PRECISION POULTRY FARMING IN CAGE-FREE LAYING HEN SYSTEMS: A REVIEW OF COMPUTER VISION, ARTIFICIAL INTELLIGENCE AND SENSOR TECHNOLOGIES FOR WELFARE AND PRODUCTION MONITORING

A. Hamzău, A. A. Ionete*, S.-T. Vlad, M. Tudorache, I. Custura

University of Agronomic Sciences and Veterinary Medicine of Bucharest, Romania

Abstract

The global transition toward cage-free egg production has increased opportunities for laying hens to express natural behaviors, while simultaneously creating new challenges for monitoring large flocks in complex housing environments. Precision Poultry Farming offers technological solutions for continuous and automated assessment of bird behavior, welfare, health and production. This review examines recent applications of computer vision, artificial intelligence and sensor-based technologies in cage-free laying hen systems. Particular attention is given to deep-learning models for bird detection and tracking, recognition of perching, dustbathing, feeding, nesting and feather-pecking behaviors, spatial distribution and activity monitoring, as well as RFID, accelerometers, acoustic sensors and thermal imaging. Current research demonstrates high potential for automated detection of welfare and management indicators under experimental conditions. However, occlusion, variable lighting, flock density, equipment interference, sensor attachment, data requirements and limited validation under commercial conditions remain important constraints. Integrating multiple sensing technologies with artificial intelligence could enable earlier detection of welfare problems and support more precise, individual and flock level management in future cage-free egg production.

Key words: *precision poultry farming; laying hens; cage-free systems; computer vision; welfare monitoring*

1. INTRODUCTION

The transition from conventional cages to cage-free housing systems represents an important development in modern egg production, driven by growing concerns regarding animal welfare and the need to provide laying hens with opportunities to express natural behaviours. Unlike conventional cages, alternative housing systems offer greater freedom of movement and access to resources that support activities such as perching, dustbathing, scratching, foraging and nesting. However, providing a more complex environment does not automatically guarantee better welfare. Cage-free systems may also expose hens to challenges related to feather pecking, keel bone injuries, uneven resource use and increased interactions within large flocks. Consequently, the welfare advantages of alternative housing depend not only on the housing system itself, but also on its design, management and the ability to identify potential problems at an early stage [1–3].

Assessing laying hen welfare in these environments requires reliable information about both individual birds and the flock as a whole. Traditional assessment methods generally rely on direct observations, behavioural scoring and periodic evaluation of animal-based indicators, including plumage condition, injuries, mortality and

*Corresponding author: andreeaionete@yahoo.com
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locomotor activity. Although these methods provide valuable information, their application can become increasingly demanding in large commercial facilities. Moreover, observations made at particular moments may fail to capture short-lasting behaviours, individual differences or gradual changes in flock activity. The development of practical assessment protocols, such as the Aviary Transect method, has improved opportunities for systematic welfare evaluation, but continuous monitoring remains difficult to achieve through human observation alone [2, 4].

Precision Livestock Farming (PLF) has emerged as a promising approach to addressing these limitations by introducing automated methods for collecting and interpreting information directly from the production environment. According to Berckmans [5], the central principle of PLF involves the continuous monitoring of animals through technological systems capable of measuring biological responses and supporting more informed management decisions. In laying hen production, this approach offers the possibility of moving beyond occasional welfare assessments towards a more detailed understanding of behavioural patterns, environmental interactions and changes occurring throughout the production cycle.

Among the technologies currently being investigated, computer vision and artificial intelligence have attracted considerable scientific attention. Camera-based systems combined with deep learning algorithms can detect birds, estimate their distribution within different housing areas and recognise specific behaviours without requiring physical contact. Yang et al. [6] demonstrated the potential of deep learning for monitoring the spatial distribution of cage-free hens, while Paneru et al. [7, 8] developed approaches for automatically detecting perching and dustbathing behaviours. Similarly, Subedi et al. [9] investigated machine vision for identifying pecking-related behaviours, and Yang et al. [10] applied advanced tracking methods to evaluate flock activity. Together, these studies illustrate how automated image analysis can contribute to monitoring welfare-related indicators that are difficult to assess continuously through conventional methods.

