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Identification and characterization of clusters of potentially new vocalizations in broiler chickens using advanced acoustic analysis

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ABSTRACT

This study investigates and characterizes vocalizations in broiler chickens from 1 to 35 days of age using advanced acoustic analysis and machine learning techniques. Understanding broiler behavior, particularly vocalizations, is crucial for improving animal welfare in both on-farm and laboratory conditions. While four known vocalizations (distress calls, short peeps, warbles, and pleasure notes) are well documented using sound analysis, there remains a gap in understanding the full vocal repertoire of broiler chickens, which may hold key insights into their emotional and physiological states. Using a deep learning-based vocalization recognizer and recursive clustering algorithms, we identified 42 distinct sound clusters - in addition to the 4 known vocalizations - from recordings of healthy broiler chickens, eventually narrowing them down to 10 key clusters that potentially represent novel vocalizations. These vocalizations were analyzed for their frequency, duration, and acoustical power, and their temporal distribution was examined. The findings suggest that broilers expand their vocal repertoire as they age, presenting a more diverse repertoire in the later stages of life. Despite the limited sample size and absence of statistical replicates, this study offers valuable insights into the complexity of broiler vocalizations. This research contributes to the growing body of knowledge on broiler auditory communication and opens new possibilities for automated vocalization monitoring in chicken farming.

Introduction

Ross 308, the most widely used broiler strain worldwide (Aviagen, 2024), is typically raised for 35-42 days, reaching 1.8–2.2 kg to meet demand for smaller birds (Aviagen, 2018; Tuyttens et al., 2014). Chicken meat production has expanded rapidly due to its fast growth, cost-efficiency, high nutritional value, and broad cultural acceptance (Mottet and Tempio, 2017). However, this growth has intensified poultry farming, increasing flock sizes and management complexity, and raising concerns about potential impacts on animal welfare (Jones et al., 2005; Norton et al., 2019; Tuyttens et al., 2022).

Understanding broiler behavior and affective states is increasingly recognized as essential for improving animal welfare and optimizing management strategies (Anderson et al., 2021). On farms, it presents the potential to monitor large flocks in real-time, detecting signs of stress, illness, or discomfort. In laboratories, a behavioral indicator that complements physiological data under controlled conditions. One promising method for monitoring welfare is the analysis of vocalizations, critical behavioral indicators that can reflect animals' emotional and physiological states (Briefer, 2012; Zimmerman et al., 2000). By decoding the nuances of broiler vocalizations, researchers and farmers can gain valuable insights into how birds experience and respond to their

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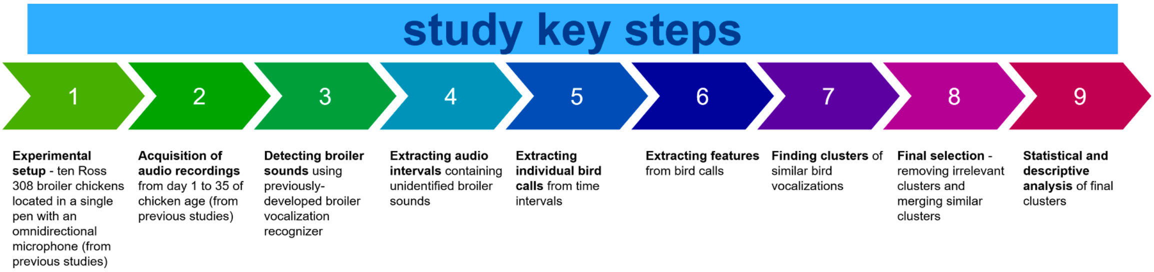

Fig. 1. Summary of the study presented in the form of nine steps.

environment, supporting the development of more effective welfare monitoring systems (Cloutier et al., 2022; Marx et al., 2001).

Despite this potential, only a limited range of vocalizations has been identified in broiler chickens, especially compared to the more extensive vocal repertoire of laying hens (Neethirajan et al., 2023; Zimmerman et al., 2000). While four main vocalizations (distress calls, short peeps, warbles, and pleasure notes) have been documented in broilers and used in acoustic monitoring (Soster et al., 2025; Thomas et al., 2023), little is known about other potential vocal types. This underrepresentation may result from the focus of vocalization research on laying hens (Jung, 2021; Neethirajan, 2023), which have longer lifespans and are exposed to more complex environments, allowing for a broader development of vocal behaviors.

The differences in vocal repertoire between broilers and layers may also stem from their divergent breeding histories and production purposes. Laying hens undergo longer physiological development and often engage in more intricate social interactions, conditions that support a richer vocal profile. In contrast, broilers are raised for rapid growth and meat production and are typically slaughtered at 35 to 42 days of age, limiting the window for behavioral maturation. Nevertheless, emerging evidence suggests that even within their short lifespan, broilers may develop a more diverse vocal repertoire than previously assumed. In many avian species, including chickens, vocal development is known to progress with age and is influenced by neurological, physiological, and social factors (Catchpole and Slater, 2003, 2008; Gill, 2007). These findings raise the possibility that broiler vocalizations could similarly increase in complexity with age, providing further motivation to explore and characterize these behaviors in detail.

Building on this, technological advances in sound analysis and machine learning have opened new possibilities for decoding vocal communication in poultry. Recent advances in sound analysis and machine learning have enabled considerable progress in deciphering chicken vocal communication (Aydin and Beckman, 2016; Fontana et al., 2015; Herborn et al., 2020). Machine learning models have revolutionized the automated identification of similar sound groups in unlabeled audio data. Neural network-based models can generalize well across different environments and are well-suited for the analysis of broiler vocalizations (Kong et al., 2020; Soster at al., 2025; Thomas et al., 2023).

Current research builds on the work of Thomas et al. (2023) and Soster et al. (2025). In these earlier studies, ten Ross 308 broilers were housed together in a single pen and continuously recorded from day 1 to 35. The recordings were automatically processed using a general-purpose, publicly available sound event detection model (PANN; Kong et al., 2020) to identify relevant bird sounds. A subset of these sounds was manually labeled and used to train a neural network–based broiler vocalization recognizer capable of detecting four distinct vocalizations—distress calls, pleasure notes, short peeps, and warble notes—as well as identifying other, currently unclassified, broiler sounds and distinguishing them from background noise.

Distress calls were defined as repetitive, vigorous vocalizations; short peeps as low-intensity, short-duration calls with diminishing energy;

Fig. 2. Experimental setup of the trial.

pleasure notes as brief, low-energy sounds with rising pitch; and warble notes as ascending or descending, bow-shaped vocalizations of low energy and repetitive character (Marx et al., 2001). The “other vocalizations” category encompassed all sounds initially identified as bird calls by the PANN model but not fitting into the four known types during manual expert labeling (Soster et al., 2025).

In the present study, we re-analyzed the same continuous recordings of the ten Ross 308 broilers. Using the previously developed broiler vocalization recognizer, we specifically targeted all unidentified broiler sounds, including those missed by the PANN model or not previously labeled. The objective was to extract these unidentified vocalizations and cluster them into groups of acoustically similar sounds, with the goal of identifying potential new vocalization types.

