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Practical evaluation of sensor-based technologies on pig fattening farms

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In this explorative study, we evaluated the reliability of commercial, modified commercial, and non-commercial systems across three fattening cycles on four pig farms. Based on failure rates, interventions, and data gaps, cluster analysis revealed a low-effort group containing both modified commercial, non-commercial, and one simple commercial system; and a high-effort group, consisting of complex commercial systems. Most failures were caused by network issues, followed by occasional damage due to accumulation of dirt or corrosion. However, regression analysis of monthly failure counts suggests that for this experimental period failures were mainly random and acute. For practical on-farm use, simple yet robust commercial systems characterised by a low component count, few processing layers, clear data pathways, and straightforward installation can be recommended, when data continuity and a low maintenance burden are prioritised.

Keywords

Precision livestock farming, sensor technology, sensor failures, sensor evaluation, animal welfare

Meeting the rising expectations of consumers and policymakers regarding sustainability and particularly animal welfare in pig farming while simultaneously enhancing financial incentives, production efficiency, and managing high stocking densities poses significant challenges for farmers (Kittawornrat und Zimmerman 2011, Domun et al. 2019). To overcome these challenges, a promising approach is the adoption of sensor-based technologies on farms, which enable the continuous and automated monitoring of animals and their environment (Maselyne et al. 2014, Fuchs et al. 2022, Li et al. 2023).

In research, several types of commercially available monitoring systems for pigs have been predominantly investigated in relation to their potential benefits for animal welfare (Banhazi et al. 2012, Vranken and Berckmans 2017, Gómez et al. 2021). The application of environmental sensors was shown to provide accurate measurements of key environmental indicators known to negatively impact pig health, such as temperature, humidity, carbon dioxide (CO_2), ammonia (NH_3) (Chantziaras et al. 2020, Moser et al. 2024), and even dihydrogen sulfide (H_2S) (Cao et al. 2022). Similarly, sound-based sensors were shown to aid in the early detection of respiratory diseases in pigs (Chae et al. 2024), as well as in monitoring social stress and abnormal social behaviours (Reza et al. 2025). Automated weighing systems in turn enabled the monitoring of growth rates on an individual basis, thus reflecting on both animal welfare, health issues, and production quality (Kashiha et al. 2014; Decarie et al. 2025). Optical weighing systems thereby present a promising approach of non-invasive and stress-free weight estimation, while ensuring a high temporal resolution of data (Kashiha et al. 2014; Hou et al. 2024). In addition to commercially available systems designed specifically for pig husbandry, numerous studies have highlighted the potential of RGB cameras to monitor and even pre-

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dict tail biting, thus allowing to reduce tail injuries and potential infections and health risks (D'Eath et al. 2018, Hakansson and Jensen 2022, Witte et al. 2024).

Despite these advantages, only a minority of farmers currently employ sensor based technologies, (Reichardt and Jürgens 2009, Groher et al. 2020b). Especially pig farms have consistently low adoption rates, most likely due to high investment costs, high additional workload, and negligible perceived benefit in the pig farming industry (Groher et al. 2020a, Heitkämper et al. 2021). Consequently, there is a substantial demand for affordable sensor-based solutions in pig production, which puts a focus on non-market available, development-stage and modified technologies (Werkheiser 2020, Khan et al. 2025). Non-commercially available systems may furthermore provide glimpses into the potential of state-of-the-art prototypes and directions of future research into sensor technologies. For instance, the Sensor Array Measuring Ball (SAMBa) was designed for simultaneous measurements of multiple pollutants, while also recording wind speed, wind direction and air pressure, thus allowing to determine emissions of open stable systems (Kazda et al. 2025). Additional advancements can be achieved by complementing commercial sensor systems with other technologies. For example, although receiving little attention in literature, water flow meters may provide data about total water usage and wastage (Tavares et al. 2014, Little et al. 2022). When integrated with other RFID (radio frequency identification)-based systems, individual water intake can be recorded, which in turn may provide insight into pig health (Maselyne et al. 2016, Bruijn et al. 2023) and has been shown to have the potential to predict the onset of farrowing (Probst et al. 2023).

Although sensor systems often demonstrate satisfactory results prior to commercialisation, they frequently fail under real-life applications (Banhazi et al. 2015). The discrepancy largely arises because the validation of sensor-based technologies is typically conducted under controlled conditions at experimental sites (Maselyne et al. 2014, Chen et al. 2020, Li et al. 2023). Consequently, most validation studies lack the representativity of long-term conditions leading to technical failures and unexpected issues that can be encountered on commercial farms (Banhazi et al. 2024). As a result, a majority of market-available sensor-based technologies exhibit insufficient external scientific validation (Williams 2019, Gómez et al. 2021, Stygar et al. 2021).

A large blind spot is the lack of systematically documented and evaluated causes for technical sensor failures, required interventions, and solutions, which is crucial information for a successful troubleshooting and implementation at the farm scale. Few studies document and report failures of tested technologies at all, although not systematically and in sufficient detail, and instead focus on post-processing and data quality issues, such as dealing with missing data (Neethirajan 2020, Zou et al. 2023, Schodl et al. 2024). A high number of sensor failures and data gaps severely affects the data quality and reliability, and thus the capacity to provide support for farmers (Banhazi et al. 2015). Consequently, technical failures might increase workload and reduce farmers' trust in sensor systems, leading to correspondingly low adoption rates (Tuyttens et al. 2022, Banhazi et al. 2024, Marku et al. 2024). Technical failures may even result in harm to the animals, e.g. by failing to detect harmful situations (Jesus et al. 2017, Tuyttens et al. 2022).

The aim of this study is to 1) identify underlying patterns in the number of system failures, required interventions, and resulting data gaps across selected sensor systems under practice-oriented on-farm conditions, 2) investigate what kind of failures occur and what interventions are most frequently required, and 3) examine whether the number of failures increases over time, e.g. due to corrosion and damage caused by the barn environment. This study will thus provide a quantitative assessment of the reliability of various sensor systems that are already commercially available, modified, and still in development. The selected sensor systems in this study represent sensor types of high interest for monitoring applications. These include image-based sensors, audio-sensors, and electro-chemical sensors (Gómez et al. 2021, Trabachini et al. 2025).