Alongside image-based monitoring, sensor technologies provide additional opportunities for investigating laying hen behaviour and physiological responses. Radio-frequency identification (RFID) systems can support individual tracking and the assessment of movement between different areas of aviary housing, although their accuracy may vary according to the location and configuration of the detection system [11]. Wearable inertial sensors, including accelerometers and gyroscopes, offer a complementary approach by recording movement patterns and enabling the classification of several behavioural activities [12]. Thermal imaging, combined with artificial intelligence, has also been investigated for estimating surface temperature characteristics in cage-free laying hens [13]. These technologies capture different aspects of animal activity and may therefore provide complementary information when integrated into a broader monitoring framework.

Beyond welfare assessment, precision monitoring may also support decisions related to egg production and housing management. For example, automated observation of nest access and movement through aviary structures can provide information about how hens interact with equipment and potentially contribute to understanding the occurrence of floor eggs. Nevertheless, technological performance must be distinguished from demonstrated improvements in productivity. In a recent study, Paneru et al. [14] reported highly accurate automated detection of ramp use, while the relationship between ramp access and egg-laying location varied across the

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production period. Such findings highlight the importance of evaluating not only whether a technological system can measure a particular activity, but also whether the resulting information supports meaningful management decisions.

Despite substantial progress, translating experimental technologies into reliable commercial applications remains challenging. Camera occlusion, variable illumination, high stocking density, sensor attachment, computational requirements and differences between housing environments may affect monitoring performance. Furthermore, models developed under controlled conditions may not maintain the same reliability when applied to other flocks or farms. A recent assessment by Willems et al. [15] emphasised the continued need for integrated welfare monitoring approaches that combine technological measurements with practical assessment methods and management priorities. These considerations suggest that the future value of precision poultry farming will depend as much on biological validation and practical applicability as on improvements in algorithm performance.

Therefore, the aim of this review is to critically examine recent applications of computer vision, artificial intelligence and sensor-based technologies for monitoring welfare, behaviour and production-related indicators in cage-free laying hen systems. Particular attention is given to bird detection and tracking, automated behavioural recognition, individual monitoring, multimodal sensing and the relationship between technological performance and biological relevance. By comparing the available evidence, this review seeks to identify current achievements, methodological limitations and research priorities that may support the development of reliable, practical and welfare-oriented precision monitoring systems for commercial egg production.

2. MATERIAL AND METHOD

This paper was developed as a structured narrative review of scientific literature addressing the application of Precision Poultry Farming technologies in cage-free laying hen production. The methodological approach was informed by Snyder [16], who emphasised the importance of a clearly defined research purpose, appropriate literature selection and critical synthesis when conducting scientific reviews.

The literature considered for this review primarily included peer-reviewed publications from 2015 to October 2026, with particular attention given to recent studies reflecting current technological developments. Earlier publications were also considered when they provided relevant scientific foundations. Priority was given to experimental research, technological validation studies and review articles investigating automated monitoring of laying hen behaviour, welfare and production-related indicators. Research involving other poultry categories was considered when it offered relevant methodological insights.

The selected studies were examined in relation to their research objectives, monitoring approaches, experimental conditions, principal findings and reported limitations. Particular attention was given to the reliability of technological measurements, their biological relevance and the extent to which results obtained under experimental conditions could be applied in commercial production systems.

The available evidence was organised into thematic sections and critically compared to identify common findings, differences between studies and areas requiring further investigation. In line with the quality considerations proposed by Baethge et al. [17], emphasis was placed on balanced interpretation, scientific reasoning and the appropriate use of supporting literature.

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3. RESULTS AND DISCUSSIONS

3.1. Precision Poultry Farming and the Challenges of Cage-Free Laying Hen Systems

Cage-free housing systems provide laying hens with greater opportunities to express natural behaviours, including perching, dustbathing, foraging and nesting. However, the increased complexity of these environments also introduces challenges related to flock management, resource accessibility and welfare monitoring. In multi-tier aviaries, birds move between different functional areas, creating variations in spatial distribution, activity patterns and interactions throughout the day. Consequently, providing greater freedom of movement does not necessarily guarantee better welfare, particularly when issues such as feather pecking, keel bone injuries or overcrowding remain insufficiently controlled [1–3].

