematics respondents answer

Future Decision Making and Telematics Use

43. Do you intend to use telematics in the future?

- Yes
- No
- Unsure

Only “No” I do not use telematics respondents answer

44. Please give up to 3 reasons why.

Only “Yes” I use telematics respondents answer

45. Do you use previously recorded telematics data to aid and inform future decision making?

- Yes
- No

Only “Yes” I use previously recorded telematics data to inform future decision-making respondents answer

46. Please give an example(s) of this.

All respondents answer

47. Please name up to 3 features you would like future agricultural machinery telematics systems to include.

End of questionnaire.

Appendix 2: Raw unadjusted data of number of individual agricultural sectors respondents operate in.

Sector	Number of respondents
Cereals, Fresh produce (salad & root crops)	6
Cereals	50
Cereals, Beef cattle	18
Cereals, Beef cattle, Sheep	19
Cereals, Dairy	11
Cereals, Potatoes	8
Cereals, Dairy, Beef cattle	5
Sheep	2
Cereals, Dairy, Beef cattle, Sheep	6
Cereals, Other	5
Cereals, Beef cattle, Sheep, Other	1
Beef cattle, Sheep	3
Dairy, Beef cattle, Sheep	2
Other	3
Poultry	1
Dairy, Beef cattle	2
Cereals, Potatoes, Dairy, Beef cattle	1
Cereals, Dairy, Beef cattle, Sheep, Poultry	1
Cereals, Potatoes, Pigs, Other	2
Dairy	6
Beef cattle	2
Cereals, Pigs	5
Cereals, Potatoes, Beef cattle	4
Cereals, Fresh produce (salad & root crops), Potatoes	3
Cereals, Potatoes, Dairy	1
Cereals, Dairy, Beef cattle, Pigs	1
Cereals, Potatoes, Dairy, Beef cattle, Sheep, Poultry	1
Cereals, Beef cattle, Poultry	1
Cereals, Sheep	2

Dairy, Sheep	1
Cereals, Potatoes, Other	1
Cereals, Beef cattle, Sheep, Pigs	1
Cereals, Fresh produce (salad & root crops), Potatoes, Beef cattle, Sheep	2
Cereals, Beef cattle, Pigs	1
Cereals, Poultry	5
Cereals, Potatoes, Dairy, Beef cattle, Sheep	2
Cereals, Beef cattle, Other	3
Beef cattle, Sheep, Poultry	1
Cereals, Fresh produce (salad & root crops), Beef cattle	1
Cereals, Fresh produce (salad & root crops), Dairy	1
Cereals, Dairy, Beef cattle, Sheep, Pigs, Poultry	1
Beef cattle, Sheep, Other	2
Cereals, Potatoes, Pigs	1
Cereals, Dairy, Pigs, Poultry	1
Beef cattle, Pigs, Other	1
Cereals, Dairy, Beef cattle, Other	1
Cereals, Fresh produce (salad & root crops), Pigs, Other	1
Cereals, Fresh produce (salad & root crops), Potatoes, Beef cattle, Sheep, Pigs	1

Appendix 3. Thematic analysis of respondents answers to why the use telematics data.

Themes /& Ideas	Improved Management	Streamlining of Operations	Precision Farming	Record Keeping	Machine Operation Settings Set Up	Fuel	Transmission of Data
Count Frequency	68	50	28	14	14	14	11
	Fertiliser Spray Machinery management Manage operators Informed remote management Performance bonuses Adjust plans in real time Less phone calls Less driving around in pickup	Maximisation of machine Efficient working Working direction Reduced idle hrs Less productive areas Quick data Quick machine set up Greater understanding of productivity	Variable rate maps Yield amps Prescription maps Wireless transfer of precision data Real time precision data Accuracy Repeatability Reduce waste CTF Field health	Automatic data transfer to the office Reduced office labour Paper free Ease recording data Managing records Individual job fuel recording Better understanding of businesses	Determine if machine needs optimising Effective staff Training Max output Less time setting up Wireless exchange setting between machines Minimal multiple improvements add up Compare combine setting Benchmarking	Efficient fuel use Saving fuel Monitoring fuel Accurately recording fuel Comparing fuel usage	No wasted time Quick Fast Streamlined Remote Direct to Machines On the go

Appendix 4 Chi squared results

Validity 20% of expected cells <5)	Factors influencing telematics use	Test	Chi square value	Critical value	Degrees of freedom	P value	Association
Valid	Occupation	Chi Squared	18.000	11.070	5	0.003	Significant association
Valid	Sector	Chi Squared	0.345	3.841	1	0.549	No significant association
Valid	Agricultural enterprise size (ha)	Chi Squared	36.601	12.592	6	0.000	Significant association
Invalid	Region	Chi Squared	8.591	18.307	10	0.571	No significant association
Invalid	Age	Chi Squared	5.627	9.948	4	0.229	No significant association
Valid	Self-propelled agricultural machinery	Chi Squared	27.823	9.488	4	0.000	Significant association
Valid	Single or mixed brand of tractors	Chi Squared	2.497	7.815	3	0.114	No significant association
Invalid	Number of tractors	Chi Squared	29.705	16.919	9	0.000	Significant association
Valid	Tractor hp	Chi Squared	98.047	15.507	8	0.00	Significant association
Valid	Tractor place of purchase	Chi Squared	12.936	11.070	5	0.002	Significant association

Appendix 5: Chi Squared test output to test the association of agricultural enterprise size with telematics use.

