INNOVATIVE TECHNOLOGIES IN PEKIN DUCK FARMING

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Abstract

The development of precision technologies offers new opportunities for optimizing Pekin duck production through process automation and efficient resource management. This paper reviews the scientific literature on automated feeding and drinking systems, radio-frequency identification (RFID), microclimate control, and digital monitoring. Electronic feeding systems integrated with RFID technology enable the individual recording of feed intake and feeding behavior, providing data for assessing feeding efficiency. Microclimate control contributes to maintaining appropriate rearing conditions, while computer vision enables non-contact estimation of body weight and monitoring of flocks. The integration of these technologies supports data-driven management and efficient resource utilization; however, their large-scale commercial application requires the assessment of costs, infrastructure requirements, and the possibilities for integrating digital systems.

Key words*: Pekin duck; innovative technologies; precision livestock farming; RFID; digital monitoring.*

INTRODUCTION

World poultry production has expanded substantially over recent decades, and poultry meat accounts for approximately 34% of the global meat supply, making it an important component of the animal-production sector [1, 2]. Global poultry meat output increased by approximately 46 million tonnes between 2003 and 2018 and was projected to rise from around 123 million tonnes in 2018 to 139 million tonnes by 2027 [1]. Duck farming is also an important branch of poultry production. In the United States and the European Union alone, more than 200 million ducks are estimated to be slaughtered annually for meat [3]. Commercial duck production systems and housing practices vary across regions, reflecting differences in climate, management practices, available resources and animal-welfare requirements [3]. The development of the duck-production sector is influenced by a combination of opportunities and constraints, including its contribution to agricultural diversification and rural livelihoods, particularly in Asian rice-growing regions [6]. The Pekin duck (Anas platyrhynchos domesticus) is the predominant breed used for meat production and forms the basis of many commercial meat-type duck lines [3, 4]. Through systematic genetic selection, commercial breeding programmes have improved economically important traits, including growth rate, meat yield and feed efficiency. Although several major breeding companies are based outside Asia, their breeding objectives also reflect the substantial demand for duck meat in Asian markets [5].

Alongside the quantitative growth of poultry production, livestock management is increasingly incorporating digital monitoring and data-driven decision-making technologies. Precision Livestock Farming

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(PLF) involves the continuous or frequent, automated monitoring of animals and their environment, the processing of collected data into meaningful indicators, and the use of these indicators to support management decisions [7, 8]. The integration of Industry 4.0 technologies, including the Internet of Things (IoT), cloud computing, big-data analytics and artificial intelligence (AI), is expanding the potential of PLF to improve production efficiency, animal-health monitoring and welfare assessment, while supporting more sustainable livestock management [8]. Recent reviews indicate that IoT and AI applications offer promising opportunities for addressing challenges in large-scale poultry production; however, many applications remain at the research or prototype stage, and wider adoption is constrained by implementation costs, data security concerns and the limited validation of systems under commercial farm conditions [2].

The technical architecture supporting precision livestock farming (PLF) applications can be described using a layered framework comprising sensing, data transmission and application or decision-support functions [2, 7, 8]. The sensing layer includes environmental sensors for monitoring parameters such as temperature, relative humidity and gas concentrations, as well as imaging, acoustic and weighing systems for assessing animal behaviour and performance. The communication layer enables the transfer of collected data, while the application layer processes these data using analytical methods, including artificial intelligence, to generate actionable information such as alerts, growth estimates and behavioural indicators [2]. The potential value of this architecture lies in its capacity to automate data collection and provide more frequent, consistent and less intrusive monitoring than conventional manual observations, potentially supporting the assessment of feed intake, body weight, activity, spatial distribution, vocalisations and litter conditions. However, the feasibility of measuring these indicators depends on the sensing technology used, its accuracy and the conditions in which it operates. Reviews of PLF technologies indicate that their potential effects on productivity, animal welfare and environmental sustainability depend on data quality, appropriate interpretation, personnel competence and the effective integration of the resulting information into routine management decisions [9].

Ducks, however, differ biologically and behaviourally from broiler chickens, making the direct transfer of poultry technologies between the two production systems to require careful evaluation. Differences in growth patterns, locomotor behaviour, foot-pad health, plumage, and species-specific behavioural needs can influence how housing conditions and welfare indicators should be monitored in Pekin ducks [3, 10]. The European Food Safety Authority (EFSA) has identified several important welfare hazards for ducks, geese and quail kept on farms, including inadequate opportunities for bathing, unsuitable flooring, high stocking density, poor litter quality and inappropriate lighting conditions [10]. Furthermore, waterfowl production encompasses diverse systems, including intensive indoor rearing, litter-based housing, extensive production, free-range systems and organic farming, each presenting different requirements for housing management and technological solutions [11]. Research on Pekin ducks has also shown that rearing conditions can influence fattening performance and meat quality, highlighting the importance of considering the production system when evaluating technological interventions [12].

Housing design and management are therefore important determinants of production outcomes and animal welfare. Experimental research involving French Pekin ducks has demonstrated that stocking rate and housing system can affect growth performance, carcass characteristics, blood parameters and meat quality [13]. Similarly, studies comparing housing systems for meat-

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type ducks have reported effects on growth, carcass traits, meat quality, immune responses and oxidative-stress indicators [14]. Research on White Pekin ducks has further shown that stocking density during different rearing phases can influence body weight and weight gain, although effects on feed conversion, mortality and foot-pad lesions may vary with the conditions examined [15]. In addition, comparisons among duck breeds and slaughter ages have demonstrated differences in carcass composition and meat-quality characteristics, indicating that genotype and slaughter age should be considered when establishing biological baselines for evaluating technological interventions [16–19].

The purpose of this paper is to review the scientific literature concerning innovative technologies applicable to Pekin duck farming - automated feeding and drinking systems, individual identification by radio-frequency (RFID), microclimate control and digital monitoring of flocks and of the environment - and to evaluate, on the basis of the published experimental data, their current performances, their limitations and the conditions required for their large-scale commercial adoption. Unlike zootechnical reviews that concentrate on nutrition or genetics, the present synthesis treats technology as the object of study and asks a practical question: which of the technologies already available on the market or in an advanced stage of research presents potential for application on Pekin duck farms, and what level of performance can be expected under practical rearing conditions. The paper is intended both for researchers who need a documented overview of the field and for specialists in duck production who must decide on the technological modernisation of a farm.