The relationship between housing conditions and animal welfare is influenced by several interacting factors. Jeon et al. [18] reported differences in plumage condition, behavioural responses and mortality between hens housed in cages and aviaries, highlighting the need to consider multiple welfare indicators rather than relying on housing type alone. Similarly, Montalcini et al. [19] demonstrated that keel bone fracture severity could influence subsequent vertical movement in aviary-housed hens, suggesting that changes in activity patterns may provide useful information about existing health problems. These findings underline the importance of interpreting behavioural data within their biological context rather than assuming that increased or reduced activity always reflects better or poorer welfare.

Spatial distribution and resource utilisation represent additional challenges in cage-free production. Campbell et al. [20] documented variations in litter use, dustbathing and piling behaviour in commercial aviaries, while Grebey et al. [21] identified differences in dustbathing patterns among laying hen strains. Environmental enrichment and housing conditions may further influence behavioural expression and welfare outcomes [22]. More recently, Bordignon et al. [23] demonstrated the potential of continuous environmental monitoring to investigate relationships between hen distribution and microclimatic conditions within a multi-tier aviary. These studies indicate that behavioural patterns are dynamic and influenced by genetics, environmental conditions and management practices. Furthermore, inadequate nest utilisation and floor egg laying remain relevant production concerns, reinforcing the need to understand how hens interact with housing resources [24].

Traditional welfare assessment methods, including direct behavioural observations and physical examinations, remain valuable but provide limited information about changes occurring between monitoring periods. The Aviary Transect method represents a practical approach to assessing welfare indicators in commercial flocks [4], while recent research has explored the use of automated video analysis to identify spatial behavioural responses to environmental disturbances [25]. Although these technologies show considerable potential, their reliability as indicators of welfare problems requires further validation under commercial conditions.

Overall, the complexity of cage-free systems highlights the need for monitoring approaches capable of capturing behavioural and environmental changes over time. Precision Poultry Farming offers opportunities to complement conventional welfare assessments through continuous, objective and potentially individual-level monitoring, while supporting more informed management decisions. Within this framework, computer vision, artificial intelligence and sensor-based technologies are

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increasingly being investigated as tools for understanding flock dynamics and improving welfare-oriented management [5, 6].

3.2. Computer Vision and Deep Learning for Bird Detection, Identification and Tracking

Computer vision has emerged as a promising technology for monitoring laying hens in cage-free systems, allowing researchers to observe birds continuously without direct human intervention. By combining video recordings with artificial intelligence, these systems can automatically detect laying hens in images, estimate their location and analyse movement patterns. Recent developments in deep learning, including object detection models such as YOLO, have improved the ability to process large amounts of visual information, creating new opportunities for understanding flock behaviour and housing utilisation.

Several studies have demonstrated the potential of these technologies under different experimental conditions. Yang et al. [26] reported detection accuracy exceeding 90% when monitoring hens on the litter floor, although performance was influenced by bird age and environmental interference. Similarly, Guo et al. [27] obtained high detection accuracy in crowded cage-free environments, demonstrating that automated systems can distinguish birds even when they partially overlap. However, such findings should be interpreted carefully, as successful detection under experimental conditions does not necessarily guarantee comparable performance in commercial facilities.

Beyond detecting birds, computer vision can provide valuable information about their distribution and movement throughout the housing environment. Yang et al. [6] demonstrated the feasibility of automatically monitoring hens across different functional areas, including feeding, drinking, nesting and perching zones. More recently, Yang et al. [10] investigated automated tracking methods capable of following bird movements across consecutive video frames and evaluating changes in overall flock activity. These approaches may contribute to identifying unusual movement patterns or changes in resource utilisation, although further biological validation is necessary before such measurements can be considered reliable welfare indicators.

An important distinction must be made between detecting birds, tracking their movements and maintaining individual identification over extended periods. In large cage-free flocks, birds frequently overlap, move behind equipment or leave the camera's field of view, making continuous identification particularly challenging. Furthermore, Ajibola et al. [28] demonstrated that estimating a bird's physical position from camera images can introduce spatial inaccuracies, even when its location within the image is correctly identified.

