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A systematic review linking welfare and automated analysis of acoustic signals in broiler chickens and layers

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SUMMARY

Automated vocalisation analysis is advancing to link chicken behaviour with welfare assessment. This systematic review investigates which vocalisations produced by broilers and laying hens can be detected through sound analysis and how they relate to animal welfare, using the Five Domains model and the PICo framework. The search strategy ((broiler OR chicken) AND (sound OR vocalisation OR 'voice recognition')) was applied across PubMed, Scopus, Web of Science, and SciELO, identifying 57 relevant peer-reviewed articles published between 2000 and 2025. Seventeen distinct vocalisation types or noises were identified. Most studies were conducted under experimental conditions and focused on the on-farm production phase. In the nutrition domain, pecking sounds showed high predictive accuracy for feed intake and growth, but indicators like hunger, thirst, or malnutrition remain underexplored. In the physical environment domain, vocalisations signalled thermal discomfort and poor air quality, though responses to stocking density, ammonia, and other factors need further study. The health domain was most researched, linking coughs and sneezes to diseases, though most models were developed in small, controlled settings. Behavioural interactions were least studied, mainly focusing on feather pecking in laying hens. The mental state domain links vocalisations to emotions, but challenges remain in interpreting their consistency and contextual meaning. Only 36% of studies met preferred recording standards, with most relying on basic statistical methods over advanced machine learning. Model performance often dropped in real-world settings, highlighting the need for standardised protocols and robust, generalisable training data. Much more work is needed to understand what vocalisations mean, how they vary by context, and how reliably they reflect welfare. No studies addressed transport or slaughter phases. Future research should prioritise standardisation, open data sharing, and broader coverage across all production phases to support practical and meaningful welfare monitoring applications.

KEYWORDS
Poultry; chicken; precision livestock farming; sound analysis; well-being

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Introduction

The growing global demand for animal protein has driven the chicken industry to increase productivity. At the same time, a reduction in the number of farmers has made individual flock monitoring more difficult (Norton *et al*., 2019), while public concern over animal health, welfare, and environmental impact has intensified (Gorton *et al*., 2023). In response, Mellor and Reid (1994) proposed the Five Domains model, which integrates physical and mental states to offer a more holistic view of animal welfare.

However, assessing behaviours within these domains remains challenging in large-scale, commercial chicken systems with limited human interaction. In this context, sound analysis has emerged as a promising, non-invasive tool for monitoring welfare-related vocalisations, including distress calls, coughing, sneezing, or altered pecking patterns (Bright 2008; Manteuffel *et al*., 2004). Microphones are affordable, require no physical contact, and allow for continuous group monitoring (Lee *et al*., 2015). Yet, challenges persist, such as background noise, overlapping calls, and difficulty distinguishing individual birds.

Typically, vocal analysis involves the extraction of spectral and temporal features (e.g. pitch, duration, amplitude) using spectrograms. Manual analysis, while informative, is labour-intensive, subjective, and lacks scalability (D. F. Pereira *et al*., 2015). To address these limitations, automated approaches using artificial intelligence, especially machine learning and deep learning, have gained popularity due to their high accuracy and ability to process large datasets (Aydin and Berckmans 2016; Cuan *et al*., 2020; Rizwan *et al*., 2016).

This systematic review aims to identify and summarise current evidence on the use of vocalisation analysis in broilers and laying hens as a welfare monitoring tool. Based on the Five Domains model, it explores which vocalisations can be detected through sound analysis, how they relate to animal welfare, and what methodologies have been employed for their classification and interpretation.

Material and methods

This systematic review followed the PICo framework to formulate the research question, focusing on the Population (broilers and laying hens), Interest (vocalisations and noises, such as sneezing and coughing), and Context (animal welfare). The guiding question was: ‘Which vocalisations produced by broilers and laying hens can be detected through sound analysis, and how do they relate to their welfare?’ A comprehensive search was conducted using the terms: (chicken OR broiler OR hen) AND (sound OR vocalisation OR vocalisation OR ‘voice recognition’), across four databases: PubMed, Scopus, Web of Science, and SciELO. The initial search occurred on 1 June 2024, and was updated on 31 March 2025. No language restrictions were applied, and the search included terms found in the title, abstract, and keywords. A snowball strategy was also used, involving manual searches through references and relevant journals to ensure broad coverage. Studies were included based on the following criteria:

(i) Only original, peer-reviewed journal articles reporting results from research projects were included; conference proceedings, reviews, editorials, and other non-peer-reviewed sources were excluded,
(ii) use of broilers or laying hens,

(iii) analysis of vocalisations using sound analysis techniques (not only recording), and
(iv) relevance to at least one of the Five Domains of animal welfare. For example, studies evaluating feeding behaviour were classified under 'Nutrition'; those analysing housing conditions were assigned to 'Physical Environment'; health-focused studies involving disease fell under 'Health'; research assessing natural behaviours, social interactions, or activity patterns were categorised under 'Behavioural Interactions'; and studies that inferred affective states through behavioural or physiological proxies were associated with 'Mental State'. Where studies addressed multiple domains, the most prominent focus was used for classification.

Only studies published from 2000 onward were considered, as this period marks a significant increase in the accessibility of acoustic tools and machine learning technologies for animal monitoring.

The search results were compiled in Excel, and duplicates were removed. Two reviewers independently assessed the eligibility of studies by screening titles, abstracts, and full texts. Disagreements were resolved by consensus or, if needed, by a third reviewer. Studies that lacked welfare context or did not analyse vocalisations acoustically were excluded. The methodological quality of included studies was assessed using a structured checklist.

Key data extracted from each study included: year of publication, country, animal type (broiler/layer), production stage (hatchery, farm, transport, or slaughter), study setting (experimental or commercial), number of birds used in the study, and the welfare domain addressed. For layers, the 'farm' stage was classified as either pullet rearing or laying phase, depending on the production stage addressed in the study. Technical data included microphone specifications, sound targets, analysis tools, extracted features, classification methods, and model accuracy.

No meta-analysis was conducted due to the heterogeneity of methods, outcomes, and measurement units. As such, risk of bias and effect size measures (e.g. risk ratios or confidence intervals) were not calculated. Instead, a narrative synthesis approach was used to compare study results based on shared themes and objectives. It is important to note that this review was not prospectively registered in any public database. Its exploratory design aimed to provide a broad overview of the current literature, highlight methodological trends, and identify research gaps rather than test a predefined hypothesis.

Results and discussion

The final selection comprised 57 studies published between 2000 and 2025 (Figure 1). Only nine were published between 2000–2010, while 46 were published from 2015 onward, reflecting the growing interest in acoustic monitoring for chickens welfare. From 2010 to 2015, only 2 papers were published. A summary of the included studies is shown in Table 1.

