SMART FARM MANAGEMENT IN BROILER PRODUCTION: TECHNOLOGIES AND PRODUCTIVE PERFORMANCE - A REVIEW

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Abstract

This narrative review assessed smart technologies and their implications for broiler productive performance. A structured search of ScienceDirect, PubMed, Web of Science and Scopus identified 46 references published in 2015-2026. Topics included microclimate monitoring, automated weighing, feed and water monitoring, precision feeding, IoT platforms and predictive analytics. Studies mainly demonstrated measurement and prediction capabilities, with more consistent results for live weight than mortality. Evidence of productive benefits from technology-guided interventions remained limited. Adoption barriers included costs, calibration, maintenance and interoperability. Wider use requires commercial validation, reliable data and evidence of productive and economic benefits.

Key words: *broiler production, Internet of Things, machine learning, precision livestock farming, predictive analytics.*

INTRODUCTION

Poultry meat had the highest global production volume among the major meat categories in 2022-2024, averaging approximately 145 million tonnes per year, and is projected to account for 62% of the increase in global meat production by 2034 [1]. This projected growth, together with labour constraints and increasingly complex production systems, has strengthened the need for objective and timely information. Smart poultry management addresses these demands by connecting sensors, automated equipment and analytical platforms, making farm data available to support decisions concerning production conditions and resource use [2]. This approach is grounded in precision livestock farming (PLF), which uses continuous automated measurements of animals and their environment to support management decisions or activate control systems in real time [3]. Its contribution must be evaluated against clearly defined objectives, which may include production efficiency, animal health and welfare, or a combination of these outcomes.

This distinction is important because technologies developed for one purpose do not necessarily provide sufficient information to assess another [4]. The need to reconcile these objectives is also recognised in other poultry sectors, where automated monitoring, smart feeding and data-driven health assessment are considered tools for balancing productivity, welfare and sustainability across housing systems [5].

In broiler farming, PLF applications include monitoring temperature, humidity, air composition, body weight, feed and water consumption, and animal activity. These measurements provide

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complementary information about rearing conditions and flock development, helping farmers identify deviations from expected growth trajectories or target environmental conditions. Their managerial value depends on connecting these observations within a coherent framework, since many available tools assess individual parameters or closely related groups of variables [6]. Linking environmental records with production measurements provides a basis for investigating relationships between rearing conditions and productive outcomes. In a 35-day broiler trial, IoT monitoring and machine learning were combined to analyse thermal conditions alongside feed intake, body weight and feed conversion ratio. The findings illustrate the potential of integrated datasets for modelling growth performance. However, predictive capability should be distinguished from evidence that using these models improves performance through subsequent management interventions [7].

The interpretation of such results must also account for nutritional conditions. In organically reared Barred Plymouth Rock chickens, reduced dietary crude protein or metabolizable energy resulted in poorer feed conversion despite comparable overall weight gain. Although this experiment did not evaluate smart technologies, it illustrates why growth and feed utilisation should be considered together when assessing production responses to management practices [8].

Beyond production indicators, IoT and machine learning applications extend to poultry health and welfare, broadening the information available for flock assessment [9]. Examples from other livestock sectors illustrate complementary uses of connected technologies. In cattle farming, IoT platforms enable microclimatic parameters to be examined alongside air pollutant measurements [10], while in pig production, sensors, cameras and artificial intelligence support animal monitoring and informed farm decisions [11]. Across these applications, the usefulness of analytical outputs depends on appropriate validation.

In cattle behaviour recognition, comparisons between support vector machine, random forest and extreme gradient boosting models showed that high overall accuracy can coexist with poor recognition of less frequent behaviours [12]. A systematic review of sensor-based cattle monitoring similarly emphasised evaluating precision, recall and F1-score alongside accuracy and selecting algorithms according to the task and data characteristics [13]. These findings offer methodological considerations for poultry monitoring, subject to species-specific datasets and validation. Reliable evaluation must be accompanied by practical integration into farm operations.