Materials and methods

Study locations

The sensor systems were installed and evaluated at four test sites in Lower Saxony, Germany over a period of three fattening cycles: an experimental farm under management by the Chamber of Agriculture of Lower Saxony and three commercial pig fattening farms, representing different husbandry types (HT) for pigs (type 2, 3 and 4) in accordance with Germany's Federal Ministry of Agriculture, Food and Regional Identity (BMLEH 2025). Each location featured differing infrastructure, affecting the selection and configuration of sensor installation.

The experimental site (farm A, HT 2) was a forced ventilation housing system, consisting of six pens, each measuring 2.65 × 6.53 m, located within a compartment. Fifteen pigs were housed within each pen. The first commercial farm (farm B, HT 2) was also a forced ventilation housing barn. Due to farm-specific management practices, three different compartments, one for each fattening cycle, were used for data collection. Pen size and consequently number of animals per pen differed accordingly. The first compartment contained eight pens, each measuring 4.80 × 3.30 m and typically housing 17 or 18 animals each. In the second compartment 14 pens of 2.50 × 3.00 m were included, accommodating five or six animals each. The third compartment contained eight pens measuring 2.50 × 4.30 m and keeping typically ten or eleven animals. The second commercial farm (farm C, HT 3) employed a naturally ventilated indoor-housing system, containing 16 pens within the fattening compartment. Each pen measured 6.00 × 6.90 m and accommodated 32 or 33 animals. Finally, the third commercial farm (farm D, HT 4) was a naturally ventilated indoor housing system, comprising four pens (8.40 × 6.00 m), each housing 42 animals and providing access to an outdoor run (6.50 × 3.80 m). During the study, all farms followed their own management routine, the pens remained unchanged and the animals did not undergo any experimental procedures.

Sensor systems

Although the assessment of measurement accuracy was not an objective of this study, sensors were installed at representative locations in accordance with manufacturer specifications to ensure appropriate and typical application conditions. All systems were mounted beyond the animals' reach or adequately protected against physical interference. The following sensor systems were investigated in this study:

The cough monitoring system is an AI-supported live audio monitoring system for early detection of coughing in pig populations. The system also records temperature and relative humidity as complementary data. It consists of one detector unit and one gateway used for wireless transfer of data from the detector. The data can then be accessed remotely via an online user interface, where events, such as coughing and warnings of potential disease outbreaks, can be monitored. The daily average, minimum and maximum of air temperature and air humidity as well as the respiratory health status, as determined by an AI algorithm from audio recordings, are stored as daily values. One cough monitoring system was installed in the centre of the fattening compartment at 2.00 m height, designated for data collection in each of the three commercial farms (B, C and D).

The climate measurement suite constitutes a mobile system integrating commercial sensors. Each suite consists of two measurement units, one primary and one secondary, performing simultaneous measurements at two locations in a fattening compartment. Both units are equipped with sensors measuring air temperature and humidity (DOL 114, dol sensors A/S), CO_2 (DOL 119), and NH_3 concentration (DOL 53 f); the primary unit is additionally equipped with an H_2S sensor (Dräger SensorAlive H_2S) and the secondary unit with a light intensity sensor (DOL 16). The secondary unit is connected via an ethernet cable to the primary unit, which in turn transmits data via a second ethernet connection to a router and to an online data platform. A live-feed and history of recorded data generated in one-minute-resolution can be accessed via a user interface remotely and thus used in real-time for supporting farm management. Each commercial farm was equipped with one climate measurement suite. The measurement units were installed at around 1.20 m height in the centre of two pig pens at opposite ends of the fattening compartment.

The climate sensor board is synonymous to the abovementioned climate measurement suite regarding the use and application, and represents an adapted lower cost alternative using commercially available sensors. The construction of the sensor boards and configuration of the monitoring software was performed by the respective company. Each board is equipped with the same sensors as the climate measurement suites, with the exception of H_2S sensors, which were not installed on the boards. A total of six climate sensor boards, one above each pen with sensors at 1.20 m heigh, were installed in a fattening compartment at the experimental site (farm A). Each climate sensor board is connected to a programable logic controller, which in turn sends the data via an ethernet connection to an industrial computer for storage in an SQL database and to an online data platform. Similar to the climate measurement suites, the data from the climate sensor boards can be accessed and monitored remotely in real-time in one-minute resolution.

Six Sensor Array Measuring Balls (SAMBa, Kazda et al. 2025) were deployed in four outdoor areas of the pens of farm D, with two outdoor runs facing south and two facing north. The SAMBa system was recently developed at the Thünen Institute of Agricultural Technology in Brunswick and measures CO_2, NH_3, air temperature, relative humidity, air pressure, wind speed, wind direction, and airborne particulate matter in one-minute resolution, and served in measuring emissions from pig pens. The SAMBa system can be regarded as a mobile, low-cost alternative to the climate measurement suites. Each SAMBa system transmits data via a separate cable connection to a router for external storage.

A total of six optical pig weighing systems were installed in a total of three pens at farm A. The systems recorded pig weights and growth using 3D camera imaging. The weighing systems furthermore included an RFID antenna, which allowed assigning the weights to individual animals by reading the RFID ear tags. RFID ear tags were the default tags used at farm A. The optical pig weighing systems were integrated with the nipple drinkers in the three pens, whereby weighing occurred every time a pig accessed a nipple drinker. A history of all individual recorded weights and a live-video feed can be accessed remotely via user interface. An installation of the optical pig weighing systems could not be implemented at the commercial farms due to an increased spatial requirement in the pens by the weighing systems.

Six water flow meters were installed at the nipple drinkers at farm A to record the total volume of water used by the pigs. In order to adapt the meters to barn environment, they were encased in a protective steel casing with rubber seals in order to prevent damage by corrosive gases. The water flow meters were used in conjunction with the RFID-antennae of the optical pig weighing systems by reading RFID ear tags in order to allow assigning the water uptake (amount and frequency) to individual pigs. A remote user interface allowed access to the history and live monitoring of both the cumulative daily water consumption as well as individual uptake events per nipple drinker. The configuration and installation of the required software was conducted by the respective company.

The monitoring of animal behaviour was facilitated by a total of twelve RGB cameras. Each three cameras were installed above the pens selected for data collection on farms C and D, while six cameras in total were installed above six pens at farm A. RGB cameras were not deployed at farm B because the fattening compartment changed with each fattening cycle. Consequently, relocating all sensor systems for each fattening cycle would have been logistically and financially demanding. Both a live-stream and recordings of video data were accessible remotely via user interface. Video data were stored in 30-minute intervals, resulting in 48 files across a single day per camera.

