Assessment of Sensor Technologies for Detecting Slurry Emissions in Irish Agriculture

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Abstract - **There is a rising demand for the reduction of ammonia and greenhouse gases in Ireland to meet European Union targets for climate neutrality by 2050. This has led to considerable interest in the use of various technologies, particularly sensors to aid in mitigation of emissions in slurry life cycle management. In our previous study, a review of publications on the general use of sensors for the detection and determination of ammonia and greenhouse gases was conducted. This extended version builds on the previous findings through validation using responses from Irish farmers. A questionnaire on the use of sensors for slurry management was administered to Irish farmers, and a total of 106 responses were collated. The findings revealed that 22.6% of farmers in this study have adopted sensor technology on farms, and only ~2% utilize it for emission detection. Despite the limited adoption of sensor-integrated technology for the detection of slurry emissions on Irish farms, farmers agree that sensor technologies would be beneficial for slurry management. Some perceived benefits are real-time monitoring and decision support, enhanced detection capabilities, improved emission quantification, spatial and temporal precision, and support for sustainable practices. However, there are currently limitations in their adoption and application, such as high cost and maintenance, limited technical knowledge, inadequate sensor sensitivity and accuracy, operational constraints, limited capability for slurry characterization, and fragmented design. This study revealed a poor correlation between pairs of perceived benefits: real-time monitoring of emissions and emission quantification, and improved detection capabilities and better decision-making. Thus, suggesting that farmer perception of sensor-driven emission detection might be regulatory or compliance-based rather than informing better farm decisions. Therefore, there is a need for a clearer communication strategy that highlights the importance of improved decision-making through sensor-based real-time emission detection. Additionally, this study underscores the importance of subsidies to help reduce costs and encourage the adoption of sensor technologies on Irish farms, supporting the reduction of emissions in slurry management and promoting sustainable agriculture.**

Keywords - Sensors; Precision Agriculture; Ammonia; Greenhouse Gas; Emissions; AgriTech.

I. INTRODUCTION

A preliminary version of this study was presented at the International Conference on Sustainable and Regenerative Farming, 2025 [1]. While the conference paper was limited to a review of articles on the use of sensors for the mitigation of ammonia and greenhouse gases through the slurry life cycle, with a summary of the benefits and challenges of sensor usage, this current study is a substantial extension of those findings. Sections I and II of this current study were adapted from the conference paper.

Irish agriculture is mainly dominated by livestock production, resulting in the generation of a large quantity of animal waste [2]. While livestock slurry is a valuable agricultural resource, its mismanagement poses significant environmental challenges. Slurry contains valuable nutrients like nitrogen and phosphorus, but improper management can lead to significant losses through runoff, leaching, and volatilization. This can cause water pollution (e.g., eutrophication) and air pollution (e.g., ammonia emissions). A recent publication from the Agriculture and Food Development Authority of Ireland (Teagasc) estimates that 40 million tonnes of animal manure is generated and subsequently used annually [2]. It follows therefore, that there is immense pressure on the agricultural sector in Ireland to minimize Ammonia (NH_3) and Greenhouse Gas (GHG) emissions [3][4]. This sector accounts for the majority of Irish national NH_3 (99%) and GHG (37.8%) emissions [3][5][6]. Methane (CH_4) emissions from slurry management represent 10.6% of agricultural GHG in Ireland [4]. It follows therefore, that minimization of Irish national NH_3 and GHG emissions, especially from agriculture, is crucial in meeting emission reduction targets and ensuring the sustainability of the agricultural sector.

Efforts to reduce emissions occur within the many processes involved in the management of slurry, such as removal and storage management, treatment adjustments, slurry application rates, soil uptake, and so on. However, these are not without challenges. For example, the storage of slurry is accompanied by the release of pollutant gases, such as NH_3 and CH_4 emissions [3][7]. In an attempt to minimize this, Ireland developed the Nitrates Action Plan (NAP) in line with the European Union (EU) Nitrates Directives, which specifies guidelines on slurry storage duration and time of application [8]. In addition, Ireland Climate Action Plan (CAP) outlines measures specifically for the agricultural sector with focus on 25% reduction in emissions by 2030, with key target being slurry management to reduce ammonia emissions [4]. Several manure management approaches have been proposed with the possibility of reducing these dangerous gases associated with slurry management. [9] found that the use of additives, which encourage acidification, reduces CH_4 and NH_3 emissions from slurry storage. Guidance from the United Nations Economic Commission for Europe (UNECE) Task Force on Reactive Nitrogen: Ammonia Guidance Document [10] sets out emission abatement measures in the nitrogen lifecycle from livestock feeding strategies, animal housing techniques, manure storage techniques, through manure application techniques. Also, research conducted by [11] in which the impact, potential, and costs associated with abating national NH_3 emissions up to 2030 likewise sets out common mitigation strategies.

Since the UNECE and Teagasc guidance documents [10] [11] were published, there have been exponential advancements in technology. Sensor technology enables the Internet of Things (IoT). Big data is gathered from sensors, hosted on cloud platforms, and analysed using statistical methods or artificial intelligence to enable real-time predictions - driving the Industrial Revolution known as Industry 4.0 [12]. Agriculture 4.0, using the nomenclature of Industry 4.0, promises the same revolution in smart farming. Indeed, many industry consortia, fora and solution providers propose slurry management solutions, which use sensors, and make claims that emissions are reduced [13 - 16]. A rigorous journal review process is necessary to substantiate claims and conclusions made in these channels [1, 17]. Furthermore, whilst the adoption rate of sensor technologies is known to be particularly low in emerging and developing countries [18, 15], it is not clear to what extent those sensors have been adopted in high-income EU contexts such as Ireland, which is primarily comprised of relatively small family-run farms.

In this research, the application of advanced sensor technologies for real-time monitoring and control of emissions in slurry management processes in Irish farms was investigated. The research questions posed are (1) How are sensors used in Irish farms? (2) To what extent are sensors used for the reduction or mitigation of ammonia and greenhouse gas emissions in slurry management on Irish farms? (3) What are the perceived benefits and perceived challenges associated with the use of sensor technologies for slurry management?

To answer these research questions, first a narrative literature review was conducted on sensor utilization for detection of ammonia and greenhouse gases in slurry management, which is set out in Section II. Thereafter, the research method in which Irish Farmers were surveyed is set out in Section III. In Section IV and Section V, the results and discussion on the same are presented. The paper concludes with a summary, limitations, and proposed future research.

II. Sensor Utilisation in the Slurry Lifecycle

The emergence of smart farming and precision agriculture is due to advancements in technology. There has been an increase in the applications of such technologies for sustainable agriculture, and an emerging area is the mitigation of emissions in agriculture. An example is the use of IoT technology for the improvement of slurry management on farms. These field-based IoT sensors record and monitor soil-related conditions targeted at helping farmers make better decisions on best timing for slurry applications to minimize losses and maximize nutrient use. However, these sensors were unable to measure key slurry parameters (such as pH, dry matter, temperature, and nutrient content), perform in situ and online monitoring, or provide data for comprehensive slurry management [19].

Several authors [20 - 25] report on the application of sensors for determination of nutrient components of slurry. However, few reports have been published on the use of sensors for the quantification of gas emissions, such as ammonia and greenhouse gases (methane, nitrous oxide and CO_2). This literature review addresses that gap and covers the quantification of emissions in the three major stages in the traditional management of slurry: slurry production in animal houses, slurry storage and field application.

A. Slurry Production

Livestock production results in the generation of animal waste. Particularly, housing of animals comes with the challenge of handling and management of slurry. Efficient manure management reduces environmental impact, thus maintaining animal health. Environmental sensors measuring factors like air quality and humidity, generate vast amounts of data providing crucial insights into the well-being of the herd and the optimization of the farm environment [12].

Air quality in farmhouses is linked with ammonia, CO_2, Particulate Matter (PM) and Hydrogen Sulphide (H_2S) concentrations. These gases have negative effects on animals and human health in the environment. The quality of air is affected by some other factors, such as frequency of slurry removal and floor type [26]. A 21-day study which utilized an IoT gas and environmental sensors for continuous detection of NH_3, CO_2, H_2S and PM concentrations in two piggeries revealed that housing structures and slurry management systems had a huge impact on the gas emissions in the piggeries. Specifically, slurry management resulted in increased H_2S up to 1.9 ppm and increased NH_3 concentration of 63%. In addition, the structure of housings resulted in accumulation of gases, CO_2 and NH_3 increasing up to 52% and 34% than daily average value respectively [26]. The use of sensors at different times of the day, further confirms the need for advanced technology for the mitigation of environmental impacts of agriculture.

Optimum environmental conditions (temperature, moisture, air quality, etc.) must be maintained in livestock houses. The maintenance of these conditions results in huge electrical energy consumption particularly in poultry houses (broiler houses - 75.5%, laying hen houses - 58.9%) due to the use of various equipment [27]. This is predicted to increase in the future due to technological advancement, which indirectly leads to increased GHG emissions. Consequently, for improved efficiency and sustainability, the prediction of the energy consumption of the indoor environmental condition for intensive poultry farming is expedient [28].

