Journal of Poultry Sciences and Avian Diseases

Journal homepage: www.jpsad.com

Artificial Intelligence Applications in Poultry Health and Welfare Monitoring: A Systematic Review and Meta-analysis of Model Performance

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Article Info

Article type:
Review Article

How to cite this article:
Janani, M. & Hajipour, P. (2026). Artificial Intelligence Applications in Poultry Health and Welfare Monitoring: A Systematic Review and Meta-analysis of Model Performance. *Journal of Poultry Sciences and Avian Diseases, 4*(4), 1-11.
http://dx.doi.org/10.61838/kman.jpsad.226

ABSTRACT

Artificial intelligence (AI), machine learning, computer vision, sensor-based systems, and Internet of Things (IoT) technologies are increasingly used for automated monitoring of poultry health and welfare, but reported model performance varies across tasks, data sources, validation strategies, and production settings. This systematic review and meta-analysis evaluated the reported performance of AI-based models for poultry health and welfare monitoring. PubMed/MEDLINE, Scopus, and Web of Science were searched for peer-reviewed studies involving poultry, reporting health- or welfare-related monitoring outcomes, and providing extractable model-performance data. Data were extracted independently by two reviewers, and pooled accuracy was estimated using a Restricted Maximum Likelihood random-effects model in STATA version 17. Twenty-one studies published between 2012 and 2025 were included, of which ten were eligible for meta-analysis. Included systems used convolutional neural networks, random forests, support vector machines, and other machine-learning approaches for behavior recognition, disease detection, lesion assessment, mortality detection, environmental monitoring, and welfare assessment. The pooled accuracy estimate was 90.39% (95% CI: 84.89–95.89; $p<0.001$), with substantial heterogeneity among studies. Reported performance varied by application domain, data source, model type, assessment dimension, sample size, and integration with IoT-based systems. AI-based technologies show promise for automated poultry health and welfare monitoring; however, heterogeneous methods and limited external validation restrict the generalizability of pooled estimates. Future studies should prioritize standardized reporting, open datasets, external validation, and testing under commercial farm conditions.

Keywords: *Artificial intelligence; Machine learning; Poultry; Welfare; Health monitoring*

Article history:
Received 4 April 2025
Revised 13 July 2025
Accepted 29 July 2025
Published online 01 October 2026

1 Introduction

Continuous monitoring in poultry farms is essential for the timely identification of abnormal behavior, environmental stress, and early signs of disease (Cruz et al., 2025; Fan et al., 2025). Due to the high density and flocks' sensitivity to environmental changes and diseases, early detection is crucial; delays in identifying problems can lead to mortality and economic losses. Early detection and timely alarms enable rapid intervention, reduce mortality, and improve welfare and productivity. Traditional monitoring methods entail high costs, require significant staff, and entail the risk of human mistake (Elwakeel, 2025). The assessments are often time-consuming, labor-intensive, and costly, especially in large-scale poultry (Michels et al., 2025). In addition, manual evaluations are highly subjective, and inter- or intra-observer variation or errors may affect the assessments (He et al., 2022). Artificial intelligence is an effective solution to these limitations by enabling continuous, automated, and objective monitoring of poultry (Li et al., 2020).

Artificial intelligence and machine learning technologies are increasingly used across all fields (Naeem et al., 2025). Poultry production, health surveillance, welfare assessment, growth prediction, and automated decision-making are areas where artificial intelligence provides accurate assessments (Kalita et al., 2025; Srinivasagan et al., 2025). The literature has reported high performance of AI applications in poultry. Tasks such as disease detection from chicken images, behavioral monitoring through video analysis, sound-based stress recognition, and prediction of growth or productivity outcomes or outbreaks are common applications of AI in modern poultry (Kalita et al., 2025). However, due to rapid expansion in this field, the evidence-based review remains unstructured. The literature on the application of AI in poultry management varies widely in sample sizes, data types, analytical models, validation methods, and reporting, which makes it difficult to draw consistent conclusions about overall AI performance. Although previous reviews have summarized AI, IoT, and computer vision applications in poultry production, a quantitative synthesis of reported model performance estimates across poultry welfare and health monitoring tasks remains limited. The aim of this systematic review and meta-analysis was to evaluate the reported performance of AI- and machine-learning-based models for poultry welfare and health monitoring, with particular attention to model accuracy, heterogeneity, application domains, data sources, and validation-related limitations.