MATERIAL AND METHOD

The study is a narrative review, carried out according to the logic of a structured documentary synthesis, without a formal meta-analytical treatment of the data. The bibliographic search was conducted in the main international databases (Web of Science, Scopus, Google Scholar) and on the platforms of the relevant publishers, using combinations of the following search terms: Pekin duck AND precision livestock farming; duck AND computer vision; duck AND RFID OR electronic feeding; duck house AND environmental control OR microclimate; duck AND welfare assessment; duck AND deep learning OR machine learning; duck AND genomic selection. The search was completed with the snowball technique, by consulting the reference lists of the reviews identified, a procedure frequently used in technological syntheses of this type [3, 7].

The bibliographic research included studies published between 2012 and 2026, with the last search conducted in October 2026.

The selection of the sources observed four criteria: (i) the study had to be published in a peer-reviewed journal indexed in an international database, or in a specialised book of recognised circulation in the field of poultry science; (ii) the study had to concern Pekin ducks directly, or ducks of the genus Anas, or - where the technology is not yet validated in ducks - poultry in general, with an explicit mention in the text regarding the species of origin of the data; (iii) the study had to describe a technology, an automated system, a sensor or a digital method of measurement, monitoring or decision support; (iv) the study had to report quantitative performance indicators (body weight, feed conversion ratio, mortality, accuracy, mean absolute error, coefficient of determination, economic indicators) allowing a comparative evaluation. Purely descriptive papers without data, conference abstracts and commercial presentations were excluded.

For each source the following information was extracted and systematised: the type of technology and its principle of operation; the species and the zootechnical category studied; the conditions of the experiment (number of

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animals, age, housing system, duration); the performance indicators reported; the limitations declared by the authors. The results were then grouped into seven thematic domains, which structure the Results and Discussion section of the paper: (1) genetic and genomic technologies, which generate the phenotypes that digital systems must measure; (2) environmental control, including ventilation, air quality and lighting; (3) automated feeding, drinking and individual identification; (4) computer vision and digital monitoring of flocks; (5) welfare assessment and health surveillance; (6) hatching and incubation technologies; (7) economic performance and the constraints on adoption. The grouping follows the sequence of the production flow, from the genetic material and the hatchery to the fattening house and the economic result of the farm.

Two methodological limitations must be stated from the outset. First, the number of studies carried out specifically on Pekin ducks is much smaller than the number of studies carried out on broiler chickens, and for several technologies (edge computing, RFID-based individual feeding, predictive models of air quality) the most relevant data come from research on other poultry species; in these cases the extrapolation to ducks is indicated explicitly in the text. Second, the performance indicators reported in the literature are obtained in experimental or pilot conditions, on limited numbers of animals and for short periods, and they cannot be extrapolated to the scale of a commercial farm without an assessment of the infrastructure, of the maintenance costs and of the digital competence of the personnel. These limitations are not specific to the present review; they are characteristic of the entire field, and the most recent syntheses draw attention to the fact that most precision livestock farming applications remain, at present, at the research scale [2].

RESULTS AND DISCUSSION

Genetic and genomic technologies: the biological foundation of precision duck farming

Precision technologies applied in duck houses operate within populations whose productive potential is partly determined by genetic selection. Genetic and genomic technologies therefore provide a useful starting point for examining how digital systems may contribute to the further development of Pekin duck production. In recent years, genomic research in Pekin ducks has investigated the genetic basis of economically important traits, including reproductive performance, growth and feed efficiency. A genome-wide association study of egg-production traits identified significant single-nucleotide polymorphisms (SNPs) and potential candidate genes associated with reproductive performance, providing a basis for further research into the genetic improvement of these traits [20]. Subsequent work has evaluated genetic parameters and the potential application of genomic selection to reproductive traits in Pekin ducks, illustrating how genomic information may be incorporated into breeding strategies [21].

Feed efficiency is another important trait because it affects production costs and the resources required to produce duck meat. Genetic studies have examined growth and feeding-related traits in Pekin ducks, identifying genomic regions and candidate markers associated with body weight and feed-efficiency indicators [22]. Further genome-wide association research has investigated feed-efficiency-related traits in ducks, including residual feed intake and feed conversion-related measures, expanding the evidence available for genetic improvement [23]. These findings also highlight the importance of obtaining reliable phenotypic records. Integrating genomic information with accurate measurements of individual growth and feed intake can improve the

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assessment of genetic merit. Automated weighing, electronic identification and individual feed-intake recording may therefore complement genomic selection by facilitating the collection of consistent phenotypic data. However, the practical value of these technologies depends on measurement accuracy, system cost and the suitability of the recording method for the production or breeding environment.

Population structure and genetic diversity are also relevant to breeding programmes. A genome-wide analysis of four indigenous Chinese duck breeds demonstrated that genomic data can be used to characterise population differentiation and genetic diversity, with potential applications in genetic-resource management and conservation planning [24]. In addition, a review of genetic markers associated with duck plumage coloration summarised advances in the identification of genes and genomic regions associated with pigmentation, indicating possible applications in marker-assisted selection and breed characterisation [25]. Although these studies do not directly evaluate precision technologies in commercial Pekin duck houses, they illustrate the broader role of genetic information in modern duck production.

Overall, genetic and digital technologies address complementary aspects of production improvement. Genomic approaches help identify and select desirable inherited traits, whereas precision livestock farming systems can provide more frequent and consistent information about animal performance and the rearing environment. Where individual animals can be identified and their records reliably linked, data collected during rearing may also contribute to the development of phenotypic datasets for breeding programmes. The extent to which this feedback can be implemented in commercial Pekin duck production will depend on the availability of appropriate identification, monitoring and data-management systems, as well as collaboration between commercial farms and breeding organisations.