In order to minimize reliance on additional equipment, [28] developed a customized hourly model for the interpretation and analysis of electronically collected data. In this study, gas sensors were utilised for the measurement of CO_2 (Model 336, Huakong Xingye Technology, Beijing, China) and ammonia gas concentration (Model 458, Zhize, Jinan, China) emitted in a poultry house. The average CO_2 and ammonia concentration detected by the sensors were similar to the average predicted data using the developed model [28]. On the other hand, there is need for improvement in the sensitivity levels for the gas sensors to enable accurate detection at extremely low concentrations.

As indicated previously, NH_3 is typically an odorous compound produced from the decomposition of organic nitrogen and is a precursor of secondary inorganic aerosols. Similarly, H_2S, a strong odorous and toxic compound that affects animal and human health, is mainly produced from anaerobic digestion of organic sulphur [29]. These gases are usually at high concentrations in animal houses. A study evaluated the use of Electrochemical (EC) gas sensors for the quantification of odours from ammonia (Model #SO1198 Senko LTD. Korea) and hydrogen sulphide (Model #SO1N8 Senko LTD Korea) in a piggeries' manure treatment facility. Acceptable values were obtained for linearity, accuracy, repeatability, lowest detection limit and response time for the sensors, thus confirming their suitability for on-field testing. However, a longer sampling time of at least 15 minutes might be necessary for ammonia monitoring to reach target concentration point [29].

B. Slurry Storage

Upon excretion of faeces in animal houses, the slurry (manure) is usually stored for a specific amount of time. Sensor networks that monitor real-time changes in ammonia concentrations assist in minimizing losses of plant-available nitrogen during manure storage [30]. The duration of storage varies and is affected by several factors, such as time of the year, regulation governing spreading as organic fertilizer, farm slurry storage capacity and so on. Sensors were used in a study for the development of a prediction model for methane and ammonia gas emissions in piggeries with two different types of manure management systems: Long Storage (LS) in deep pits and Short Storage (SS) by daily flushing of a shallow pit with sloped walls and partial manure dilution [31]. The study revealed a positive correlation between calculated and measured CH_4 and NH_3 emissions on an annual basis. This confirms the reduction potential of the studied measures for CH_4 and NH3 emissions from pig houses. In addition, the developed model provides a possibility for the assessment of mitigation measures on CH_4 and NH_3 emissions. This provides a robust basis for assessing the impact of management and housing strategies on CH_4 and NH_3 emissions from pig houses, which in turn, helps support more sustainable practices in pig farming [31].

In a similar study, manure management and sensor location played a huge role in the determination of gas concentration [32]. Higher ammonia concentration was recorded for open slurry pit compared to the slurry management system with daily removal of slurry. Meanwhile, electro-chemical DOL53 ammonia sensors (DOL Sensors, Denmark) located at 1.0m above floor level recorded approximated ammonia concentrations and were more vulnerable to local fluctuations in comparison to those located at 1.8 m above floor level [32].

In contrast to the previous studies where electro-chemical sensors were used for gas concentration determination, a Fourier-Transform Infrared (FTIR) spectroscopy monitor was used to measure gas transport and concentrations of greenhouses gases [methane, carbon dioxide, and nitrous oxide] and ammonia inside manure piles at various depths. Results showed that carbon dioxide dominated the greenhouse gas emissions. An interesting observation in this study was the reduction of gas emissions with increased moisture content in manure with high water holding capacity [33]. Results obtained using FTIR Spectroscopy monitor provided insights into management strategies for emission reduction from solid dairy manure [33].

Drones are used as platforms to carry and deploy sensors**,** such as RGB cameras, multispectral, hyperspectral, and thermal sensors for aerial imaging and mapping, multispectral or LiDAR sensors for soil and field analysis, and gas sensors (e.g., methane, ammonia), infrared or laser-based detectors sensors to detect and map emission. Drones are effective in counting animal populations and detecting methane leaks in natural gas infrastructure. These techniques have been applied on a small scale to assess and determine livestock-related methane emissions on farms [34].

Electrochemical sensors were found to have several advantages, such as multi-gas non-specific detection, high sensitivity and precision, making them the preferred alternative for emission detection, albeit they have a long response time and short service life. Similarly, FTIR spectroscopy has the advantage of multi-gas non-specific detection but has higher operating cost in comparison with electrochemical sensors [34].

A UAV-based active AirCore system for the estimation of CH_4 emissions from dairy cow farms is outlined in [30]. The inclusion of local wind speed and direction measurement would result in increased accuracy of methane estimation [30]. In addition, there is need for further research in the use of aerial technology for the assessment of emissions from livestock farming.

C. Field Application of Slurry

The application of fertilizers and manure on fields is the largest source of NH_3 in the atmosphere. Ammonia emission from agriculture has negative environmental consequences and is largely controlled by the chemical microenvironment and the respective biological activity of the soil [12]. While gas phase and bulk measurements can describe the emission on a large scale, those measurements fail to unravel the local processes and spatial heterogeneity at the soil-air interface [12].

For better understanding of some of these processes, a two-dimensional (2D) imaging approach which visualized three of the most important chemical parameters associated with NH_3 emission from soil was developed by [35]. Ammonia, O_2 and pH microenvironments were imaged using reversible optodes in real-time with a spatial resolution of <100µm. This NH_3 optode enhanced the understanding of microscale factors influencing NH_3 emissions, allowing for visualization of the soil's chemical microenvironment following manure application [12]. Though there is a surge in the incorporation of precision agriculture tools, these systems often operate in isolation, focusing on specific parameters without providing a holistic view of the agricultural environment [36]. There is a need to bridge this gap by integrating multiple sensors and data sources into a unified monitoring system.

In [36] a comprehensive monitoring system using sensors was developed for the measurement of gases, such as CO_2, methane, and ammonia. This system, known as Agri-Guard, consists of two sets of devices: the IoT based Agri-cones and a centralized camera stand. The Agri-cones consisted of an array of sensors including temperature, humidity, moisture, CO_2 and methane gas sensors. Upon manure application to the soil, substantial increase in sensor readings were observed in the CO_2 and methane gas sensor (MQ9), due to the organic matter decomposition in the manure. Similarly, as microbial decay progressed, the ammonia sensor (MQ135), showed a slight increase, signifying the breakdown of organic nitrogen compounds in the manure [36].

The applications of sensors in slurry management are outlined in Table 1, covering housing, storage, and field use. Their advantages and challenges are summarized in Table 2, highlighting benefits for monitoring and quantification alongside limitations related to sensitivity, cost, and system integration. These advantages and challenges are evaluated from the farmer's perspective in the survey described in the following section.

TABLE 1. SUMMARY OF APPLICATION OF SENSORS FOR THE MITIGATION OF EMISSIONS IN SLURRY MANAGEMENT [1]

	Purpose of Study	*Sensor*	*Monitored animal/slurry source*
1	Evaluation of slurry management in two different housing structures	Environmental Sensor	Pigs
2	Development of energy consumption model for animal houses	Gas Sensors	Pigs
3	Emission monitoring and odour intensity estimation	Electrochemical Sensor	Pigs
4	Development of prediction models for emissions from various slurry storage systems	Gas Sensors	Pigs
5	Effect of manure management and sensor location on emission concentration	Electrochemical	Piggeries
6	Evaluation of compaction effects on emissions from dairy manure	FTIR	Cattle
7	Estimation of emissions from dairy cows' manure	UAV	Cattle
8	Visualization of emissions from soil upon manure application	Optical sensors	Livestock (unspecified)
9	Monitoring of gaseous emissions from manure in farms	Gas sensors	Livestock (Unspecified)

TABLE 2. ADVANTAGES AND DISAVANTAGES OF SENSORS FOR EMISSION REDUCTION IN SLURRY MANAGEMENT [1]

	Advantages/Opportunities	**Disadvantages/Challenges**
1	Real time monitoring and decision support [26][36]	Limited capabilities for slurry characterization [19]
2	Enhanced detection capabilities [33][28]	Variation in sensor sensitivity and accuracy [28][29]
3	Improved emission quantification [31]	Operational constraint [32][34]
4	Spatial temporal precisions [12][38]	High cost and maintenance [33]
5	Support and sustainable practices [39]	Fragmented system design [36]

III. MATERIALS & METHOD

According to the 2020 Census of Agriculture, there were just over 135,000 farms in Ireland, of which 75% (approximately 101,250 farms) were classified as cattle rearing, dairy, or other cattle enterprises [37]. These farms constituted the target population for this study. A questionnaire survey was employed as the primary data collection method. The questionnaire served as a structured data collection instrument and was designed to systematically gather information from a sample of participants in order to understand attitudes, opinions, behaviours, and characteristics of the target population.

The questionnaire was designed to capture both quantitative and qualitative data, comprising of a mix of closed-ended questions (including check boxes, Likert-scale ratings, and multiple-choice items) as well as open-ended questions to allow for elaboration on individual experiences. The mixed-question format allowed for both statistical analysis and contextual understanding of farmer perspectives, aligning with best practices in agricultural technology adoption studies [40][41]. The study was not designed to test or operationalize established behavioural adoption models; rather, it aimed to provide a descriptive mapping of usage patterns and perceived advantages and disadvantages. Accordingly, the survey instrument was developed to align with this objective.