2 Material and Methods

2.1 Reporting Framework

This study was designed as a systematic review and meta-analysis of peer-reviewed studies evaluating AI-based methods for poultry welfare and health monitoring. The review followed the PRISMA 2020 reporting guideline. The review protocol was not prospectively registered; eligibility criteria and the synthesis plan were defined prior to screening.

The research question was structured according to the PICOS framework. The population comprised poultry, including broilers, layers, breeders, and chicks. The intervention or index technology included artificial intelligence-based, machine-learning, deep-learning, computer-vision, sensor-based, Internet of Things, or related computational monitoring systems. A comparator was not mandatory because many eligible AI-monitoring studies reported model performance against reference labels or validation datasets rather than against a conventional monitoring method. The outcomes of interest were model-performance metrics and poultry welfare- or health-related monitoring outcomes, including accuracy, sensitivity, specificity, precision, area under the curve, behavior recognition, disease detection, lesion assessment, mortality detection, and environmental or welfare monitoring. Eligible study designs were peer-reviewed original studies reporting extractable AI model-performance data; reviews, editorials, commentaries, conference abstracts, book chapters, studies without full-text availability, and non-English studies were excluded.

2.2 Search Strategy

This systematic review was conducted using PubMed/MEDLINE, Scopus, and Web of Science. The objective was to identify peer-reviewed studies evaluating AI-based approaches for poultry welfare and health monitoring. The search strategy followed the PRISMA 2020 guidelines (Page et al., 2021; Sadeghi et al., 2023) and combined poultry-related terms, including “broiler,” “layer,” “chicken,” “poultry,” and “farm,” with AI-related terms, including “artificial intelligence,” “machine learning,” “deep learning,” “neural networks,” “computer vision,” “image processing,” “automated detection,” "behavior analysis," "prediction," and "precision agriculture." Boolean operators were used to combine terms within each concept block using "OR" and to combine poultry- and AI-related blocks using "AND." No date restrictions were applied. All records were imported into EndNote and Rayyan for deduplication and screening.

2.3 Inclusion and exclusion criteria

Studies were included if they met the following criteria: (1) they involved poultry, including broilers, layers, breeders, or chicks; (2) they applied AI, machine learning, deep learning, computer vision, sensor-based, or related computational methods; (3) they reported poultry welfare- or health-related monitoring outcomes; and (4) they were published in English in peer-reviewed journals. Studies were excluded if they did not provide extractable performance data, were reviews, editorials, commentaries, conference abstracts, or book chapters, lacked full-text availability, or were not published in English.

2.4 Study selection and data extraction

The data extraction process was independently conducted by two reviewers using Rayyan. At the first step, the titles, abstracts, and keywords of all included records were screened. In the next step, the full texts of potentially eligible studies were assessed. The data were extracted by using a standardized Excel extraction sheet. The extracted variables including AI or machine learning methods, data sources, sample size, model performance metrics, and relevant outcomes. The discrepancies between reviewers were resolved through group discussion and adjudicated by the corresponding author.

2.5 Quality assessment of included studies

The methodological quality and reporting completeness of the included studies were assessed using a structured appraisal framework adapted for AI-based animal monitoring studies. Each study was evaluated across the following domains: clarity of dataset description; poultry population and production setting; data source and acquisition method; ground-truth or labeling procedure; model development approach; validation strategy; reporting of performance metrics; risk of overfitting; real-world applicability; and reproducibility. Particular attention was given to whether studies used independent test datasets, cross-validation, or external validation, and whether model performance was evaluated under commercial or field conditions. Each domain was rated as low, moderate, or high concern. Disagreements between reviewers were resolved by discussion, and unresolved disagreements were adjudicated by the corresponding author.

2.6 Statistical analysis

STATA Version 17 (StataCorp, College Station, Texas, USA) was used for statistical analysis. The primary outcome measure was the accuracy of the models. The Restricted Maximum Likelihood (REML) method was used to calculate the pooled effect sizes and their 95% of confidence intervals (CIs). In addition, the heterogeneity of the included studies was assessed with the Higgins I-squared (I^2) statistic and the between-study variance estimate (τ^2). The publication bias of the included studies was visually assessed using funnel plots, as well as with the Begg's rank correlation test and Egger's linear regression test. In addition, the trim-and-fill test was used to estimate the possible impact of missing studies on the pooled effect size. All analyses were conducted as two-tailed, and a *p*-value less than 0.05 was statistically considered significant.