Materials and methods

The study was conducted under the general certification number LA1400564, which authorizes Poulpharm to carry out animal trials. According to the Royal Decree of May 29, 2013, on the protection of animals used for scientific purposes (published on July 4, 2013), specific approval from an Ethics Committee was not required for this trial, as the procedures did not induce significant pain or suffering beyond what is typically associated with minor procedures. An overview of the study, presented in the form of nine key steps, is depicted in Fig. 1. Steps 1 and 2 are common with, and were previously described in Thomas et al., 2023 and Soster at al., 2025.

Experimental setup and audio acquisition – steps 1 and 2 (from previous studies)

Ten one-day-old male Ross 308 chicks were selected by a skilled stockperson through visual assessment according to commercial hatchery standards, ensuring they were active and alert, with bright eyes, healthy legs, a well-healed navel, and free from deformities, weakness, or signs of infection (Aviagen, 2018). The selected chicks were then placed at Poulpharm (Izegem, Belgium). The chicks were housed in a single pen measuring 2m^2, located in an isolated room at Poulpharm (Fig. 2). Concrete walls formed a barrier, isolating this room from both other broiler houses and the external surroundings. The pen was equipped with a galvanized cylindrical hanging feeder and a nipple drinker system connected to a horizontal PVC pipe. The floor consisted of concrete covered with wood shavings at a density of 2.5 kg/m^2, providing a comfortable and absorbent bedding material. The pen walls were made of rigid-framed metal mesh panels, which ensured proper ventilation and visibility while securely containing the birds. All birds received the same commercial pelleted diets, consisting of a starter feed from days 1 to 14 and a grower feed from days 15 to 36. Feed and water were provided *ad libitum*, and diets were formulated according to the nutritional recommendations for Ross 308 broilers.

The pen’s temperature and lighting followed the prescribed standards for the Ross 308 breed (Aviagen, 2018). Temperature and humidity were controlled using an environmental control system and monitored daily by a caretaker. The room was a climate-controlled chamber equipped with built-in heating and air conditioning units to maintain stable ambient conditions. Additionally, a heat lamp was installed inside the pen to provide localized warmth during the first week of life, ensuring adequate brooding temperature for the chicks. At placement, the temperature at chick level was set at 33°C and gradually reduced by approximately 0.5°C per day. From the fourth week onward, a stable temperature of 21°C was maintained.

During the first week, birds were maintained on a 23-hour light and 1-hour dark (23L:1D) lighting schedule, with a light intensity of 30 lux at bird level. Starting in the second week and continuing until the end of the experiment, the lighting schedule was adjusted to 18 hours of light and 6 hours of darkness (18L:6D), with a light intensity of 10 lux at bird level. To ensure the removal of moisture, ammonia, and CO_2, a minimum ventilation rate of 0.1 m^3/kg/h was provided and adjusted as necessary throughout the experimental period. Relative humidity was maintained at approximately 60 %. Every day, the chickens were carefully observed for any indications of sickness or death. Their overall health, instances of mortality, and the presumed cause of death were documented daily.

A low-cost sensor node equipped with a Knowles FG-23329 microphone (Van Renterghem et al., 2010) was installed at a height of 90 cm in the center of the pen to continuously record chicken vocalizations. The pen measured 1.10 m by 2.10 m, and the microphone placement was selected to balance uniform audio capture throughout the area with the need to reduce background noise and wall reflection interference, thus improving the signal-to-noise ratio. A sampling rate of 48 kHz was applied, as supported by previous research (Huang et al., 2019; Liu et al., 2020; Lv et al., 2023), and is considered adequate for capturing the full range of chick vocal frequencies with precision.

Detecting broiler sounds – step 3

The recordings were processed with a deep learning–based broiler vocalization recognizer, originally developed by Thomas et al. (2023) and further extended by Soster et al. (2025). This recognizer detected four well-described broiler vocalizations and also indicated the presence of additional, currently unidentified sounds. To further analyze these vocalizations, clustering based on advanced acoustic features was performed to identify and characterize groups of similar calls.

Recordings were processed in 60-second segments. The recognizer applied a detection window of 1,940 ms, sliding over the input signal every 240 ms. Each prediction generated a set of six probability scores corresponding to the following classes: distress calls, pleasure notes, warbles, short peeps, other chicken sounds (not fitting into the previous four categories), and background noise. The six scores within each window summed to 100 %.

Extracting audio intervals containing unidentified broiler sounds – step 4

Based on the broiler vocalization recognizer’s predictions, time intervals potentially containing previously unidentified vocalizations were extracted using two decision rules: (1) intervals where the probability for the “other chicken sounds” class was high, and (2) intervals where probability scores were consistently low across all recognized classes, indicating lack of a clear classification. The first rule targeted sounds that the recognizer explicitly categorized as “other,” while the second rule was designed to capture novel vocalizations not included during training, acknowledging the risk of including non-vocalization noise.

For the first rule, intervals were identified as sequences of at least five consecutive predictions where the “other chicken sounds” probability exceeded 0.7, a threshold empirically determined to indicate confident detection. Each such interval was defined from 520 ms before the first prediction to 520 ms after the last, ensuring capture of all sounds contributing to detection. Consequently, the minimum interval length was 2.0 s, corresponding to four 240 ms prediction windows (960 ms), extended by 1,040 ms of margins (2 × 520 ms). This length was chosen to match the recognizer’s effective receptive field. For the second rule, the procedure was similar but applied to sequences of at least five consecutive predictions where all probability scores were below 0.7. Using these two approaches, 6,794 intervals were extracted under the first rule and 26,578 under the second, with lengths ranging from 2.0 to 9.4 s.

Extracting individual bird calls from time intervals – step 5

The 33,372 time intervals identified in Step 4 were processed to extract individual sounds suitable for cluster analysis. Because these intervals often contained multiple or heterogeneous sounds, classical