Recent developments in intelligent poultry farming include non-contact body weight estimation, multi-sensor approaches and edge computing for timely data processing. Nevertheless, high system costs, difficulties in combining heterogeneous measurements and limited algorithmic robustness across environments remain important constraints [14]. The wider adoption of these technologies therefore requires solutions that deliver reliable information and can be incorporated into routine management under commercial production conditions. The predominance of experimental studies and the limited availability of practical implementation evidence further highlight the need to examine the contribution of these technologies under commercial broiler conditions [6].

The present review therefore aims to analyse the main technologies used in smart broiler farm management and critically examine their implications for productive performance. Particular attention is given to environmental sensors, automated weighing, feed and water monitoring, and IoT-based platforms for data collection and

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interpretation. The analysis focuses on how these technologies support managerial decisions, the evidence linking their application to productive outcomes, and the barriers affecting their implementation.

MATERIAL AND METHOD

This narrative review was based on a structured literature search in the ScienceDirect, PubMed, Web of Science and Scopus databases. Search terms combined the production system (*broiler*, *poultry*), technological approaches (*smart farming*, *precision livestock farming*, *Internet of Things*, *sensor*, *machine learning*) and monitored parameters or applications (*microclimate*, *ammonia*, *body weight*, *automatic weighing*, *machine vision*, *feed intake*, *water consumption*, *precision feeding*, *early warning*). Reference lists of relevant publications were also screened to identify additional sources. A total of 46 references were included in the review.

English-language, peer-reviewed original studies and reviews published between 2015 and 2026 were considered. Publications were selected for their relevance to environmental monitoring, automated weighing, feed and water consumption, automated feeding, farm data integration, predictive analytics and barriers to implementation in broiler production. Priority was given to studies reporting quantitative findings on measurement accuracy, predictive performance, productive outcomes or production costs. Studies involving other livestock species or poultry categories were included only when they provided methodological or contextual information relevant to the review.

Information was extracted on the technology evaluated, monitored parameters, experimental or commercial setting, sample size, evaluation period and reported performance indicators. Evidence was synthesised qualitatively, distinguishing between measurement validation, predictive capability, effects of management interventions on productive performance, and contextual findings concerning implementation. Particular attention was given to validation conditions, sampling representativeness and limitations affecting applicability to commercial broiler farms.

Where appropriate, relative percentage changes were calculated from published mean values as the difference between the treatment and reference means divided by the reference mean and multiplied by 100. Figures summarised reported data and technological approaches; results obtained under different experimental conditions were not treated as directly comparable.

RESULTS AND DISCUSSION

Microclimate monitoring

This section first outlines the microclimatic factors with documented effects on broiler performance, then examines how they are measured, interpreted and linked to productive outcomes. Thermal conditions are among the environmental factors with the most direct influence on broiler performance. Under heat stress, feed intake decreases by approximately 1.5% for each degree Celsius under cyclic exposure and by about 3.5% per degree under constant exposure between 22 and 35 °C. Reduced intake explains most, but not all, of the associated growth depression, since heat stress also alters protein and energy utilisation. Continuous temperature recording is therefore relevant not only for bird comfort but also for interpreting variations in growth and feed efficiency [15].

Field data from commercial broiler flocks indicate that temperatures below the recommended range can also adversely affect performance, particularly during the first weeks of rearing. In 80 broiler flocks monitored with hourly temperature and humidity sensors, each hour spent 5 °C below the target temperature was associated with an estimated 4.9 g lower body weight at 21 days,

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while prolonged exposure to temperatures 2.5 °C below the recommendation increased mortality at 28-35 days. Relative humidity, by contrast, showed only weak and inconsistent associations with performance, and the temperature-humidity index was related mainly to feed conversion at 21 days. These results suggest that the value of microclimate data lies in recording the duration and timing of deviations, rather than average conditions alone [16].