A summary of all systems, their number, and farms at which they were deployed can be found in the following Table 1.

Table 1: Summary of deployed sensor systems, with function and number deployed at the given farms

System	Function	Deployed at farms	Number deployed
Cough monitoring system	Audio monitoring of respiratory distress	Farm B Farm C Farm D	1 1 1
Climate measurement suite	Measuring H_2S, CO_2, NH_3, relative humidity, air temperature, and light intensity within compartments	Farm B Farm C Farm D	2 2 2
Climate sensor board	Measuring CO_2, NH_3, relative humidity, air temperature, and light intensity within compartments	Farm A	6
SAMBa	Measuring CO_2, NH_3, air temperature, relative humidity, air pressure, wind speed, wind direction, and airborne particulate matter in outdoor runs	Farm D	6
Optical pig weighing system	Optical weighing of pigs	Farm A	6
Water flow meter	Measurement of individual-based pig water uptake	Farm A	6
RGB camera	Observation of pig behaviour	Farm A Farm C Farm D	6 3 3

In order to compensate for the fact that only two sensor systems (cough monitoring system and climate measurement suite) were installed on farm B, which might pose a caveat to the comparability with different husbandry types, a wide range of sensor systems (RGB cameras, optical pig weighing systems, water flow meters, climate sensor boards) were installed on farm A, which is under the same husbandry type as farm B.

In addition to the sensor systems, a network infrastructure and data storage systems (Network Attached Storage – NAS, Synology DS923+) were installed on the farms, to store the video data generated locally, and to control the data flow via remote access. On farms A and D, this consisted of a dedicated barn computer, router, switch, and a NAS system. On farm C, only a barn computer and NAS system needed to be installed, as a network structure was already in place. On farm B it was only necessary to connect the installed sensors to the existing network, as no video data was collected on that farm. The data from the climate measurement suites, climate sensor boards, optical pig weighing systems, water flow meters, and the cough monitoring systems were being reposited in real-time directly on an external data platform. Data from the SAMBa systems were temporarily (i.e. for the duration of about two weeks) stored locally on site, with a backup to an external data platform occurring daily.

Data collection and failure logging

Sensor data were continuously collected across three fattening cycles for one year (August 2024 to July 2025). The corresponding environmental conditions to which the systems were exposed in the fattening compartments are summarised in Table 2. One fattening cycle lasted between 110 and 124 days per farm (average: 115 days), with idle periods of up to 23 days (average: 7 days) between fattening cycles, resulting in 345 days of data per farm on average. During idle periods, power washing of the compartments was performed on all four farms. For this purpose, the climate measurement suites, climate sensor boards, and the cough monitoring systems were removed from the compartments for the duration of the washing process, manually cleaned and re-installed after the power-washing, before the beginning of the next fattening cycle. The RGB cameras were packed into water-proof protective plastic cover in order to avoid damage during the power washing process, and were unpacked and manually cleaned after the power washing. The remaining systems were able to withstand power washing (water flow meters, optical pig weighing systems) or were installed in the outdoor runs (SAMBa) and were thus unaffected by the washing process. Proper functionality of all systems was ensured prior to the beginning of the next fattening cycle by on-site inspections. Cleaning of the systems during a fattening cycle was deliberately avoided in order to ensure data continuity (as removal would have been necessary in individual cases) and to avoid additional stress for the animals. In exceptional cases, RGB cameras had to be manually cleaned of fly droppings during the fattening cycles in order to ensure a proper field of view and functionality.

Table 2: Mean concentrations ± standard deviation of indoor ammonia, carbon dioxide, dihydrogen sulfide, and mean relative humidity and air temperature across the one-year survey period on the four farms used for data collection[1)]

Site	NH_3 concentration in ppm	CO_2 concentration in ppm	H_2S concentration in ppm	Relative humidity in %	Air temperature in °C
Farm A	10.4 ± 8.4	1515.8 ± 740.8	-	66.1 ± 6.6	22.3 ± 2.8
Farm B	19.2 ± 12.0	2084.0 ± 937.8	0.3 ± 0.9	65.9 ± 7.5	24.2 ± 1.9
Farm C	7.2 ± 5.0	1239.2 ± 544.7	0.0 ± 0.2	61.6 ± 8.9	20.0 ± 3.9
Farm D	14.3 ± 6.0	2632.1 ± 1271.9	0.6 ± 1.0	66.2 ± 7.9	23.6 ± 1.6

[1)] Indoor climate data at farm A were recorded using the climate sensor boards, which were not equipped with H_2S sensors, while at farms B, C and D indoor environmental data were recorded using the climate measurement suites.

Daily remote inspections of system failures were performed from Monday to Friday to monitor system integrity and data flow. Each inspection systematically logged all failures that occurred since the last check, with Monday inspections additionally covering the period since the previous Friday. A comprehensive failure logging protocol was implemented during the designated data survey period. A failure was defined as either a) a given sensor not transmitting and/or storing data, b) a sensor transmitting implausible (e.g. beyond measurement range or negative values) and substantially different data from other similar sensors types deployed in the same compartment, c) the associated software responsible for managing the sensor not working properly or producing and error message, d) the associated software not running at all, or e) the associated hardware, storage devices or technical infrastructure not working properly, resulting in no data being stored (Jesus et al. 2017, Zou et al. 2023).

Each failure incident was classified by system (i.e. associated sensor unit and software), failure type (technical or software), duration of failure (i.e. time from detection to successful intervention), required intervention (on-site intervention, remote solution) as well as a detailed description of the cause and solution. In some cases, a clear failure type and, consequently, intervention could not be identified. This occurred predominantly when a failure was only temporary and self-solved before any active intervention could be performed and before causes could be identified. In such instances, the failure type and intervention were classified as unknown. This documentation enabled a quantitative assessment of system reliability, maintenance demand, and data loss rates. At the time of failure detection, simultaneous failures of two or more sensors of the same sensor system type were initially classified as separate instances. In case of a confirmed common underlying cause affecting multiple sensors at once (e.g. software failure resulting in a failure of all sensors belonging to one system, internet connectivity issues, or power outage) the failure incident was reclassified as one instance *post hoc*. This procedure ensured a consistency of classification and avoided artificial over-inflation of failure reports due to varying quantity of sensors installed on the farms. Failures were furthermore recorded only on the initial day of occurrence and not every day until the issue was resolved in order to avoid misrepresentation of the number of failures due to possible non-sensor-related delays in interventions.