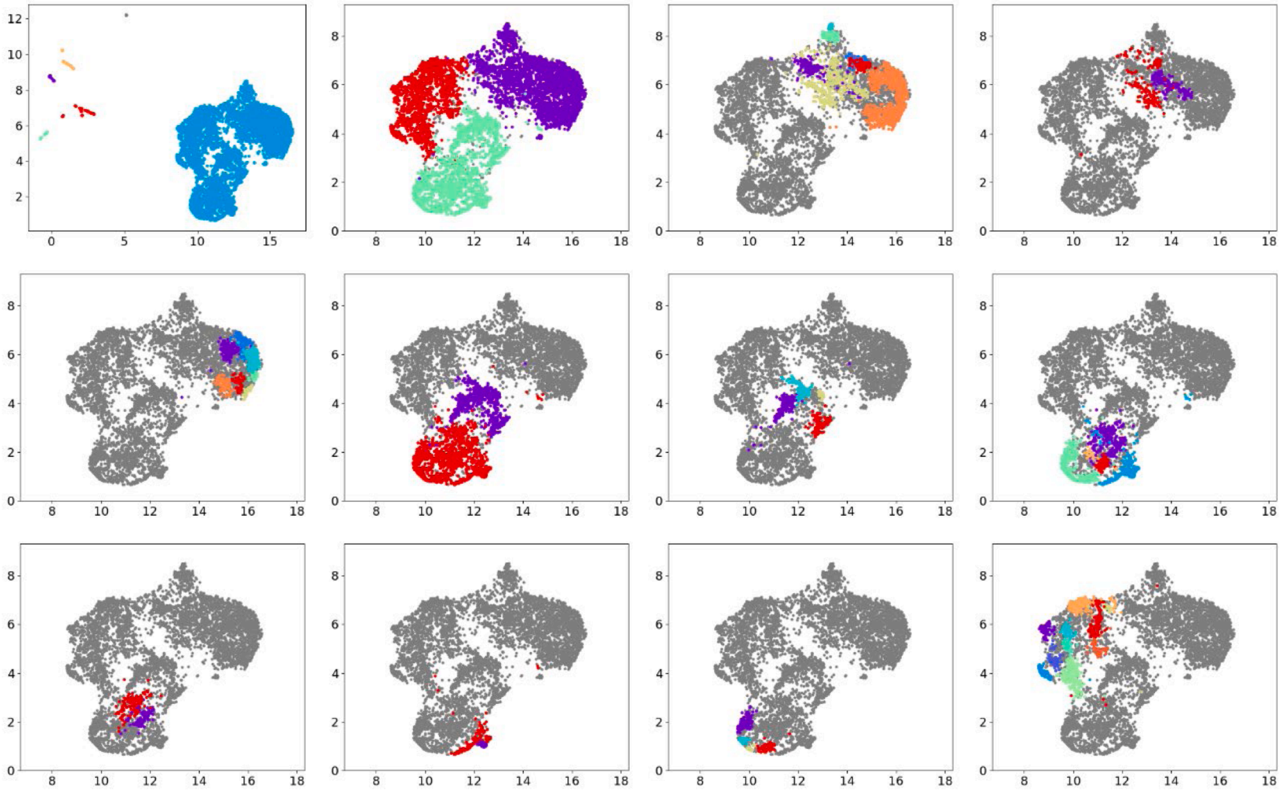

Fig. 3. Clustering of the potential new broiler vocalizations using a recursive invocation of UMAP and HDBSCAN algorithms in a depth-first manner. Sequential analysis of the 12 small graphs should commence from the top left corner, proceeding in a left-to-right manner within each row, and then transitioning to the subsequent row. The sequence of 12 data splits is also visualized in Fig. 3.

signal processing techniques were applied to isolate distinct vocalizations. The procedure included: (1) resampling to 16 kHz using high-quality FFT-based bandlimited interpolation; (2) non-stationary noise suppression via spectral gating (Sainburg et al., 2020); and (3) calculation of signal power in a 125 ms sliding window.

Individual sounds were segmented by identifying optimal cutting points based on short-term power profiles. Cutting points were determined using a greedy search and required two conditions: (1) the maximum sound level between cutting points had to exceed -70 dB; and (2) the sound level at both cutting points had to be at least 10 dB below the maximum level within that segment. The search was performed in windows of increasing size to encourage separation of individual calls. A fade-in and fade-out was then applied to the first and last 500 samples of each extracted sound.

This process yielded 3,891 sounds from intervals classified as “other chicken sounds” and 3,451 sounds from intervals with low probabilities across all classes. Extracted sounds ranged from 190 ms to 2,710 ms in duration (mean = 751 ms). The procedure was designed to accommodate vocalizations of variable length without a priori assumptions, while prioritizing the extraction of high-quality, distinct calls with minimal contamination by overlapping sounds or background noise. This ensured reliable inputs for subsequent clustering and interpretation in relation to broiler behavior and welfare.

Extracting features from bird calls – step 6

The 7,342 extracted sounds were processed for feature representation prior to clustering, following approaches commonly used in studies of animal vocalizations (Best et al., 2023; Ntalampiras et al., 2021; Parcerisas et al., 2023). Each sound, represented by a short audio recording, was converted into a deep audio embedding using the Animal Vocalization Encoder based on Self-Supervision (AVES) (Hagiwara, 2022). AVES is built on the HuBERT base model (Hsu et al., 2021), a transformer architecture comprising seven one-dimensional convolutional layers operating directly on raw audio samples, followed by 12 transformer blocks, a projection layer, and a code embedding layer.

HuBERT was originally trained on human speech to generate highly descriptive acoustic representations and was later fine-tuned on a diverse range of animal vocalizations. Using AVES, each extracted sound was transformed into a 768-dimensional embedding vector, enabling efficient comparison and clustering of acoustically similar calls.

Finding clusters of similar bird vocalizations – step 7

Cluster analysis was performed using a recursive combination of **UMAP** dimensionality reduction (McInnes and Healy, 2018) followed by **HDBSCAN** clustering (Campello et al., 2013; McInnes and Healy, 2017). UMAP was first applied to reduce the feature space from 768 to 10 dimensions, a setting recommended by McInnes et al. (2017) as a balance between preserving structural information and improving computational efficiency. This step mitigates the “curse of dimensionality,” which can reduce the effectiveness of distance-based clustering methods. HDBSCAN was then applied to assign cluster labels. The main algorithm parameters were set as follows:

- UMAP: *n_neighbors* = 30, *min_dist* = 0.0, metric = “euclidean”
- HDBSCAN: *min_cluster_size* = 25, *min_samples* = 25, *alpha* = 1.0, metric = “euclidean”

Most values followed the default recommendations, with minor adjustments to reflect dataset size and the assumed minimum usable cluster size.

Preliminary experiments indicated that one-shot clustering often resulted in either very large heterogeneous clusters (containing multiple