Air quality represents a further component of the microclimate, with ammonia providing an important example of the relationship between gaseous exposure and productive performance. During a 21-day exposure trial, a concentration of 15 ppm did not significantly affect growth, whereas 25 ppm reduced body weight gain by approximately 9% and increased feed conversion ratio by about 8% compared with the unexposed control. At 35 ppm, feed intake decreased by about 17%, body weight gain by about 45%, and these changes were accompanied by alterations in the intestinal microbiota (Figure 1). These findings support the relevance of ammonia monitoring for identifying exposure levels that may warrant ventilation or litter-management interventions [17].

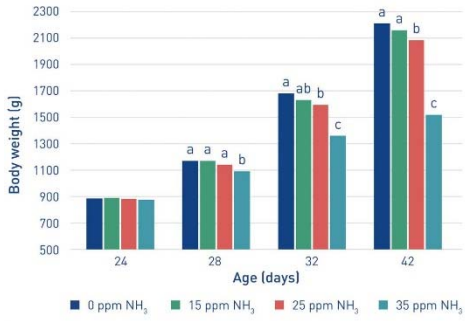


Figure 1. Effect of ammonia on the body weight of broiler chickens between 22 and 42 days of age [17].

The usefulness of environmental monitoring also depends on where measurements are taken. In tunnel-ventilated houses, geostatistical analysis of the temperature-humidity index has been used to identify the most representative sensor positions for ventilation control during the hottest hours of the day [18]. In a climate-controlled house monitored at nine points over a 42 day cycle, only about one quarter of the floor area was classified as thermally comfortable during weeks 3-5, with lower index values near the evaporative pads and higher heat load near the exhaust fans in the final weeks. Weeks with unfavourable conditions coincided with performance below the genetic target [19]. Together, these findings indicate that spatial variability should be considered when selecting monitoring locations, as a single measurement point may not adequately represent conditions across the house.

Recent IoT developments aim to make continuous multi-parameter monitoring more accessible. A wireless network of six nodes measuring temperature, humidity, carbon dioxide and ammonia was connected to a controller that applied age-specific set points and actuated fans, curtains, heaters and misting systems. However, field testing covered only one daily cycle, and only the ammonia sensor was calibrated against a reference instrument [20]. Similarly, a low-cost, solar-powered unit combining temperature, humidity, ammonia and methane sensors with SMS alerts showed strong correlations with measurements from commercial reference devices ($r > 0.96$) at roughly 12% of their cost, but was tested only under laboratory conditions, without birds [21]. These studies support technical feasibility within their respective testing conditions, but do not establish effects on growth, feed conversion or mortality.

Beyond data acquisition, microclimate records are increasingly processed with machine learning to classify thermal discomfort. In four commercial houses sampled at 12 points three times daily, a random forest model identified discomfort with 97.1% accuracy on a randomly selected

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test set, but accuracy decreased to 82.2% and recall to 64.7% when the model was validated on flocks not used for training. Bird weight, air speed and air temperature were the most influential predictors. The gap between the two validation approaches shows that results obtained on data from the same flocks may overestimate model reliability when the model is applied to new production cycles [22].

Overall, the reviewed studies demonstrate the relevance of temperature and ammonia measurements for interpreting broiler performance, while the extent of technical and field validation varies between monitoring applications. Evidence that monitoring itself improves productive outcomes is more limited and comes mainly from comparisons between housing systems, in which sensor-based control cannot be separated from ventilation design, cooling capacity and management. Comparisons conducted under similar housing conditions, with and without clearly defined sensor-guided interventions, would help quantify the specific contribution of monitoring to productive outcomes. This need for further commercial validation is consistent with the broader limitations identified for precision technologies in broiler production [6].