The reliability of computer vision also depends on image quality, camera positioning, lighting conditions and the availability of representative datasets. Bhujel et al. [29] highlighted limitations in the diversity and standardisation of publicly available datasets, which may restrict the application of models across different housing conditions.

Overall, computer vision offers considerable opportunities for automated monitoring of laying hens, particularly for assessing spatial distribution and flock activity. Nevertheless, its practical value depends not only on detection accuracy, but also on the reliability of tracking and the biological relevance of the information obtained. These considerations provide a foundation for developing technologies capable of recognising specific behaviours associated with welfare and production management.

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3.3. Automated Recognition of Natural and Welfare-Related Behaviours

The ability to recognise specific behaviours represents an important advancement in the application of precision technologies to cage-free laying hen production. While bird detection and movement tracking provide information about flock activity, behavioural recognition offers a more detailed understanding of how hens interact with their environment. Activities such as perching, dustbathing, feeding and nesting are particularly relevant because they reflect the use of available resources and contribute to welfare assessment.

Recent research has demonstrated that artificial intelligence can distinguish several behaviours automatically using video recordings. Yang et al. [30] developed a system capable of recognising six activities, including feeding, drinking, walking, perching, dustbathing and nesting, achieving an overall classification accuracy of approximately 95%. The study also showed that recognition performance varied with bird age, suggesting that behavioural monitoring systems may require adjustments throughout the production cycle. Although these findings are encouraging, recognising behaviours in individual images does not necessarily provide reliable information about their frequency or duration under commercial conditions.

Particular attention has been given to perching and dustbathing, two behaviours closely associated with the welfare of laying hens. Paneru et al. [7, 8] demonstrated that both activities could be automatically detected with high precision in cage-free environments. Nevertheless, detection performance was influenced by bird age, overlapping individuals and interference from housing equipment. These findings suggest that automated monitoring could help assess resource utilisation, although differences in behavioural expression must be interpreted alongside housing conditions and flock characteristics.

Feeding, drinking and nesting behaviours are equally important from a management perspective. Italiya et al. [31] developed a camera-based system for monitoring feeding and drinking activities in small-scale laying hen facilities, demonstrating the feasibility of relatively accessible technological solutions. However, its evaluation involved only small groups of birds, limiting the extent to which the findings can be generalised to large commercial flocks. Similarly, automated recognition of nesting behaviour may help investigate nest utilisation and identify potential management difficulties, although detecting nest visits alone cannot establish whether successful egg laying has occurred [14, 30].

Beyond natural behaviours, automated monitoring may contribute to identifying potentially harmful interactions. Subedi et al. [9] investigated the detection of feather pecking in cage-free hens, highlighting opportunities for recognising welfare-related problems through image analysis. However, distinguishing damaging feather pecking from aggressive interactions remains important because these behaviours have different biological characteristics and welfare implications [32]. Consequently, automated identification of pecking events should not automatically be interpreted as evidence of injury or severe welfare impairment.

More recent research has extended behavioural classification to several activities simultaneously. Subedi et al. [33] demonstrated the feasibility of recognising multiple behaviours within a single monitoring framework, although performance remained sensitive to environmental interference and image characteristics. Such findings underline the challenges of developing systems capable of recognising diverse behaviours consistently across different production environments.

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Overall, automated behavioural recognition provides opportunities to complement conventional welfare assessment by generating continuous information about the activities of laying hens. However, the biological interpretation of behavioural patterns remains as important as their accurate detection. Future applications should therefore focus on monitoring behavioural frequency, duration and changes over time, while establishing reliable relationships between automatically recorded activities and validated welfare indicators.

3.4. Sensor-Based Monitoring: RFID, Accelerometers, Acoustics and Thermal Imaging

Sensor-based technologies offer complementary approaches to computer vision by providing information about individual movements, behavioural activity and physiological responses in laying hens. These systems include radio-frequency identification (RFID), wearable motion sensors, acoustic monitoring and thermal imaging. Their main advantage lies in the possibility of collecting continuous measurements that would otherwise require repeated human observations. However, the suitability of each technology depends on the type of information required, the housing environment and its practical application.