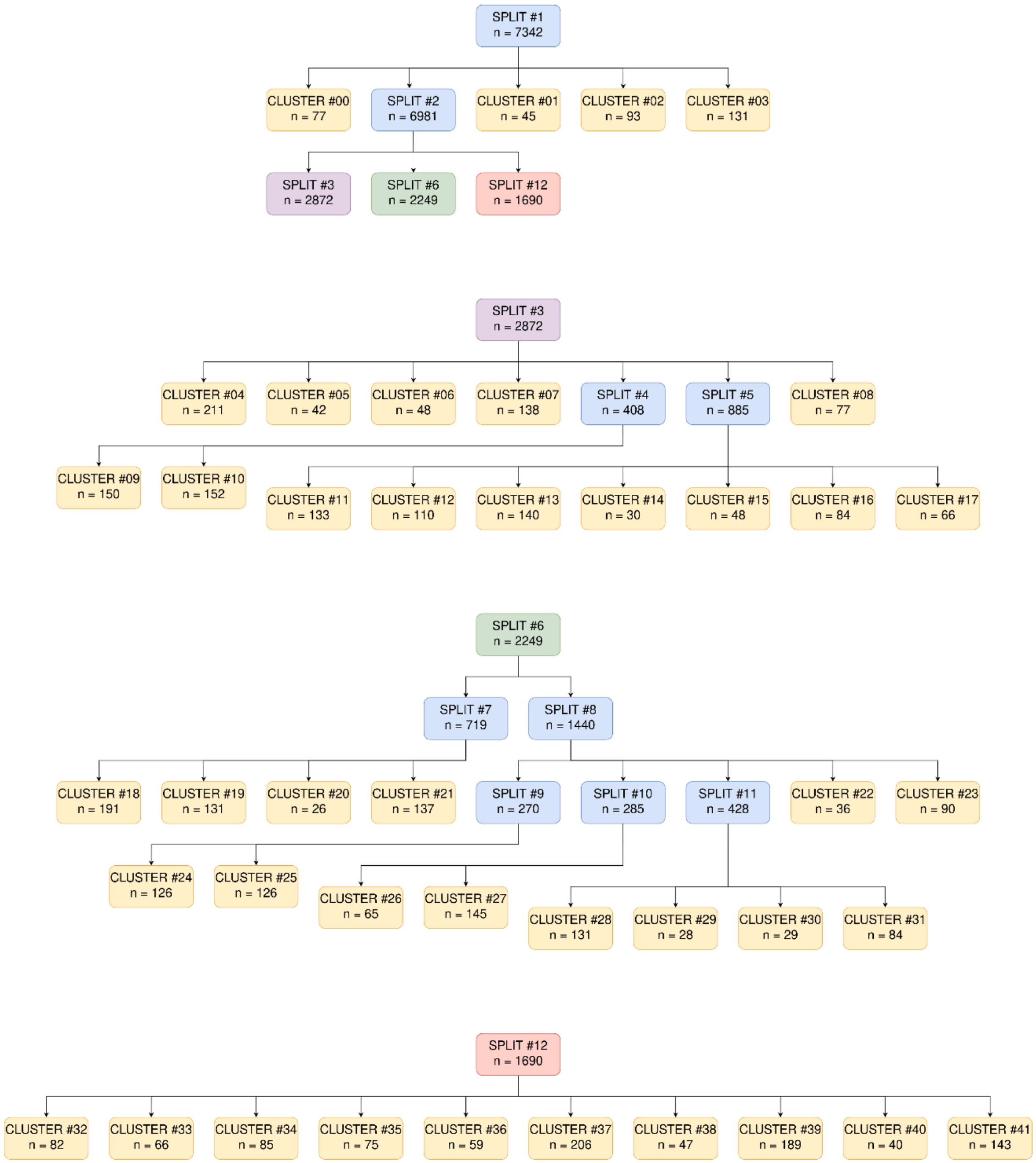

Fig. 4. A tree-view denoting the recursive invocation of UMAP and HDBSCAN algorithms to cluster the potential new broiler vocalizations. The large tree has been broken down into 4 smaller ones for better readability. Each block in the graph represents a single cluster of sounds. If a block contained more than 250 sounds, it was broken down into smaller clusters. The sequence of 12 invocations of the UMAP and HDBSCAN algorithm (splits) matches the scatter plots presented in Fig. 2.

vocalization types) or very small clusters (often non-broiler sounds). To address this, clustering was applied recursively to all clusters with more than 250 sounds. This strategy improved separation of distinct vocalizations, with the accepted trade-off of potential over-clustering, which could later be semi-manually merged if necessary.

In total, twelve recursive iterations were performed (Fig.s 3 and 4). In the first step, four small clusters were identified as non-chicken sounds originating from loudspeaker playbacks used during testing; these were excluded from subsequent analyses. The remaining sounds were progressively divided in a depth-first manner, ultimately yielding 42 clusters, each containing between 26 and 211 sounds.

Removing irrelevant clusters and merging similar clusters – step 8

Each of the 42 clusters obtained in Step 7 was manually reviewed by a poultry expert. Clusters containing sounds unrelated to broiler vocalizations—such as human voices, environmental noises, and equipment sounds—were excluded. To address potential over-clustering (i.e., splitting the same vocalization into multiple clusters), the Euclidean distances between cluster centers were calculated, and pairs of clusters were ranked in ascending order of distance. A poultry expert then defined a Euclidean distance threshold for merging clusters, aided by both visual inspection and auditory evaluation. Limiting human input to the selection of a single threshold value minimized subjectivity in the

Table 1
Cluster pairs with the shortest Euclidean distance between their mean embeddings. The first column indicates identifiers of two clusters (numbering consistent with Figs. 4 and 5) between which the distance is calculated. The final column depicts the acceptance of clusters merging.

Pair of clusters	Euclidean distance	Merge accepted
16 and 17	2.592	Yes
15 and 16	3.046	Yes
15 and 17	3.189	Yes
14 and 15	3.488	Yes
11 and 12	3.722	Yes
11 and 17	3.848	No
5 and 12	3.902	No
13 and 14	3.940	No
5 and 11	3.959	No
4 and 9	3.973	No
12 and 13	4.020	No
14 and 17	4.029	No
14 and 16	4.058	No
11 and 13	4.061	No
11 and 16	4.064	No

Table 2
The total number of known and unknown vocalizations distributed per week (broiler age).

Vocalizations	Week 1	Week 2	Week 3	Week 4	Week 5
Known Vocalizations					
Distress call	2490	651	5610	421	204
Short peep	5663	32619	7145	545	86
Warbles	25	111	143	63	13
Pleasure notes	3760	279	80	10	1
Subtotal	11938	33660	12978	1039	304
Unknown Vocalizations					
Cluster 4	0	2	21	96	92
Cluster 5	1	0	1	36	4
Cluster 6	2	41	1	3	1
Cluster 9	0	2	0	109	35
Cluster 10	1	6	24	96	25
Cluster 11 + 12	1	3	15	158	66
Cluster 13	0	0	3	45	92
Cluster 14 - 17	1	1	2	12	212
Cluster 39	12	32	113	28	4
Cluster 41	27	30	38	44	4
Subtotal	45	117	218	627	535
Total	11.983	33777	13196	1666	839

merging process.

Of the initial 42 clusters, 22 were excluded due to irrelevance, while six were removed after being identified as previously characterized vocalizations (two clusters of warble notes and four clusters of pleasure notes). The remaining 14 clusters were considered novel or insufficiently characterized. Based on Euclidean distances and expert-guided comparisons, acceptance thresholds for merging ranged from 2.592 to 3.722. Four clusters were consolidated into a single group, and two additional clusters were merged, resulting in 10 final clusters (Table 1).

Statistical and descriptive analysis of final clusters – step 9

In the final step, each cluster of potential novel broiler vocalizations was statistically and descriptively characterized. Three acoustic parameters were calculated for each sound: (1) fundamental frequency (Hz), estimated using the probabilistic YIN method (pYIN; Mauch et al., 2014); (2) maximum acoustic power (dB); and (3) sound duration (s), defined as the interval during which the power did not fall below 20 dB of the maximum. Cluster-level descriptors were obtained by computing mean values of these parameters. The temporal distribution of sounds was then visualized relative to broiler age (in days). In addition, for each cluster, the five sounds with the smallest Euclidean distance to the cluster center were selected for spectrographic visualization. These sounds were arranged sequentially with 1 s of silence between samples and normalized to their maximum power to facilitate comparison.