Automated weighing and growth monitoring

Body weight and flock uniformity are complementary indicators of growth, and their monitoring provides the basis for comparing flock development with genetic targets. The coefficient of variation of body weight describes relative weight variability, with lower values indicating greater uniformity. Uniformity may also be expressed as the proportion of birds within a specified range around the flock mean; therefore, the definition used should be stated when comparing studies. Modern broiler flocks typically show body weight coefficients of variation of 10-15% at market age. Reductions in uniformity of approximately 2.5-15% have been reported across studies examining environmental, nutritional, infectious and management challenges, although their magnitude depends on the conditions investigated. Since processing lines are designed for birds of similar weight, variation in slaughter weight has implications for processing efficiency and economic returns, making uniformity a relevant output of automated weighing systems [23].

Floor-level weighing platforms collect measurements when birds voluntarily step onto the weighing surface. In a system with two strain-gauge sensors and cloud-based data processing, tested over 101 production cycles, the mean relative error compared with the live-bird sales weighing system was -0.54%, and the correlation between estimated and reference weights reached 0.99. However, the number of valid daily readings decreased linearly with age, potentially reflecting reduced mobility and less frequent platform visits by heavier birds. In one validation trial, uniformity, expressed as the proportion of birds within ±10% of the mean weight, was 52.5% for the platform and 29.0% for the live-bird sales system. The authors questioned the representativeness of the reference data for estimating variability; therefore, this discrepancy does not establish that the platform overestimated flock uniformity [24].

Weighing elements can also be integrated into structures that birds use voluntarily. Elevated platforms fitted with load cells provided daily mean weights that correlated closely with manual weighing (Spearman's $\rho = 0.987$), although the reported relative absolute estimation error averaged 11%. The combination of a high correlation and a measurable estimation error illustrates why correlation alone is insufficient to establish agreement between methods. These platforms also allowed the monitoring of platform use and activity, extending their application beyond body weight estimation [25].

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The amount of data generated by automated scales requires processing before it can support decisions. [26] collected data from 36 farms using a system with three electronic scales. In the illustrated preprocessing example, noise removal left approximately one fifth of the records missing, which were subsequently imputed using MissForest. Validation against delivery-day weights was also affected by the removal of some birds during transport operations. These findings highlight the importance of data preprocessing and representative reference measurements when evaluating automated weight estimates.

Camera-based systems estimate body weight without requiring birds to step on a scale. A top-view machine vision model developed for broilers reared for 42 days achieved a high coefficient of determination (R^2 = 0.98), although relative errors were greater during the early stages of growth. The study used images of individual birds acquired under controlled imaging conditions, which should be considered when assessing its applicability to commercial group settings [27].

Beyond estimating current weight, automated records can support growth forecasting. Johansen et al. (2017) used data from 12 production cycles in a commercial house, allocating ten cycles to model training and separate batches to prediction and evaluation. The dynamic neural network incorporated environmental measurements and control references and jointly modelled body weight and cumulative feed and water consumption, with forecasts extending from day 7 to day 34. However, weighing-pad measurements were negatively biased from approximately day 15 and had been corrected using a manually configured, time-varying factor, introducing additional uncertainty. The authors noted that the model could learn characteristics of the weighing-pad measurements rather than actual bird weight, illustrating how measurement bias can affect forecast interpretation and validation.

Overall, automated weighing provides frequent estimates of flock body weight, but its reliability depends on the measurement method, sampling representativeness, data processing and validation conditions. The studies discussed here identify distinct challenges in estimating weight distributions, applying image-based methods beyond their development conditions and using potentially biased measurements in forecasting models. They primarily evaluate measurement or forecasting performance, rather than testing whether management interventions informed by automated weighing improve growth, feed conversion or flock uniformity. The three weighing approaches described above, together with their main strengths and limitations, are summarised in Figure 2.

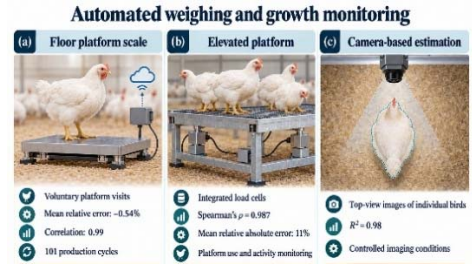


Figure 2. Automated weighing approaches in broiler production: (a) floor platform scale; (b) elevated platform with integrated load cells; and (c) camera-based body weight estimation. Reported results and methodological limitations are summarised from [24], [25] and [27], respectively. Results derive from different experimental settings and are not directly comparable. Illustrations are schematic.