The questions were divided into sections covering demographic information (such as age, farm size, location, number of animals, and principal farm activity) and technology-related items, which explored current use of sensor technologies on the farm. Further questions that align with the perceived benefits of the use of sensors, and challenges to adoption as found in the literature review were included for the purposes of validation.

Due to practical constraints, a non-probability sampling approach was employed, and the findings should therefore be interpreted as indicative rather than statistically representative of the national population. Irish farmers were recruited through a range of agricultural networks, including Teagasc advisory services, farmer database contacts associated with the AgriNext and SoilCrates projects, livestock marts, farming networks, social media platforms (e.g., LinkedIn), and third-level Agricultural Science students. Responses were collected anonymously, and participation was voluntary. Data were entered in Microsoft Excel spreadsheet for initial data cleaning and categorization.

With regard to qualitative data, a mix of inductive–deductive coding approaches were used. Initially, deductive coding was conducted using categories informed by the literature review and research objectives. While inductive coding was used to identify emergent concepts and patterns arising directly from respondents' experiences and perspectives. This ensured that various groups and sub-groups generated were data-driven rather than from predetermined themes, thus enabling the identification of novel insight arising from the data.

With regard to quantitative data, exploratory data analysis, which included statistical analysis of the data, examination of descriptive patterns and characteristics, and visualization through frequency distributions and graphical summaries, were performed in Microsoft Excel. Measures of central tendency, including the mean, median, and mode (where appropriate), were calculated to describe typical values, while measures of dispersion such as the range, mean deviation, and semi-interquartile range (SIQR) were used to assess variability within the sample. Data distributions were examined using graphical methods, including histograms, frequency polygons and bar charts, to identify skewness and the presence of outliers. Categorical variables were summarized using frequency counts and percentages; where variables allowed multiple responses, frequencies were reported, and percentages were interpreted accordingly.

Following the Exploratory Data Analysis, associations between binary-coded response themes were examined using Jaccard similarity coefficients and Phi (Φ) coefficients. Jaccard coefficients were used to examine proportional overlap and co-occurrence between selected response themes, and Phi coefficients were calculated to describe the strength of association between the binary-coded variables.

Responses to the multiple-selection question were coded into binary variables (1 = selected, 0 = not selected). Pairwise co-occurrence frequencies were calculated by counting the number of respondents selecting each pair of benefits or challenges, resulting in a co-occurrence matrix. To examine the co-occurrence patterns between perceived challenges/disadvantages and benefits/advantages while accounting for differences in overall selection frequency, Jaccard similarity coefficients were calculated for all pairs of coded themes. The Jaccard coefficient values reflect proportional similarity and co-occurrence between coded response themes rather than statistical dependence or causality between the options selected by the farmers. The resulting coefficients, ranging from 0 (no co-occurrence) to 1 (complete overlap), are illustrated in heatmaps. Generally, the similarity coefficient thresholds between two coded options, and chosen *a priori*, can be interpreted as follows: A value of < 0.20 represents a weak association, a value between 0.20 - 0.40 represents a moderate association, a value between 0.40 - 0.60 represents a strong association, and values above 0.60 represent very strong associations.

In addition to Jaccard similarity coefficients, Phi (Φ) coefficients were calculated as descriptive measures of association for pairwise comparisons of binary-coded variables derived from 2×2 contingency tables. Phi coefficients range from −1 to +1, where values of 0 represent no association, and values approaching ±1 represent stronger inverse or positive associations. For interpretive purposes, coefficient thresholds of approximately ±0.10, ±0.30, and ±0.50 were considered indicative of small, medium, and large associations, respectively, and were chosen *a priori*.

In the analysis, responses selecting 'all of the above' were treated as distinct categories and were not disaggregated into individual response options to avoid overestimation or interpretive bias, and which would have artificially increased joint occurrences and biased Jaccard and Phi estimates upwards.

In the next section, the results are set out.

IV. RESULTS

An exploratory examination of farmers' practices and views is presented in this section. The findings are intended to identify patterns and relationships within the data rather than to provide definitive population-level inference. A total of one hundred and six (n=106) valid responses were collected from participants across the target population. This sample size is in line with, and exceeds, related peer-reviewed studies where questionnaires were used: n=56 [42], n=53 [40], and n=32 [41]. Thus, the achieved sample size is sufficient for exploratory and descriptive analysis of the survey responses.

A. *Respondents and their Farm Enterprises*

The geographical distribution of participants was spread across all four provinces of Ireland, Munster, Connaught, Leinster and Ulster, and from twenty different counties of the possible twenty-six in the Republic of Ireland.

The farmers were from a wide range of age groups, see Fig. 1, with a larger frequency from younger farmers. The use of an online questionnaire partly explains that distribution, as younger people are more likely to be able to access online forms. In fact that was borne out by anecdotal evidence, when one lady was asked would she ask her father to complete the form, she said "I won't ask Dad, he's in his late 70s and wouldn't be able, but I'll ask my brother who mainly looks after the farm anyhow". This joint farm enterprise illustrated in this response is popular in Ireland, when older farmers tend to be supported by younger members of the family in multi-generational farms, and further explains the age-distribution in responses. The sample comprised 75.5% male and 24.5% female respondents, with no participants identifying as non-binary or other.

With respect to Farm Size, respondents had farms within the range of 16 to 1700 acres, indicating substantial heterogeneity among respondents. The farm size distribution is right-skewed and is illustrated in Fig. 2. This heterogeneity arises because the dataset includes both small-scale and large-scale farming operations, which differ considerably in scale, production capacity, and management practices. As a result, measures of central tendency alone may not adequately describe the data, and measures of dispersion such as the range, interquartile range, and mean deviation are required to capture the variability within the sample.

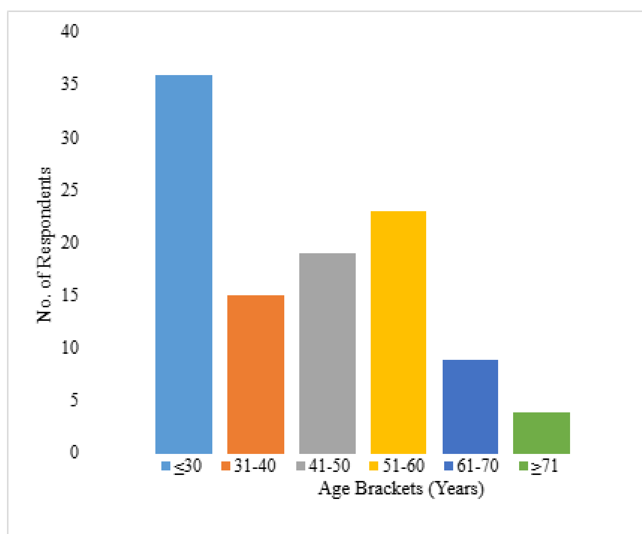

Figure 1. Age Distribution of Respondents

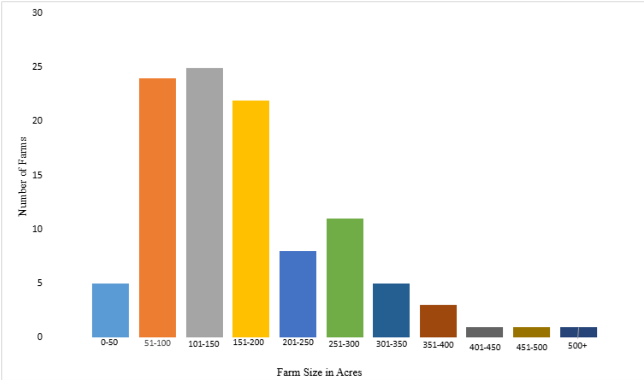

Figure 2. Farm Size Distribution

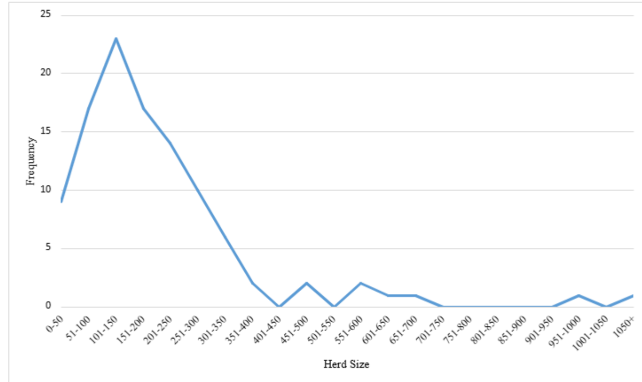

Figure 3. Herd Size Distribution

The mean value is 194, with a median of 150 and a modal value of 100 acres. A semi-interquartile range of 71indicates that the middle 50% of the data is moderately spread out, while the larger mean deviation of 94 indicating that extreme values (range = 1,684 acres) increase the overall variability in farm size.