Statistical evaluation

Statistical evaluation was carried out using the open source software R version 4.3.0 and R Studio version 2023.03.01 (R Core Team 2019). Data curation was performed using the packages *readr* (Wickham et al. 2024), *tidyr* (Wickham 2020), *dplyr* (Wickham et al. 2023a), *lubridate* (Grolemund and Wickham 2011), *ISOweek* (Block 2011), *broom* (Robinson et al. 2024), and *purrr* (Wickham and Henry 2025); and data visualisation using the packages *ggplot2* (Wickham 2016), *GGally* (Schloerke et al. 2021), *ggpubr* (Kassambara 2020), *patchwork* (Pedersen 2025), *cowplot* (Wilke 2024), *ggplotify* (Yu 2023), and *scales* (Wickham et al. 2023b).

For the evaluation, first the following descriptive performance indicators were extracted from the failure logging protocol for each system per day:

- number of failures,
- number of resulting data gaps,
- number of all required interventions,
- number of remote interventions,
- number of on-site interventions.

Since failure duration, i.e. the time between initial failure occurrence and successful intervention, impacts the number of failures, it was evaluated descriptively by determining the mean, median, mode, and maximum duration. Descriptive analysis was chosen because none of the evaluated sensor technologies generated automatic failure alerts, resulting in a potential gap between failure occurrence and detection, especially when failures occurred over the weekend (i.e. Saturday and Sunday) when no inspections and interventions were performed. Furthermore, the time from failure detection to successful intervention then depends on the practical workload, which in turn is influenced by the type of required intervention (remote vs on-site) as well as the availability of personnel to resolve the issue. These non-sensor related limitations might otherwise artificially prolong the failure duration, and by extension the data gap length, thus heavily misrepresenting the consequences of sensor failures (Gómez et al. 2021). This descriptive assessment of the failure duration complements the quantitative analyses below.

In order to account for the varying total numbers of sensors installed per system, it was hypothesised that the number of failures, interventions, and data gaps scales linearly with sensor count. Thus, in order to provide comparable numbers, the raw quantitative count data for the indices above were normalised via sensor count, i.e. by multiplying them with 12, as this was the highest number of sensors installed in total (RGB cameras) and dividing by n, whereby n was the number of sensors installed for the corresponding system (3 cough monitoring systems; 12 RGB cameras; and 6 climate measurement suites, climate sensor boards, SAMBas, water flow meters, and optical pig weighing systems each). All subsequent quantitative analysis was performed using the normalised dataset.

The performance indicators of the investigated systems were then rated based on a descriptive three-tier system as poor, mediocre and good. A relatively poor performance was determined by accounting for the upper quartile of the indices calculated for all sensors, while a relatively good performance accounted for the lower quartile, and a mediocre performance for the interquartile range.

A correlation analysis was then performed for the five performance indices using the *corrplot* (Wei and Simko 2017) and *ggcorrplot* packages (Kassambara 2023). As initial data inspection indicated heteroscedastic patterns and several outliers, a rank correlation analysis was performed using the Kendall method (Kendall 1938, Hollander et al. 2015), which furthermore increases robustness to the sample size and potential ties. The correlation analysis served to identify underlying patterns between the normalised number of failures in general, resulting gaps, and types of interventions.

To avoid introducing a priori assumptions and bias when exploring relationships and similarity in failures, interventions, and data gaps between the systems, we refrained from pre-classifying sensor systems by categories, e.g. by hardware type or commercial status. Instead, we applied an exploratory, data-driven approach based on the five quantitative performance indices outlined above and performed cluster analysis using the *tibble* package (Müller and Wickham 2023). Euclidean distances were used to compute the distance matrix following Ward‘s minimum variance method for hierarchical clustering (Murtagh and Legendre 2014). The optimal number of clusters (k = 2) was identified following the silhouette method (Rousseeuw 1987), measuring the similarity of each observation to its own cluster and other clusters on a scale from -1 (observation poorly matched to the cluster) to +1 (observation well-matched to its own cluster) using the *cluster* (Maechler et al. 2024) and *factoextra* (Kassambara and Mundt 2020) packages. The average silhouette width gives a measure of overall cluster quality given for k clusters (Rousseeuw 1987). Following this, mean performance indices were calculated for the two clusters in order to identify properties defining the clusters. A clustering was initially also performed based on k = 3, k = 4, k = 5, and k = 6 as a form of exploratory data analysis and in order to identify potential smaller-scale common properties between different sensor types.

To determine the effect of system usage duration on the number of failures, the temporal changes in the normalised monthly number of failures per sensor system were analysed using generalised linear models (GLM) with count distributions. For each sensor, a separate model was fitted with the predictor variable *month*. Sensors with insufficient temporal variation (i.e. fewer than two time points) were excluded from the analysis to avoid estimation errors. To account for potential misspecification of the Poisson distribution, which is typically assumed for count data, we calculated the Pearson overdispersion statistic (ratio of the sum of squared Pearson residuals to the residual degrees of freedom) for each model (Dean and Lawless 1989, Hilbe 2014). Depending on the degree of dispersion, models remained fitted with a Poisson distribution (dispersion values close to 1), or were re-fitted with quasi-Poisson (dispersion value <0.7, underdispersion) or negative binomial (dispersion values >1.3, overdispersion) regressions. Model fitting was carried out using the base R *glm()* function for Poisson and quasi-Poisson models, and the *glm.nb()* function from the *MASS* package (Venables and Ripley 2002) for negative binomial models. For each fitted model, regression coefficients were extracted, including estimates, standard errors, and associated p-values using the *performance* package (Lüdecke et al. 2021). An exploratory weekly analysis was initially also attempted but proved unsuitable due to strong short-term fluctuations, including many weeks with zero values, which resulted in severe overdispersion.