Feed and water consumption monitoring and automated feeding systems

Water use can be recorded continuously at flock level using flow meters, providing information on changes throughout the production cycle. In two commercial broiler flocks reared to 63 days, cumulative consumption between days 8 and 63 averaged approximately 14.6 L per bird, while daily consumption relative to body weight decreased with age, from

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approximately 240-280 to 80-90 mL/kg/day. Water use declined in one flock between days 55 and 58 during an outbreak of gangrenous dermatitis, whereas the other flock showed reduced early water consumption and growth associated with a runting-stunting challenge and high house temperatures. These observations illustrate how continuous water records can reveal deviations associated with health and environmental disturbances, although their interpretation requires consideration of possible differences between water supplied and water actually ingested [29].

Such records should nevertheless be interpreted as indicators of change rather than as diagnostic measurements. In a study of 50 commercial broiler flocks, water consumption, body weight and mortality were less informative for predicting footpad dermatitis and hockburn at slaughter than camera-based measures of flock movement, which provided earlier indications of subsequent welfare problems. Water records therefore offer complementary information, but their interpretation benefits from integration with other flock measurements and observations [30].

Measuring feed intake presents additional challenges, particularly when consumption must be assigned to individual birds and distinguished from feed wastage. An acoustic approach tested on ten 39-day-old broilers used feeding sounds to estimate intake, achieving a coefficient of determination of $R^2 = 0.994$ against a reference weighing system [31]. An automated feeder combining RFID identification with load cells for body weight, feed and spilled feed achieved static weighing errors below 1 g. It also recorded approximately 1.7 g of spillage from 6.1 g of feed removed per meal, indicating that approximately 28% of feed disappearance represented wastage rather than ingestion [32]. These small-scale studies demonstrate approaches to measuring feeding activity and accounting for spillage, while their applicability to routine commercial monitoring requires further assessment.

Beyond measuring consumption, automated feeding systems can adjust dietary composition to estimated requirements. Growth is sensitive to nutrient supply: in meat-type quails, maintaining 24.8% crude protein until six weeks of age, rather than reducing it to 22.5% from week four, increased body weight at 42 days by about 15% [33]. In a precision feeding trial in broilers, two concentrates were blended daily and compared with a standard four-phase feeding programme. Feed cost per kilogram of gain was approximately 4% lower, although this difference was not statistically significant. The trial was conducted in experimental pens containing 11 birds each; consequently, the results support the approach under the tested conditions but do not establish its effectiveness in commercial flocks [34].

Overall, these studies distinguish between monitoring resource use and actively adjusting nutrient supply. Water records can reveal deviations requiring investigation, while individual feed monitoring must distinguish ingestion from wastage. Precision feeding offers a means of adapting nutrient supply, but its productive and economic benefits require further validation under commercial conditions, together with equipment reliability and the feasibility of updating feeding plans.

IoT platforms, data integration and predictive analytics

A cloud platform integrating inspection robots with environmental and audiovisual data was tested for three months in a commercial caged broiler house. Backend availability reached 99.95%, while dead-bird detection achieved 90.6% precision and 90.4% recall. False alarms involved resting or feeding birds, and occlusion contributed to missed detections. These results support operational feasibility under the tested conditions, although applicability to other housing systems requires further validation [35].

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Platform architecture also influences information availability. A dependability study compared edge-, fog- and cloud-based configurations for a poultry monitoring system. In the modelled cloud-based architecture, estimated annual downtime decreased from 34.14 hours without redundancy to approximately 9.18 hours when hot-standby redundancy was introduced at the office node. These estimates depend on the assumed failure and repair parameters and should not be interpreted as observed farm downtime. Nevertheless, they illustrate how architectural choices can influence service continuity when monitoring supports time-sensitive decisions [36].