Fresh water sources were present on or near 90% of respondents' farms of the variety of River, Stream, Pond, Dam, Well or Borehole.

Farm enterprise type was recorded as a multiple-response categorical variable, as farms could engage in more than one enterprise, and in fact 36.89% of farmers indicated more than one principal farming enterprise. Dairy farming was the most frequently reported enterprise (68 farms - 64.15%), followed by cattle rearing (44 farms - 41.51%) and other cattle enterprises (19 farms - 17.92%).

With respect to herd size, a total of 23,132 were reported across all respondents. As expected, the distribution follows a similar pattern to that of the farm size. Respondents reported herd sizes with a minimum herd size of 10 cattle for a young farmer (age ≤ 30 years), up to two farms reporting a herd size of more than 1,000 cattle. The herd size distribution is right-skewed and is illustrated in Fig. 3. As with the farm size, herd size heterogeneity arises because the dataset includes both small-scale and large-scale farming operations. The mean herd size is 220 with a median of 177 and a modal value of 200. The middle 50% of the data shows moderate dispersion (SIQR = 72.65), while overall variability is higher (mean deviation = 122) due to extreme values, reflected in a range of 1,690 animals.

With respect to the type of slurry storage system used on the farm, respondents were provided with a list of categorical labels for which multiple choices were permitted. Underground slatted tanks are used by 96% (n=102) of the farms, overground concrete (or steel) towers (or tanks) are being used by 18% (n=20) farms, lagoons by 7% (n=8) farms, and 0% reported use of slurry bags. More than one method of slurry storage is being used on 24% (n=26) farms.

B. *Use of Sensors on the farm*

Responses regarding the integration of sensors into farm equipment were dominated by negative responses, with 70.7% of respondents indicating that sensors were not integrated. Less than a quarter of respondents (22.6%) reported sensor integration, while a small proportion (6.6%) indicated that integration may be present. This proportion of responses is seen in Fig. 4.

Farmers indicated through an open-ended question where sensor technologies are currently being used. Example responses included 'sat nav and flow meter on slurry tanker', 'sensors on our milking equipment to know when cows are finished milking so the automatic cluster remover can activate', and 'heat detection sensors on cows'. These were grouped into five main categories: Fertilizer Application, Feeding, Fertility Management, Milking and Others, and General Farm maintenance, as seen in Table 3. Dairy Farmers were more likely to employ sensor technologies than farmers of other enterprises, with 58% of all sensors used on farms that identified their main activity as 'dairy'. The types of farm enterprises using sensors are illustrated in Fig. 5.

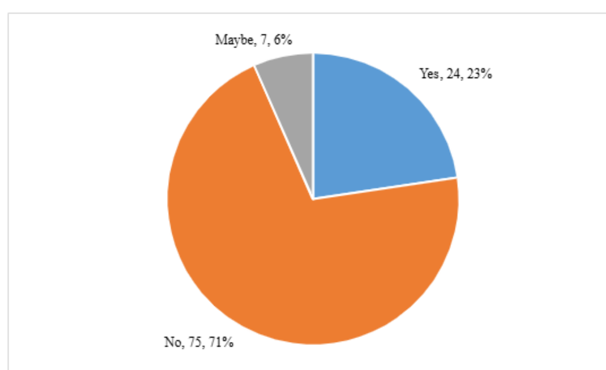

Figure 4. Sensor Integration on Farms

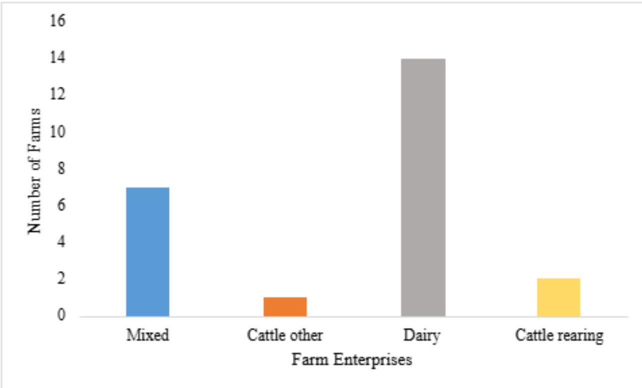

Figure 5. Farm Enterprises with Sensor Devices

When asked is any form of sensor integrated equipment utilized for the measurement of any gas emission in your sheds, only 2 (1.8%) answered yes, another 2 answered maybe (1.8%), with the remaining (96.4%) negative.

When asked do you have slurry sensors for the estimation of slurry level in your storage tank/pit/tower? and do you have any designated sensor for the estimation of emissions in the slurry storage systems? The same two respondents (1.8%) answered yes, with the remaining (98.2%) negative. These two respondents came from different sized farms, one with a 700 acre farm, the other, a younger man, with a farm of 150 acres.

There was slightly higher take-up of sensors in slurry spreading machinery with 12.3% (n=13) of respondents reporting the use of integrated sensor technology in machinery. Of those, 3.8% (n=4) reported that the sensor in the machinery can be used for the estimation of emissions from the field.

C. *Attitude and Perceptions on the Use of Sensors on the farm*

In this section, the results of the attitudinal questions collected using a Likert-scale and multiple-choice questions, are laid out. These measured farmers' perceptions and/or beliefs regarding the benefits and challenges of sensor technologies in supporting emission reduction on farms.

1) Perceived Usefulness of Sensors in Emission Reduction: The respondents indicated how useful they thought sensors were in the fight against greenhouse gas emissions and pollution. Responses were collected using a five-point Likert-type scale, visually represented using star ratings, where one star indicated strong disagreement, and five stars indicated strong agreement. 23% respondents reported not useful (with a star rating of 1 or 2), 28.57% as neutral (star rating of 3), and 48.35% as useful (with a star rating of 4 or 5). The mean response is 3.3, with a mode of 4. With 3 being neutral, this mean response of 3.3 indicated a slight tendency towards agreement, and this is clearly illustrated in the left-skew on the frequency distribution in Fig. 6. The mean score increases to an average of 4.5 for those respondents who have adopted sensor technologies.

TABLE 3. FARMER RESPONSES ON THE USAGE OF SENSORS ON FARMS

Usage of Sensors	Sample verbatim responses
Fertilizer Application	Reversing sensors, on fertiliser spreader, automatic scraper, on sprayer, on loader to prevent it from turning over
	Dribble bar
	Variable rate technology in fertilizer spreader
	Spreading fertiliser GPS
	Sprayer and fertiliser
	Sat nav and flow meter on slurry tanker
Feeding	Automatic calf feeder
	Feed to yield sensors (feeding selection for cows)
	Calf feeder, drafting system for cows
	Cow collars for heat detection Calf tags for auto-feeder
Fertility Management	Heat detection on cows, Feeding cows in milking parlour
	Heat detection sensors on cows
	Health and fertility management
	We have collars on the cows to detect heat, health, activity etc.
Milking and Others	Automatic scraper, Vacuum tanker, Milking parlour, Automatic ration feeders, Automatic milk feeders, Tractors, Water pumps
	We use sensors to know how much water has been pumped out to the drinkers throughout the day and night. There are sensors on our milking equipment to know when cows are finished milking so the automatic cluster remover can activate. We use sensors to know the temperature of the milk on our milk storage.
	Sensors on the milking parlour, that make sure tap on tank is closed, that take off cluster when cow is finished milking, movement sensors on lights
	Robotic milking
General Farm maintenance	Cameras down in the farmyard the light turns on in them when they pick up something
	GPS
	Drafting gate
	Lights seatbelts
	JCB loader
	Diggers
	Balers

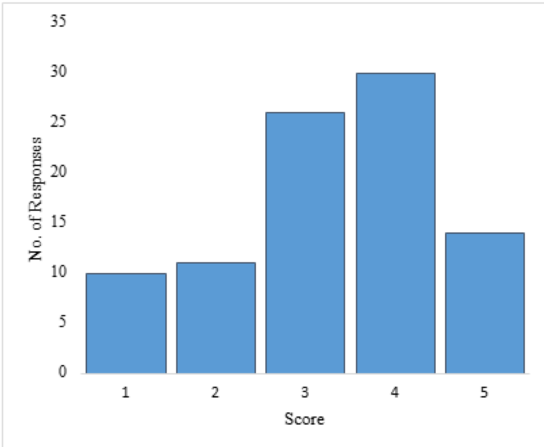

Figure 6. Perceived usefulness of sensors in reducing greenhouse gas emissions and pollution

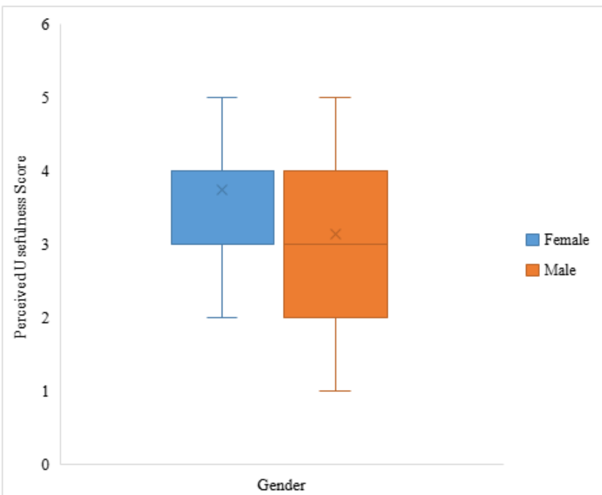

Figure 7. Perceived usefulness of sensors in reducing greenhouse gas emissions and pollution by gender

A visual inspection of the means plot does indicate a U-shape relationship between age (ordered categorical) and perceived usefulness. Younger respondents, ≤30 years, reported a mean score of 3.6, the three groups between 31 and 60 years with a mean score of 3.16, rising again to a mean of 3.65 to those over 60 years of age.