Results

The total number of vocalizations per type and week was tabulated in Table 2, and the spectrograms of the top 5 sounds from each cluster are represented in Fig. 5. Fig. 6 shows the plots of the number of sounds from each day of the broilers' life for all newly identified clusters. Two vocalizations were consistently present throughout the 36-day evaluation period, while seven out of ten vocalizations emerged primarily from the middle to the end of the observation period.

The characteristics of each selected cluster are outlined in Table 3. Notably, the characteristics of sounds vary. The duration of sounds in cluster 5 in week 4 presents the shortest average duration at 0.39 (± 0.10) s, while the longest, observed in cluster number 10 in the same week, was 0.85 (± 0.38) s. In terms of frequency, cluster 39 had the highest average value during week 1 (2936 ± 190 Hz), while cluster 5 hit the lowest frequency in week 5, although it exhibited very high deviation of values (303 ± 871 Hz). It is worth highlighting that, contrary to the observations made in Pereira et al., 2015, the present study did not uncover a consistent pattern of frequency decrease with age across all clusters. However, it is discernible that certain clusters, such as 5, 9, 10, 11, 12, and 39, exhibited a decrease in frequency. The power of the sounds, measured in decibels (dB), exhibited the lowest average power during week 2 in cluster 6 (−59.3 ± 3.4 dB), whereas clusters 14, 15, 16, and 17 registered the highest power in week 5 (−45.2 ± 4.0 dB).

Distress calls, short peeps, warbles and pleasure notes presented the higher number of vocalizations throughout the entire period evaluated, except in week 5. However, the four vocalizations initially analyzed predominated in the first three weeks in particular. Toward the middle to the end of their lives, broiler chickens expand their vocal repertoire. As evident from the plot illustrating the temporal distribution of sounds within each cluster, out of the 10 selected vocalizations, seven predominantly occurred from the middle to the end of the evaluated period. However, two vocalizations were consistently present throughout the entire period, with a higher number of observations in the medium age.

Discussion

This study set out to identify and characterize previously unexplored clusters of vocalizations in broiler chickens using advanced acoustic analysis. Through a comprehensive approach involving machine learning-based sound recognition and recursive clustering, a total of 42 initial clusters of sounds were successfully identified, of which 10 final clusters were retained for analysis. The findings highlight the complexity of broiler vocalizations and suggest that broilers may possess a more diverse vocal repertoire than previously recognized, especially as they mature.

The potential expansion of the vocal repertoire in broilers with age stands out as one of the key findings of the present study, although it remains speculative. While earlier research on broiler vocalizations using sound analysis focused on four types (distress calls, short peeps, warbles, and pleasure notes) (Marx et al., 2001), our study identified possible additional vocalizations, most of which emerged in the later stages of the broiler's life. For instance, short peep, pleasure notes, and distress calls were more frequent in the early stages of life. However, as the birds matured, there was a noticeable shift in the types of vocalizations, with more varied and complex sounds emerging. Just as distress calls are linked to stress, short peeps to increased activity, warbles to drowsiness or relaxation, and pleasure notes to positive welfare states (Andrew, 1973; Guyomarc'h, 1966; Marx et al., 2001), the newly identified clusters should be further investigated to determine their association with specific contexts, behaviors or emotional states.

The temporal distribution of vocalizations observed in this study, with seven out of ten clusters emerging primarily from week 3 onward,

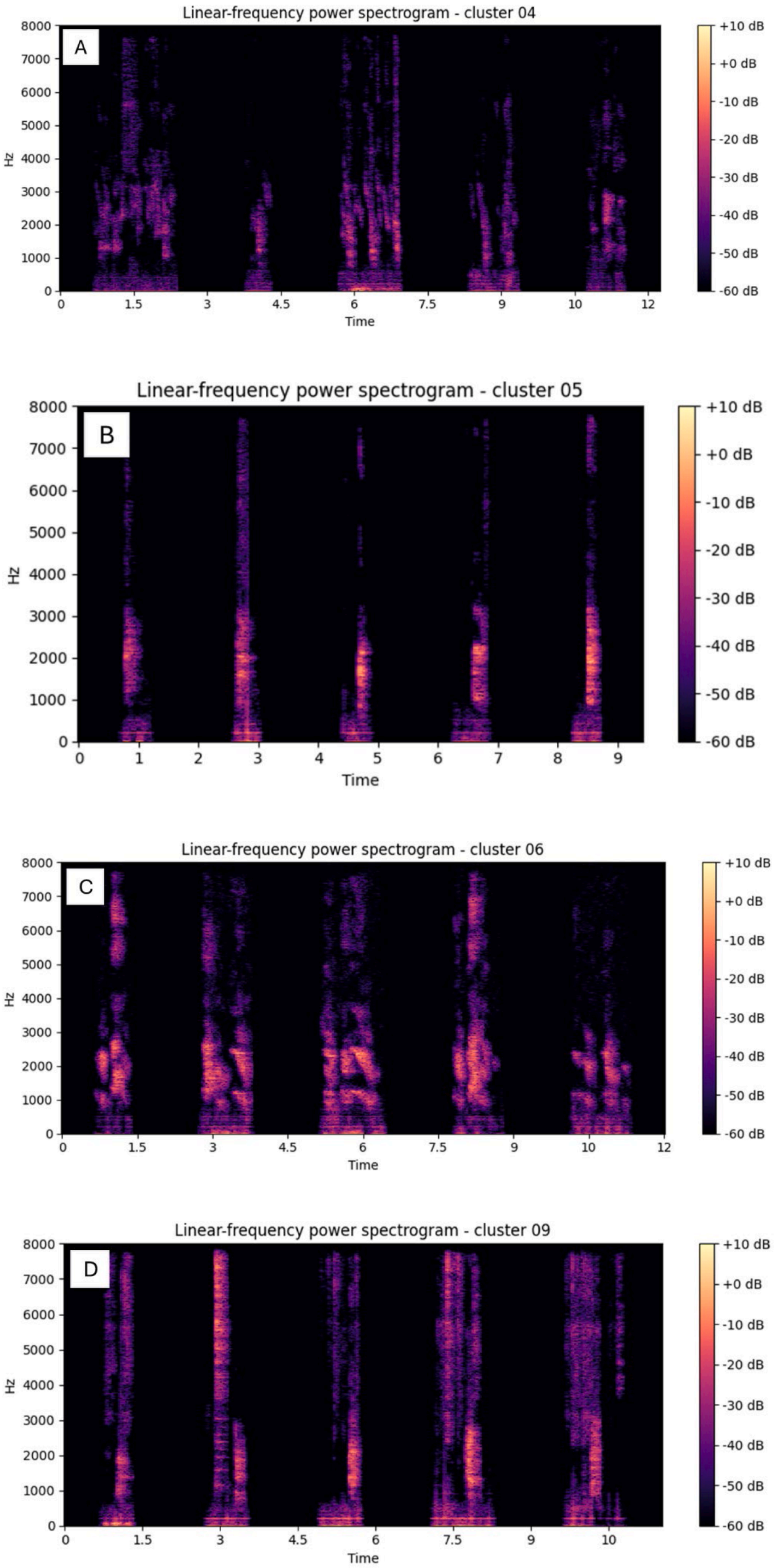

Fig. 5. Spectrograms of the 10 selected sounds. A – Cluster 4; B – Cluster 5; C – Cluster 6; D – Cluster 9; E – Cluster 10; F – Clusters 11+12; G – Cluster 13; H – Clusters 14+15+16+17; I – Cluster 39; J – Cluster 41. Clusters considered together respected the smallest Euclidean distance from each cluster mean, separated by 1 second of silence. All spectrograms were normalized with respect to the maximum sound power.