Integrated production records also support the prediction of performance indicators. Using commercial farm data, tree-based machine learning models achieved live-weight prediction R^2 values of up to 0.97, although root mean square errors increased to approximately 121-128 g in the oldest age category. Mortality prediction was less reliable, with R^2 values ranging from -1.63 to 0.53; negative values indicate performance worse than a prediction based on the observed mean. Forecasts of the performance efficiency factor from day 21 to day 28 had relative errors of 4.42-5.40%, with live-weight prediction contributing strongly to the accuracy of this composite indicator. Results therefore differed substantially between prediction targets, highlighting the need to assess each output separately [37].

Whereas dead-bird detection identifies an event that has already occurred, individual behavioural records may support earlier identification of birds at risk. Electronic feeders with RFID identification recorded approximately 99.5 million feeding visits from 95,711 pure-line broilers across 146 consecutive trials. Depending on the behavioural trait, group-level differences between healthy birds and those subsequently culled or found dead became apparent approximately 7-17 days before removal, defined here as culling or death. These differences did not establish reliable individual prediction over the same interval. Classification models achieved an area under the receiver operating characteristic curve of up to 0.87 for prediction one day in advance, compared with approximately 0.80 at three days. The authors also described a possible threshold adjustment yielding approximately 67% sensitivity and 50% precision, meaning that about half of positive predictions would not correspond to removal the following day. These findings demonstrate predictive potential within the studied pure-line population, but require validation in commercial broiler populations [38].

Overall, integrated platforms combine environmental, production and behavioural records to support broiler flock management (Figure 3). The studies reviewed demonstrate distinct capabilities, including maintaining service availability, detecting dead birds, forecasting live weight and identifying birds at risk of removal. These functions require separate validation because they address different management tasks and use different performance metrics. Their practical contribution ultimately depends on whether the information provided leads to timely actions and measurable improvements in productive performance under commercial conditions.

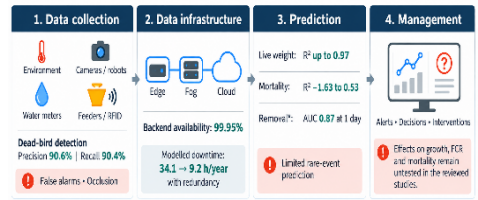


Figure 3. Data collection, infrastructure, predictive analytics and management applications in broiler production. Selected results and limitations are summarised from [35–38]. Metrics derive from different studies and are not directly comparable. Removal refers to culling or death; FCR = feed conversion ratio; AUC = area under the receiver operating characteristic curve.

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Implications for productive performance

Smart technologies may influence productive performance through four potential pathways: maintaining housing conditions closer to their targets, detecting deviations in growth, intake or behaviour earlier, matching nutrient supply more closely to requirements, and reducing losses of feed, water and energy. Evidence from other poultry categories provides context for these pathways. In Ross 308 breeder roosters, sub-standard light intensity, stocking density and litter type were associated with lower ejaculate volume at 25 and 35 weeks of age [39]. In laying hens, similar laying intensity between aviary and improved battery systems was accompanied by higher feed consumption per egg and more frequent flock exits in the aviary system [40]. These findings illustrate the relevance of housing and resource-use efficiency, but do not directly demonstrate benefits from smart technologies in broilers.

The economic relevance of these technologies depends substantially on feed efficiency. On a Polish commercial broiler farm, feed represented 69.6-76.1% of total production costs between 2020 and 2023, suggesting that even modest improvements in feed conversion could be economically relevant [41]. However, the reviewed evidence is concentrated on measurement validation and prediction, while improvements resulting from technology-guided management interventions have been quantified less frequently. Technical performance should therefore be distinguished from demonstrated productive and economic benefits.