Environmental control of the duck house: ventilation, temperature, humidity and air quality

Environmental control is a major component of precision livestock farming because it influences animal comfort, litter condition, indoor air quality, production performance and the operating conditions of other monitoring and automation systems. A recent review focusing on intensive duck houses describes the transition from naturally ventilated or poorly controlled housing towards integrated systems that manage temperature, moisture, ventilation and ammonia as interconnected variables rather than as isolated parameters [26]. The review reports several environmental reference values relevant to system design. For Pekin and Muscovy ducks, the literature reports an approximate thermoneutral range of 7–23 °C, with an increased risk of heat stress occurring at around 26–27 °C [26]. These values should be interpreted in relation to the birds' age and rearing conditions and should not be considered general recommendations applicable to all age groups. Summer temperatures averaging 27–29 °C, particularly when accompanied by peaks of 35–46 °C, may create substantial heat-stress risks. Relative humidity of approximately 60–74% has been reported under specific experimental conditions involving Pekin ducks; this range should not, however, be interpreted as a universal commercial target. The review also identifies ammonia concentrations below 25 ppm as a general air-quality reference, while concentrations exceeding 50 ppm have been reported under poorly controlled winter conditions. Reported PM_{10} concentrations range from approximately 35 to more than 500 $\mu g/m^3$ in the cited studies. Regarding airflow, reference values of approximately 0.25–1.0 m/s under cold-season conditions and 0.8–1.8 m/s during hot-weather tunnel

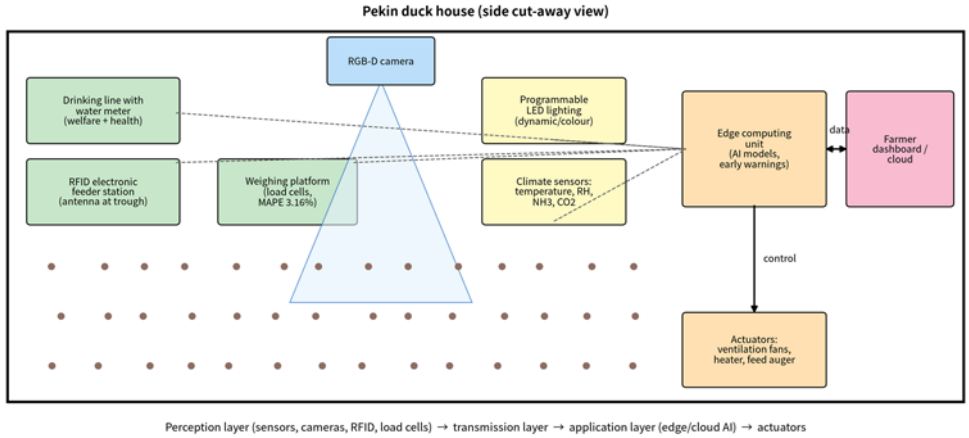
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ventilation are discussed, although these values require careful interpretation in relation to bird age, housing design and the measurement location [26]. These figures should be treated as indicative values drawn from different studies, universally applicable reference values for all duck houses. Table 1 summarises the environmental parameters and reference ranges relevant to control-system design, while Scheme I illustrates the proposed spatial arrangement of the monitoring and control architecture.

Table 1 Reference values for the environmental control of intensive duck houses

Parameter	Reference value	Observation
Reported thermoneutral range	7–23 °C	Reported for Pekin and Muscovy ducks
Heat stress threshold	26–27 °C	Heat stress begins around this value
Summer averages / peaks	27–29 °C / 35–46 °C	Potentially severe heat-stress conditions
Relative humidity	60–74%	Reported under specific Pekin duck experimental conditions
Ammonia (NH3)	< 25 ppm	Concentrations above 50 ppm reported in poorly controlled winter conditions
Particulate matter (PM10)	approx. 35 to more than 500 µg/m³	Reported range in duck houses analyzed
Air speed at bird level (cold conditions)	0.25–1.0 m/s	Cold-condition air speed
Air speed at bird level (tunnel ventilation, hot conditions)	0.8–1.8 m/s	Common target range

Note: Source: adapted from Hasan et al. [26].



Scheme I Architecture of a smart Pekin duck house: perception layer (sensors, cameras, RFID, load cells), transmission layer, application layer (edge/cloud AI) and actuators

These thresholds define the technical specification of the monitoring layer. The technologies proposed for the envelope and for the climate system include reflective roof covers and external shading for the control of the solar load, hybrid ventilation, air-source, ground-source and exhaust-air heat pumps, heat recovery units, dehumidification systems and sensor-based control [26]. The monitoring component has been approached both conceptually and experimentally. A conceptual study of

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wireless environmental monitoring and control in poultry houses described the architecture of a system based on wireless sensor nodes for temperature, humidity and gas concentration, with a central unit that adjusts the actuators of the ventilation system [27]. At the level of data analysis, machine learning applied to environmental records has been used to predict the risk of ammonia exposure in broiler housing, an approach that converts continuous monitoring into an anticipatory tool rather than a simple alarm system [28]. The principle has been extended to health surveillance: the early warning of chicken diseases by monitoring clinical symptoms showed that the systematic recording of behavioural and physiological alterations allows the detection of health problems before mortality becomes visible [29].

A critical point, frequently neglected in the literature, is the validation of the sensors themselves. The development and validation of a low-cost IoT weighing platform for cage-free poultry houses, based on four load cells, a microcontroller, a Raspberry Pi 5 and a Node-RED interface, reported a mean absolute percentage error of 3.16%, equivalent to an accuracy of 96.84%, on the first weighing date, improving to 2.74%, equivalent to 97.05% accuracy, on the second date [30]. This result highlights the potential for using low-cost components for the automated monitoring of body weight; however, the required precision depends on the purpose of the measurement and the conditions of use. The limitation is that such systems measure the total weight of the group of birds present on the platform, and the conversion of group weights into individual growth curves remains a modelling problem.

Heat stress deserves a separate discussion because it is the environmental constraint that most severely limits duck production in the warm months and in the subtropical and tropical regions where duck farming is expanding. The impact of heat stress on poultry health and performance, and the potential mitigation strategies, have been reviewed in detail, with emphasis on the physiological mechanisms (respiratory alkalosis, oxidative stress, reduction of feed intake, impairment of the immune response) and on the nutritional and management countermeasures available [31]. The transmission of the effect between generations has also been documented: Pekin ducks whose parents experienced heat stress showed increased stress and fear responses, which indicates that the thermal history of the breeding stock has consequences on the behaviour of the commercial generation [32]. From a technological point of view, these findings justify the investment in continuous monitoring of temperature and humidity, because the relevant variable is not the average temperature of the day but the duration and the intensity of the periods in which the birds leave the thermoneutral zone.