Descriptive analysis revealed gender differences in perceived usefulness, see Fig. 7. Female respondents reported higher perceived usefulness (Mean = 3.74, Mode = 4) compared to male respondents (Mean = 3.15, Mode = 3).

2) Perceived benefits/advantages of the use of sensor technology on the farm: The question posed 'Which of the following sensor benefits would be most useful for your farm?'. This was a multiple-response categorical data point, which was binary in nature (selected / not selected), and allowed more than one option per respondent. The primary descriptive result, which is the frequency of benefits selected by respondents, is illustrated in Fig. 8. These have been sorted in ranking from the highest occurrence to the lowest occurrence.

The most frequently cited benefits are related to decision-making, sustainability, and emissions management, such as 'help us make better decisions' (25.24%, n = 26), 'better for sustainability' (23.3%, n = 24), and 'real-time monitoring of emissions' (22.33%, n = 23) among the highest-ranked responses.

A second tier of benefits related to measurement precision and operational support, including 'supports access to grants and funding' (18.45%, n = 19) and 'accurate emission quantification' (16.5%, n = 17). Less frequently selected benefits were those associated with spatial and longitudinal data granularity, such as 'access to precise data around different locations on the farm' (13.59%, n = 14) and 'access to changes in data over time' (8.74%, n = 9).

Overall, co-occurrence among benefits was moderate rather than strong (Jaccard Similarity Heatmap, Fig. 9). Associations among perceived benefits were generally of moderate magnitude ($\Phi \approx 0.20$-0.40), reflecting consistent but not dominant thematic overlap, as further illustrated in the Phi (Φ) Coefficient Matrix of Co-selected Perceived Benefits Heatmap (Fig. 10).

The strongest association was observed between 'access to changes in data over time' and 'supports access to grants and funding' (Jaccard = 0.40, $\Phi = 0.56$). 'Access to changes in data over time' is the most interconnected variable. It has the highest or near-highest correlations with almost every other benefit grants/funding ($\Phi = 0.56$) and sustainability ($\Phi = 0.48$), and moderate correlations with 'real time monitoring of emissions' ($\Phi = 0.41$), 'help us to reduce our emissions' ($\Phi = 0.41$) and 'help us make better decisions' ($\Phi = 0.37$).

Grants/funding sits in its own cluster. Beyond its strong link to temporal data ($\Phi = 0.56$), it correlates moderately with sustainability ($\Phi = 0.39$) and real-time monitoring ($\Phi = 0.35$), but weakly with accurate quantification ($\Phi = 0.19$) and detection ($\Phi = 0.18$). Two benefit pairings demonstrated weak co-occurrence (Jaccard = 0.14, $\Phi = 0.10$), 'help us to reduce our emissions' and 'real-time monitoring of emissions' were rarely co-selected, as were 'better detection capabilities' and 'help us make better decisions' showed weak co-occurrence. While most pairwise associations have weak or moderate co-occurrence similarity, 'supports access to grants and funding' emerged as the benefit with the most consistent moderate co-occurrence across multiple other benefit categories, with co-occurrence coefficients such as 'real time monitoring of emissions' (Jaccard = 0.31, $\Phi = 0.35$), 'better for sustainability' (Jaccard = 0.34, $\Phi = 0.39$), 'help us make better decisions' (Jaccard = 0.32, $\Phi = 0.36$). Overall, there was absence of consistently strong associations and a limited number of large effect sizes ($\Phi \geq 0.50$).

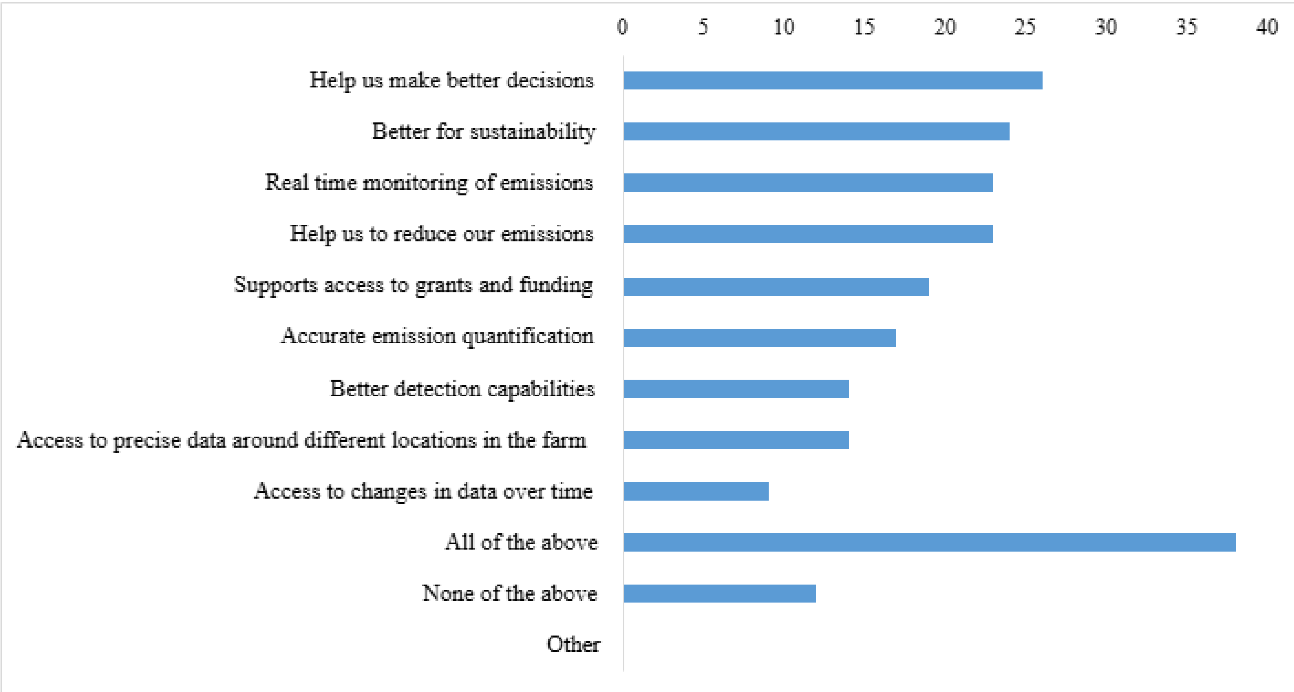

Figure 8. Perceived benefits associated with on-farm sensor adoption

	Help us make better decisions	Better for sustainability	Real time monitoring of emissions	Help us to reduce our emissions	Supports access to grants and funding	Accurate emission quantification	Better detection capabilities	Access to precise data around different locations in the farm	Access to changes in data over time
Help us make better decisions		0.35	0.23	0.32	0.32	0.23	0.14	0.25	0.25
Better for sustainability	0.35		0.27	0.24	0.34	0.24	0.27	0.23	0.32
Real time monitoring of emissions	0.23	0.27		0.18	0.31	0.33	0.16	0.32	0.28
Help us to reduce our emissions	0.32	0.24	0.18		0.24	0.33	0.28	0.23	0.28
Supports access to grants and funding	0.32	0.34	0.31	0.24		0.20	0.18	0.22	0.40
Accurate emission quantification	0.23	0.24	0.33	0.33	0.20		0.29	0.29	0.18
Better detection capabilities	0.14	0.27	0.16	0.28	0.18	0.29		0.27	0.21
Access to precise data around different locations in the farm	0.25	0.23	0.32	0.23	0.22	0.29	0.27		0.21
Access to changes in data over time	0.25	0.32	0.28	0.28	0.40	0.18	0.21	0.21	

Figure 9. Jaccard Similarity Heatmap on Benefits and Advantages of Using Sensors in the Farm.