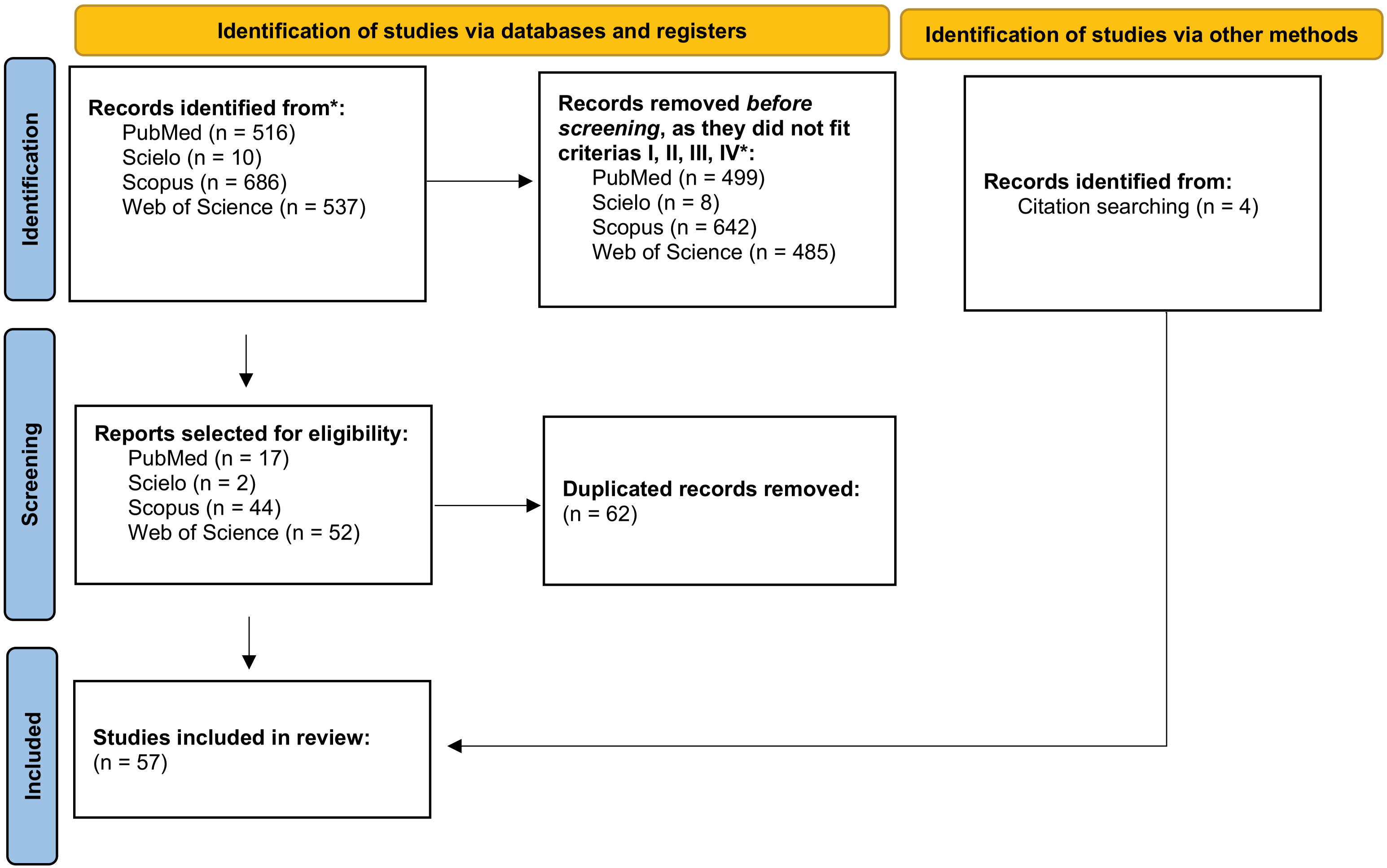

Figure 1. Diagram showing the results from the four databases (PubMed, SciELO, Scopus, and Web of Science) after searching the keywords *(broiler or chicken) and (sound or vocalization or 'voice recognition')*. The first row presents the initial search results. The second line shows the results after excluding irrelevant papers. The final line represents the selection of 53 studies after removing duplicate papers and adding four papers that could not be found by the research, totalising 57 papers. *(i) inclusion of original papers published in peer-reviewed journals, (ii) studies involving broilers or laying hens with no age limitations, (iii) inclusion of assessment that not only recorded vocalizations but also analyzed them using sound analysis techniques, (iv) relevance to animal welfare, specifically linked to one of the Five domains framework.

Table 1. Overview of reviewed studies on broiler and layer vocalizations: animal and technological perspectives.

Study	Year of publication	Country	Animal type	Production site	Domain of welfare	Setting	N° birds
Zimmerman *et al.*, a	2000b	Netherlands	Layer	On-farm	Mental state	Experimental	20
Zimmerman *et al.*, b	2000a	Netherlands	Layer	On-farm	Mental state	Experimental	16
Marx *et al.*,	2001	Germany	Layer	On-farm	Behavior	Experimental	50
Zimmerman *et al.*,	2003	Sweden	Layer	On-farm	Mental state	Experimental	40
Bamelis *et al.*,	2005	Belgium	Broiler	Hatchery	Physical environment	Experimental	40
Gras and Altimiras	2007	Sweden	Broiler	Hatchery	Physical environment	Experimental	40
Bright	2008	UK	Layer	On-farm	Behavior	Commercial	>1000
Moura *et al.*,	2008	Brazil	Broiler	On-farm	Physical environment	Experimental	120
Silva *et al.*,	2010	Belgium	Not mentioned	Hatchery	Physical environment	Commercial	>1000
Al Awam	2011	Not mentioned	Layer	Hatchery	Physical environment	Experimental	51
Exadaktylos *et al.*,	2011	Belgium	Not mentioned	Hatchery	Physical environment	Experimental	>1000
Aydin *et al*	2014	Belgium	Broiler	On-farm	Feeding	Experimental	12
Carroll *et al.*,	2014	USA	Broiler	On-farm	Health	Experimental	6
Curtin *et al.*,	2014	USA	Broiler	On-farm	Physical environment	Experimental	NM
Pereira *et al.*,	2014	Brazil	Broiler	On-farm	Behavior	Commercial	432
Toro-Velasquez and Mortola	2014	Canada, Brazil	Layer	Hatchery	Physical environment	Experimental	30
Whitaker *et al.*,	2014	USA	Broiler	On-farm	Health	Experimental	12
Aydin *et al.*,	2015	Belgium	Broiler	On-farm	Feeding	Experimental	10
Fontana *et al.*,	2015	UK	Broiler	On-farm	Feeding	Commercial	>1000
Lee *et al.*,	2015	South Korea	Layer	On-farm	Physical environment	Commercial	>1000
Sadegui *et al.*,	2015	Iran	Broiler	On-farm	Health	Experimental	120
Aydin and Berckman	2016	Belgium	Broiler	On-farm	Feeding	Experimental	30
Banakar *et al.*,	2016	Iran	Broiler	On-farm	Health	Experimental	14
Rizwan *et al.*,	2016	USA	Not mentioned	On-farm	Health	Experimental	12
Fontana *et al.*,	2017	UK, Netherlands	Broiler	On-farm	Feeding	Commercial	>1000
Kim *et al.*,	2017	South Korea	Layer	On-farm	Physical environment	Commercial	64
McGrath *et al.*,	2017	Australia	Layer	On-farm	Mental state	Experimental	12
Du *et al.*,	2018	China	Layer	On-farm	Health	Experimental	15
Carpentier *et al.*,	2019	Belgium	Broiler	On-farm	Health	Experimental	51
Huang *et al.*,	2019	China	Layer	On-farm	Health	Experimental	14
Jakovljevic *et al.*,	2019	Serbia	Broiler	On-farm	Behavior	Experimental	NM
Mortola	2019	Canada	Layer	Hatchery	Physical environment	Experimental	22
Cuan *et al.*,	2020	China	Not mentioned	On-farm	Health	Experimental	NM
Du *et al.*,	2020	China	Layer	On-farm	Physical environment	Experimental	100
Ginovart-Panisello *et al.*,	2020	Spain	Broiler	On-farm	Physical environment	Commercial	>1000
Herborn *et al.*,	2020	UK	Broiler	On-farm	Behavior	Commercial	>1000
Liu *et al.*,	2020	China	Broiler	On-farm	Health	Commercial	>1000

(*Continued*)

Table 1. (Continued).

Study	Year of publication	Country	Animal type	Production site	Domain of welfare	Setting	N° birds
Huang *et al.*,	2021	China	Layer	On-farm	Feeding	Experimental	18
Mahdavian *et al.*,	2021	Iran, USA	Broiler	On-farm	Health	Experimental	150
Ginovart-Panisello *et al.*,	2022	Spain	Broiler	On-farm	Physical environment	Commercial	>1000
Mao *et al.*,	2022	China	Not mentioned	On-farm	Behavior	Commercial	>1000
Pereira *et al.*,	2022	Brazil	Broiler	On-farm	Behavior	Experimental	30
Adebayo *et al.*,	2023	Nigeria	Not mentioned	On-farm	Health	Experimental	100
Lv *et al.*,	2023	China	Broiler	On-farm	Health	Experimental	30
Neethirajan	2023	Canada	Layer	On-farm	Behavior	Experimental	52
Sun *et al.*,	2023	China	Broiler	On-farm	Health	Commercial	30
Tao *et al.*,	2023	China	Broiler	On-farm	Health	Commercial	60
Amirivojdan *et al.*,	2024	USA	Broiler	On-farm	Feeding	Commercial	10
Collins *et al.*,	2024	USA	Layer	On-farm	Behavior	Experimental	38
Genc and Ozenturc	2024	Turkey	Layer	On-farm	Behavior	Experimental	>1000
Ginovart-Panisello *et al.*,a	2024	Spain	Broiler	Hatchery	Mental state	Commercial	>1000
Ginovart-Panisello *et al.*,b	2024	Spain	Layer	On-farm	Health	Commercial	NM
Golfidis *et al.*,	2024	Belgium	Layer	On-farm	Mental state	Commercial	4
Lev-Ron *et al.*,	2024	Israel	Broiler	On-farm	Physical environment	Experimental	80
Maldarelli	2024	Italy	Broiler	On-farm	Mental state	Experimental	130
Sun *et al.*,	2024	China	Broiler	On-farm	Health	Commercial	NM
Xu and Chang	2024	Taiwan	Not mentioned	On-farm	Health	Experimental	NM

Genetic strain	Nº / type microphones	fs [ksps]	Nº bits	tool	Analysis	Features	Model Accuracy and Evaluation Metrics	ML:
ISA Brown, ISA White Leghorns	NM	NM	NM	NM	Manual counting	NM	none	none
Brown Warrens, White Leghorn	Bandridge BMC 660 mic	NM	NM	Signal software	Manual counting	Mean duration, mean number of notes, mean lenght of the first four notes	none	none
White Leghorn	Tape recorder	51,2		Manual labelling	NM	Call duration, shape of line of pitch, energy content	none	none
Lohman Brown	2 directional microphones	NM	NM	NM	Manual counting	NM	none	none
Cobb	1	44,1	8	LabView	FIR filtering	PSD (2-6 kHz; 0,5 s)	none	none

(*Continued*)

Table 1. (Continued).