Lighting is the environmental factor that can be modified most easily and with the most rapid effect on the behaviour, the welfare and the productivity of Pekin ducks, and it has therefore become a preferred target for precision control. A recent study evaluated a dynamic LED lighting programme designed to reproduce a more naturalistic photoperiod for Pekin ducks, compared with a conventional commercial programme, and reported a substantial reduction of stress indicators: bilateral asymmetry of 1.92 +/- 0.10 mm compared with 2.53 +/- 0.23 mm ($p = 0.015$), heterophil-to-lymphocyte ratio of 0.51 +/- 0.03 compared with 0.61 +/- 0.04 ($p = 0.045$) and plasma corticosterone of 16,628 +/- 2,349 pg/mL compared with 24,870 +/- 2,042 pg/mL ($p = 0.011$) [33]. The fear response was also reduced: during the inversion test the ducks from the dynamic programme performed 3.86 +/- 0.25 flaps compared with 7.12 +/- 0.58 flaps, with a flapping intensity of 1.11 +/- 0.05 flaps/s compared with 2.86 +/- 0.14 flaps/s ($p < 0.001$), and during the tonic immobility test the latency to the first head movement was 66.3 +/- 10.33 s compared with 123.6 +/-

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14.45 s, while the time to right was 166.9 +/- 17.16 s compared with 277.6 +/- 21.46 s ($p < 0.001$) [33]. The essential conclusion of that study is that a dynamic lighting programme can reduce stress and fear without a negative effect on growth, which changes the economic status of lighting: it is no longer a simple cost factor but a welfare technology with neutral or positive productive consequences. The stress and fear indicators reported for the dynamic and conventional lighting programmes are compared in Figure 1.

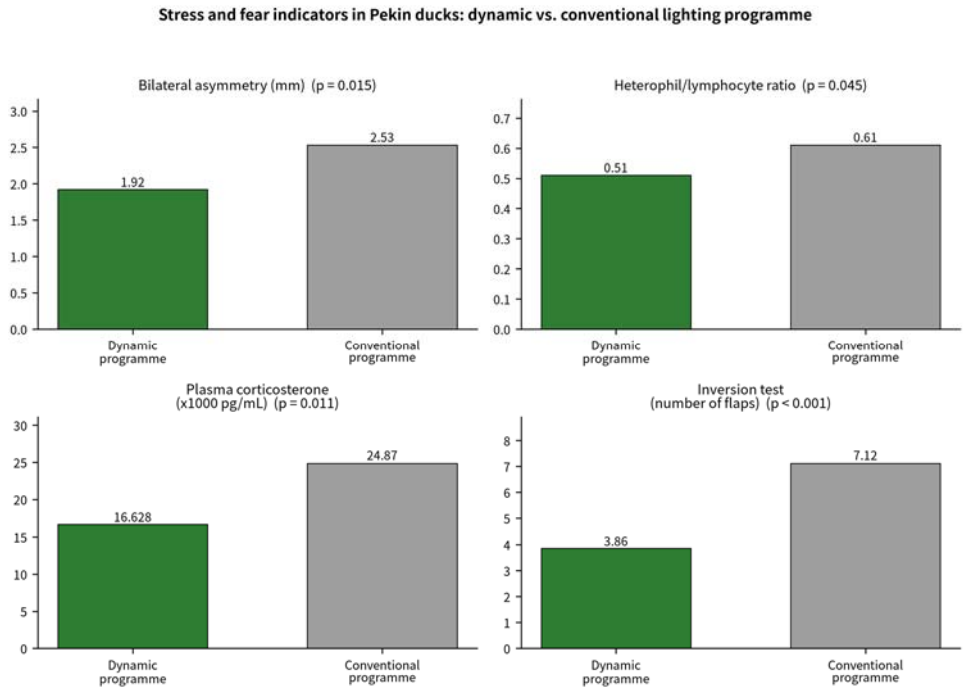


Fig. 1 Stress and fear indicators in Pekin ducks reared under a dynamic LED lighting programme compared with a conventional commercial programme (data from Watson et al. [33])

Data on the spectral composition of the light converge with the conclusion that the light regime must be treated as a biological variable and not only as an element of the electrical installation. Grow-out Pekin ducks reared under blue light (approximately 425 nm) had a significantly lower body weight at every age until processing at 35 days, and showed a higher level of anxiety, panting and reduced inquisitiveness in the presence of the observers, whereas no differences were recorded between the reared ducks illuminated in red (approximately 625 nm) and in white light [34]. The authors concluded that, unlike in chickens, blue light may be inappropriate for raising Pekin ducks in a commercial setting [34]. At the interface between lighting and computer vision, the use of deep learning to evaluate the effect of the photoperiod on the activity of meat ducks demonstrated that the level of activity of the flock can be quantified automatically from video recordings and used as an indicator of the adequacy of the light programme [35]. In technological terms the light regime thus becomes a closed-loop control problem: the programme is set, the activity of the birds is

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measured by the cameras and the programme is adjusted.

Automated feeding, drinking and individual identification

Feeding represents the largest single component of the production cost of a meat duck, and the automation of feeding has followed two distinct directions: the automation of distribution, which is already standard in commercial houses, and the automation of measurement, which is still in development. Electronic feeding stations coupled with individual identification allow the recording of the quantity of feed ingested, of the duration and frequency of the meals and of the competition around the feeder, and these variables are the raw material for the estimation of individual efficiency. The integration of RFID with electronic feeding stations has been described as the most mature example of individual-level precision livestock farming in poultry, and as the element that makes possible the estimation of individual feed conversion ratio, of the social hierarchy around the feeder and of the variability of consumption within the flock [7, 8, 9].

The biological justification for this approach comes from the behavioural phenotyping of feed efficiency. The systematic analysis of feeding behaviours and their effects on feed efficiency in Pekin ducks showed that the way in which a duck distributes its meals in time is significantly associated with the efficiency with which it converts feed, which means that the simple measurement of total consumption, without the temporal structure of the meals, loses a large part of the information [36]. Individual recording also allows the study of the effect of feed restriction programmes, which are used in breeding stock to control body weight and to preserve reproductive performance. The evaluation of a 15% feed restriction on production, gait and immune function in Pekin ducks quantified the compromise between the reduction of the feed cost, the quality of gait and the competence of the immune system [37], a compromise that on a commercial farm can only be managed in real time if the consumption of each bird or of each duck is recorded automatically.