3 Results

In this systematic review, 21 studies were included. The included studies, published between 2012 and 2025, focused on poultry health and welfare monitoring (Figure 1). The characteristics of included studies were reported in Supplementary Table S1. The study period ranged from short-term experimental assessments (a few days) to long-term observational studies lasting up to 3.5 years. The geographical distribution of the included studies spanned across the world, including Europe (Netherlands, Belgium, UK, Italy), Asia (China, Saudi Arabia, Republic of Korea, Japan, Thailand), Africa (Egypt, Ethiopia), North America (USA), and South America (Brazil).

Overall, the included studies varied considerably in methodological quality and completeness of reporting. Most studies described the AI model architecture and input data type, but reporting of ground-truth labeling procedures, external validation, dataset availability, and reproducibility was inconsistent. Several studies relied on controlled or curated datasets, whereas fewer evaluated model performance under commercial farm conditions. These quality-related limitations were taken into account when interpreting the pooled estimates, particularly given the substantial heterogeneity across studies. The detailed study-level quality assessment is presented in Supplementary Table S2.

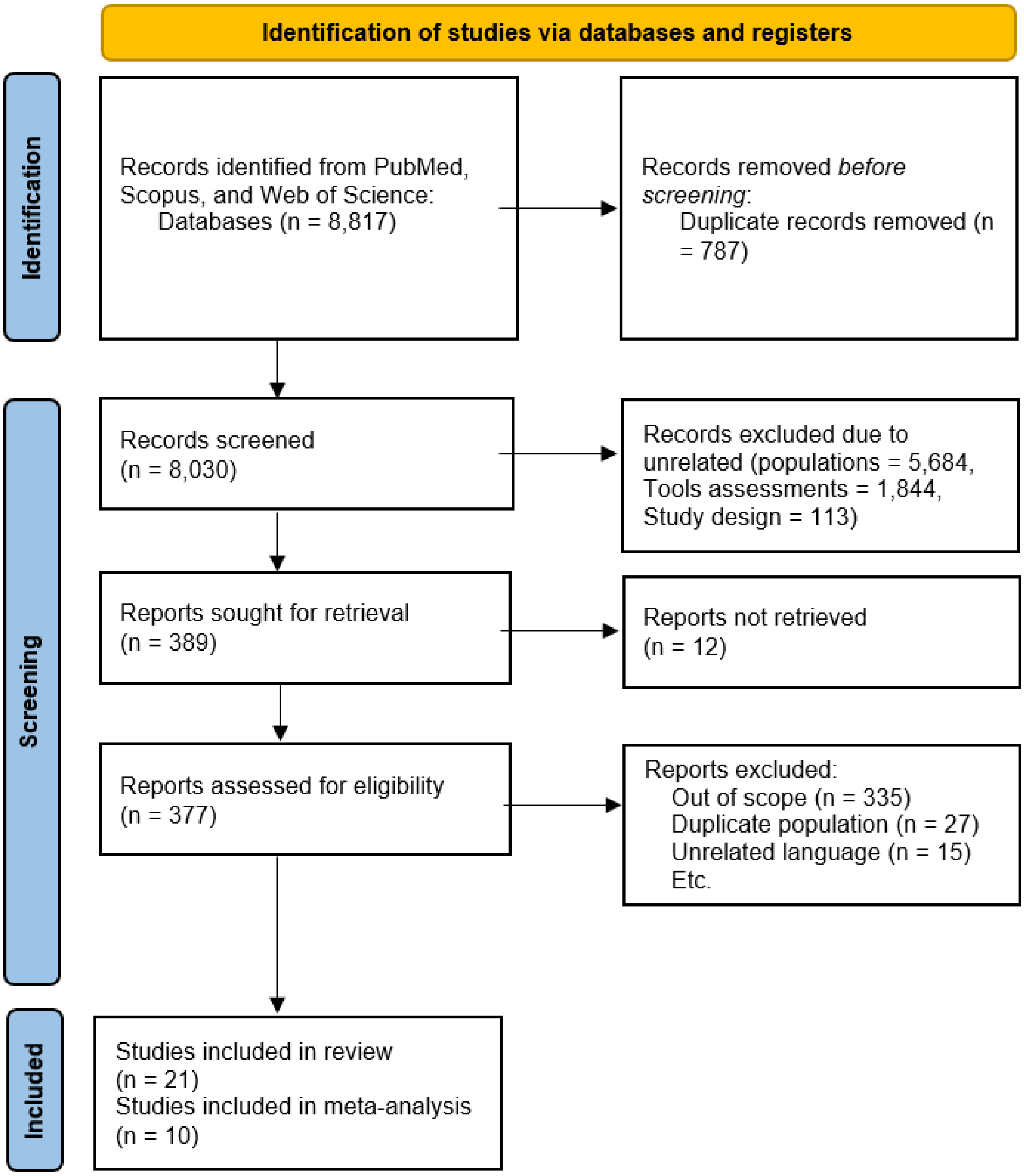

Figure 1. PRISMA 2020 flow diagram of study identification, screening, eligibility assessment, and inclusion.

The included studies assessed different domains of poultry health and welfare monitoring. These domains include behavior classification and movement algorithm (De Montis et al., 2013; Guo et al., 2020; Jaihuni et al., 2023; Rocha Merenda et al., 2024; Shimmura et al., 2024), leg health assessment (Aydin, 2017; Fodor et al., 2025), lesion and bone health detection (Castro Júnior et al., 2022; Kaewtapee et al., 2022; Vanderhasselt et al., 2013), disease identification (Degu & Simegn, 2023; Elmessery et al., 2023; Huang et al., 2019), dead-bird detection and inactivity monitoring (Bao et al., 2021; Khanal et al., 2024), distress recognition and welfare assessment (Du et al., 2020; Srinivasagan et al., 2025), and production performance prediction in breeder farms (Ji et al., 2025).