Genetic strain	Nº / type microphones	fs [ksps]	Nº bits	tool	Analysis	Features	Model Accuracy and Evaluation Metrics	ML:
Ross 308	Condensor mic	11,025	8	Adobe Audition	NM	freq, duration, intensity, composition	none	none
Lohman, Hy-line, Hebden Black, Oakhan Blue	NM	22,05	16	AviSoft-SASlab	60s spectrograms	Manual (visual and audio), call duration, sound intensity, peak freq, mean freq, interQuartile freq range, -16dB BW	none	none
Cobb	Cardioid mic comp sound card	NM	NM	Cool Edit / Audacity	NM	Spectrum	none	none
Not mentioned	Standard elektret	22,05	NM	MatLab	Bandfilter 2.5-3.3 kHz; moving average ;use of threshold	NM	none	none
Not mentioned	1	44,1		Audacity	Manual counting	Amplitude (dB), peak freq	none	none
Not mentioned	1 electret	22,05	16	DSP	Filter 2-4kHz, FFT	Peak freq	none	none
Ross 308	1	44,1	16	MatLab	Envelope (adaptive) threshold and Frequency based classification	PSD (1-5 kHz)	Accuracy: 93%	none
Cobb	1	NM	NM	Audacity (labelling)	NM	MFCC	none	Clustering (k-means) use decision tree on cluster histogram of wide window
NM	2 stereo	96	24	NM	Noise removal (Spectral Oversubtraction System) and vocalization detection algo	NM	none	none

(*Continued*)

Table 1. (Continued).

Genetic strain	Nº / type microphones	fs [ksps]	Nº bits	tool	Analysis	Features	Model Accuracy and Evaluation Metrics	ML:
Cobb and Ross 308	Unidirectional microphone with high frequency response coupled to a digital recorder	NM	NM	Praat/Matlab	Test of welfare condition	Energy, BW, F0, F1	none	none
White Leghorn	NM	44,1		NM	Manual counting	NM	none	none
Cobb	NM	48	NM	NM	Unsupervised sparse decomposition of spectrograms as dictionary learning	NM	Accuracy: 97.85%	SVM
Ross 308	1	44,1	16	MatLab	Envelope (adaptive) threshold and frequency based classification	PSD (1-5 kHz)	Accuracy: 86%	none
Cobb 500	2 different directional microphones	44,1	16	Manual, Adobe Audition	NM	Peak freq	Accuracy: 96%	none (statistics GLM)
Hy-line brown	Sony camcorder	44,1	16	NM	NM	Root mean square (RMS), power, energy, absolute extremum, intensity, shimmer, jitter, harmonic-to-noise ratio (HNR), and pitch; freq; PSD	none	SVM
Ross 308	NM	44	NM	MatLab	NM	23 features, selected 5 with FDA: Fisher Discriminate Analysis	Accuracy: 78–83%	NN (single hidden layer)
Ross 308	1	NM	NM	MatLab	Statistical feature reduction	25 statistical features (FFT and DWT)	none	SVM classifier

(*Continued*)

Table 1. (Continued).

Genetic strain	Nº / type microphones	fs [ksps]	Nº bits	tool	Analysis	Features	Model Accuracy and Evaluation Metrics	ML:
Ross 308	2 different directional microphones	44,1	16	Manual, Adobe Audition	Manual counting	Peak freq	Accuracy: 83.33% → 91.15% (with Dempster-Shafer)	none
Not mentioned	1 mic -SOMO - Soundtalks	22,05	16	MatLab	PSD	Peak freq, PSD,	SVM Accuracy: 97.6%, ELM Accuracy: 97.1%	none
Not mentioned	NM	NM	NM		Anova linear model	freq	Accuracy: 96%	none
Hy-line Brown	Tascam DAT recorder; Sennheiser ME66 shotgun	44,1		Raven Pro, R (GLMM)	Manual counting and CART(classification and regression Tree) and RandFor	Duration, syllable length, nr of syllables, peak freq, max feq, … (table 2)	none	Random Forest
ISA Brown	2 Kinect camera's for Windows (each 4 microphones)	16	32	LabView	TDOA source localisation	NM	none	none
Hy-line brown	1	44,1	16	MatLab	NM	Advanced features (with LDA for feature grouping)	Accuracy: 74.7% (lab), 73.6% (real group)	none
Ross 308	1 T&F-91 enhanced 32G digital HD microphone	48	NM	NM	NM	MFCC	Sensitivity: 66.7%, Precision: 88.4%	SVM
White Leghorn	ReSpeaker 4 Mic Array for Raspberry Pi card	16	16	NM	NM	Basic, MFCC, MFBE	none	PCA, LDE, SVM

(*Continued*)

Table 1. (Continued).

Genetic strain	Nº / type microphones	fs [ksps]	Nº bits	tool	Analysis	Features	Model Accuracy and Evaluation Metrics	ML:
NM Not mentioned	one AT9904 (subminiature)	44,1	NM	Audacity	Manual counting	Average amplitude, peak amplitude, peak freq	none	none
White Plymouth Rock	1	44,1	16	NM	Sound detection: double threshold method (advanced method) and CNN for classification	MFE and MFCC	none	CNN
NM	1 channel of Kinect recorder	16	32	MatLab / LabView		9 advanced temporal/ spectralfeatures	Accuracy: 97.43%	SVM classifier
Jingfen	Zoom recorder	NM	NM	MatLab	Standard (FFT)	Leq, Peaf freq (PF), PF variation	none	none
Ross 308	9mm condensor (Arbimon acoustic recorder)	44,1	NM	R (tuneR)	NM	spectral entropy and many others	none	random forest parameter selection; statistical ME
Ross 308	4 HD-B-1001, Youanhong Technology Limited Company	48	NM	NM	NM	wavelet transform MFCC	none	HMM
Ross 308		44,1		NM	NM	Short time energy (STE) and short time zero crossing rates (STZ)	Accuracy/ precision	PV-net: DNN or RNN
White Leghorn	voice recorder Sony	44,1	16	NM	NM	MFCC	none	CNN (2D ConVnet en LSTM)
Mix of Chinese 'spotted' and 'three-yellow' breeds	NM	32	16	MatLab	Noise reduction: basic and improved spectral subtraction	NM	none	sparse decomposition: OMP-orthogonal matching pursuit/GA: Genetic Algorithm, and kNN classifier and RF classifier
NM	Superlux ECM999 condenser microphone	22.05	NM	Python, scikit	NM	MFCC, spectral centroid, number of vocalizations	none	Gaussian Naive Bayes classifier

(Continued)

Table 1. (Continued).

Genetic strain	Nº / type microphones	fs [ksps]	Nº bits	tool	Analysis	Features	Model Accuracy and Evaluation Metrics	ML:
NM	unidirectional microphone Yoga Ht-320a	51.2	NM	MatLab	FFT	Energy, spectral centroid	none	kNN, Decision Tree, Random Forest
NM	Zoom H4n Pro	22.05	16	NM	Log-Mel spectrogram	NM	none	CNN (and others)
NM	HD-32 K dGuangzhou PeakFire Electronics Co)	100	12	MatLab	Mel spectrogram	Image features (texture, edges, color)	none	RF, kNN, SVM
Cobb, Ross	Tascam microphone (GoPro)		NM	MatLab	NM	MFCC	none	CNN
Super Nick	NM	96	24	NM	NM	NM	none	NM
NM	8-channel MPA201 (Bei-jing Shengwang Sound and Electric Technology Co.	32	16	NM	NM	60 (energy, spectral centroid, spectral entropy, statistical, …)	none	kNN, SVM, Naive Bayes, Dec Tree, Random Forest
Arbor Acre	NM	NM	NM	NM	NM	60 (energy, spectral centroid, spectral entropy, statistical, …)	none	RF
NM	Marantz PMD661	48			Linear mixed moldes with PCA	9 (peak freq, min/max freq, duration, interval, entropy, rms, ..)	none	
NM	Measures vibrations from the feeder device (out of scope)	NM	NM	NM	NM	NM	Accuracy: 93%	NM
NM	Only sound intensity; no sound type study/ details (out of scope)	NM	NM	NM	NM	NM	none	NM

(*Continued*)

Table 1. (Continued).