The technology of individual identification most frequently proposed for this purpose is radio-frequency identification (RFID). The principle is simple: a passive transponder carried by the bird is read by an antenna placed at the feeder or at the drinker, and the visit is registered with the identification number, the time and the duration. In poultry houses the main technical difficulty is the reading rate in a dense group of animals, and the literature on the subject shows that the problem is one of antenna geometry and of the physical separation of the reading zones rather than of transponder performance [8, 38].

Automated drinking raises a different set of problems because, in ducks, water has two functions that cannot be separated: the physiological function and the function of behavioural need for bathing and for the maintenance of the plumage. The scientific opinion on the welfare of ducks, geese and quail on farm identified the restriction of water for bathing as one of the main risk factors for duck welfare, and described the consequences of its absence on the hygiene of the plumage, on the thermal balance of the birds and on their behaviour [10]. A technology that measures the individual water consumption of each duck, in correlation with temperature and with feed intake, therefore becomes a welfare instrument and not only a management instrument: an increase in water consumption at constant temperature is one of the earliest indicators of a health problem, and a decrease in the time spent at the drinker is an indicator of a restriction of access [10, 29].

The automation of the distribution of feed and of the collection of eggs has also been approached through mobile robotics. A visual guidance and egg collection scheme for a smart poultry robot intended for free-range farms demonstrated that a

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mobile platform can navigate between the rows of a house, identify the eggs on the floor and collect them without human intervention [39]. The direct application to Pekin duck houses is limited by the behaviour of the birds, which are more sensitive to the movement of a machine than chickens, but the principle is relevant for the automation of the collection of floor eggs, a labour-intensive operation in duck farms that use nests on the floor.

The nutritional technologies that are evaluated experimentally interact with all of the above, because the response to a nutritional programme is not independent of the housing technology in which it is applied. The experimental literature has quantified, in Pekin ducks, the effects of phytase supplementation in diets with or without inorganic zinc [40], of dietary L-methionine [41], of the interaction between feeding regimens and the level of methionine [42], of a multi-carbohydrase enzyme complex [43], of feed fermented with Lactobacillus plantarum [44], of probiotics in general [45] and of the supplementation of drinking water with organic acids and oregano oils [46]. The evaluation of production efficiency and of the utility features of broiler ducks under different rearing programmes confirmed, in the same sense, that the rearing programme and not only the diet determines the final economic result [47]. For a review dedicated to technology, the relevant observation is that all these interventions were evaluated with the classical zootechnical protocol - groups of birds, manual weighing, periodic sampling - and that the precision technologies described in this paper offer the possibility of evaluating the same interventions with individual and continuous data, which would considerably increase the sensitivity of the experiments and reduce their duration. The experimental interventions reviewed in this sense are synthesised, with their biological material, in Table 2.

Table 2 Experimental nutritional interventions evaluated in duck production and reviewed in the present paper

Intervention	Biological material	Reference
Phytase supplementation of diets with or without inorganic zinc	White Pekin ducks	[40]
Dietary L-methionine supplementation	Pekin ducks	[41]
Interaction between feeding regimens and dietary methionine level	Pekin ducks	[42]
Multi-carbohydrase enzyme complex	Pekin ducks	[43]
Feed fermented with Lactobacillus plantarum-81	Muscovy ducks	[44]
Probiotics in poultry production (overview)	Poultry in general	[45]
Organic acid and oregano oils in drinking water	Pekin ducks	[46]
Different rearing programmes	Broiler ducks	[47]

Note: All interventions were evaluated with the classical group-based zootechnical protocol; the precision technologies described in the text allow their re-evaluation with individual and continuous data.

Computer vision and digital monitoring of flocks

Computer vision is, among the precision technologies, the one with the largest number of published studies on ducks and the one closest to commercial maturity, because it uses equipment that is already present in modern houses (cameras, network connections, local computers) and because it produces information that the breeder can interpret directly. A first important direction is the detection of abnormal situations. An automatic perception system based on computer vision was developed for cage-reared ducks and demonstrated that events such as the accumulation of birds in a restricted area, the absence of movement or an abnormal distribution can be detected without human observation [48]. The same research group

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used the YOLOv5 architecture to identify and analyse emergency behaviour in cage-reared laying ducks, which shows that object-detection algorithms trained on duck images can distinguish between normal activity and behavioural events that precede mortality [49].

A second direction is the estimation of body weight without handling. The practical aspects of weight measurement using image processing methods in waterfowl production were evaluated on birds weighing between 1100 and 1800 g, and three data-science models were compared; the random forest method gave the most reliable results, with a mean absolute error between 3.55% and 9.54%, and the transformation of the regression problem into a classification problem with classes of 50 g improved the accuracy of the estimation by 10-15 g on average [50]. More recent work has added the depth channel to the analysis. A two-stream bidirectional interaction network based on RGB-D images, validated on a dataset of 2865 images, achieved the lowest mean absolute error of 0.1550, with a coefficient of determination of 0.9682, reducing the error by 62.9% compared with the RGB-only model and by 78.7% compared with the depth-only model [51]. The simultaneous prediction of body dimensions and of weight from multimodal data (two-dimensional images, depth images and three-dimensional point clouds) reached a mean absolute percentage error of 5.73% with an R2 of 0.953 for seven morphometric parameters, and a mean absolute percentage error of 10.49% with an R2 of 0.952 for body weight [52]. The technological significance of these results lies in the possibility of non-invasively estimating body weight without the need to handle the birds and of monitoring its progression more frequently. However, the accuracy of these estimates varies depending on the method used and the experimental conditions, and the applicability of such systems in commercial farms requires further validation. The accuracy of the main approaches to non-contact weight estimation is synthesised in Table 3 and Figure 2.