Also, the sample sizes and dataset scales varied across studies, ranging from small laboratory cohorts (Huang et al., 2019) to large commercial datasets of flock-level production records (Hepworth et al., 2012; Ji et al., 2025). The populations under study were included broilers (Aydin, 2017; Bao et al., 2021; De Montis et al., 2013; Elmessery et al., 2023; Fodor et al., 2025; Guo et al., 2020; Hepworth et al., 2012; Jaihuni et al., 2023; Ji et al., 2025; Kaewtapee et al., 2022; Khanal et al., 2024; Rocha Merenda et al., 2024; Vanderhasselt et al., 2013), laying hens (Huang et al., 2019; Shimmura et al., 2024; Srinivasagan et al., 2025), broiler breeders (Ji et al., 2025), and newly hatched chicks (Goldman & Wood, 2015). Data sources were collected by CCTV video recordings (De Montis et al., 2013; Elmessery et al., 2023; Fodor et al., 2025; Guo et al., 2020; Jaihuni et al., 2023; Khanal et al., 2024; Shimmura et al., 2024; Vanderhasselt et al., 2013), wearable inertial sensors (Bao et al., 2021; Shimmura et al., 2024), environmental IoT sensors measuring temperature, humidity, and THI (Ji et al., 2025), farm management and production records (Hepworth et al., 2012; Ji et al., 2025), and bioacoustics recordings (Du et al., 2020; Huang et al., 2019; Srinivasagan et al., 2025).

In terms of the modeling methods, the included studies used machine learning (ML), deep learning (DL), computer vision (CV), TinyML, and explainable AI frameworks. In addition, the YOLO variants and CNN-based models were used for Vision-based assessment systems (Degu & Simegn, 2023; Elmessery et al., 2023; Fodor et al., 2025; Guo et al., 2020; Jaihuni et al., 2023; Kaewtapee et al., 2022; Khanal et al., 2024; Rocha Merenda et al., 2024; Vanderhasselt et al., 2013). Also, the MFCC, SVM or 1D CNN were used for audio-based monitoring approaches (Du et al., 2020; Fontana et al., 2017; Huang et al., 2019; Srinivasagan et al., 2025). In term of the environmental and production, the datasets were analyzed by using Random Forest, XGBoost, LightGBM, SVR, MLP, ANN, and kNN (Aydin, 2017; Bao et al., 2021; Castro Júnior et al., 2022; Hepworth et al., 2012; Ji et al., 2025; Shimmura et al., 2024). The most common development platforms were python-based environments (TensorFlow, PyTorch, scikit-learn, OpenCV) (Degu & Simegn, 2023; Fodor et al., 2025; Guo et al., 2020; Jaihuni et al., 2023; Ji et al., 2025; Khanal et al., 2024; Rocha Merenda et al., 2024; Srinivasagan et al., 2025), MATLAB (Aydin, 2017; Castro Júnior et al., 2022; Du et al., 2020; Fontana et al., 2017), Edge Impulse (Bao et al., 2021; Srinivasagan et al., 2025), TensorFlow Lite Micro, and Darknet-based implementations (Degu & Simegn, 2023).