Genetic strain	Nº / type microphones	fs [ksps]	Nº bits	tool	Analysis	Features	Model Accuracy and Evaluation Metrics	ML:
NM	condenser microphone Superlux ECM999	22.05	8 (compressed)	NM	NM	Freq, MFCC	none	NM
Hy-Line Brown	1/2″ condenser microphone (class 1 sound level meter)	48	24	NM	Correlation	Pitch, BW, centroid, nr of vocalisatons, MFCC	none	NM
NM	Feeder experiment (out of scope)	NM	NM	NM	NM	NM	none	NM
NM	ZOOM H5	44.1	NM	NM	Mel spectrogram	NM	Accuracy: 97.85%	Transformer ANN
NM	AKG C1000S	44.1	16	NM	Spectrogram	Min/max freq,	Accuracy: 86%	NM
Ross	NM	NM	NM	NM	NM	60 (energy, spectral centroid, spectral entropy, statistical, …)	Accuracy: 96%	RF, Naive Bayes, SVM, 1D-CNN
NM	NM	NM	NM	NM	NM	MFCC	none	LSTM

NM: Not mentioned.
ML: Machine learning.

Animal aspects

Among the selected papers, 30 focused on broilers, 20 on laying hens, and 7 did not specify bird type. The imbalance is notable, especially considering that laying hens have longer lifespans and extended exposure to potential welfare stressors. Seventeen studies were conducted under commercial conditions, while 40 were performed in experimental settings. This reflects the need for controlled environments during early-stage technology validation before broader commercial application.

Regarding production phases, eight studies focused on the hatchery, 49 on-farm phase, and none on transport or slaughter. This absence likely reflects the short duration and high logistical complexity of these final production stages.

While vocalisations are traditionally defined as syrinx-generated sounds, such as internal pipping, external pipping, crowing, squark calls, short peeps, distress calls, pleasure notes, alarm calls, food calls, warbles, and gakel-calls (Goller 2022); other sounds produced by chickens also hold significance. These include purrs, rale sounds, coughing, sneezing, and snoring, which are associated with health status, as well as pecking-related sounds linked to feeding behaviour. Although not classified as vocalisations, these sounds can nonetheless provide valuable information about the animal's condition and welfare. A total of 17 distinct syrinx-generated or other sounds were identified across the studies (Table 2). These include:

- Incubation-related: internal and external pipping.
- Health-related: coughing, sneezing, rales, snoring, squawks, and purring.
- Feeding-related: pecking sounds, food calls, and crowing.
- Stress-related: distress and alarm calls.
- Positive valence: pleasure notes, warbles (somnolence), and short peeps (activity).
- Frustration-related: gakel-calls.

Recordings were taken at various ages, depending on the study focus. In chicks, recordings ranged from E17 to 2 days post-hatch (6 papers), with 1 additional study unspecified. For broilers, ages ranged from 1 to 65 days (26 papers; 4 unspecified), and for layers, from 1 day to 44 weeks (17 papers; 2 unspecified). Hatchery studies analysed embryonic and peri hatch sounds, while broiler studies focused on the 1–42 day growth cycle. Studies on layers varied in timing, reflecting their longer productive lifespan. Interestingly, most vocalisations studied were associated with negative valence, indicating stress, pain, or illness. This aligns with the traditional welfare science focus on detecting adverse conditions. However, recent research has started to emphasise positive welfare indicators, such as pleasure, comfort, and social bonding. Interestingly, most vocalisations (11 of 17) studied were associated with negative valence, indicating stress, pain, or illness. Understanding both negative and positive vocal cues is vital for a comprehensive welfare assessment, particularly when considering the mental state domain of the Five Domains model.

Table 2. Syrinx-generated and other sounds identified in broiler chickens and laying hens in the literature, including their likely valence, descriptions and age of occurrence.

Vocalization	Likely valence	Description*	Context	Type of bird	Strain/Breen	Age	Authors
Internal pipping[a]	Neutral	Occurs during incubation when the chick has cut the air cell membrane, allowing lung respiration and vocalization.	Hatching process.	NM	NM	17–21d egg	Silva *et al.*, (2010); Exadaktylos *et al.*, (2011)
External pipping[a]	Neutral	Occurs 12 to 24 hours after internal pipping when the chick breaks the eggshell.	Hatching process.	NM	NM	17–21d egg	Silva *et al.*, (2010); Exadaktylos *et al.*, (2011)
Crow[a]	Negative	A loud, ear-splitting call used to attract attention over long distances; typically emitted by healthy broilers when hungry or foraging, characterized by a loud and sharp tone.	Health and diseased chickens (not specified)	Broiler	Ross 308	14d; 28d	Sun *et al.*, (2021, 2023); Lv *et al.*, (2023);
Purr[a]	Negative	A continuous, undulating, relatively low-intensity sound produced when broilers experience the presence of unwanted material in their throat.	Experimentally infected with infectious bronchitis virus and Newcastle disease.	NM Broiler	NM Ross 308	8 weeks 21–35d	Sun *et al.*, (20211, 2023); Lv *et al.*, (2023)
Rale sound[b]	Negative	A relatively quiet gurgling or rattling noise produced when a chicken attempts to breathe through excess mucus.	Experimentally infected with infectious bronchitis virus	NM	NM	1–25d	Rizwan *et al.*, (2016); Carroll *et al.*, (2014); Whitaker *et al.*, (2014)
Squark call[a]	Negative	A soft, light call with a wide frequency range and short notes, featuring an abrupt onset and offset; produced by broilers when startled or experiencing momentary pain, stressing higher frequencies.	Feather pecking-related, different thermal conditions (thermoneutral: 24°C, cold stress: 12°C and heat stress: 30°C), and natural flock activity during daytime.	Layers	Jingfen, hy-line brown	18–20 weeks 35–36 weeks	Bright, (2008); Du *et al.*, (2020); 18Kim *et al.*, (2017)
Short peep/ notes[a]	Neutral / Positive	A brief vocalization with descending frequency and low energy, characterized by its short duration. Suggested to be related to activity level.	Gradual increasing levels of social isolation and food deprivation (0, 8, 23 and 47 h)	Layer	White leghorn, brown warrens, white leghorn	6–8d	Max *et al.*, (2001); Zimmerman *et al.*, (2000a)

(*Continued*)

Table 2. (Continued).

Vocalization	Likely valence	Description*	Context	Type of bird	Strain/Breen	Age	Authors
Distress call[a]	Negative	A repetitive, high-energy, loud vocalization that signals a state of distress.	Gradual levels of social isolation; short-term social isolation, in typical commercial broiler house; and in healthy and diseased conditions.	Broiler Layer	Ross 308 White Leghorn	6–8d 1-65d	Herborn *et al.*, (2020); Mao *et al.*, (2022); Marx *et al.*, (2001); Adebayo *et al.*, (2023)
Pleasure note[a]	Positive	A brief vocalization with ascending frequency and low energy that tends to swing upward in pitch.	Gradual increasing levels of social isolation.	Layer	White Leghorn	6–8d	Marx *et al.*, (2001)
Alarm call[a]	Negative	A soft, low-frequency, high-pitched vocalization of short duration with a distinct harmonic structure, serving as a reaction to turmoil or environmental changes.	Feather pecking-related, and in natural flock activity during daytime.	Layers	Lohmann, hy-line, hebden black, oakham blue	35–36 weeks	Bright, (2008); Kim *et al.*, (2017)
Cough[b]	Negative	A prolonged, abnormal, relatively low-pitched sound that may indicate respiratory diseases in broilers.	Typical commercial broiler house.	NM Broiler	NM Ross 308	8 weeks 1–35d	Liu *et al.*, (2020); Sun *et al.*, (2021, 2023); Whitaker *et al.*, (2014); Lv *et al.*, (2023)
Sneeze[b]	Negative	A short, forceful, abnormal sound that may indicate respiratory diseases in broilers.	Vaccinated by a conventional Newcastle vaccine.	Broiler	Ross 308	1d–9weeks	Carpentier *et al.*, (2019)
Snore[b]	Negative	An abnormal, continuous sound produced during sleep that may indicate respiratory issues in broilers.	Typical commercial broiler house.	Broiler	Ross 308	30–37d	Liu *et al.*, (2020)
Food call[a]	Negative	An excited vocalization that becomes deeper and more rapid (often almost stuttering) and may end with a low moan when food is present.	Food rewards (mealworms, regular feed), a non-food reward (dustbathing substrate), a neutral event (sound cue without reward), or by presenting a food dish in a controlled arena after the removal of a familiar imprinting object.	Layer Broiler	ISA Brown Ross 308	18 weeks 1–4d	Mcgrath *et al.*, (2017); Maldarelli, (2024)

(*Continued*)

Table 2. (Continued).