Table 3 Reported performance of non-contact body-weight and body-dimension estimation technologies in ducks

Method / model	Input data	Reported performance	Reference
Random forest on image-derived features	Two-dimensional images	Mean absolute error 3.55–9.54% of body weight	[50]
Two-stream bidirectional interaction network	RGB-D images (2,865 images)	Mean absolute error 0.1550; R^2 = 0.9682; error reduced by 62.9% (vs. RGB) and 78.7% (vs. depth) compared with single-channel models	[51]
Multimodal feature-driven deep learning	2D images, depth images and 3D point clouds	MAPE 5.73%, R^2 = 0.953 for seven body dimensions	[52]
Multimodal feature-driven deep learning	2D images, depth images and 3D point clouds	MAPE 10.49%, R^2 = 0.952 for body weight	[52]
Low-cost IoT weighing platform (group weight)	Load cells, microcontroller, edge interface	MAPE 3.16% (96.84% accuracy) at first weighing; 2.74% (97.05%) at second weighing	[30]

Note: MAPE = mean absolute percentage error; MAE = mean absolute error.

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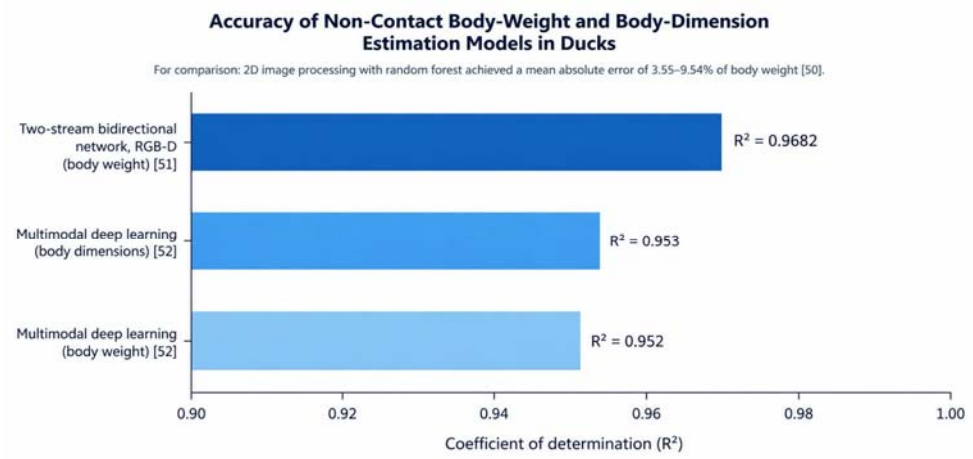


Fig. 2 Coefficients of determination of deep-learning models for non-contact estimation of body weight and body dimensions in ducks (data from Zhang et al. [51] and Xiao et al. [52])

A third direction is the analysis of behaviour and of the vocal expression of the flock. The YOLO family of algorithms has been reviewed specifically for animal phenotyping applications, and the review concluded that the transfer of pre-trained models to new species and new housing conditions is the main practical obstacle to large-scale deployment [53]. In ducks, deep learning applied to sound analysis allowed gender recognition in Cherry Valley ducks, which is relevant for the automation of sexing [54], and few-shot learning models such as SSNFNet were proposed to reduce the quantity of annotated data required for the detection of birds in commercial houses [55]. Tracking systems developed for the assessment of dual-purpose chicken housing and welfare demonstrated that the trajectories of individual birds can be reconstructed automatically and converted into indicators of space use and of activity [56]. The same logic has been applied to the evaluation of the effect of the photoperiod on the activity of meat ducks, already mentioned, in which the activity of the flock quantified from video recordings was used as an indicator of the adequacy of the light programme [35].

The transfer of these methods from the experimental to the commercial scale requires an architectural decision that is rarely discussed in the zootechnical literature: whether the images are processed in the cloud or at the edge of the network, inside the house. Edge artificial intelligence, implemented on dedicated hardware inside the farm, has been developed specifically for smart poultry farms using deep learning and high-performance computing, and it offers three advantages over cloud processing: the reduction of the bandwidth required, the reduction of the latency of the response and the possibility of operating during interruptions of the internet connection [38]. For a duck house, in which the critical events (a failure of the ventilation, an accumulation of birds, a predator) require a reaction within minutes, this architectural choice is not neutral; it determines whether the system can act autonomously or only inform a remote operator.

Image analysis has also been applied to products and not only to live birds. An automatic system based on computer vision for egg grading and defect detection demonstrated that the classification of eggs by size, shape and shell integrity can be performed at commercial speed without human intervention [57]. For a Pekin duck

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farm that sells hatching eggs, this technology replaces a manual operation that is both slow and subjective.

Welfare assessment and health surveillance

The assessment of welfare in a commercial duck house raises a methodological difficulty that does not exist in experimental settings: the number of birds is too large for individual observation and too small for the observation of the group to be representative. The solutions proposed in the literature belong to two categories, the transect walk and the automated measurement, and the two are complementary. The transect walk method was evaluated on a commercial farm on four flocks of 2000 Orvia ST5 Pekin ducks each, assessed at 5, 6 and 7 weeks of age on the basis of indicators such as immobility, lameness, dirtiness, small size, head, back and tail wounds, feather loss, illness, terminal illness and inverted birds; all the indicators except head and tail wounds proved equally effective and accounted for up to 82.13% of the variation in welfare, lameness emerged as the most prevalent factor associated with reduced welfare and as strongly correlated with immobility, and the percentage of featherless ducks varied from 0.29% to 3.50% and was significantly influenced by age and flock [58]. The practical conclusion of that study - that ten indicators are sufficient and that head and tail wounds can be excluded - is directly usable in a monitoring protocol, and it shows that a structured visual assessment carried out by a trained observer remains a valid reference against which automated systems must be validated.

The systematic review of the welfare of Pekin ducks provides the framework in which such indicators must be interpreted, because it identifies the housing and management factors that generate them: the type and condition of the floor, the availability of water for bathing, the density of birds, the quality of the air and the light regime [3]. The scientific opinion on the welfare of ducks, geese and quail on farm reaches similar conclusions and adds a warning that is relevant for technology: the risk factors act in combination, and the improvement of a single parameter without a simultaneous intervention on the others does not necessarily improve the welfare of the flock [10]. Experimental data support this view: the comparison of environments during the summer season in Muscovy ducks showed that the production environment acts simultaneously on performance, on welfare and on the health of the birds [59], and the comparison of sexes in backyard production systems showed that the quality of the meat is influenced by the interaction between sex and system, which means that the technological evaluation of a system must include product quality and not only growth [60].