	Help us make better decisions	Better for sustainability	Real time monitoring of emissions	Help us to reduce our emissions	Supports access to grants and funding	Accurate emission quantification	Better detection capabilities	Access to precise data around different locations in the farm	Access to changes in data over time
Help us make better decisions		0.37	0.17	0.33	0.36	0.22	0.10	0.29	0.37
Better for sustainability	0.37		0.26	0.20	0.39	0.25	0.32	0.25	0.48
Real time monitoring of emissions	0.17	0.26		0.10	0.35	0.39	0.13	0.40	0.41
Help us to reduce our emissions	0.33	0.20	0.10		0.23	0.39	0.33	0.26	0.41
Supports access to grants and funding	0.36	0.39	0.35	0.23		0.19	0.18	0.25	0.56
Accurate emission quantification	0.22	0.25	0.39	0.39	0.19		0.36	0.36	0.23
Better detection capabilities	0.10	0.32	0.13	0.33	0.18	0.36		0.34	0.28
Access to precise data around different locations in the farm	0.29	0.25	0.40	0.26	0.25	0.36	0.34		0.28
Access to changes in data over time	0.37	0.48	0.41	0.41	0.56	0.23	0.28	0.28	

Figure 10. Phi (Φ) Coefficient of Co-selected Perceived Benefits and Advantages of Using Sensors in the Farm.

3) Perceived challenges/disadvantages of the use of sensor technology on the farm: Respondents were asked to identify the perceived challenges and/or disadvantages associated with sensor use on the farm. This was a multiple-response categorical variable, dichotomous in nature (selected / not selected), permitting more than one selection per respondent. Three null values were removed, leaving 103 valid responses. The frequency of responses is presented in Fig. 11.

Overall, the most frequently cited challenges related to cost, maintenance, and knowledge barriers. 'High initial costs' were the most reported issue by 61.17% of respondents (n=63), followed by 50.49% reporting perceived 'high maintenance effort and associated costs' (n=52). A substantial proportion, 40.78%, of respondents also identified a 'lack of knowledge about sensors' as a challenge (n=42).

A second group of challenges related to practical and operational issues. These included 'operational difficulties' by 19.42% (n=20) and concerns regarding 'inadequate sensor sensitivity and accuracy', 15.53% (n=16). Fewer respondents, 10.68%, cited 'lack of time' as a limiting factor (n =11).

The least frequently selected challenges were associated with data interpretation and system integration, including perceptions that sensors are too fragmented and solve only one problem at a time, 8.74%, (n = 9), 'limited capabilities for slurry characterization', 5.83%, (n = 6), and 'difficulty in reading or interpreting sensor data', 4.85%, (n = 5).

A small proportion of respondents selected 'none of the above' (n=6, 5.83%), indicating that they did not identify with the specific challenges listed in the questionnaire. This response does not necessarily imply the absence of challenges, but rather that respondents did not identify with the challenges listed. Another proportion selected 'don't know the challenges' (n=16, 15.53%), suggesting uncertainty or limited familiarity with sensor technologies among some participants. Half of these also selected 'lack of knowledge about sensors' or 'high costs'.

As with the benefits and advantages, responses to the multiple-selection question were then coded into binary variables (1=selected, 0=not selected). A Jaccard similarity analysis was employed to quantify the proportional overlap between themes, independent of joint absences. The associations are illustrated in Jaccard Similarity Heatmap labelled Fig. 12. Phi coefficients of co-selected perceived

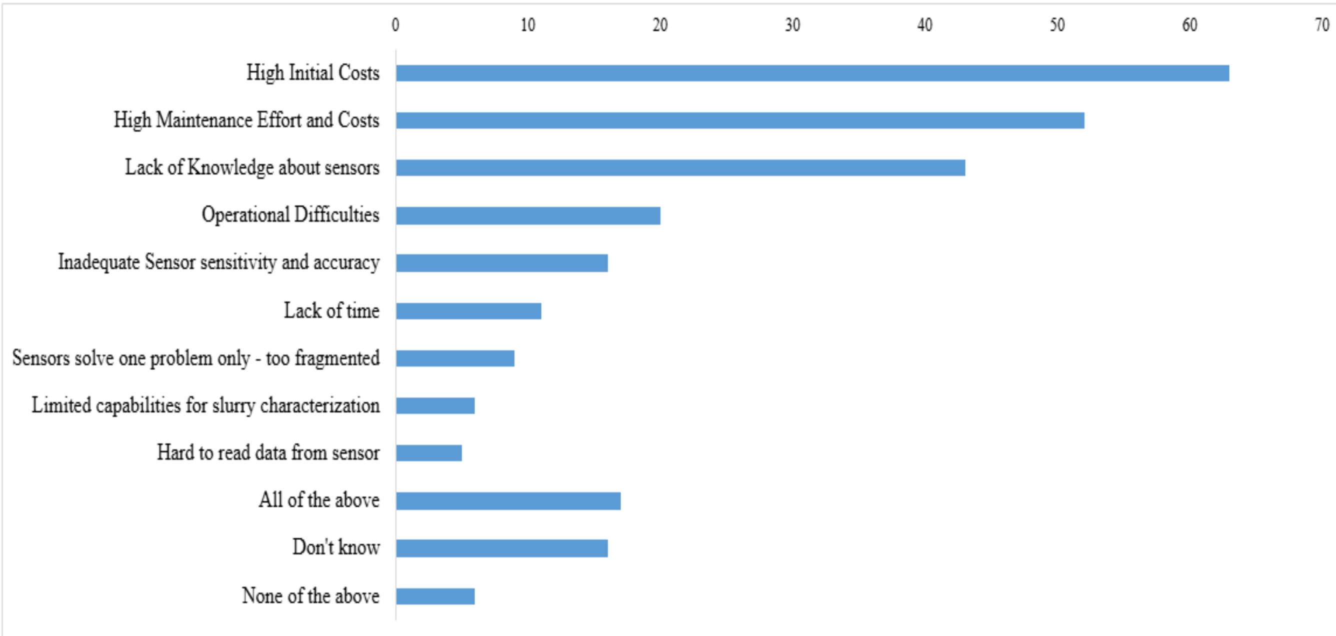

Figure 11. Perceived challenges/disadvantages associated with on-farm sensor adoption

	High Initial Costs	High Maintenance Effort and Costs	Lack of Knowledge about sensors	Operational Difficulties	Inadequate Sensor sensitivity and accuracy	Lack of time	Sensors solve one problem only - too fragmented	Limited capabilities for slurry characterization	Hard to read data from sensor
High Initial Costs		0.67	0.46	0.32	0.25	0.17	0.09	0.08	0.08
High Maintenance Effort and Costs	0.67		0.34	0.31	0.26	0.21	0.11	0.05	0.10
Lack of Knowledge about sensors	0.46	0.34		0.32	0.26	0.13	0.16	0.12	0.12
Operational Difficulties	0.32	0.31	0.32		0.38	0.24	0.16	0.13	0.19
Inadequate Sensor sensitivity and accuracy	0.25	0.26	0.26	0.38		0.17	0.19	0.10	0.11
Lack of time	0.17	0.21	0.13	0.24	0.17		0.05	0.13	0.14
Sensors solve one problem only - too fragmented	0.09	0.11	0.16	0.16	0.19	0.05		0.15	0.17
Limited capabilities for slurry characterization	0.08	0.05	0.12	0.13	0.10	0.13	0.15		0.10
Hard to read data from sensor	0.08	0.10	0.12	0.19	0.11	0.14	0.17	0.10	

Figure 12. Jaccard similarity heatmap on challenges and disadvantages of using sensors in the farm

	High Initial Costs	High Maintenance Effort and Costs	Lack of Knowledge about sensors	Operational Difficulties	Inadequate Sensor sensitivity and accuracy	Lack of time	Sensors solve one problem only - too fragmented	Limited capabilities for slurry characterization	Hard to read data from sensor
High Initial Costs		0.57	0.30	0.39	0.34	0.28	0.03	0.11	0.18
High Maintenance Effort and Costs	0.57		0.11	0.34	0.32	0.34	0.10	0.00	0.22
Lack of Knowledge about sensors	0.30	0.11		0.34	0.30	0.10	0.23	0.22	0.27
Operational Difficulties	0.39	0.34	0.34		0.47	0.31	0.20	0.19	0.35
Inadequate Sensor sensitivity and accuracy	0.34	0.32	0.30	0.47		0.20	0.25	0.12	0.15
Lack of time	0.28	0.34	0.10	0.31	0.20		0.00	0.18	0.21
Sensors solve one problem only - too fragmented	0.03	0.10	0.23	0.20	0.25	0.00		0.22	0.25
Limited capabilities for slurry characterization	0.11	0.00	0.22	0.19	0.12	0.18	0.22		0.14
Hard to read data from sensor	0.18	0.22	0.27	0.35	0.15	0.21	0.25	0.14	

Figure 13. Phi (Φ) coefficient heatmap of c0-selected perceived challenges and disadvantages of using sensors in the farm

challenges and disadvantages were calculated and are illustrated in Fig. 13. Jaccard similarity coefficient values range from 0.05 to 0.67, suggesting one particularly strong cluster, several moderate cross-links, and many weak peripheral relationships. The coefficients with distinct high and low values suggest potential clustering among specific themes. Moderate to strong associations were shown between 'high initial costs', 'high maintenance effort and costs', 'lack of knowledge about sensors', 'operational difficulties', 'inadequate sensor sensitivity and accuracy', and 'lack of time'.

The strongest association was observed between 'high initial costs' and 'high maintenance effort and costs' (J=0.67, Φ = 0.57) indicating a large effect size and substantial co-occurrence between financial barriers.