RFID technology allows individual birds to be identified through electronic tags and their movements to be recorded when they pass specific detection points. Gebhardt-Henrich et al. [11] evaluated an RFID system involving 1,125 laying hens housed in a multi-tier aviary. The system successfully identified most transitions between housing levels, although its ability to determine precise positions was more limited. These findings suggest that RFID can provide useful information about individual movement and resource utilisation, particularly in complex housing environments. Nevertheless, the installation of multiple antennas and the need to equip birds with identification tags may increase costs and management requirements.

Wearable motion sensors, particularly accelerometers and gyroscopes, provide another opportunity to investigate behavioural activity. By recording body movements, these devices can distinguish between different activities and reveal changes in individual behavioural patterns. Shimmura et al. [12] developed a monitoring approach capable of recognising eleven behaviours, including resting, scratching, preening and dustbathing. Their findings highlighted differences in behavioural diversity and transitions between activities in alternative housing compared with conventional cages. Unlike camera-based systems, wearable sensors can continue recording movements when birds are visually obscured. However, device attachment, battery life and potential interference with natural behaviour remain important considerations, especially when monitoring large commercial flocks.

Acoustic monitoring represents a non-contact alternative based on the analysis of poultry vocalisations. Changes in sound frequency, intensity and vocalisation patterns may provide information about environmental discomfort or stress-related responses. Neethirajan [34] investigated the use of artificial intelligence to analyse vocal responses to acute environmental stressors, demonstrating that sound recordings can reveal differences associated with stressful conditions. More recently, Lin et al. [35] identified changes in vocalisation patterns among laying hens exposed to heat stress. Although these results indicate potential for early welfare monitoring, environmental noise and overlapping vocalisations may complicate the interpretation of recordings in commercial poultry houses.

Thermal imaging offers an additional non-invasive method by measuring surface temperature without directly handling the birds. Saeidifar et al. [13] developed an

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automated approach for analysing thermal images of individual cage-free laying hens, demonstrating the feasibility of extracting temperature-related information under experimental conditions. Such measurements may complement environmental monitoring and help investigate thermal responses. However, surface temperature is influenced by several factors, including ambient conditions, feather coverage and body region, and should not be interpreted as a direct measurement of internal body temperature or as independent evidence of disease.

Overall, sensor-based technologies provide different but potentially complementary perspectives on laying hen welfare. RFID and wearable devices are particularly useful for individual-level monitoring, whereas acoustic and thermal systems allow contact-free assessment of selected flock or physiological indicators. Nevertheless, as highlighted by Kafle et al. [36], practical implementation continues to face challenges related to equipment costs, technical reliability and scalability. Combining these technologies with computer vision may therefore offer a more comprehensive approach to monitoring welfare and production-related conditions in cage-free systems.

3.5. Artificial Intelligence and Multimodal Sensor Integration

The integration of different monitoring technologies represents an important step towards a more comprehensive understanding of laying hen welfare. Although computer vision, acoustic monitoring and wearable sensors can provide valuable information independently, each technology captures only certain aspects of animal behaviour or physiological responses. Multimodal monitoring aims to overcome these limitations by combining information from several sources, allowing artificial intelligence to identify relationships that may not be apparent when measurements are analysed separately.

For example, a reduction in flock activity detected through video analysis may be more informative when considered alongside environmental temperature, humidity and vocalisation patterns. Similarly, changes in movement or resource utilisation could be interpreted more reliably when information about housing conditions is also available. Bordignon et al. [23] demonstrated the relevance of this approach by investigating relationships between environmental conditions and the spatial distribution of hens in a multi-tier aviary. Their findings highlighted the importance of considering environmental and behavioural measurements together, although the observed associations did not establish direct causal relationships.

Recent literature has increasingly explored the potential of artificial intelligence to integrate these complementary measurements. Essien and Neethirajan [37], in a review of 130 studies, highlighted the opportunities offered by combining visual, acoustic, environmental and physiological information for welfare assessment. However, the authors also identified important limitations, including high implementation costs, inconsistent data quality and insufficient validation across commercial farms. Their findings suggest that multimodal monitoring is a promising direction, although its practical advantages over individual technologies remain to be consistently demonstrated.