Also, the performance metrics, the accuracy, sensitivity, specificity, precision, and AUC, are reported in Table 1. The meta-analysis included 10 studies and reported a pooled estimate of accuracy for health & welfare monitoring of 90.39% (95% CI: 84.89-95.89; $p<0.001$). Heterogeneity across studies was statistically significant ($\tau^2=69.2591$; $I^2=99.86\%$; $p<0.001$). The CNN model achieves the best performance, particularly in AUC and behavior detection task accuracy. Also, some studies report that TinyML for real-time audio classification enables early detection of poultry distress or abnormal behavior, and the XGBoost predicts production performance in broiler breeders.

The regression-based Egger test reports potential small-study effects ($p=0.015$); however, Begg's test reports no significant effect ($p=1.0000$). In addition, trim-and-fill reports show no change after potential imputation for missing data (Table 1, Figure 2).

Table 1. Accuracy of artificial intelligence-based technologies in poultry welfare and health monitoring

Study / Summary	Effect Size (Accuracy %)	95% CI	Weight (%)
Srinivasagan et al.	96.60	95.01 – 98.19	11.25
Shimmura et al.	96.30	86.90 – 100	8.53
Castro Júnior et al.	73.00	67.19 – 78.81	10.08
Aydin et al.	93.00	89.84 – 96.16	10.95
Goldman and Wood	65.00	41.63 – 88.37	3.72
Guo et al.	95.44	92.52 – 98.36	11.01
Degu and Simegn	98.70	98.48 – 98.92	11.36
Huang et al.	90.00	88.53 – 91.47	11.27
Kaewtapee et al.	82.40	77.62 – 87.18	10.46
Bao et al.	95.60	95.40 – 95.80	11.36
Pooled Effect (Random-Effects Model)	90.39	84.89 – 95.89	—