Moderate associations were identified between operational and technical performance-related themes, particularly between 'operational difficulties' and 'inadequate sensor sensitivity and accuracy' (J=0.38, Φ=0.47); and 'operational difficulties' and 'hard to read data' (J=0.19, Φ=0.35), and 'operational difficulties' and 'lack of knowledge' (J=0.32, Φ=0.34).

Lack of time demonstrated generally weak-to-moderate Jaccard similarity coefficients with other barriers (0.05–0.24), with moderate Phi associations observed between lack of time with 'high maintenance effort and costs' (Φ = 0.34), 'operational difficulties' (Φ = 0.31), and 'high initial costs' (Φ = 0.28).

V. Discussion

The primary aim of the study is to evaluate the usage of sensor technologies for the real time monitoring and control of emissions in slurry management processes in Irish farms. The findings are discussed in relation to the three central research questions: firstly, how are sensors used on Irish farms. Secondly, to what extent are sensors integrated for the mitigation or reduction of emissions in slurry management. Thirdly, what are the Irish farmers' perceptions about the benefit/advantages and challenges/disadvantages of use of sensors for monitoring of emissions in slurry management on farms.

A. *How are sensors used in Irish farms?*

The aim of employing sensors is to minimize negative environmental impacts while optimizing nutrient recovery and beneficial use. Data-driven management facilitated by sensors enables more efficient and environmentally friendly slurry handling.

Findings reported in this study revealed slightly less than a quarter (22.6%) of farmers integrated sensors on the farm, corroborating a report by Teagasc which stated that the adoption of precision agriculture technologies have been slow in Ireland [43]. This is lower than the 25% reported for Northern Europe, and 60% for the Global North overall [44].

In this study, sensor technologies were reported mainly integrated in field fertilizer application, milking, fertility management, water pumps, balers, slurry tank and other general farm operations (Table 3).

Costs are often reported as the main determinants of adoption of smart farming technologies on Irish farms [41, 43]. This study revealed that farms engaged majorly in dairy enterprises have the highest number of sensor integrated devices. This might be a cost issue, and linked to affordability, as dairy enterprises are deemed to be more profitable than others in Ireland [45].

Previous research found that advanced technologies are mostly integrated on Irish farms which are big in production and employ technologically sophisticated personnel [43]. The findings of the present study provide limited support for this relationship, if a link between farm size and big in production is assumed. In this study, farm size was positively skewed; therefore, farms above the 75th percentile were additionally examined as a 'large farm' subgroup. This threshold approximately corresponded to farms exceeding 242 acres, which is broadly comparable to larger farm classifications reported by the Central Statistics Office. Within the present sample, farmers operating larger farms were not substantially more likely to report the use of advanced sensor technologies than those operating farms closer to the sample median size. Respondents who reported that sensors were integrated into farm equipment or machinery had a median farm size of 150 acres. Similarly, respondents reporting sensor integration within slurry spreading machinery had a median farm size of 150 acres, while those reporting the use of sensor-integrated equipment for gas emission measurement in sheds had a median farm size of 170 acres. However, no sensor use was reported among farmers within the lowest quartile of farm size (<100 acres). Although the findings suggest that very small farms may have lower levels of sensor adoption, the overall low adoption rates observed across the sample indicate that barriers to implementation extend beyond farm size alone.

B. *How are sensors used in the mitigation of ammonia and greenhouse gas emissions in slurry management on Irish farms?*

Exploration of the distribution of the use of sensors throughout the slurry lifecycle, (production, storage and application) revealed significantly low adoption. Integrated sensors for the estimation of slurry levels in storage (tanks) were only reported on two farms of the 106 in the study. The use of sensors in field application of slurry revealed a slightly higher number (13 farms; 12.3%). However, only four (3%) reported that integrated sensors are being used for the estimation of emissions during field application, and only two (~2%) reported the use of sensors for the estimation of emissions from sheds. These data revealed very low adoption and integration of sensors for slurry management and mitigation of emissions on Irish farms overall.

Currently, sensors can be integrated into several aspects of farm activity [43]. Although adoption of specific sensors is dependent on several factors with high cost and maintenance reported as the main factor, farmers' decisions to integrate specific sensors are still mainly affected by perceived usefulness in solving a problem. Agriculture media, farm advisors, farm discussion groups and trade shows in ploughing championships are main influencers for the adoption of various farming technologies by the Irish farmer [46] and could be leveraged. A scheme such as the Knowledge Transfer Program aimed at encouraging knowledge exchange and innovation between advisors, farmers and other stakeholders play an important role in assisting farmers to meet current and future challenges [47]. Schemes such as this would ensure farmers are skilled to utilize different technologies like GPS, computer-based imaging, robotics, etc. [48]. "Targeted Agricultural Modernization Scheme II (TAMS II)" was a scheme from the Irish Government in 2018 to encourage young farmers to use up-to-date technology in their farms by providing grants of 40–60% on the technology used [48]. There is a need for similar schemes which will provide financial support and the required skills to farmers encouraging greater adoption of advanced technologies in the fight against emissions.

C. *What are the perceived benefits and challenges of sensor technologies when used for slurry management?*

Within this study, 'supports access to grants and funding' emerged as the benefit with the most consistent moderate co-occurrence across multiple other benefit categories indicating that respondents frequently selected funding-related benefits alongside a range of other perceived sensor benefits. The strongest association observed between 'access to changes in data over time' and 'supports access to grants and funding' indicates a relatively strong co-selection of these benefits compared to other pairings, suggesting that respondents who value longitudinal data are also more likely to perceive sensor technologies as facilitating access to funding or support schemes. Respondents didn't strongly link technical precision to funding access but did link broader environmental narrative benefits to grants and funding. The fact that perceived support for grant and funding access showed moderate associations with multiple other benefits suggests that farmers view funding-related outcomes as dependent on broader data and monitoring capabilities, rather than as a standalone function of sensor technologies. This pattern indicates an understanding that access to funding is often contingent on the ability to generate, maintain, and demonstrate evidence over time.

Several benefits have been reported from the adoption of sensors for the detection of emissions on farms. Perceived benefits of the use of sensors are that they allow real-time measurement of environmental parameters, such as temperature, humidity, and gas concentrations (e.g., NH_3, CO_2, H_2S), which supports better decision-making regarding optimal slurry application timing to reduce emissions [26][36]. In this study, farmers showed agreement with that, as reflected in the positive score on the Likert scale. This study revealed that several farmers agree with other research findings, that integration of sensor technology can enhance detection capabilities [33][28], improved emission quantification [31], increase spatial and temporal precision [12][38] and support sustainable practices [39]. In this study, higher-frequency responses though tended to emphasise practical and outcome-focused benefits, while lower-frequency responses reflected more technical or analytical uses of sensor data.

Notably, two benefit pairings demonstrated weak co-occurrence suggesting these benefits were perceived as largely independent by respondents. 'Help us to reduce our emissions' and 'real-time monitoring of emissions' were rarely co-selected despite their apparent conceptual proximity, indicating that respondents may have decoupled emissions reduction as an outcome from real-time monitoring as a process. Similarly, 'better detection capabilities' and 'help us make better decisions' showed weak co-occurrence, suggesting respondents may have perceived detection-oriented benefits as serving a different purpose, potentially regulatory or technical compliance, rather than directly informing on-farm decision-making. These distinctions may have implications for how monitoring technologies are framed and communicated to farming stakeholders. In [18] using the Technology Acceptance Model, it was found that attitude, perceived usefulness, and ease of use predicted intention well to adopt sensor technologies in agriculture. Technology Acceptance Models [49] consider acceptance at an individual level, that is usefulness to the person, how easy it is to use, and so on, when considering attitude towards the technology, intention to use technology, or actual use of the technology. Ease of use is found to predict intention to adopt sensor technologies in agriculture [18]. However, with respect to perceived usefulness and attitude, the impact of sensors in tackling the overwhelming environmental and sustainability challenges is quite small [50]. It is arguable that in this study, perceived usefulness in respect of helping to reduce emissions or make better decisions may have limitations where the environmental challenge is perceived as disproportionately large relative to the capabilities of the technology itself.

This study also identified challenges such as high cost and maintenance, fragmented design, and operational constraints, indicating a technology that is far from easy to use. This concurs with the findings in [13] which considered the Theoretical Framework of Acceptability in Smart Agriculture. Their analysis found that opportunity costs and burden are considerable challenges. Similarly, in this study, 65% of all respondents raised financial concerns as challenges, in either or both, of the options ‘high initial costs’ and ‘high maintenance costs and rarely considered acquisition cost in isolation. The financial burden associated with sensors appears to be understood in terms of total cost of ownership, where perceived ongoing maintenance requirements contribute significantly to perceived economic risk. This figure of 65% is higher than reported for a survey of North American farmers in which 52% identified cost as a concern in the adoption of precision agricultural technologies including sensors [44]. Irish farms tend to be smaller than the large commercial intensive scale farms found in North America, and it's possible that the importance of financial concerns is reflective of the amount for investment that smaller Irish farmers have at their disposal. Therefore, this finding suggests that reducing the purchase price of sensors alone may not substantially improve adoption if maintenance complexity and recurring operational costs remain high. The result aligns with broader technology adoption literature in which lifecycle costs are often more influential than initial capital expenditure in determining long-term acceptance and implementation.