Results

Descriptive assessment of sensor performance

A thorough examination of the normalised number of system failures, required interventions, and resulting data gaps reveals that the RGB cameras, climate measurement suites, and optical pig weighing systems consistently showed the relatively poorest performance across these indices. The RGB cameras had a normalised total of 122 failures (corresponding to 33.3 % of all reported failures), 39 required interventions (18.0 % of all interventions), and 71 resulting data gaps (28.3 %). The climate measurement suites in turn displayed 94 failures (25.7 %), 48 interventions (22.1 %), and 34 gaps (13.6 %). The optical pig weighing systems had 64 failures (17.5 %), 60 interventions (26.7 %), and 64 data gaps (25.5 %). Together, these three systems accounted for 76.5 % of all reported failures, 67.8 % of all required interventions, and 67.4 % of all resulting data gaps. Covering the mid-range, water flow meters had 36 failures (9.8 %), 24 interventions (11.1 %), and 34 gaps (13.6 %), and the cough monitoring systems had 32 failures (8.7 %), 28 interventions (12.9 %), and 32 gaps (12.8 %). The relatively best performance displayed the climate sensor boards and the SAMBa systems. The climate sensor boards had only 16 failures, required interventions, and resulting data gaps each (corresponding to 4.37, 7.37 and 6.37 %), while the SAMBa systems had two failures and interventions (corresponding to 0.55 and 0.92 % respectively), and no data gaps. The largest normalised number of required on-site interventions had the cough monitoring systems (28), followed by the climate measurement suites (22), RGB cameras (17), climate sensor boards (12), optical pig weighing systems (10), and water flow meters (6), while the SAMBa systems had no required on-site interventions. Figure 1 visualises the relative performance of the sensors based on the normalised number of failures (Figure 1a), required interventions (Figure 1b), resulting data gaps (Figure 1c), and required on-site interventions (Figure 1d).

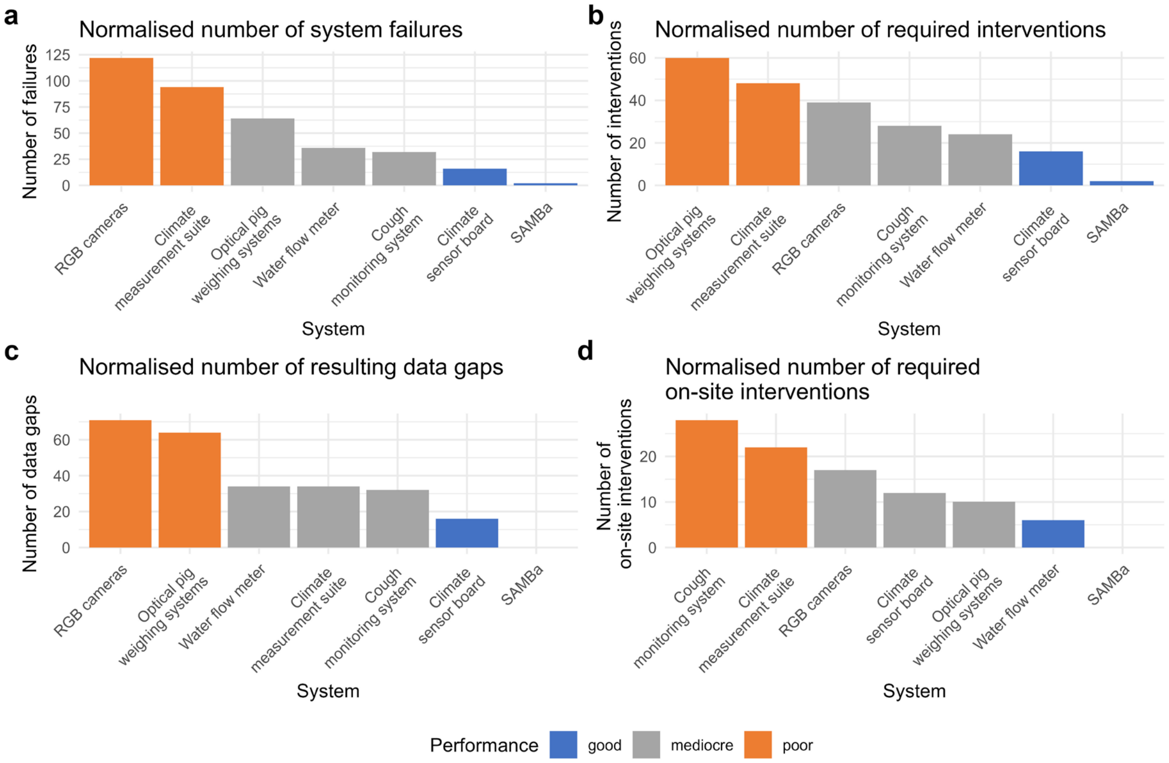

Figure 1: a) Number of system failures, b) required interventions, c) resulting data gaps, and d) required on-site interventions of the investigated systems, with relative performance rating determined by the upper (poor) and lower (good) quartile as well as interquartile range (mediocre); number of failures, interventions, and data gaps were normalised via sensor count

Beyond the indices above, the ratio of on-site interventions to all performed interventions for the corresponding system was highest for the cough monitoring systems (100 %), followed by the climate sensor boards (75.0 %), climate measurement suites (45.8 %), RGB cameras (43.6 %), water flow meters (25.0 %), optical pig weighing systems (16.7 %), and finally the SAMBa systems (0 %). In case of failures, an intervention was necessary most frequently for the SAMBa systems and climate sensor boards (100 % both), followed by the optical pig weighing systems (93.8 %), the cough monitoring systems (87.5 %), water flow meters (66.7 %), climate measurement suites (51.1 %), and finally the RGB cameras (32.0 %). Failures resulted in data gaps most often in the optical pig weighing systems, the cough monitoring systems, and climate sensor boards (in 100 % of cases each), followed by water flow meters (94.4 %), RGB cameras (58.2 %), climate measurement suites (36.2 %), and the SAMBa systems (0 %).

A summary of the mean, median, mode, and maximum failure duration can be found in Table 3. The mean duration ranged between 1.5 (climate sensor boards) and 11.8 days (water flow meters), the median duration between 0 (climate measurement suites) and 8.0 days (cough monitoring systems). As per the mode, most failures lasted for one day or less for all but the SAMBa and cough monitoring systems. Regardless, the longest continuous failure duration for individual sensors, across all fattening cycles and farms, was encountered for the water flow meters (121 days) and the RGB cameras (132 days), followed by the climate measurement suites (50 days). The remaining systems displayed maximum failure durations below 10 days.