Heterogeneity: $\tau^2 = 69.2591$; $I^2 = 99.86\%$; $H^2 = 720.83$

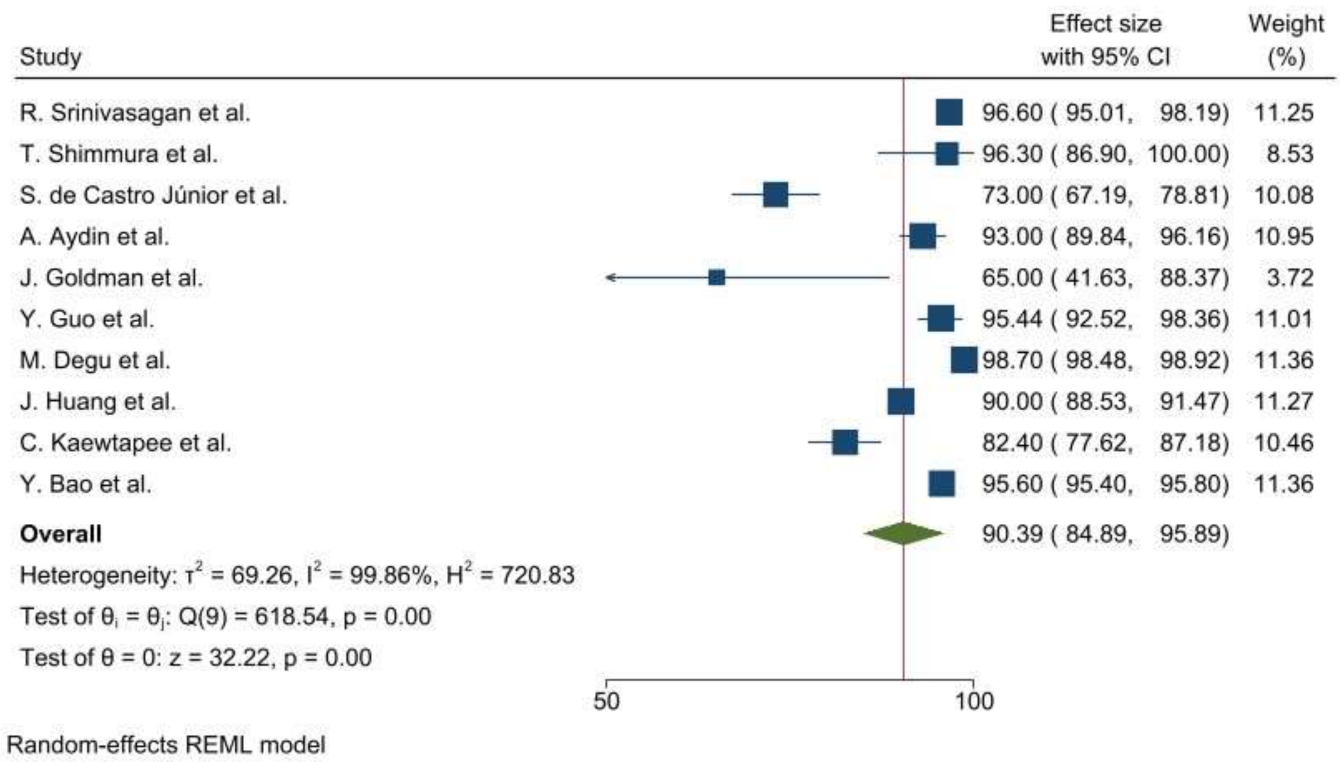

Figure 2. Forest plot of studies assessing artificial intelligence-based poultry welfare and health monitoring.

Table 2. The results of the subgroup analysis of AI and technologies in Welfare and Health monitoring

Subgroup Analysis	Group	studies	Effect size	95% CI	*p* for pooled estimate
Sample Size	under 200	4	82.98	70.03-95.94	<0.001
	over 200	4	92.22	86.17-98.26	<0.001
Domain of AI Application	Welfare	7	87.83	79.92-95-74	<0.001
	Disease/Mortality	3	94.81	89.86-99.77	<0.001
Assessment Dimension	Whole-Animal Monitoring	7	93.96	91.57-96.36	<0.001
	Anatomical / Biological Substra	3	84.93	70.11-99.75	<0.001
Data Source Type	field/real world	6	93.30	89.13-97.48	<0.001
	controlled curated	4	83.85	69.66-98.03	<0.001
AI Model Type	deep learning	3	92.82	83.02-100.00	<0.001
	classical ML/non DL	7	89.03	81.77-96.29	<0.001
Data Acquisition Strategy (Hybrid vs. Fully Automated AI)	Hybrid Systems (AI + IoT)	3	95.77	95.05-96.50	<0.001
	Just AI	7	87.45	79.77-95.13	<0.001

Subgroup analyses were exploratory because of the small number of studies in each category and the substantial overall heterogeneity. Disease/mortality studies showed numerically higher pooled accuracy than welfare studies (94.81%, 95% CI: 89.86–99.76 vs. 87.83%, 95% CI: 79.92–95.74). Higher pooled estimates were also observed for larger datasets, whole-animal monitoring approaches, field/real-world datasets, deep-learning models, and hybrid AI+IoT systems. However, most between-subgroup differences were not statistically significant, and these findings should be interpreted as hypothesis generating rather than confirmatory. The clearest subgroup difference was observed for data acquisition strategy, where hybrid AI+IoT systems showed higher pooled accuracy than AI-only systems.