Experimental evidence has also begun to emerge. Dhaliwal et al. [38] investigated a multimodal monitoring approach involving 150 young laying hens observed from hatching to 20 weeks of age. The researchers combined thermal imaging, acoustic recordings, video-based movement analysis and environmental measurements. Their results revealed developmental changes in surface temperature, vocalisations and responses to human presence, while also

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showing that different sensors captured partly independent information. Nevertheless, the study was conducted under controlled conditions, with detailed acoustic and video analyses limited to one group of 30 birds, and did not validate an automated welfare classification system.

Beyond poultry production, Mao et al. [39] reviewed multimodal approaches used across different livestock species, emphasising the potential benefits of combining complementary measurements. However, the integration process introduces additional challenges related to data synchronisation, sensor reliability and differences between production environments. These considerations are particularly relevant in cage-free housing, where large flocks and complex structures can complicate continuous data collection.

Overall, multimodal monitoring may provide a more complete understanding of laying hen behaviour and welfare than individual technologies alone. Its future value will depend on demonstrating that combined measurements improve the reliability of welfare assessment and support practical management decisions, rather than simply increasing the amount of information collected. Further validation under commercial conditions is therefore essential before these approaches can be widely adopted in cage-free egg production.

3.6. Applications for Welfare Assessment and Egg Production Management

The practical value of Precision Poultry Farming lies in its ability to transform continuous monitoring data into information that supports animal welfare and production management. In cage-free systems, automated technologies may help farmers identify behavioural changes, assess resource utilisation and recognise potential problems at an early stage. However, their usefulness depends on whether the information collected can be translated into timely and appropriate management decisions.

From a production perspective, nest utilisation and floor egg laying represent important management concerns. Eggs deposited outside designated nesting areas may increase collection labour and the risk of contamination or damage [24]. Subedi et al. [40] demonstrated that computer vision could automatically detect floor eggs with high precision. The models were developed using images from experimental cage-free facilities and further evaluated using images from commercial houses. Although these findings indicate practical potential, the effects of continuous automated monitoring on labour requirements and floor egg incidence remain to be established.

Another promising application involves recognising behaviours associated with welfare risks. Automated monitoring of feather pecking, abnormal activity and excessive crowding could support earlier identification of potentially harmful situations [9, 10]. Bist et al. [41] demonstrated the feasibility of automatically detecting piling behaviour, while van Veen et al. [25] showed that changes in spatial activity could provide information about flock responses to environmental disturbances. Nevertheless, recognising behavioural changes does not necessarily demonstrate that automated systems can prevent injuries or mortality. Reliable warning thresholds and appropriate management responses require further investigation.

Precision technologies may also contribute to assessing physical welfare indicators. Jung et al. [42] developed an automated approach for evaluating keel bone damage in laying hens at the slaughter line. Although this method provides retrospective information rather than continuous monitoring, it may support longer-term evaluation of flock welfare and housing management.

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Monitoring resource utilisation offers additional opportunities for improving management decisions. Paneru et al. [14] investigated ramp use in cage-free hens, illustrating that accurate behavioural monitoring does not automatically translate into reduced floor egg laying. Similarly, information about flock distribution and environmental conditions may help identify areas requiring closer attention [23]. These findings underline the importance of evaluating technological measurements in relation to actual management outcomes.

From a production perspective, it is important to distinguish the automated monitoring of production-related activities from the direct assessment of productive performance. Information about nest utilisation, floor eggs and feeding behaviour can help identify management difficulties, but does not necessarily indicate changes in egg production, egg quality or feed efficiency. Although previous studies have demonstrated promising monitoring capabilities [14, 40], evidence of consistent improvements in productive performance remains limited. Future investigations should therefore examine the relationship between automatically recorded indicators and production outcomes over longer periods, particularly under commercial conditions.