Observed Values			
Agricultural Enterprise Size (ha)	Yes	No	Total
Less than 51	3	6	9
51-100 ha	7	9	16
101-200 ha	11	12	23
201-500 ha	44	19	63
501-1000 ha	33	4	37
1001-2000 ha	23	2	25
Over 2000 ha	25	2	27
Total	146	54	200

Expected Values			
Agricultural Enterprise Size (ha)	Yes	No	Total
Less than 51	6.57	2.43	9
51-100 ha	11.68	4.32	16
101-200 ha	16.79	6.21	23
201-500 ha	45.99	17.01	63
501-1000 ha	27.01	9.99	37
1001-2000 ha	18.25	6.75	25
Over 2000 ha	19.71	7.29	27
Total	146	54	200

O	E	O-E	$(O-E)^2$	$(O-E)^2/E$
3	6.57	-3.57	12.7449	1.940
7	11.68	-4.68	21.9024	1.875
11	16.79	-5.79	33.5241	1.997
44	45.99	-1.99	3.9601	0.086
33	27.01	5.99	35.8801	1.328
23	18.25	4.75	22.5625	1.236
25	19.71	5.29	27.9841	1.420
6	2.43	3.57	12.7449	5.245
9	4.32	4.68	21.9024	5.070
12	6.21	5.79	33.5241	5.398
19	17.01	1.99	3.9601	0.233
4	9.99	-5.99	35.8801	3.592
2	6.75	-4.75	22.5625	3.343
2	7.29	-5.29	27.9841	3.839
Chi Squared				36.601

p value	0.00048
Degrees of freedom	6
Critical value	12.592
Chi sq.	36.601

Appendix 6: First Chi Squared test to test the association of Source of Tractor Purchase

Observed Values			
Tractor Source of Purchase	Yes	No	Total
From an official manufacturer dealership	98	24	122
From an independent farm machinery dealer	8	9	17
From an official manufacturer dealership / From an independent farm machinery dealer	13	7	20
From an official manufacturer dealership / From a private seller	4	4	8
From an official manufacturer dealership / From a farm machinery auction	4	1	5
Other sources	16	9	25
Total	143	54	197

Expected Values			
Tractor Source of Purchase	Yes	No	Total
From an official manufacturer dealership	88.55838	33.44162	122
From an independent farm machinery dealer	12.3401	4.659898	17
From an official manufacturer dealership / From an independent farm machinery dealer	14.51777	5.482234	20
From an official manufacturer dealership / From a private seller	5.807107	2.192893	8
From an official manufacturer dealership / From a farm machinery auction	3.629442	1.370558	5
Other sources	18.14721	6.852792	25
Total	143	54	197

First Chi Squared (20% of expected values where <5).

Expected Values less than 5. More than 20% of the expected values are less than five. Test is invalid.

Appendix 7: Second Chi Squared test using adjusted data to test the association of Source of Tractor Purchase

Observed values			
Tractor source of purchase	Yes	No	Total
From an official manufacturer dealership	98	24	122
Other sources	45	30	75
Total	143	54	197

Expected values			Total
Tractor source of purchase	Yes	No	
From an official manufacturer dealership	88.55838	33.44162	122
Other sources	54.44162	20.55838	75
Total	143	54	197

O	E	O-E	$(O-E)^2$	$(O-E)^2/E$
98	88.55838	9.441624	89.14427	1.006616
45	54.44162	-9.44162	89.14427	1.637429
24	33.44162	-9.44162	89.14427	2.665668
30	20.55838	9.441624	89.14427	4.336153
Chi^2 Calc				9.645866

Chi square value	Critical value	Degrees of freedom	p value
18.000	9.646	11.070	1

Appendix 8: Why respondents do not use telematics

Common themes / ideas	Financial cost	Do not understand telematics	Small enterprise	Old machinery	Contractors
Count frequency	17	13	12	10	4
	Too costly to justify Expensive Additional cost Another cost	Not sure of benefits Need to know more about Dealer never shown us how to use it Don’t know anything about it	Ring fenced farm Small scale 100-acre farm Small farm	Tractor to old Tractor not modern Age of current machines	Use contractors Contractors for arable Field work done by contractors