Information technologies have been reviewed specifically as instruments for addressing broiler welfare, in a systematic analysis based on the Welfare Quality assessment framework, and the conclusion was that the technologies available can measure a part of the welfare dimensions - behaviour, activity, distribution, vocalisation - but not the affective state of the animal, which remains dependent on the interpretation of the observer [61]. This is an honest limitation and it should temper the enthusiasm for fully automated welfare certification. The realistic model is a hybrid one, in which the cameras and the sensors produce continuous indicators and the trained observer validates them periodically with a structured protocol such as the transect walk [58].

Health surveillance follows the same logic. The early warning of diseases by monitoring clinical symptoms requires the detection of alterations that are subtle at the level of the individual and obvious at the level of the group: a reduction of the consumption of water, an increase in the time spent sitting, a change in the distribution of the birds in the house, an alteration of the vocal expression [29]. In ducks, the health technology with the greatest economic

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impact is vaccination, and the experimental literature has quantified the protective efficacy of inactivated vaccines in Pekin ducks [62], the development of inactivated vaccines against the H9N2 avian influenza virus circulating in chickens and ducks [63] and the advances in the research on vaccines against the duck Tembusu virus [64]. The innate immune responses of ducks to avian influenza viruses have also been characterised, and they explain the particular epidemiological role of the species, which frequently carries the virus without clinical signs [65]. For the technology of the farm, this means that the surveillance system must be sensitive to a deterioration of performance in the absence of mortality, because in ducks the absence of mortality is not evidence of the absence of infection.

Hatching and incubation technologies

The hatchery is the segment of the duck production chain in which precision technologies have the most direct economic return, because a small improvement in hatchability applied to a large number of eggs has an immediate effect on the number of ducklings delivered. Three lines of research are relevant. The first is the non-destructive detection of the fertility and of the stage of development of the embryo: the detection of hatching information of meat duck eggs based on deep learning demonstrated that the internal state of the egg can be classified automatically from images or from spectral data, which allows the removal of infertile eggs before incubation and the optimisation of the capacity of the incubator [66]. The second is the counting and the classification of the eggs and of the ducklings in the hatchery, for which lightweight multi-target detection methods have been developed and evaluated on duck eggs [67]. The third is the control of the incubation process itself: the application of precision agriculture principles to artificial waterfowl hatching, illustrated with the Black Muscovy duck, showed that the temperature, the humidity and the turning regime can be regulated by a control system that adapts the parameters to the phase of development, with measurable effects on the rate and on the uniformity of hatching [68].

These technologies are technically mature and their adoption is limited mainly by the investment required and by the scale of the hatchery. For a farm that purchases day old ducklings rather than producing them, the relevant technology is different: the quality of the duckling at delivery, which can be assessed with the same image based methods used for the estimation of body weight and which determines the uniformity of the flock at the end of the fattening period [50, 52].

Economic performance and the constraints on the adoption of precision technologies

The economic evaluation of precision technologies in duck farming is the least developed part of the literature, and this is a paradox, because the decision to invest is always an economic decision. The available data allow three levels of analysis. At the level of the individual technology, the economic benefit can be estimated from the biological effect measured in controlled experiments. A 20L:4D photoperiod reduced the feed conversion ratio from 1.43 to 1.34 kg/kg an improvement of approximately 6% [69]. This result suggests a potential for reducing feed consumption; however, the economic justification for investing in a programmable lighting system requires an assessment of installation and operating costs against the estimated savings, based on the specific conditions of the farm. Similarly, the automation of the weighing of the birds replaces a manual operation that is performed on a sample of animals and that provides a delayed and imprecise estimate of the growth of the flock, whereas a system with an error of 3% delivers a daily growth curve [30, 51]. Table 4 synthesises the photoperiod interventions whose effects have been quantified in terms that can enter an economic calculation.

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Table 4 Photoperiod interventions in Pekin ducks with quantified productive or welfare effects usable in an economic evaluation

Intervention	Main reported effect	Reference
20L:4D photoperiod vs. 16L:8D	Feed conversion ratio reduced from 1.43 to 1.34 kg/kg (approx. 6%)	[69]
Dynamic LED lighting programme	Stress and fear indicators reduced (corticosterone, H/L ratio, tonic immobility); growth unaffected	[33]
Blue light (approx. 425 nm)	Significantly lower body weight at every age until 35 days; higher anxiety; unsuitable for commercial rearing	[34]

Note: H/L = heterophil-to-lymphocyte ratio. Sources: [33], [34], [69].

At the level of the production system, the economic comparison of breeds and of systems provides the reference values against which the technology must be evaluated. In a comparison of Pekin, Muscovy and Mulard ducks, Muscovy ducks showed a superior body weight, weight gain, feed conversion ratio, dressing percentage and breast percentage, and achieved the highest gross margin and the lowest cost of production of one kilogram of live body weight, while Pekin ducks had a significantly higher fat content of the leg and of the breast [70]. In White Pekin ducks reared in a backyard system on a rice-bran-based diet, a final body weight of 2.003 kg was obtained at 56 days with a feed conversion ratio of 3.2, a dressing percentage of 57.9% and a maximum growth rate of 58.17 g/day, values that indicate the biological and economic ceiling of an unimproved system [71]. The comparison of three production systems (intensive, free-range and pool with yard) in American Pekin ducks showed that the system that included a pool and a yard produced the highest growth rate until day 75, the best morphometric parameters, a more favourable serum chemistry and a higher cellular immunity [72], a result that must be read together with the higher cost of the infrastructure required. Detailed growth, body measurement and carcass data of Pekin ducks [18] provide the quantitative baselines against which the effect of any technological intervention must be measured.

The production-system dimension is completed by the experimental data on alternative feeding resources, which are relevant for the economic evaluation of a farm in a region where the price of conventional feed is high. The effect of different levels of an alfalfa pellet ration on the productive performance and on the economic feasibility of Pekin ducks showed that a ration of 25% alfalfa improved the production performance, while a ration of 50% improved the economic values, with significant differences in the accumulated feed intake, in the feed conversion ratio and in the mortality percentage, and with significant effects of sex on the live body weight at marketing age [73]. These results illustrate the type of data that a decision-support system must be able to integrate: the optimum from the point of view of the biological performance is not always the optimum from the point of view of the economic result.