Vocalization	Likely valence	Description*	Context	Type of bird	Strain/Breen	Age	Authors
Warbles[a]	Positive	A repetitive, bow-like vocal element with either ascending or descending frequency and low energy.	Gradual increasing levels of social isolation.	Layer	White Leghorn	6–8d	Marx *et al*., (2001)
Gakel-call[a]	Negative	A whining, elongated note that rises in frequency, followed by a variable number of short notes. Indicative of frustration	Food (0, 8, 23, and 47h), water and dustbathe deprivation.	Layer	Lohman brown, ISA brown, ISA brown warrens, white leghorn, white leghorns	23 weeks	Zimmerman *et al*., (2000a,b, 2003)
Pecking feed[b]	Neutral	The sound produced by a chicken when pecking the feed.	Feeding activity.	Broiler	Ross 308	28–31d 39-46d	Aydin *et al*., (2014, 2015); Aydin and Berckmans, (2016)

*Descriptions based on the referenced papers.
NM: Not mentioned.
[a]Syrinx-generated: internal pipping, external pipping, crow, squark call, short peep, distress call, pleasure note, alarm call, food call, warbles, and gakel-call.
[b]Other sounds: purr, rale sound, cough, sneeze, snore, and pecking feed.

Animal welfare

Nutrition

Seven studies addressed the relationship between vocalisations and the nutritional status of chickens (Table S1). Six focused on broilers, and one on laying hens. Five were conducted under experimental conditions, and two on commercial farms, all during the on-farm production phase.

Vocalisations related to feeding behaviour, particularly pecking sounds, have been widely studied due to their strong correlation with feed intake and growth. Aydin *et al.*, (2014) developed a system capable of identifying pecking events with 93% accuracy by positioning microphones near feeders. In a follow-up study, Aydin *et al.*, (2015) estimated feed intake with 86% accuracy and a near-perfect correlation with actual feed data ($R^2 = 0.994$). Aydin and Berckmans (2016) expanded this to multi-bird settings, estimating meal size and feeding rate with high precision.

Huang *et al.*, (2021) used a time-sequence model and audio recordings to detect eating behaviours in broilers, reaching 93.5–96% accuracy. More recently, Amirivojdan *et al.*, (2024) introduced ChickenSense, a low-cost system using piezoelectric sensors and a VGG-16-based CNN to classify pecking and estimate daily feed intake. Their model reached 92% accuracy and an F1-score of 91%, with a Pearson correlation of 0.85 and an R^2 of 0.71 for hourly intake estimates.

Beyond direct intake estimation, vocalisation frequency has been linked to growth rates. Fontana *et al.*, (2015, 2017) found a negative correlation between vocal frequency and body weight, with a predictive model achieving 96% accuracy when validated against automated weighing systems. Vocal frequency decreased from 3200 Hz to 1250 Hz over the first three weeks of life, corresponding with weight gain. Similar findings were reported by Ginovart-Panisello *et al.*, (2020).

These studies demonstrate the potential of sound-based systems to monitor feeding behaviour and growth performance in chickens. However, important limitations remain. None of the reviewed studies addressed stereotypic pecking behaviour, such as pecking at empty feeders, which could confound data in broiler breeders. Additionally, most systems were developed and tested under controlled experimental settings, and their applicability in commercial environments with high variability and background noise remains limited.

Breed differences, stocking density, and environmental factors like light and temperature were not consistently accounted for, representing important gaps for future research. Also, while feeding sounds were thoroughly explored, vocalisations related to hunger, thirst, or malnutrition, critical aspects of the nutrition domain, remain underexplored. The nutrition domain shows promising applications of acoustic analysis, particularly in feed intake estimation and growth monitoring. However, broader validation, attention to welfare-specific indicators (such as hunger-related calls), and exploration in commercial settings are still needed to enhance real-world utility.

Physical environment

Fifteen studies addressed the physical environment domain, with four conducted on commercial farms and 11 under experimental conditions. Seven were conducted in hatcheries, whereas eight were conducted during the on-farm production cycle. Six studies focused on laying hens, seven on broilers, and two did not specify the bird type.

In hatchery settings, vocalisations were used to monitor embryo development and thermal discomfort. Chicken embryos begin vocalising around day 19 of incubation, coinciding with the onset of lung respiration (Silva *et al*., 2010). Distinct vocal patterns were identified for internal pipping (IP), external pipping (EP), and hatch (HT) stages (Exadaktylos *et al*., 2011). EP-stage embryos emitted more frequent and higher-frequency vocalisations compared to IP.

Temperature deviations during these stages, particularly cold exposure, triggered distress calls, defined by high-intensity, repetitive patterns (Nichelmann and Tzschentke 1997). Bamelis *et al*., (2005) and Mortola (2019) confirmed that both heat and cold stress increased vocal activity. Such patterns may serve a communicative function, especially in the absence of maternal care. Real-time acoustic monitoring of these sounds has been shown as a way to optimise incubator conditions and improve chick quality.

On farms, vocal behaviour has been used to detect thermal and environmental stress. Curtin *et al*., (2014) applied acoustic radar processing to monitor broilers exposed to heat stress, approximately 9°C above standard temperatures for three hours daily over six days, and found that vocal frequency increased with rising ambient temperatures. Lee *et al*., (2015) developed a system that detected heat-, cold-, and fear-related stress in hens with over 96% accuracy by exposing birds to temperatures of 10°C, 21°C, and 34°C. To induce fear as a mental stressor, one group was exposed to sudden cage strikes with a stick while maintained at 21°C. Similarly, De Moura *et al*., (2008) found that chick vocal intensity decreased under optimal thermal conditions (32–35°C), whereas suboptimal temperatures led to increased vocal activity, assessed indirectly through noise level analysis. Recent work by Du *et al*., (2020) and Lev-Ron *et al*., (2024) used machine learning to detect stress-induced vocalisations. Du *et al*., (2020) defined thermal stress indicators based on the Temperature-Humidity Index (THI), recorded every five minutes and classified into four levels: comfort (<70), alert (70–75), danger (76–81), and emergency (>81). Vocalisations were categorised into four types: gakel, alarm, squawk, and other. While Lev-Ron *et al*., (2024) exposed broiler chicks to four treatments: cold (8°C below standard), heat (8°C above standard), windy (increasing wind speed from 0.5 to 2.5 m/s over five weeks), and a control group under standard thermal conditions. These models relied on squawk and alarm calls as reliable indicators of thermal discomfort.

Beyond temperature, other environmental factors like CO_2 and humidity affect vocal behaviour. Ginovart-Panisello *et al*., (2020, 2022) observed that lower CO_2 and humidity levels increased vocalisation frequency, particularly between days 15 and 40 of broiler development. However, few studies directly addressed stocking density. Kim *et al*., (2017) showed that hens in high-density environments emitted more squawk calls, particularly in the afternoon, indicating stress. Although promising, most models were tested under controlled laboratory settings. Field validation remains limited. Also, many studies did not explore environmental challenges common in commercial settings, such as ammonia levels, dust concentration, and variations in the Temperature-Humidity Index (THI).

Vocalisations have been shown to reflect physical discomfort and environmental stress. Their use in hatcheries to monitor embryonic development and in farms to detect heat or air quality stress represents an important advance in precision welfare monitoring. However, the generalisability and specificity of these vocal indicators, particularly in complex real-world environments, require further investigation. Additionally, inherent biological variability, such as differences in early-life experiences or individual coping styles, can also influence vocal outcomes, further complicating cross-study comparisons.

Health

Eighteen studies focused on health-related vocalisations in chickens, all conducted during the on-farm production phase. Of these, five were carried out on commercial farms, and thirteen in experimental conditions. Eleven studies involved broilers, three layers, and four did not specify the bird type.