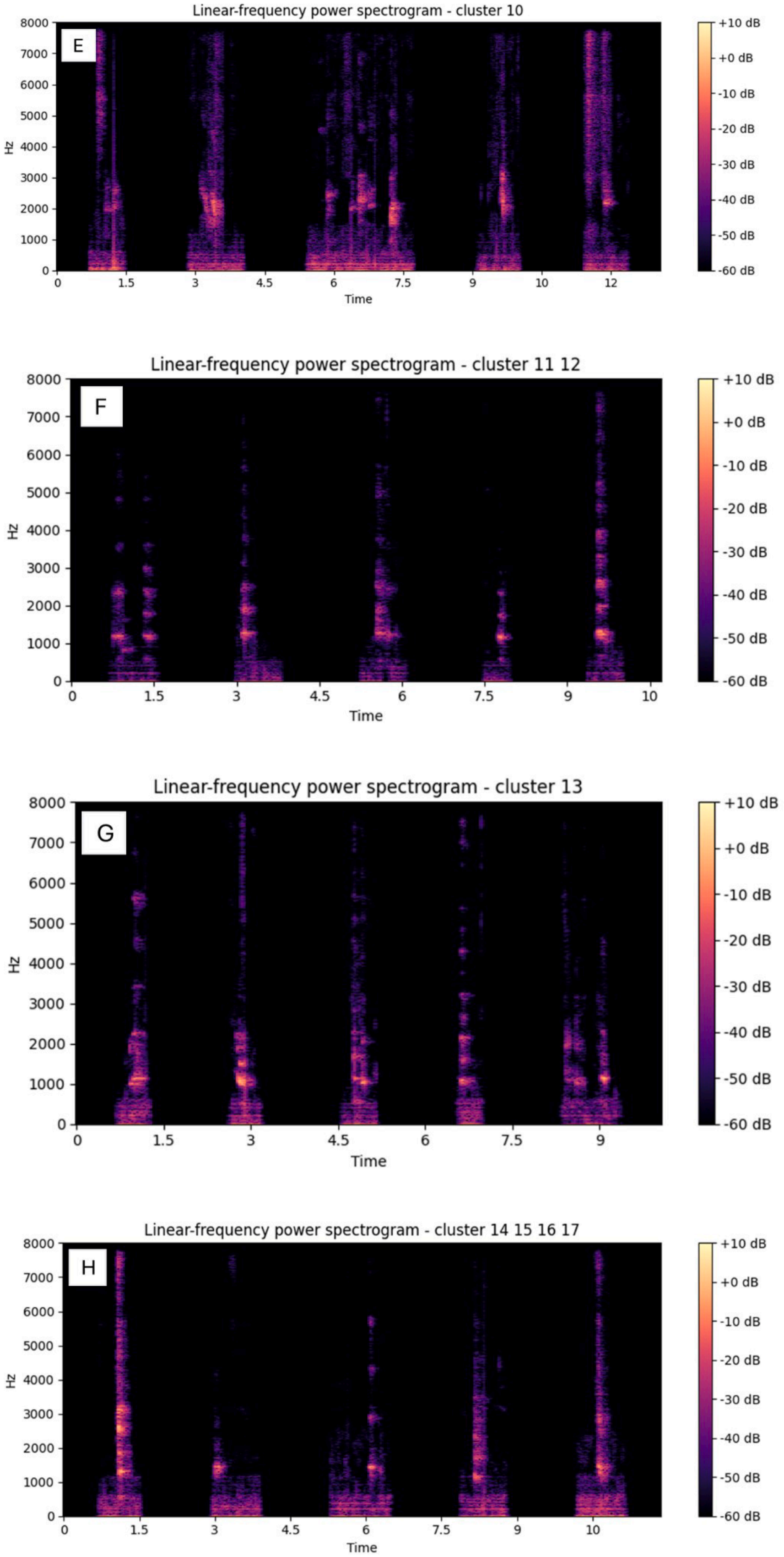

Fig. 5. (*continued*).

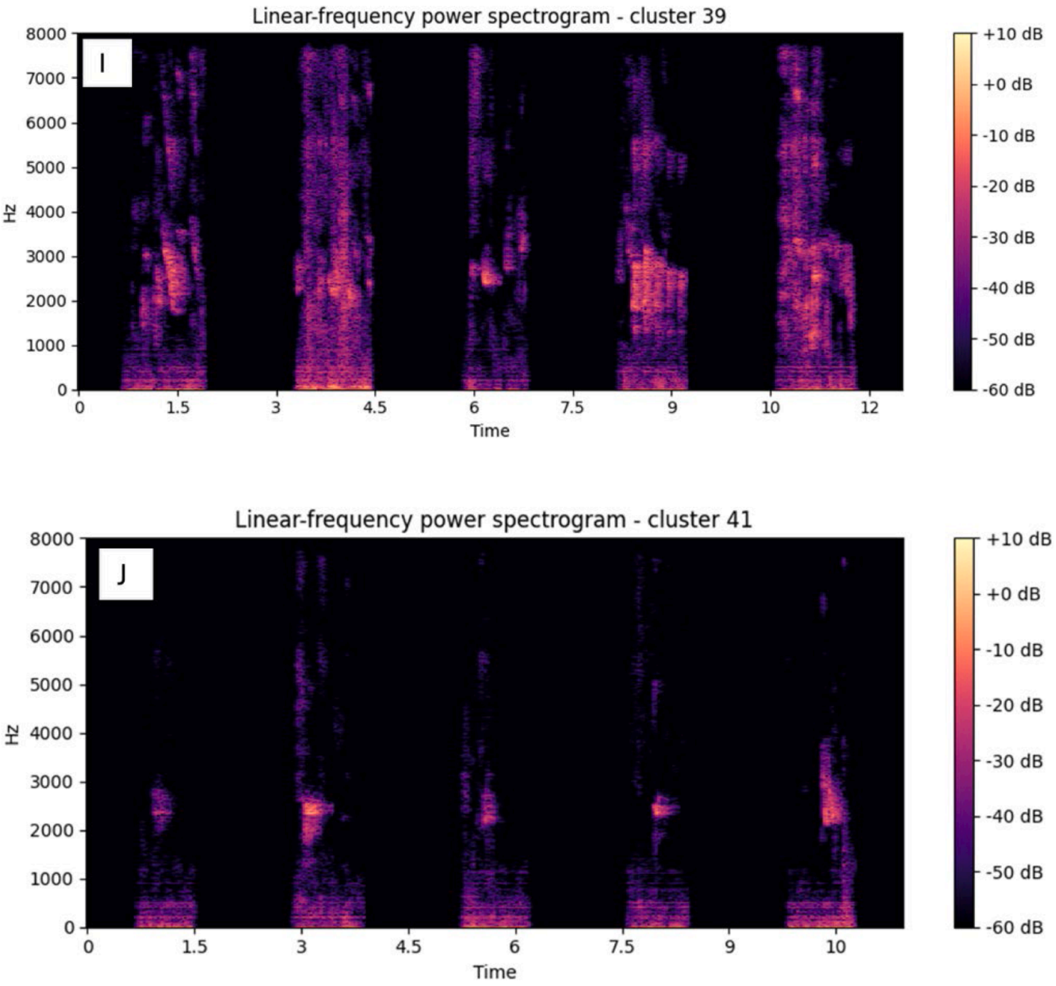

Fig. 5. (*continued*).