At the level of the individual decision, the literature offers a consistent set of obstacles to adoption, which can be grouped into four categories. The first is the cost of the equipment and of its maintenance, which is particularly restrictive for small and medium farms and which explains why the most successful applications are those based on equipment that already exists in the house, such as the cameras [2, 30]. The

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second is the availability of a reliable internet connection and of the electrical infrastructure required by the sensors and by the computing units [27, 38]. The third is the digital competence of the personnel, which determines whether the data produced by the system are converted into decisions or remain an unused archive; the reviews of precision livestock farming insist on the fact that the human factor, and not the sensor, is the limiting element [7, 8, 9]. The fourth is the integration between systems: a farm that installs a climate controller, an electronic feeding system and a camera system from three different suppliers obtains three separate databases, and the value of the information resides precisely in their correlation [2, 74].

The review of modern technologies for improving broiler production and welfare provides a useful synthesis of this last point, because it shows that the technologies with the greatest effect are not the most sophisticated ones but those that close a control loop: the measurement of a parameter, the comparison with a reference value and an automatic corrective action [74]. A climate controller that measures the temperature, the humidity and the ammonia concentration and that adjusts the ventilation accordingly is a closed loop; a camera that records the flock without generating an alert is not. From this perspective, technologies that transform manual operations into continuous monitoring processes may offer solutions for modernizing Pekin duck farms, particularly when the data collected enable practical interventions in the production process. Farm size influences the economic feasibility of the proposed technologies. Programmable lighting systems and automated weighing platforms may represent viable options even for small-scale farms, whereas the implementation of RFID systems and computer vision technologies requires an individual economic assessment based on flock size, implementation costs, and expected benefits [8, 38]. The logic of the closed control loop, which the review identifies as the practical selection criterion for technology investment, is illustrated in Figure 3.

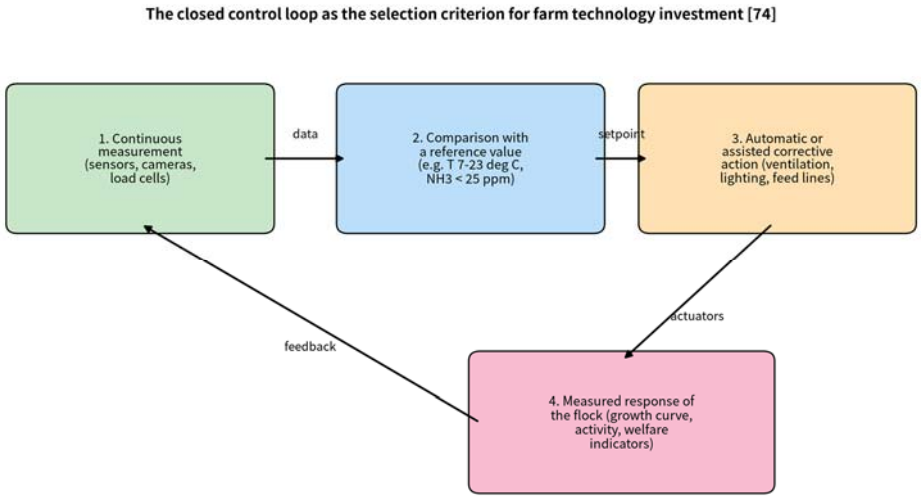


Fig. 3 The closed control loop as the selection criterion for technology investment on a Pekin duck farm (adapted from Brassó et al. [74])

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CONCLUSIONS

The review of the scientific literature on innovative technologies applicable to Pekin duck farming allows the formulation of five conclusions. First, precision livestock farming is no longer a theoretical perspective for this species: automated feeding and drinking, individual identification by RFID, microclimate control, computer vision and digital monitoring have all been validated experimentally in ducks or in waterfowl, and several of them have reached a level of performance that is compatible with commercial use. The estimation of body weight from RGB-D images, with a coefficient of determination of 0.9682 and a mean absolute error of 0.1550 [51], and the estimation of weight from two-dimensional images with an error of 3.55-9.54% [50] are examples of technologies that have demonstrated promising performance under experimental conditions but require further validation before commercial application.

Second, some relatively simple technologies, such as programmable lighting systems and automated weighing platforms, show potential for application in Pekin duck farms. The studies reviewed indicate beneficial effects of lighting programmes on stress indicators and feed conversion [33, 69], as well as the possibility of automatically monitoring changes in body weight [30]. These technologies may represent suitable options for the initial stages of farm modernization; however, the economic viability of their adoption should be assessed in relation to investment costs, flock size, and estimated economic benefits."

Third, environmental control within duck houses represents the technological domain with the strongest scientific foundation, as the scientific literature provides quantified reference values for several environmental parameters. These include a reported thermoneutral range of 7–23°C, an increased risk of heat stress at approximately 26–27°C, ammonia concentrations below 25 ppm, relative humidity of 60–74%, and bird-level air speeds of 0.25–1.0 m/s under cold conditions and 0.8–1.8 m/s under tunnel ventilation [26]. These values provide a basis for defining the specifications of monitoring and control systems and can support both the design of new duck houses and the modernization of existing facilities.

Fourth, the limitation of the field is not the sensor but the interpretation. The systematic review of information technologies applied to broiler welfare concluded that the available technologies measure behaviour, activity and vocalisation but not the affective state of the animal [61], and the reviews of precision livestock farming converge on the observation that most applications remain at the research scale and that their adoption depends on cost, on connectivity, on the competence of the personnel and on the integration between systems [2, 7, 9]. The realistic model for a Pekin duck farm is therefore a hybrid one, in which automated indicators are validated periodically by a structured visual assessment such as the transect walk [58], and in which the data produced by different systems are correlated in a single management platform.

Fifth, the technologies described in this paper are not independent of the biological material and of the production system. Genomic selection creates a demand for individual phenotypes [20, 21, 22, 23], the rearing system modifies the response to any technological intervention [13, 14, 72], and the economics of the farm determine which technologies are accessible [71, 73]. The digitalisation of a Pekin duck farm is therefore a systemic project, which must be designed together with the genetic programme, the housing design and the commercial strategy of the farm, and not as a sequence of independent purchases. In this sense, the most useful contribution of the present review is not a list of devices but the demonstration that the technologies with the greatest effect are those that close a

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control loop between a measurement, a reference value and an action, and that the design of this loop - and not the choice of the sensor - is the real object of the technological decision.

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