Moderate associations identified between operational and technical performance-related themes, suggest that although difficulty interpreting sensor data is not widespread across the sample overall, when it does occur, it is strongly linked to broader operational concerns suggesting that perceptions of technological reliability and are closely linked with practical usability concerns for that cluster. Whilst this association between operational difficulties and difficulty interpreting sensor data was moderately strong, the low frequency of the latter category suggests this relationship should be interpreted cautiously, it does however indicate a clustering of implementation-related challenges. The barriers to adoption may involve both technical performance and data literacy challenges. However, these findings should be interpreted in the context of the very low reported adoption of sensor technologies among respondents. Given the limited direct experience likely present within the sample, these concerns may reflect perceived or anticipated barriers rather than operational difficulties arising from extensive practical use. Indeed, this interpretation is supported by the association between ‘operational difficulties’ and ‘lack of knowledge’. Respondents may associate sensor technologies with unreliable measurements, difficult implementation, or inconsistent performance based on anecdotal information, peer discussions, or broader perceptions of technological complexity. This suggests that uncertainty and lack of trust in sensor reliability may play a significant role in limiting adoption decisions. In this context, perceived implementation challenges may be as important as actual technical challenges, highlighting the importance of demonstration, user training, and evidence of practical reliability under real farm conditions.

Themes related to technological fragmentation and limited slurry characterization capabilities demonstrated weak associations with economic concerns suggesting these represent more independent or specialized barriers. Contrary to initial expectations, 'lack of time' was not typically perceived as a standalone dominant constraint. However, moderate 'associations were observed between 'lack of time' with 'high maintenance effort and costs', 'operational difficulties', and 'high initial costs'. This indicates that time-related concerns may be embedded within wider perceptions of operational burden and resource demand. In practice, respondents may associate sensor adoption with additional workload, setup requirements, maintenance responsibilities, and learning commitments, rather than viewing lack of time as an isolated issue, thus, lack of time may function more as an amplifying contextual barrier than a primary technical concern.

Taken together, the results suggest that farmers primarily perceive barriers to sensor adoption as being driven by economic cost and ongoing maintenance requirements, alongside knowledge and capability constraints, while more technical issues related to data interpretation and system integration were less frequently reported. Overall, the co-occurrence structure suggests three interrelated but distinct domains of barriers: economic constraints, technical/operational challenges, and organizational knowledge limitations.

Whilst this study showed that the farmers perceive several benefits that could be derived from the integration of sensors for mitigation of emission from slurry management, there is low adoption, and therefore the benefits are not being realized. There are perceived challenges identified in the literature, which the farmers in this study agreed with. These include high cost and maintenance [33] and limited technical knowledge about sensors. Others are inadequate sensor sensitivity and accuracy [28][29], operational constraints [32][34], limited capability for slurry characterization [19] and concerns about overly fragmented design [36] (Figs. 11 and 12).

VI. Conclusion

Traditional slurry management practices often lead to pollution and greenhouse gas emissions. There is potential within slurry management to reduce these emissions and have a positive impact on national emissions targets. Significant efforts to reduce emissions occur within the lifecycle of slurry, from livestock feed selection through manure spreading or the alternative pathway of biomethane production. In the past ten years there have been exponential developments in technology that have fuelled Smart Agriculture. At the core of these developments are the use of sensors, which capture and, in some instances, analyse data at source. An overview of the various applications of sensors for the monitoring of emissions in slurry management in Irish farms is provided, and as such provides an insight to the reduction of emissions in the slurry lifecycle in livestock farming.

Determinants of technological innovation adoption have been extensively examined through established behavioural frameworks such as the Theory of Reasoned Action, the Theory of Planned Behaviour, the Unified Theory of Acceptance and Use of Technology, the Theoretical Framework of Acceptability, and the Technology Acceptance Model [15][51]. Given the maturity of this literature, the present study did not aim to operationalize or evaluate these established models. Instead, this study adopts a system-oriented and descriptive approach, mapping the current extent of sensor technology utilization and documenting stakeholder-reported advantages and disadvantages. In doing so, it complements rather than replicates existing theory-driven research by characterizing the present implementation landscape.

In this study, Irish farmers were surveyed with respect to their views about, and adoption of, sensor technologies, with a particular emphasis on the use of sensors to measure and combat emissions. Farmers believe that sensor technologies are useful in reducing greenhouse gas emissions and pollution (mean score of 3.3 out of 5). Farmers agree that sensor technologies can provide benefits in slurry management around real-time monitoring and decision-making support, enhanced detection capabilities, improved emission quantification, spatial and temporal precision, and support for sustainable practices. They do not view sensor benefits as a single, unified construct, but rather as a set of distinct yet related functions that address different operational and environmental needs with potential economic and regulatory value, as seen in the most significant correlation between benefits is an understanding that access to data supports access to grants and funding.

Despite the high selection of advantages such as 'help us make better decisions', 'better for sustainability', help us reduce out emissions' and 'real time monitoring of emissions', adoption remains limited, with fewer than one quarter of respondents (22.6%) reporting sensor use and only ~2% utilizing sensors specifically for emission estimation or mitigation. This indicates that, despite technological advancement and policy emphasis on emissions reduction, sensor-based monitoring remains peripheral within current slurry management practice.

Current limitations include high capital and maintenance costs, limited technical knowledge, inadequate sensor sensitivity and accuracy, operational constraints, limited capability for slurry characterization, and fragmented system design.

The co-occurrence of perceived financial barriers and funding-related benefits suggests either a structural misalignment between funding mechanisms and cost realities, or a communication gap regarding available support. These findings highlight the importance of evaluating whether existing grant and incentive schemes adequately offset initial and ongoing costs associated with sensor adoption, and if so, whether these are being adequately communicated to the farmer. Greater integration of economic feasibility modelling within policy design may improve uptake and support climate mitigation objectives.

Overall, this study provides an empirical baseline of current sensor technology utilization in Irish slurry management and identifies key economic and operational barriers to wider adoption. As agriculture faces increasing regulatory and climate mitigation pressures, understanding both technological capability and farmer-level implementation constraints will be critical in aligning innovation pathways with national emissions reduction objectives.

A. *Limitations*

The survey yielded 106 valid responses. Although the achieved sample size is adequate for exploratory and descriptive analysis, it limits the precision of population-level estimates and the reliability of subgroup comparisons. Consequently, the findings should be interpreted as indicative of emerging patterns rather than as statistically generalizable conclusions. These constraints are reflected in the use of descriptive analytical methods throughout the study. Additionally, the reliance on self-reported data may introduce response bias, particularly in relation to technology adoption and perceived barriers.

B. *Further Research*

This study has shown that there is limited adoption of sensors technologies for the quantification of greenhouse gases emissions from slurry on Irish farms. Therefore, there is a need for further research to develop, calibrate, and validate robust and reliable sensor systems for measurement of greenhouse gases during all stages of the slurry lifecycle. This includes addressing challenges related to sensor fouling, durability, and data accuracy in harsh, slurry environments.

As highlighted in the literature review [1], future studies should incorporate predictive analytics, which allow forecasting future emissions or simulated scenarios, such as extreme weather events. Predictive analytics are more useful for proactive decision-making and long-term mitigation planning.

This study finds that respondents frequently associate funding-related benefits, such as ‘supports access to grants and funding’, with other perceived advantages of sensor technologies, including ‘real-time monitoring of emissions', ‘better for sustainability’, and ‘helps us make better decisions’. At the same time, financial barriers emerged as a significant concern, with a large effect size and substantial co-occurrence between cost-related factors, particularly ‘high initial costs’ and ‘high maintenance effort and costs'. While costs are therefore perceived as a major barrier, respondents also recognize that sensor adoption may enhance access to funding while delivering sustainability and data-informed decision-making benefits. Future research should incorporate dynamic economic modelling that accounts not only for capital and operational costs but also for potential grant support, environmental incentives, and funding mechanisms that may offset initial investment barriers.

Interesting patterns by age and gender were observed in the data, such as female farmers tending to agree that sensor systems were more useful in reducing greenhouse gas emissions than male famers who were more likely to provide neutral evaluations. However, these patterns should be interpreted cautiously due to the non-random sampling approach and the imbalance in age and gender representation among respondents. The study was not designed to support definitive subgroup comparisons. Future research using larger and more representative samples should explore these patterns further.

Farmers in this study perceived that sensors were useful in the fight against emissions. However, there is low adoption, and there appears to be a disconnect between the detection of emissions and informing their decision making, Further qualitative research is warranted to explore the disconnect. Further research could also integrate established behavioural adoption frameworks (e.g., technology acceptance or diffusion models) with system-level performance metrics to better understand the interaction between technological capability and farmer decision-making. This integration would extend beyond the descriptive scope of the present study and support more targeted intervention strategies.

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