In traditional chicken production systems, diseases are typically identified visually, often at later stages, leading to significant economic losses. Animal vocalisations may serve as key health indicators, with distinct sounds, such as coughs (a low, prolonged croak) and purrs (a fluctuating snoring sound produced when broilers sleep) (Sun *et al.*, 2021). However, for early disease detection, the meaningful classification and extraction of vocalisation features are necessary. Advances in acoustic analysis have explored how sound generation and resonance change due to respiratory diseases, highlighting the requirement for high-quality sound signals to ensure accurate detection.

Recent research has highlighted the effectiveness of acoustic analysis for monitoring broiler chicken health. Sun *et al.*, (2023) proposed a method that combines sound detection with transfer learning to identify and classify health-related vocalisations in broilers, enabling early disease detection and intervention. Similarly, Lv *et al.*, (2023) developed a novel approach using spectrogram analysis to extract unique features from chicken vocalisations. They introduced a fusion classification model that integrates multiple machine learning algorithms, outperforming individual classifiers in accurately distinguishing between different vocalisation types. Tao *et al.*, (2023) enhanced the accuracy of such systems through a three-step feature optimisation process: cleaning to address noise and missing data, enhancement to improve feature quality, and selection to identify the most informative health indicators. This refined approach significantly boosted the performance of the sound-based monitoring tools.

To support the development of intelligent health monitoring systems, Adebayo *et al.*, (2023) involved 100 day-old broiler breeder chicks divided into two groups. One group received prophylactic treatment against respiratory diseases, whereas the other did not. After 30 days, the untreated group exhibited signs of respiratory distress, which were captured through audio recordings. These recordings provided valuable data for training machine learning models to recognise health-related acoustic patterns. Expanding on this work, Sun *et al.*, (2024) evaluated deviations indicative of health issues, offering a practical and non-invasive solution for chicken health management. Finally, Xu and Chang (2024) developed a deep learning system that monitors chicken health by analysing vocalisations and detecting abnormal faeces. Using convolutional neural networks applied to spectrograms, their system successfully differentiated between normal and abnormal vocalisations, further supporting the role of acoustic analysis in detecting health conditions in chickens.

Given the impact of viral respiratory infections on chicken health and production (Shiferaw *et al*., 2022), researchers have developed highly accurate algorithms to detect their presence. Audible signs such as sneezing and coughing may indicate the presence of respiratory diseases in broilers. To differentiate sneezing and coughing caused by respiratory disease from similar sounds produced by healthy birds in response to dust or other irritants, it is important to consider that at 9 days of age, the chickens were vaccinated with a conventional Newcastle vaccine, which, even at standard doses, is known to provoke transient respiratory disturbances (Mayers *et al*., 2017). Carpentier *et al*., (2019) developed an algorithm to detect sneezing sounds in broiler chickens within a commercial chicken house environment. The algorithm was evaluated in a setting with multiple active birds and various background noises, showing a high accuracy in identifying sneezing events, achieving 66.7% sensitivity and 88.4% precision.

According to Ginovart-Panisello *et al*., (2024b), hens experiencing vaccine-induced inflammatory responses exhibited distinct changes in vocal behaviour, including increased call frequency and altered acoustic parameters. When treated with anti-inflammatory products, these vocal changes were significantly reduced, indicating a return to more typical vocal patterns. These results suggest that acoustic monitoring is a sensitive and noninvasive tool for detecting vaccine-induced inflammatory responses and evaluating the efficacy of therapeutic interventions in chickens. Similarly, Liu *et al*., (2020) recorded continuous sound data from 20,000 broilers to develop an automated system capable of detecting abnormal vocalisations associated with health issues and environmental stressors. To improve the sound representation, they introduced Weighted Mel-Frequency Cepstral Coefficients (MFCCs). Using these features, a Hidden Markov Model was trained to classify normal and abnormal vocalisations within a broiler house. The system achieved 93.8% accuracy and 94.4% precision in detecting abnormal sounds such as coughing and sneezing.

Another common respiratory symptom, rales (gurgling or rattling breathing sounds) was effectively detected using Mel frequency cepstral coefficients and decision trees (Carroll *et al*., 2014). Likewise, by analysing vocalisations from both healthy and infected birds, Rizwan *et al*., (2016) extracted Mel-scaled spectral features and applied machine learning algorithms. The classifiers achieved high accuracy rates of 97.1% and 97.6% in distinguishing between healthy and diseased birds (rale sounds), respectively. Whitakes *et al*., (2014) used sparse spectrogram decomposition to classify vocalisations of healthy and bronchitis-infected broilers, enabling the detection of rale sounds. Their method achieved 97.8% accuracy in identifying infectious bronchitis based on one-minute audio samples. Mahdavian *et al*., (2021) analysed five acoustic features of broiler vocalisations to assess their effectiveness in detecting health issues. They found that specific parameters correlated with health status, achieving 83% accuracy on the third day and 80% on the fourth day post-inoculation in birds infected with bronchitis and Newcastle disease.

Banakar *et al*., (2016) explored audio-based detection of avian diseases by testing 14-day-old broilers infected with Newcastle Disease, Infectious Bronchitis Virus, and Avian Influenza. The researchers recorded vocalisations over two post-infection days and extracted 100 statistical features using the Fast Fourier Transform and Discrete Wavelet Transform. After selecting the most relevant features through an improved distance evaluation method, they trained a Support Vector Machine (SVM) classifier, which achieved 83.3% accuracy. By integrating the SVM classifier results with Dempster-

Shafer evidence theory, a mathematical framework for combining evidence under uncertainty, the overall diagnostic accuracy increased to 91.1%. Huang *et al.*, (2019) developed an audio-based detection method to identify avian influenza in chickens at an early stage. By analysing the vocalisations of infected birds, the system aimed to detect subtle changes in the sound patterns associated with the disease. The researchers recorded the vocalisations of infected chickens until day six, when all subjects succumbed to the illness, and achieved an accuracy rate of 84–90% in detecting avian influenza. Advancing this approach, Cuan *et al.*, (2020) developed a convolutional neural network capable of distinguishing between healthy and avian influenza-infected chickens based on their vocalisations. The model achieved a high classification accuracy of 97.43%.

Beyond viral diseases, bacterial infections, such as necrotic enteritis caused by *Clostridium perfringens* type A, result in epithelial damage, microbiota changes, and economic losses (Daneshmand *et al.*, (2019). Sadeghi *et al.*, (2015) developed a system for identifying and classifying chickens infected with *Clostridium perfringens* type A using vocalisation analysis. SVM were applied to vocal data collected over 30 days from 30 chickens (15 infected and 15 healthy), revealing distinct differences in vocal patterns. Whereas healthy broilers exhibited more intense and uniform vocalisations, infected birds showed higher energy vocalisations in the low-frequency range. The model achieved 66.6% accuracy on day 16 and reached 100% by day 22.

To enhance chickens health monitoring, researchers have explored night-time vocalisations, when feeding and drinking activity is minimal, as a way to more easily detect abnormal sounds such as sneezes. Du *et al.*, (2018) developed a surveillance system using microphone arrays and Kinect sensors to monitor 11 hens and 4 cocks from 11:00 p.m. to 3:00 a.m. over several weeks. The system identified 53 distinct normal vocalisations and applied sound-source localisation to detect and locate abnormal sounds indicative of distress or health issues. It achieved 74.7% accuracy in laboratory settings and 73.6% in small-flock tests. Given the challenge of detecting disease-related vocalisations, evaluating sounds at night is a promising approach for early disease detection.

According to Banakar *et al.*, (2016), Huang *et al.*, (2019), and Sadeghi *et al.*, (2015), avian diseases can be diagnosed by analysing the frequency domain of broiler sounds and, reducing economic losses through early identification. Machine learning algorithms such as artificial neural networks (Cuan *et al.*, 2020) and SVM (Banakar *et al.*, 2016; Huang *et al.*, 2019; Rizwan *et al.*, 2016; Whitaker *et al.*, 2014) have shown high accuracy in automatically detecting respiratory diseases.

The 18 studies reviewed under the health domain demonstrated the growing potential of acoustic analysis as a tool for early disease detection and health monitoring of chickens. Vocalisations, such as coughs, sneezes, and rales, have shown promise as indicators of respiratory infections, inflammatory responses, and other health-related conditions. Recent advances in machine learning and deep learning techniques have achieved high levels of accuracy in detecting and classifying abnormal vocalisations. However, several critical gaps remain. Many models are trained and validated under experimental settings. In most studies, limited information is provided on how vocal signals evolve across disease stages or in response to co-infections or even the specificity of vocal responses to particular pathogens. Moreover, few studies assess the longitudinal robustness of these models or validate them across flocks with different genetic lines, housing systems, or management practices. The lack of standardised recording protocols and the variability in microphone setup, signal preprocessing, and labelling criteria also hinder reproducibility and real-world implementation.