Future evaluations should compare broiler flocks reared under similar housing conditions, with and without clearly defined sensor-guided interventions, over successive commercial production cycles. Outcomes should include body weight, feed conversion ratio, flock uniformity, mortality and production efficiency, alongside feed, energy and labour costs per kilogram of live weight. Economic assessments should also account for equipment acquisition, installation, maintenance and replacement. Recording false alarms, response times and the interventions actually applied would help establish whether, and under which conditions, the information generated translates into productive and economic benefits.

Barriers to implementation

The adoption of smart technologies depends not only on their technical performance but also on how producers assess their costs, reliability and practical demands. A survey distributed to 531 broiler producers in Tennessee found that most respondents were unfamiliar with precision livestock farming but expressed willingness to adopt it if improvements in farm productivity and profitability could be demonstrated [42]. A review of European pig and poultry projects similarly identified investment costs, particularly for smaller farms, and uncertainty about financial returns as important barriers. Additional concerns included adapting existing buildings, maintenance requirements, access to rapid technical support, system complexity and the skills needed to interpret the information generated [43]. These findings highlight the importance of evaluating technologies against the operational and economic conditions of the farms expected to adopt them.

Sensor performance varies between parameters, making calibration and field validation essential components of implementation. [44] evaluated a low-cost IoT sensor system for poultry-house microclimate monitoring and reported differences in performance between sensor types. Such differences indicate that the suitability of a monitoring system should be assessed separately for each parameter rather than inferred from the performance of its most reliable sensors. Coefficients of determination describe the relationship with

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reference measurements but should be considered alongside measurement errors and possible systematic bias.

Maintaining reliable measurements over time presents a further challenge, particularly for gas sensors exposed to poultry-house conditions. Drift and limited service life have been identified as weaknesses of semiconductor and electrochemical ammonia sensors. As an alternative, a sensor based on tunable diode laser absorption spectroscopy was tested during six days of continuous monitoring in a poultry house. Checks using standard gas supported its stability over the tested period, but this short deployment does not establish long-term performance [45]. Calibration checks, maintenance and replacement requirements therefore remain relevant considerations when selecting equipment for routine monitoring.

The house environment also creates practical demands for equipment maintenance. Dust accumulation, humidity and exposure to gases can affect sensor operation, while camera-based applications require attention to lens cleanliness and lighting conditions. These challenges mean that performance achieved during development must be reassessed under routine farm conditions and sustained throughout successive production cycles

Beyond individual devices, integration is constrained by differences in communication protocols, data formats and proprietary interfaces. These differences can complicate the combination of equipment from multiple suppliers and the transfer of analytical models between farms. Data ownership, access, sharing and security also require clear arrangements between producers and technology providers. Addressing these issues is necessary for turning separate monitoring tools into dependable systems that fit existing management practices [46].

Overall, implementation depends on sustained measurement quality, compatibility with existing infrastructure, accessible technical support and information that producers can readily interpret and use. Evaluation should therefore consider calibration, maintenance, interoperability and total operating costs alongside technical performance and demonstrated farm-level benefits.

CONCLUSIONS

Smart technologies support continuous monitoring of microclimate, body weight, feed and water use in broiler production, while integrated platforms enable data storage, analysis and decision support. The reviewed studies report promising results for temperature monitoring and mean body weight estimation, although reliability depends on calibration, sampling representativeness and validation conditions. Estimating flock uniformity, applying camera-based weighing in group settings and maintaining gas-sensor performance remain challenges. Predictive performance also varies by target, with live-weight estimates generally more promising than mortality-related predictions.

Most studies demonstrate measurement or predictive capabilities rather than improvements resulting from technology-guided management. Evidence of productive benefits remains limited and context-dependent, particularly when monitoring is combined with broader changes in feeding or housing systems. Wider adoption therefore requires validation across successive commercial production cycles, sustained data quality, interoperable equipment and accessible technical support. Ultimately, the value of smart management should be assessed through timely interventions and measurable productive and economic benefits.

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