Table 3: Normalised failure duration metrics (mean, median, mode, and maximum) for the investigated sensor systems[1)]

Sensor	Mean failure duration in days	Median failure duration in days	Mode of failure duration in days	Maximum failure duration in days
Climate sensor board	1.5	1.0	1	4
SAMBa	2.0	2.0	2	2
Water flow meter	11.8	3.5	1	121
Cough monitoring system	10.1	8.0	7	22
Optical pig weighing system	1.7	1.0	1	9
RGB camera	3.3	1.0	1	132
Climate measurement suite	2.9	0	0	50
Overall	3.8	1.0	1	132

[1)] The failure duration is defined as the number of days from initial failure occurrence until successful solution, with 0 days denoting the issue was resolved on the same day it was encountered. The mode denotes the most frequent duration. The maximum failure duration relates to the longest continuous failure recorded for a single sensor unit.

The investigated sensor systems all required different interventions. A detailed summary of all performed interventions can be found in Table A1 in the Appendix. The most frequent solutions for the RGB cameras included restarting closed monitoring software (due to automatic restart of corresponding computer) in order to continue recording (55 cases). Oftentimes, an intervention was not necessary at all, either because the error message produced by the monitoring software was a result of a temporary loss of connection to the camera, which was re-established automatically (30 cases), or because an automatic software update resulted in the computer restarting (10 cases) and temporarily losing connection. In ten other cases, the associated computer needed to be restarted on-site. The latter solutions accounted for solving 85 % of occurring issues with the RGB cameras. Remaining solutions (i.e. replacing broken components or minor required software adjustments) occurred fairly rarely (three or fewer times). Overall, the most encountered issues were temporary connectivity issues that were self-solved, and more than half of all issues could be solved remotely.

In case of the climate measurement suites, the most frequent intervention was restarting software that was closed due to automatic computer restart (18 cases), cleaning connections as well as replacing corroded cables (9 cases), re-establishing connection to the data storage server (8 cases), and restarting the computer on site due to shut-down for unknown reasons (6 cases). Further solutions included remotely restarting the computer and software (3 cases). In two cases, a sensor failure required contacting the support service and specialised personnel conducting repairs on site. In another case, no interventions were necessary, as the issue persisted only temporarily (most likely network connectivity problem).

The optical pig weighing systems required restarting software that was closed due to automated computer restart (11 cases) and restarting the computer on-site due to shut-down (9 cases). Further interventions included remotely restarting the computer and software (4 cases), repairing faulty components by specialised personnel (3 cases), and contacting the support of the sensor and issuing repairs (3 cases). In three cases, an intervention turned out to be not necessary as the recorded failure was a result of insufficient communication between the involved personnel.

For the water flow meters, the most common solution included restarting the associated computer and software (14 cases), which could be performed remotely. Furthermore, there was one case each where a re-configuration of the water flow meter was required, a network-connectivity issue needed fixing, and a broken water flow meter and cable needed replacement.

The cough monitoring systems required relocating the gateway to improve the signal strength in two cases, and in one case replacement of a faulty switch. In a total of five cases, however, an intervention was not necessary as the system was able to self-solve a likely network-connectivity issue.

The most common intervention required for the climate sensor boards was cleaning the lux meters (5 cases) due to accumulation of dirt preventing accurate reading, which occurred simultaneously on all sensors. The remaining required interventions were limited to restarting the associated computer software (2 cases), and restarting closed software due to automatic computer restart (1 case). In one case an intervention was not necessary as the apparent error was merely a result of insufficient communication between involved personnel.

Finally, the SAMBa system had only one required intervention. Thereby, the automated data back-up routine needed a manual modification by a dedicated expert. However, this resulted in no data loss and could be performed remotely.

Correlation analysis

The analysis across the investigated performance indices revealed that the highest correlation persisted between the number of data gaps and the number of failures (r = 0.88, p = 0.01), followed by a high correlation between the number of interventions and the number of remote interventions (r = 0.71, p = 0.02). Further significant correlations were found between the number of interventions and number of data gaps (r = 0.68, p = 0.03), and between the number of interventions and number of failures (r = 0.62, p = 0.05). All further remaining correlations were not significant at p > 0.05. All correlation results are presented in Figure 2.

Figure 2: Correlation plot of the normalised number of remote interventions, on site interventions, all interventions, failures, and resulting data gaps, across all investigated systems; bottom left half contains p-values and top right half correlation coefficients produced by the Kendall-test

Cluster analysis

The cluster analysis at k = 2 produced the following two clusters: Cluster 1, consisting of the water flow meters, climate sensor boards, SAMBa systems, and the cough monitoring systems; and Cluster 2, consisting of the RGB cameras, the climate measurement suites, and the optical pig weighing systems (Figure 3). The average silhouette width for k = 2 clusters was 0.51, attesting a moderate structure and reasonably well-separated clusters. The silhouette widths for k = 3, k = 4, k = 5 and k = 6 clusters were substantially lower (0.36, 0.24, 0.18 and 0.08 respectively), attesting no meaningful or only very weak clustering in comparison to k = 2, and thus, provide a worse foundation for the grouping of the investigated sensors (see also Table A2 in the Appendix).