Behavioural interactions

Among the 57 reviewed studies, only one directly addressed the domain of behavioural interactions, highlighting a significant research gap. The study, conducted by Bright (2008) on a commercial farm, focused on feather pecking in laying hens, a well-known welfare issue associated with pain, skin damage, and chronic stress.

In this study, hens identified as feather peckers emitted a higher call rate and more frequent squawks than non-peckers. These squawk vocalisations were characterised by abrupt onset, broad frequency ranges, and durations of approximately one second. Acoustic features such as intensity and frequency differed notably between the two groups, suggesting that vocalisations can serve as indicators of negative social interactions within a flock.

These findings support the potential use of sound analysis to monitor aggressive or harmful behaviours. However, the lack of studies addressing other behavioural patterns, such as social bonding (e.g. social play or mutual preening), hierarchy disputes, or mating calls; limits our understanding of how vocalisations reflect the complex social dynamics of chickens.

Given that social behaviour is a core component of animal welfare, particularly under the behavioural interactions domain of the Five Domains model, this is a critical area for future exploration. Sound analysis may provide a non-invasive means to detect and quantify subtle social behaviours at the group level, particularly in large-scale housing systems where visual monitoring is impractical.

Mental state

The mental state domain connects physical and behavioural experiences to emotional and cognitive responses. Sixteen studies specifically addressed this domain: nine on laying hens, six on broilers, and one unspecified. Eleven were conducted under experimental conditions, and five on commercial farms.

Several studies demonstrated that vocalisations reflect emotional states in chickens. Collins *et al*., (2024) reported that vocal pitch, duration, and modulation varied with emotional arousal in layer chicks. Maldarelli *et al*., (2024) identified rhythmic, structured patterns in chick vocalisations that reflected both emotional valence and social context. E. Pereira *et al*., (2023) and Marx *et al*., (2001) showed that isolation increased distress calls, while group housing produced lower-energy, comfort-related vocalisations. These effects were modulated by environmental and social conditions. E. Pereira *et al*., (2014) also found that changes in frequency, intensity, and call structure correlated with welfare indicators in broilers.

Emotional responses to human interaction were explored by Genc and Ozenturk (2024), who found that darker clothing worn by workers increased alarm vocalisations, while lighter tones elicited calmer responses. Neethirajan (2023) noted similar shifts in acoustic parameters during stress exposure in laying hens. Feeding context also influenced emotional expression. Ginovart-Panisello *et al*., (2024a) found that prolonged fasting altered vocal frequency and bandwidth in newly hatched broilers. Golfidis *et al*.,

(2024) used interactive feeders to elicit frustration and anticipation, finding that specific vocal traits correlated with emotional arousal and valence.

One particularly well-studied call is the gakel-call, associated with frustration during thwarted behaviour, such as blocked access to food or nesting (Zimmerman *et al.*, 2000b). These calls have a rising tone followed by short, low-frequency notes and occur across contexts. Zimmerman *et al.*, (2003) showed that their frequency increased in the presence of an audience, suggesting a social function. Anticipatory vocalisations have also been explored. McGrath *et al.*, (2017) found that hens anticipating dustbathing emitted lower-frequency calls than those expecting food, indicating motivational and emotional nuance in vocal output.

Automation has enabled broader monitoring. Jakovljević *et al.*, (2019) and Herborn *et al.*, (2020) applied machine learning to detect stress-related vocal features like spectral entropy and pitch. Mao *et al.*, (2022) developed a deep learning model capable of identifying distress calls in large flocks, even under noisy farm conditions.

Vocalisations in chickens are closely linked to emotional states including fear, frustration, anticipation, comfort, and satisfaction. These findings highlight the mental state domain as a valuable target for vocal-based welfare monitoring. However, most studies are based on small samples, under experimental conditions, and lack standardised definitions for vocal types and emotional states. Context sensitivity and inter-individual variation also limit interpretation. Moreover, while some studies suggest possible cognitive elements, such as expectation or social awareness, the current body of research predominantly focuses on emotional states, leaving cognitive dimensions of vocal expression largely unexplored.

Technical aspects

The technical quality of vocalisation-based chicken monitoring systems depends heavily on both hardware, especially microphones, and software used for data analysis (Manikandan and Neethirajan 2025). While audio recording equipment is widely accessible and affordable (Hill *et al.*, 2018). While audio recording equipment is widely accessible and affordable, only 36% of studies that reported both sampling rate and bit depth met the recommended criteria of at least 40 kHz sampling frequency and 16-bit resolution. These parameters are essential for preserving the spectral content of bird vocalisations, as higher resolution ensures greater accuracy in capturing the subtle frequency modulations typical of chickens calls. Surprisingly, despite the availability of suitable equipment, a large portion of the literature still relies on suboptimal recording setups, potentially affecting data quality and limiting the effectiveness of subsequent analysis.

In terms of analytical approaches, studies applied three main categories of methods: classical statistical analysis, basic machine-learned classification, and advanced deep learning. Most studies (23 out of 57) fell into the first category, relying on manual or semi-automated feature extraction followed by statistical tests or traditional modelling. Only two studies employed commonly used classifiers such as SVM or decision trees, while six used more sophisticated architectures like convolutional or recurrent neural networks. The adoption of machine learning methods began around 2014, with deep learning approaches emerging more recently, especially after 2020. However, more than

25 studies did not report sufficient detail about their analytical methods, hindering reproducibility and comparative analysis.

A key technical challenge lies in the generalisability of these models. Most were trained on data from specific experiments involving limited environmental and genetic variability. As a result, models that perform well in controlled conditions often fail when deployed in commercial environments where background noise, variable lighting, ventilation systems, and flock dynamics can differ significantly. Overfitting is also a common concern, as many models are designed to detect only a narrow subset of vocalisations selected to match the target outcome of the study, rather than capturing the full diversity of the birds' vocal repertoire. This selective approach limits the models' ability to adapt to new contexts and detect emerging welfare issues.

The robustness of models is further challenged during real-world deployment, where different microphone types, placements, and room acoustics can distort the input signal. Changes in background noise, such as from HVAC systems or alarms, not present during training can reduce detection accuracy. Moreover, subtle shifts in vocal behaviour due to flock age, time of day, or external stimuli may confound classification algorithms. These inconsistencies highlight the importance of designing flexible, noise-tolerant systems that can adapt to varying production environments.

To address these issues, researchers have proposed strategies such as data augmentation to simulate variability during training, the use of public datasets for benchmarking, and the adoption of standardised annotation protocols for vocalisations. One important step in this direction was made by Adebayo *et al*., (2023), who released a chickens vocalisation dataset to support open research. To advance this field, collaborative approaches that integrate ethology and machine learning within the same study are essential for both identifying and interpreting vocal signals in a biologically meaningful way. The development of robust and transferable sound-based monitoring systems in chickens requires improvements in hardware standardisation, consistent reporting of analytical methods, and broader testing across diverse environments. With the integration of machine learning and standardised audio pipelines, these systems have the potential to support precision livestock farming at scale, provided the current technical barriers are systematically addressed.

Microphones

There were 37 studies that provided information regarding their recording setup. For instance, Aydin *et al*., (2014, 2015) and Aydin and Berckmans (2016) employed condenser microphones placed close to feeders. These devices were selected for their high sensitivity and ability to detect short, impulsive pecking sounds with minimal distortion, which was crucial for accurately estimating feed intake. Likewise, Fontana *et al*., (2015, 2017) used directional microphones positioned near birds to track variations in vocal frequency over time, which were later correlated with body weight.

Several studies have emphasised the strategic placement of microphones to improve recording quality. Huang *et al*., (2021), for example, placed microphones at calibrated heights and distances relative to broilers, optimising the signal-to-noise ratio for behavioural sound detection. Similarly, Collins *et al*., (2024) recorded chick vocalisations in a soundproof environment using directional microphones placed close to the animals, allowing for the detection of subtle emotional variations in call features. The study identified changes in distress vocalisations by correlating acoustic parameters, such as call duration, pitch, and energy, with experimental conditions designed to induce negative affective states, specifically social isolation with or without the presence of a mirror. The mirror was included to assess its potential to buffer the emotional impact of isolation. Emotional states were inferred from systematic changes in vocal behaviour, interpreted in relation to the presumed affective responses elicited by each condition.