Overall, precision monitoring technologies can complement conventional management by providing more frequent and objective information about welfare and production-related activities. Their successful implementation should ultimately be assessed through measurable improvements in animal welfare, labour efficiency and production performance, rather than technological accuracy alone. Integrating automated monitoring with established welfare assessment protocols therefore remains essential for commercial cage-free egg production [15].

3.7. Technical Limitations, Commercial Validation and Future Research Directions

Despite considerable progress in Precision Poultry Farming, several challenges continue to limit the widespread adoption of automated monitoring technologies in commercial cage-free laying hen systems. Although computer vision, artificial intelligence and sensor-based approaches have demonstrated promising results, their performance often depends on specific experimental conditions. Differences in housing design, flock size, lighting, equipment arrangement and bird behaviour may influence the reliability of monitoring systems, making it difficult to transfer results directly between farms [15, 29].

One of the main limitations concerns the availability and quality of representative datasets. Li [43], in a survey of publicly available datasets for precision poultry farming, identified only 20 suitable image and video datasets, highlighting the need for greater diversity, standardisation and accessibility. Similarly, Paneru et al. [44] emphasised that overlapping birds, environmental interference and differences between production systems remain important obstacles to reliable computer vision applications. These findings suggest that future research should prioritise models trained and evaluated using data collected from different farms, genetic strains and production stages.

Another important challenge is the relationship between technological accuracy and biological relevance. Automated systems may successfully recognise changes in movement, vocalisation or resource utilisation, but these measurements do not necessarily indicate a specific welfare problem. Willems et al. [15] highlighted the continued need to connect automated monitoring with established welfare assessment methods and practical

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management priorities. Consequently, technological measurements should be validated against recognised animal-based indicators, such as plumage condition, keel bone damage and behavioural abnormalities, before being used to support welfare-related decisions.

Economic and operational considerations also influence commercial adoption. Monitoring systems may require substantial investments in cameras, sensors, computing equipment and maintenance, while their long-term financial benefits remain insufficiently documented. Wu et al. [45] identified implementation costs, limited interoperability and uncertainty regarding economic returns as important barriers to the wider adoption of artificial intelligence in poultry production. These challenges indicate that technological development should also consider affordability, ease of use and compatibility with existing farm management practices.

Future research should therefore move beyond improving individual detection algorithms towards developing reliable and accessible monitoring solutions. Particular attention should be given to long-term commercial validation, integration of complementary technologies and the establishment of practical warning systems that provide understandable information to farmers. Equally important is evaluating whether these systems contribute to measurable improvements in animal welfare, labour efficiency and productive performance.

Ultimately, the successful application of Precision Poultry Farming will depend on transforming accurate technological measurements into reliable, biologically meaningful and economically justified management tools. Achieving this objective will require closer collaboration between animal scientists, veterinarians, technology developers and poultry producers.

4. CONCLUSIONS

Precision Poultry Farming offers promising opportunities to improve the monitoring of laying hen welfare and production management in cage-free systems. The reviewed literature demonstrates that computer vision, artificial intelligence and sensor-based technologies can provide valuable information about bird movement, behavioural activity, resource utilisation and environmental conditions, complementing conventional assessment methods.

Computer vision has shown considerable potential for non-invasive monitoring of flock distribution and natural behaviours, while RFID, wearable sensors, acoustic monitoring and thermal imaging offer additional opportunities for individual- and flock-level assessment. Integrating these technologies may provide a more comprehensive understanding of laying hen welfare, particularly when behavioural changes are evaluated alongside environmental and physiological information.

Nevertheless, important challenges remain regarding monitoring reliability, biological interpretation and practical implementation. High technological accuracy does not necessarily translate into improved animal welfare or productive performance, particularly when monitoring systems have not been adequately validated under commercial conditions.

Future research should prioritise the development of accessible and reliable monitoring solutions, supported by long-term validation across different housing environments and laying hen populations. Greater attention should also be given to establishing meaningful relationships between automatically recorded indicators and measurable welfare and production outcomes.

Overall, the greatest contribution of Precision Poultry Farming lies not simply in automating data collection, but in

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transforming continuous monitoring into practical information that supports informed management decisions. Achieving this objective could contribute to more efficient, sustainable and welfare-oriented cage-free egg production.

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