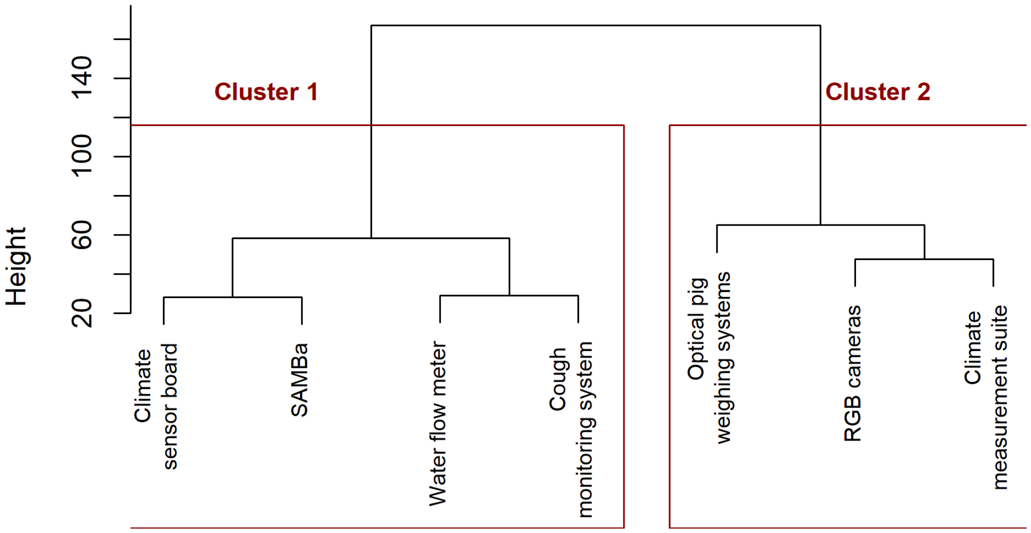

Figure 3: Dendrogram of the cluster analysis performed across the normalised number of sensor failures, all interventions, remote interventions, on-site interventions, and resulting data gaps for the investigated systems; the height (y-axis) represents the linkage distance (dissimilarity) at which clusters are merged, computed from Euclidean distances using Ward's method

At k = 2, Cluster 1 is characterised by a relatively low normalised number of failures and interventions (be it remote or on-site interventions), and minor resulting data gaps. Systems belonging to Cluster 2 on the other hand have an on average greater number of failures, required interventions, and data gaps (Figure 3 and Table 4). On average 65.7 % of all interventions in Cluster 1 and 33.3 % of interventions in Cluster 2 needed to be performed on-site.

Table 4: Averages of documented number of failures, interventions and data gaps for the determined clusters at k = 2; the data was normalised via sensor count prior to calculating averages

Cluster 1					Cluster 2				
Failures	Interventions	Remote	On-site	Gaps	Failures	Interventions	Remote	On-site	Gaps
21.5	17.5	6.0	11.5	20.5	93.3	49.0	32.0	16.3	52.5

Temporal evaluation

The regression analysis revealed no significant changes in the monthly failure reports in all sensor systems across the entire survey period (Table A3 in the Appendix). Figure 4 shows the normalised number of monthly failure reports for all systems. While the number of reports fluctuates between months, a clear pattern over time is not evident, regardless whether disaggregated by sensor systems or overall. The weekly visualisation of the number of failures per system can be found in Figure A1 in the Appendix.

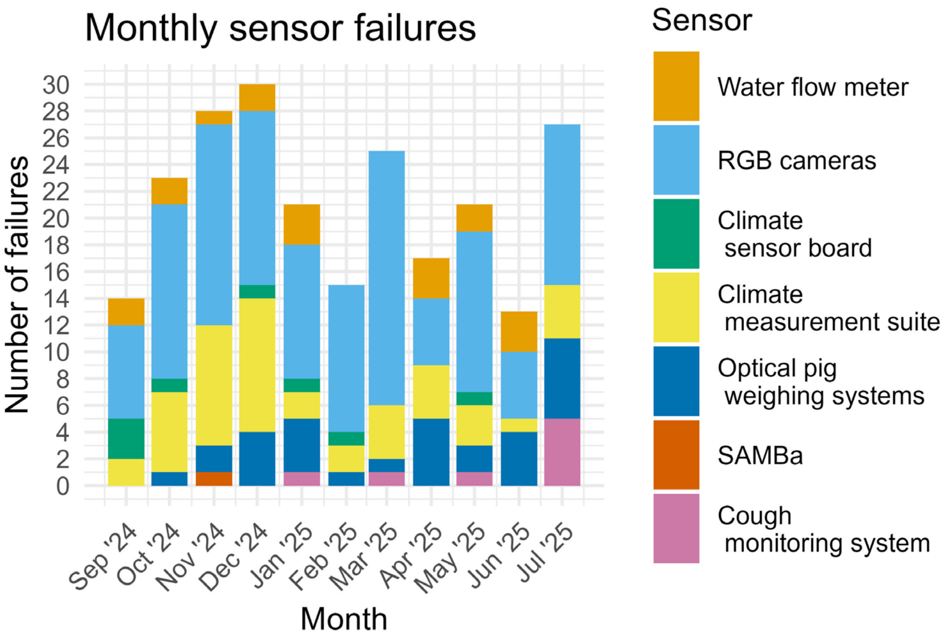

Figure 4: Monthly reported normalised number of sensor failures for all seven sensor systems across the entire survey period

Discussion

In this exploratory study, the robustness and reliability of commercially available sensor technologies, modified commercial systems, and adapted lower cost non-commercial systems under on-farm conditions were investigated. Based on five performance indices, the cluster analysis identified two groups of sensor systems: “low-effort” and “high-effort” systems.

The high-effort group consisted solely of relatively complex commercial systems (RGB cameras, climate measurement suites, optical pig weighing systems) and was characterised by a high normalised number of failures, interventions, and data gaps. From the average 345 days of data collection across all four farms during the three fattening cycles (110 to 124 days of data per fattening cycle), failures were registered on between 64 to 122 days (93 days on average), with the highest number of normalised failures for RGB cameras, which accounts for up to a third of data recording days. However, it should be noted that failures were recorded only on the initial day of occurrence and not every day until the issue was resolved. Consequently, the true number of days with failures may be substantially higher than the current number of failures recorded. The high number of failures potentially suggests a low reliability of the high-effort cluster, which seems to be consistent with farmers’ experience according to various surveys (Reichardt and Jürgens 2009, Marku et al. 2024, Reeves et al. 2025). For instance, only 47 % of farmers across Europe agreed that sensor-based technologies can be maintained at a reasonable cost and that it's easy to get technical assistance; furthermore, 39 % agreed that sensor-based technologies do not operate in a reliable manner (Banhazi et al. 2015). The seemingly low reliability of the systems in the high-effort cluster could be a consequence of their relatively high complexity, as the presence of multiple interconnected components and layered data pathways increases the number of potential failure points and the system's susceptibility to external stressors such as corrosion and network instability. Further, the low reliability could be also a result of a low robustness to a variety of typical on-farm conditions and challenges, which may result from these systems being primarily tested and validated under experimental settings and best-use practice with expert support on-site (Werkheiser 2020, Gómez et al. 2021, Stygar et al. 2021).