Amirivojdan *et al.*, (2024) introduced a different approach using piezoelectric sensors in their ChickenSense system. Unlike traditional condenser microphones, these sensors detect mechanical vibrations directly from contact points (such as feeder surfaces), offering noise immunity and specificity for pecking activities in noisy environments. A different method was observed by Du *et al.*, (2018), who combined microphone arrays with Kinect sensors to develop a sound-source localisation system. This setup went beyond sound detection, enabling spatial identification of vocalisations during night-time observations.

In contrast, Carpentier *et al.*, (2019) and Liu *et al.*, (2020) implemented recording systems optimised for noisy commercial settings. Carpentier's tool for sneeze detection used sensitive microphones with digital filters to isolate sneezing sounds, while Liu's system employed a microphone array combined with advanced preprocessing through Weighted Mel-Frequency Cepstral Coefficients and Hidden Markov Models to classify normal and abnormal vocalisations.

Although most studies relied on high-quality, directional microphones, the specific technologies varied depending on the purpose (i.e. for disease detection, feeding behaviour, stress monitoring, or emotional evaluation). Microphone type, sensitivity, and placement play critical roles in data quality and interpretation. While the majority of researchers favoured directional condenser microphones placed close to animals to maximise vocal clarity, others (such as Amirivojdan *et al.*, (2024) and Du *et al.*, (2018)) opted for more innovative or multimodal systems, reflecting the evolution of acoustic monitoring in chickens research.

Model accuracy and evaluation metrics

Across the studies reviewed, the model accuracy and evaluation metrics of sound-based systems varied depending on the analysis objectives (disease detection, identification of discomfort, or feeding behaviour monitoring), the target vocalisation type, and the algorithms employed. Studies focusing on disease detection, such as those by Whitakes *et al.*, (2014) and Cuan *et al.*, (2020), achieved some of the highest accuracies, 97.8% and 97.4% respectively, using advanced spectrogram decomposition and convolutional neural networks. Similarly, Rizwan *et al.*, (2016) reached 97.6% with SVM and 97.1% with Extreme Learning Machine (ELM) classifiers for identifying rale sounds. Liu *et al.*, (2020) further showed high robustness in commercial settings with 93.8% accuracy and 94.4% precision using Weighted Mel-Frequency Cepstral Coefficients and Hidden Markov Model for abnormal vocalisation detection in large broiler populations. However, Carpentier *et al.*, (2019) achieved slightly lower sensitivity (66.7%) but good precision (88.4%) when identifying sneezing events, suggesting that some conditions or symptoms may be harder to detect consistently, particularly in noisy environments.

Banakar *et al*., (2016) improved classification accuracy from 83.3% to 91.1% by integrating SVM with Dempster-Shafer evidence theory, reinforcing the advantage of hybrid models for complex classification tasks.

Sound-based monitoring of feeding behaviour also showed good results. Aydin *et al*., (2014) and Aydin *et al*., (2015) demonstrated accuracies of 93% and 86%, respectively, by correlating pecking sounds with feed intake. These findings were reinforced by Fontana *et al*., (2015, 2017), whose predictive models reached 96% accuracy when modelling broiler weights based on vocalisation frequency. More recently, Amirivojdan *et al*., (2024) reported 92% accuracy and an F1-score of 91% to estimate broiler chickens' feed intake using deep learning in their ChickenSense system. For stress-related vocalisations, Du *et al*., (2018) provided insight into nocturnal abnormal vocalisations, achieving 74.7% accuracy in laboratory settings and 73.6% in commercial trials. While lower than disease or feeding models, this is given the complex background noise and the unsupervised nature of night-time recordings. Sadeghi *et al*., (2015) presented moderate accuracies (78–83%) depending on the disease and day post-infection, highlighting the time-sensitive nature of acoustic biomarkers in early disease detection.

Although several studies have reported good results on performance, there are notable variations in the methodology, evaluation conditions (experimental or commercial), and target vocalisation types. For instance, Jakovljević *et al*., (2019) and Mao *et al*., (2022) reported high detection performance in stress classification and distress call identification, respectively, yet did not specify accuracy values, limiting direct comparisons. Furthermore, a few studies, such as Ginovart-Panisello *et al*., (2024a) on fasting-induced vocal changes, demonstrated relevant findings but did not report classification metrics, indicating a gap between behavioural insight and model validation.

High-performing sound-based systems show promise for real-time monitoring of broiler health, feeding, and welfare, with accuracies often exceeding 90% in controlled studies, highlighting their potential to reduce manual labour and improve early intervention in chickens farming. However, to translate these promising results into practical applications, it is essential that future studies adopt standardised reporting of performance metrics and validate their models under commercial conditions to ensure scalability, reliability, and industry uptake.

Conclusion

This review highlights major advances in acoustic analysis as a tool for chickens welfare assessment across the five domains: nutrition, physical environment, health, behaviour, and mental state. The growing number of publications in recent years reflects the increasing interest in using vocalisation monitoring as an objective approach to evaluate bird welfare.

Under the nutrition domain, pecking-related sounds have shown high predictive accuracy for feed intake and growth. However, more welfare-relevant indicators, such as vocalisations linked to hunger, thirst, or malnutrition, remain largely unexplored. In the physical environment domain, vocalisations effectively signal thermal discomfort, poor air quality, and other housing-related stressors. Embryonic and hatchling vocalisations offer promising insights for hatchery management. Still, broader applications, such as responses to stocking density, ammonia levels, and nuanced metrics like THI (Temperature-Humidity Index), are underexplored.

The health domain has seen the most research, with vocal markers like coughs, sneezes, and rales associated with respiratory and inflammatory conditions. This concentration is likely due to the presence of clearer, more distinguishable acoustic markers and the high economic impact of early disease detection in chickens production. Machine learning models have shown high accuracy but are mostly based on small-scale, controlled studies. Behavioural interactions remain the least explored domain, with studies limited to feather pecking in laying hens, highlighting a gap in understanding vocal correlates of broader behavioural patterns. Lastly, the mental state domain integrates insights from all other domains to assess affective experiences, especially emotional valence (positive vs. negative experience) and arousal (intensity of the emotional response) (Mendl *et al.*, 2010). Vocalisations in chickens vary with emotional states such as frustration, fear, anticipation, and satisfaction. However, interpreting emotional meaning from vocal data remains challenging due to a lack of standardised call definitions and limited validation across contexts.

Vocalisation analysis offers a promising, automated, and animal-centred method to complement existing welfare indicators, with the potential to improve decision-making and reduce labour demands. However, key gaps remain. A reliable understanding of the meaning and significance of most vocalisations is still lacking. More research is needed to interpret these sounds across contexts and link them to welfare-relevant emotional or physiological states. In particular, establishing clear associations between vocal parameters and emotional dimensions such as valence and arousal remains a major challenge, requiring integration of acoustic, behavioural, and physiological data.

Practical implementation on farms requires systems that are cost-effective, user-friendly, and robust. While basic microphones are affordable, effective monitoring demands high-sensitivity, weather-resistant equipment, which may increase costs. Systems must be plug-and-play, requiring minimal technical expertise for setup, calibration, and data interpretation. Continuous recording also generates large datasets, necessitating cloud-based platforms with secure storage, automated analysis, and intuitive visual outputs. Vocal data should complement existing welfare indicators – such as gait or footpad scoring – to enable early interventions rather than serve as a stand-alone tool.

Technical challenges persist, including inconsistent audio quality, background noise, and variability in microphone placement. Additionally, many current models are trained on small, context-specific datasets and lack validation in commercial settings. Most studies to date have been conducted under experimental conditions, with limited attention to real-world environments such as transport or slaughter phases.

Future research should prioritise standardisation, validation, and industry collaboration. This includes harmonising recording protocols, microphone placement, and background noise filtering techniques. Public repositories of annotated chickens vocal datasets are needed to promote transparency and model reproducibility. Biological validation should combine acoustic data with physiological (e.g. corticosterone), behavioural, and neurobiological measures to assess affective states accurately. Generalisability must be tested across breeds, production systems, and life stages – including hatchery, on-farm, transport, and slaughter.

Collaborating with chickens producers is essential to conducting real-time, on-farm trials that evaluate the impact of acoustic monitoring on early detection, intervention success, and economic outcomes. Finally, integration with welfare certification programs could support the inclusion of vocal indicators in formal welfare assessments, accelerating adoption across the industry.

With advances in automation, large-scale validation studies are now feasible, opening the door to practical and scalable applications. To realise this potential, the field must move beyond controlled studies and invest in robust, interdisciplinary solutions that bridge ethology, engineering, and industry needs.

Disclosure statement

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