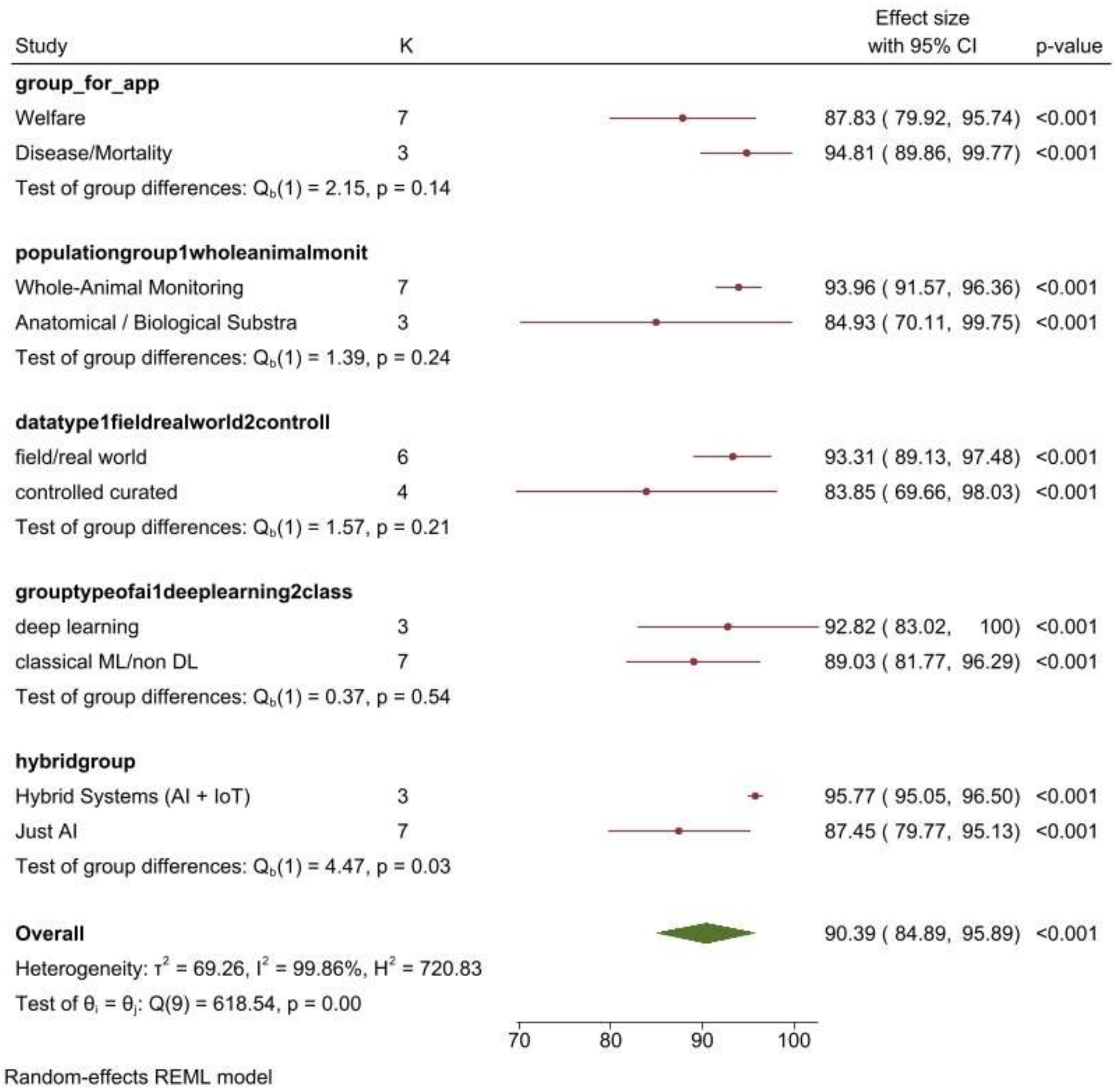

Figure 3. Forest plot of subgroup analyses of artificial intelligence-based poultry welfare and health monitoring.

4 Discussion

The aim of this systematic review was to evaluate the application of Artificial Intelligence (AI) and IoT for monitoring poultry welfare and health. The results showed a significant increase in research focused on integrating Artificial Intelligence (AI) and technologies for poultry monitoring, especially after 2017. This increase in publications can be attributed to rapid advancements in machine learning algorithms and the growing use of technologies such as cameras, sensors, and wearable devices. These advancements enable poultry to collect real-time data more efficiently and to develop automated systems that monitor poultry welfare and health. In addition, this trend suggests the industry's rising demand for more efficient, automated solutions to address challenges such as labor shortages, disease prevention, and welfare management (Attia et al., 2024; Yang et al., 2024). The studies in this review used various platforms, including Python, MATLAB, and TensorFlow, for model development and implementation. The combination of these platforms with IoT sensors, wearable devices, and cameras enables real-time data collection, which is crucial for monitoring poultry management (Lin & Suhendra, 2025; Modak et al., 2025).

The time range of methodologies used in studies spans from short-term experimental setups to long-term observational studies that assess the sustained impacts of AI and IoT technologies. The meta-analysis showed a pooled accuracy estimate of 90.39% for artificial intelligence-based poultry health and welfare monitoring. The high accuracy of AI models in poultry monitoring suggests significant benefits for poultry management and for early detection of health issues and behavioral changes (Ojo et al., 2022). This enables farmers and farm managers to monitor in real time, identify distress signals or early symptoms of disease, and intervene promptly, reducing the need for costly medical treatments or large-scale interventions (Abdel-Wareth et al., 2025; Cruz et al., 2025; Naeem et al., 2025; Shahab et al., 2024).