However, regardless of a high number of failures in the high-effort cluster, not all failures required an intervention. The majority of failures were either temporary (e.g. connectivity issues) and self-solved (automatic re-connect), or the software related to a certain system produced a warning or error message, which was documented but resulted in no required intervention. Most of the remaining failures (e.g. restarting software or computer) in the high-effort cluster could be resolved remotely, theoretically even by laymen. In contrast, on-site interventions, such as physical repairs, cleaning connections, replacing damaged or corroded cables or broken components, that were usually labour intensive occurred fairly rarely in comparison to the total number of documented failures. While the high number of self-resolving issues and remote interventions that are usually easily performed and require no in-depth knowledge greatly facilitates system management, they still might constitute a burden for the end user. This is due to the high overhead requirement, regular functionality checks, required troubleshooting and/or frequent warnings issued by the system, which in turn may disrupt the management routine of farmers (Islam and Scott 2022). Moreover, while some issues might be simple to solve, identifying the cause might not be. This in turn might demand a high degree of technical affinity and digital competence from farmers, which was shown to not meet the requirements imposed by sensor-based technologies (Zou et al. 2023, Lyu et al. 2025, Oli et al. 2025).

Further, failures in the high-effort cluster resulted in data losses in more than half of all cases, despite a low intervention demand. In line with our results, technical issues were reported to result in data gaps amounting to 28 or even 51 % of recorded hours (Bruijn et al. 2023). The data gap size may be particularly large in case of required on-site interventions due to the time-consuming logistical and administrative workload as well as technical know-how necessary to perform repairs (Tuyttens et al. 2022). In this study, interventions requiring technical support from the manufacturer were necessary three times for the optical pig weighing systems, twice for the climate measurement suites, and once for the RGB cameras, whereby the duration between initial failure occurrence and successful resolution was up to several weeks. Sensor and system failures that result in data gaps do not merely cause technical inconvenience, but may in some cases compromise animal health by failing to timely detect acute stressors or changes in the animals, thereby potentially leading to misguided management decisions (Tuyttens et al. 2022). Such issues might be noticed substantially later by farm personnel, as end-users of sensor systems may show over-reliance on the sensors and spend less time with the animals (Tuyttens et al. 2022). Consequently, a high data continuity is of paramount importance in practical applications.

Furthermore, interventions and data gaps were highly correlated in our study. Consequently, the duration of data gaps might be even longer, and the risk of missing important information correspondingly higher, if system inspections, troubleshooting and interventions are performed rarely, during the regular management routine by farmers. This might be particularly the case if farmers are less familiar with the system or not sufficiently technologically competent (Lyu et al. 2025, Oli et al. 2025). During periods where sensors do not function properly farmers are furthermore burdened with additional workload to compensate for the data loss, e.g. by performing more inspections in person (Gómez et al. 2021, Islam and Scott 2022, Tuyttens et al. 2022).

In contrast to the high-effort cluster, the low-effort cluster was composed of lower cost adapted non-commercial (climate sensor boards), low-cost non-commercial (SAMBa), modified commercial (water flow meters), and a simple commercial cough monitoring system. This cluster displayed a lower normalised number of failures, fewer interventions, and data gaps than the high-effort cluster. Across an average of 345 days of monitoring, failures were registered on between 2 and 36 days (22 days on average). A typical intervention could not be confidently identified for the low-effort systems due to the overall low number of interventions. However, in contrast to the high-effort cluster, most interventions required on-site presence (65.7 %) and, therefore, typically implied high workload. In addition, none of the failures documented for the systems in the low-effort cluster self-solved, suggesting a relatively high intervention burden. Further, the non-commercial and the modified systems had to be installed and occasionally maintained by specialised personnel, which might have also contributed to the low number of failures. However, the commercial cough monitoring systems were neither installed nor maintained by specialised personnel, but instead similarly to the other commercial systems by maintenance personnel in accordance with product instructions. The cause for the low number of failures, interventions, and data gaps might be due to the simplicity of the cough monitoring systems and the data, as it consists only of one detector unit and data transfer occurs wirelessly, which eliminates the risk of cable corrosion.

The regression analysis of the monthly number of failures did not reveal significant trends across the survey year for any of the systems, although an increase in the number of failures due to gradual accumulation of dirt and corrosion was expected. Thus, it seems conclusive that month-to-month variation is largely noise, which was even more prominent in weekly resolution (Figure A1 in the Appendix). It has to be noted, however, that some long-term related effects of the barn environment on the number of failures have been counteracted in this study by the practical necessity to replace faulty components, clean sensors, and by the removal of sensor systems for the purpose of washing the pens. Thus, due to the interventions and the study duration of only one year, with each season represented only once, a relationship between seasonal effects and long-term damage by corrosion cannot be completely ruled out.

Since the results are based on case study observations across four farms representing three pig husbandry types, with different conditions, as well as a varying number and types of sensors installed, it could be argued that all these factors may have introduced a confounding effect. However, while environmental conditions actually varied between the farms, as shown in the methods, no single farm exhibited unusually high or low number of failures or interventions. Further, all installed sensor systems were managed equally in terms of maintenance and inspections of system failures, and it was ensured that internet connections on all farms were adequate. In addition, the differing number of sensors on the farms was accounted for in our study by normalising the number of failures, interventions, and data gaps via sensor count, and by classifying events with a common underlying cause as a single failure. Finally, all commercial systems except one were installed on three of the four farms, representing a reasonably balanced distribution. For all those reasons, it is unlikely that the differences observed between the sensor systems resulted from the farms and their respective conditions.

Conclusions

This explorative study indicates that commercially available systems with potentially greater complexity exhibit a higher number of failures, require more remote and fewer on-site interventions, and have a lower data resilience compared to simpler commercial systems and systems in development or adapted systems. However, while the number of failures in the complex commercial systems was high, most of the failures were self-solving, providing an advantage over the simpler commercial systems and systems in development or adapted systems that showed fewer failures but required more on-site intervention, usually imposing higher workload. Considering that even rare on-site or frequent remote interventions require regular inspection of system failures and consequently disturb the management routine, thereby impairing reliable data acquisition, there is room for improvement in the complex commercial systems. Thus, simple commercial systems, generally characterised by e.g. low component count, limited processing layers, clearer data pathways, and straightforward installation, can be recommended for adoption on pig farms when data continuity and a low maintenance burden are prioritised.

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