suggests that broiler chickens may develop new vocal patterns as they age. This trend aligns with broader observations in avian species, where vocal repertoires typically expand with maturity, likely influenced by physiological, environmental, and social factors (Catchpole and Slater, 2003; Gill, 2007). The emergence of new clusters over time may be linked to the maturation of the chickens' vocal apparatus, enabling them to produce a wider variety of more complex calls (Grassi et al., 1993).

In broiler chickens, the emergence of distinct vocalizations in later developmental stages may be linked not only to their evolving physical characteristics but also to their emotional needs (Collins et al., 2024). As birds mature, they may express vocalizations related to mating, territoriality, or more complex social interactions, behaviors typically less prevalent or absent in earlier life stages (Catchpole and Slater, 2003). The observed variability in vocal characteristics, such as frequency, duration, and acoustic power, across the identified clusters may reflect an increasing behavioral complexity as the birds develop (Zipple et al., 2019).

One possibility for the increased vocal repertoire observed from the third week onward may lie in the rapid changes broilers experience during the production cycle. In the early starter phase, chicks are light (around 40 g) but due to genetic selection for fast growth, they can reach approximately 2.5 kg by day 36 (Aviagen, 2018). This fast weight gain may introduce physical challenges that affect their behavior and activity levels (Nicol et al., 2024; Peña Fernández et al., 2018). At the same time, litter quality tends to deteriorate over time due to increased droppings, potentially discouraging movement (Riber et al., 2024). These factors combined could contribute to changes in how and when vocalizations are expressed, potentially leading to a broader and more complex vocal repertoire as birds mature.

For instance, Clusters 5 and 10 exhibited marked differences in sound length and frequency, with Cluster 5 showing the shortest average duration and lowest frequencies by week 5. These acoustic variations may correspond to specific behavioral contexts, such as feeding, resting, or social interaction (Maldarelli et al., 2024), although additional behavioral analysis would be necessary to confirm such associations. Additionally, the characteristics of vocalizations may influence their detectability. For example, while Cluster 4 had a dominant frequency of 2275 Hz and Cluster 5 exhibited a much lower frequency of 379 Hz in week 4, some vocalizations may have been masked by louder environmental sounds or overlapping calls with higher frequencies.

Although some clusters, such as Cluster 11+12 and Cluster 13, were acoustically similar, they were identified as distinct. However, it is possible that they represent the same type of vocalization expressed under different conditions (Golfidis et al., 2024). A comparable method was used by Lev-Ron et al. (2025), who distinguished stress-related calls in broilers subjected to cold, heat, or wind through acoustic signal processing. Environmental and temporal factors, such as ambient temperature or circadian rhythms, can influence vocal behavior but were not specifically assessed in the present study. Previous research has shown that both high temperatures and environmental enrichment can alter vocal patterns in chickens (Du et al., 2020; Gandra et al., 2020; Golfidis et al., 2024; Meyer et al., 2024; Mortola, 2019). Additionally, laying hens have been observed to vocalize less at night (Sibanda et al., 2019), though this pattern has not been thoroughly studied in broilers. A

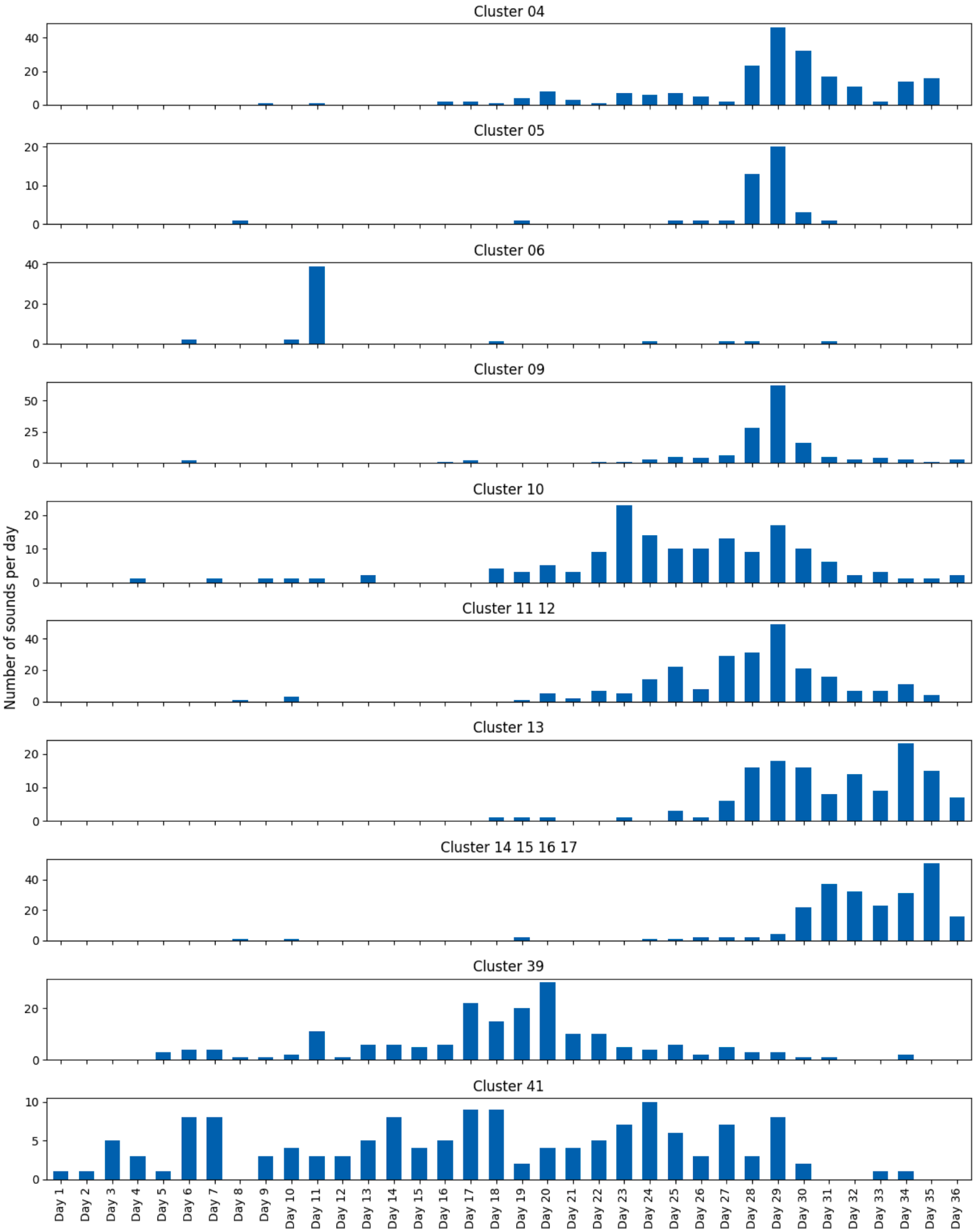

Fig. 6. Plot showing the number of sounds from each day of the broiler age for each newly identified cluster of sounds.

higher frequency of vocalizations during the day may reflect a diurnal rhythm aligned with activity–rest cycles (Deep et al., 2012), warranting further investigation.