Also, since these models can monitor environmental factors such as temperature, humidity, and ventilation in addition to chicken assessments (Elwakeel, 2025; Godinho et al., 2025; Pereira et al., 2020), the use of AI models helps achieve sustainable poultry production. Using AI to automate tasks reduced staff errors and costs to a minimum, enabling farmers to implement a 24/7 monitoring program (Natho et al., 2025). This transition to AI-powered, data-driven systems enables us to collect longitudinal, high-coverage, reliable, and valid poultry farming data with high efficiency (Essien & Neethirajan, 2025; Kumari et al., 2025). These data enable accurate decision-making and management, improve overall poultry welfare and farm productivity, support sustainable farming practices, and help to solve today's agricultural challenges, such as staff shortages, resource optimization, and environmental sustainability (Makapela et al., 2025; Niloofar et al., 2021; Sajid et al., 2024).

To maximize the benefits of AI and IoT technologies in large poultry operations, it is recommended to focus on scalable, integrated systems capable of handling large volumes of real-time data (Jebari et al., 2023; Panagi et al., 2025). Implementing AI-powered farm management tools can help reduce labor costs and ensure consistent welfare standards. In addition, emerging models such as TinyML and edge computing are gaining attention for their ability to enable real-time data processing and early detection of poultry health issues (Bhattad et al., 2025; Srinivasagan et al., 2025). Future research should focus on integrating advanced AI models, improving data quality, classifying disease severity in individual chickens, and exploring the long-term impacts of AI and IoT applications on poultry welfare and farm sustainability.

While AI implementation has a high impact, implementing AI and IoT models in poultry comes at a high cost. Primarily implementing AI; need advanced hardware, such as IoT devices, sensors, AI-powered systems, and monitoring systems. Also, it needs specialized training staff or consultants to operate and interpret data from these advanced technologies. In addition, some ongoing expenses for system maintenance, software updates, and data storage require expensive investments that can be a barrier for many farm (Issa et al., 2024; Leong, 2024; Natsir et al., 2025). However, automation management reduces labor costs and minimizes human error. These systems enable better resource optimization, improving energy efficiency, and minimizing environmental impact. Over time, these technologies lead to higher productivity and healthier poultry, ultimately resulting in greater profitability and long-term financial improvements and efficiencies.

This systematic review has several limitations. The first limitation of this systematic review is that it did not assess potential barriers to the use of AI and IoT technologies in poultry farming, such as the financial burdens associated with implementation, maintenance, and training. The studies included in this review varied in their methodologies, including sample sizes, data sources, study duration, and analytical methods. This variation may lead to excessive heterogeneity and reduced generalizability of the findings. In addition, although the review used statistical methods to assess publication bias and heterogeneity, potential small-study effects or missing studies could still affect the pooled estimates.

5 Conclusion

In conclusion, AI- and IoT-enabled systems achieve high reported accuracy in poultry welfare and health monitoring, particularly in automated, sensor-integrated applications. However, the evidence remains heterogeneous, and the generalizability of pooled model performance is limited by differences in datasets, monitoring tasks, validation approaches, and reporting standards. Future studies should prioritize standardized performance reporting, external validation, open datasets, and evaluation under commercial farm conditions before broad implementation.

Acknowledgements

None.

Use of Artificial Intelligence

The authors declare that generative AI and AI-assisted technologies were only used to assist with data extraction and to improve grammar, language, and clarity of the manuscript. These tools were not used for the generation or interpretation of scientific content, and the authors take full responsibility for the accuracy, integrity, and originality of the work.

Conflict of Interest

We declare that no conflict of interest.

Author Contributions

M.J: Conceptualization, Investigation, Data curation, Formal analysis, Resources, Validation, Project administration, Supervision, Writing – original draft. P.H: Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing.

Data Availability Statement

The data extracted and analyzed in this study are included in the article and Supplementary Materials. Additional information is available from the corresponding author upon reasonable request.

Ethical Considerations

This article is a review and meta-analysis and did not involve any new experiments on humans or animals. Therefore, informed consent was not applicable. The study protocol was reviewed and approved by the Research Council of the SANA Institute for Avian Health and Diseases Research (Approval No. 11075-P-1, dated April 10, 2025).

Funding

This study was financially supported by the SANA Institute for Avian Health and Diseases Research.

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