Interestingly, in contrast to findings from previous studies (Pereira et al., 2015), we did not observe a uniform decrease in vocal frequency with age across all clusters. This deviation suggests that certain vocalizations may serve different functions as broilers grow, or that additional environmental and social factors could be influencing the modulation of vocal characteristics. Such factors might include changes in housing conditions, flock dynamics, or stress levels, each of which could impact vocal expression. Our findings also highlight the potential for using advanced acoustic analysis and machine learning in broiler welfare monitoring. Automated systems could be trained to detect specific vocal patterns associated with both positive and negative welfare states (Lefevre et al., 2025).

This study presents promising insights into the acoustic patterns of broiler chickens. However, some limitations must be considered. First, the use of a small sample size limits the generalizability of the results, and relying on a single expert to validate clusters introduces subjectivity, despite the use of Euclidean thresholds. Another critical

Table 3

Characteristics of the cluster: fundamental frequency expressed in Hz calculated using probabilistic YIN (pYIN) method, maximum acoustical power of the sound expressed in dB (max power), and length of the sound, expressed in seconds, defined as the interval where the acoustical power doesn't drop below 20 dB of the max power.

	Sound Lenght, s					Fundamental frequency, Hz					Max power, dB				
Clusters	week 1	week 2	week 3	week 4	week 5	week 1	week 2	week 3	week 4	week 5	week 1	week 2	week 3	week 4	week 5
4	.	.	0,68	0,73	0,63	.	.	2105	2275	1740	.	.	−48,2	−48,2	−47,5
5	.	.	.	0,39	0,40	.	.	.	379	303	.	.	.	−52,2	−51,1
6	.	0,65	.	.	.	.	1367	.	.	.	.	−59,3	.	.	.
9	.	.	.	0,74	0,72	.	.	.	843	545	.	.	.	−49,7	−48,5
10	.	.	0,60	0,85	0,70	.	.	2026	1596	700	.	.	−51,0	−52,9	−49,8
11_12	.	.	.	0,59	0,56	.	.	.	898	736	.	.	.	−48,9	−48,1
13	.	.	.	0,51	0,50	.	.	.	921	976	.	.	.	−50,5	−47,4
14_15_16_17	.	.	.	.	0,77	.	.	.	.	534	.	.	.	.	−45,2
39	0,59	0,74	0,75	0,67		2936	2834	2754	2474	.	−50,6	−52,0	−51,6	−51,4	.
41	0,55	0,67	0,69	0,63	0,48	2172	2119	2387	1889	.	−55,5	−57,9	−57,3	−55,6	−50,4

limitation is the lack of simultaneous behavioral observations. It is hard to exclude the possibility that the newly identified clusters may reflect variations of known vocalizations or age-related changes rather than new call types, and some vocalizations may have been lost during data filtering. Without linking vocalizations with specific behaviors or emotional states, it remains speculative to interpret the function or affective meaning of the detected vocal clusters.

Some vocalizations described in the literature may correspond to those identified in our clusters, although many remain insufficiently characterized for direct comparison. Non-syringe-generated sounds include pecking feed, a mechanical noise produced by beak strikes on feed (Aydin et al., 2016); purr, associated with throat discomfort (Sun et al., 2021); rale sounds, linked to labored breathing caused by mucus accumulation (Rizwan et al., 2016); and abnormal respiratory sounds such as cough, sneeze, and snore, often indicative of respiratory issues (Carpentier et al., 2019; Liu et al., 2020; Lv et al., 2023). Notably, pecking feed, sneeze, and cough are typically short in duration, as reflected in Cluster 5.

Syringe-generated vocalizations offer further points of comparison: crow, a loud, far-reaching call typically produced by hungry or foraging chickens (Sun et al., 2021); squawk, a sharp, wide-frequency call elicited by pain or sudden stimuli (Bright et al., 2008); food call, an excited, rapid vocal sequence that may end with a moan when food is available (McGrath et al., 2017); and gakel-call, a whining, ascending note followed by short bursts, often associated with frustration (Zimmerman et al., 2000). While these references provide possible context for the acoustic diversity observed in our clusters, the behavioral significance of the newly identified vocalizations remains unclear. Some of these sounds may correspond to previously described vocalizations; however, experimental validation in context-specific settings is needed to reliably associate these vocal expressions with specific behaviors.

Future studies should include larger sample sizes and a broader range of environmental conditions. Integrating behavioral observations will be essential to determine whether the identified clusters represent truly distinct vocalizations, while also providing contextual meaning and deeper insight into how broilers use vocalizations to communicate their needs and respond to their environment.

Conclusion

A total of 10 final vocalization clusters were identified in addition to the 4 known ones. A key finding was the temporal distribution of the vocalizations: two vocalizations occurred consistently throughout the 36-day period, while seven emerged predominantly from the middle to the end of the observation period, suggesting a potential expansion of the vocal repertoire as broilers age. The four previously described vocalizations (distress calls, short peeps, warbles, and pleasure notes) were most prominent in the first three weeks but less so thereafter. Although no consistent frequency decrease with age was observed across the 10 new clusters, several showed a decreasing trend, indicating potential age-related changes in vocal features. These findings offer novel perspectives on the vocalizations exhibited by broilers, suggesting the presence of additional, previously undocumented vocalization types that may emerge later in their lives. Although this study was conducted with a modest number of birds and lacked statistical replicates, it provides valuable insights into the complexity of broiler vocalizations.

This study provides valuable insights into broiler chicken vocalization patterns, with potential applications in both on-farm and laboratory settings. Future research should incorporate larger sample sizes, varied environmental conditions, and behavioral correlations to better validate and contextualize vocal patterns.

CRediT authorship contribution statement

Tomasz Grzywalski: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Patricia Soster:** Writing – original draft, Visualization, Validation, Methodology, Investigation, Conceptualization. **Yuanbo Hou:** Writing – review & editing, Visualization, Validation, Supervision, Software, Formal analysis, Data curation, Conceptualization. **Pieter Thomas:** Writing – review & editing, Visualization, Supervision, Methodology, Investigation. **Frank A.M. Tuyttens:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Annelike Dedeurwaerder:** Supervision, Resources, Project administration. **Maarten De Gussem:** Supervision, Project administration, Investigation, Funding acquisition. **Paul Devos:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Gunther Antonissen:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Dick Botteldooren:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Conceptualization.

Disclosures

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

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