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Cry analysis for early detection of infantile colic: Integrating behavioral and acoustic cry patterns using machine learning

Ana Laguna[1,*], Sandra Pusil[1,*], Paolo Piras[1], Paolo Ingraito[1], Helena Cuesta[1], Jonathan Adrián Zegarra-Valdivia[2,3,#], Anna Lucia Paltrinieri[4] and Silvia Orlandi[5,6]

Abstract

Background: The study introduces an artificial intelligence (AI) cry analysis tool supporting automatic data collection and detection of crying episodes associated with infantile colic by analyzing behavioral and acoustic infant cry patterns.

Methods: The study included 22 full-term infants, divided into groups, with or without infantile colic, based on parental reports and Rome IV criteria for infantile colic. Non-elicited spontaneous cry data were automatically and longitudinally recorded in natural home environments during the infants' first 2 months. Cry characteristics were analyzed through comprehensive multimodal feature extraction, encompassing behavioral and acoustic parameters. Behavioral features included cry frequency, temporal duration, and cry types characterization (e.g. hunger and sleep). Acoustic metrics include fundamental frequency (F0) and spectral characteristics such as mel-frequency cepstral coefficients, among others. Comparative statistical analyses were then performed to evaluate significant differences between the colic and non-colic infant groups. Then, several machine learning algorithms were applied to classify the groups based on the identified cry features.

Results: Infants suffering from colic present an increased arousal state with significantly higher cry frequency and duration, interestingly peaking in the evening, with distress cries as a dominant type. The best-performing AI model based on behavioral cry analysis achieved up to 92% accuracy, automatically identifying crying episodes associated with infantile colic.

Conclusions: The potential for home-based, non-invasive, objective tools supporting automatic data collection and detection of infantile colic, combined with infant symptomatology, may facilitate a more proactive healthcare approach and enhance parental colic management strategies, reducing the burden on pediatric services. Parental education leading to timely clinical interventions could improve infant well-being and mitigate caregiver stress.

Keywords

infantile colic, cry analysis, acoustics, caregivers, home environment, machine learning

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[1]R & D Department, Zoundream Group, Barcelona, Spain
[2]Achucarro Basque Center for Neuroscience, Leioa, Spain
[3]Universidad Científica del Sur, Lima, Perú
[4]Neonatology Department, Barcelona Center for Maternal-Fetal and Neonatal Medicine (BCNatal), Hospital Clínic, Universitat de Barcelona, Barcelona, Spain
[5]Department of Electrical, Electronic, and Information Engineering "Guglielmo Marconi" – DEI; Health Sciences and Technologies, Interdepartmental Center for Industrial Research (CIRI–SDV), University of Bologna, Italy
[6]IRCCS Instituto Delle Scienze Neurologiche di Bologna, Bologna, Italy

[#]Current affiliation: Global Brain Health Institute, University of California, San Francisco, CA, USA
*Ana Laguna and Sandra Pusil contributed equally to this work.

Corresponding author:
Ana Laguna, R & D Department, Zoundream Group, Carrer de Pallars, 108, 08018 Barcelona, Spain.
Email: ana.laguna@zoundream.com

Introduction

Infantile colic is a condition where a healthy, well-fed infant cries for more than 3 hours a day, more than 3 days a week, for more than 3 weeks (commonly known as Wessel's "Rule of Three" definition).[1] It is characterized by continuous and stressful episodes of crying, especially at the end of the day, with the infant often pulling their legs up to the stomach, having a flushed face, and clenched hands.[1] While this criterion remains widely used in both research and clinical contexts, it has been debated for focusing solely on crying behavior.

Infantile colic remains a poorly understood phenomenon affecting a substantial portion of infants. Up to 30% of infants during their initial 3 months of life[2–4] compel parents to seek medical advice, although organic causes contribute to less than 5% of excessive crying cases.[1,5,6] The leading cause of infantile colic is unknown, but it is associated with underlying organic causes like gastrointestinal discomfort, constipation, lactose intolerance, and anal fissures.[7–9] According to the Rome IV criteria, infantile colic is considered a functional gastrointestinal disorder (FGID),[9] involving recurrent and prolonged periods of crying, fussing, or irritability in infants under 5 months of age without evidence of failure to thrive, fever, or illness, and likely reflecting an underlying gastrointestinal component rather than purely excessive crying.[9] The infantile colic cry has also been associated with non-organic issues, being the proposed mechanism related to an altered circadian rhythm, immaturity of the central nervous system, and alteration of intestinal microbiota.[8–10] Moreover, the absence of effective treatment options and the limited role of drug interventions make infantile colic a significant source of maternal distress and family disturbance.[11–14]

Notwithstanding significant clinical efforts, a precise definition of colic remains elusive. Diagnosing infantile colic involves clinical history, physical examination, parental reporting, and ruling out other conditions.[1,7,8] While the Rome IV criteria provide the accepted standard definition, a considerable lack of standardization remains, with clinical studies applying up to 20 different diagnostic criteria described in the literature.[9,15] Variability in diagnosis stems from factors like parental perception, cultural influences, and subjective data collection, including manual parental diaries. Confirmation of the diagnosis often occurs when symptoms resolve spontaneously.[16] This combination of factors contributes to why infantile colic remains challenging to diagnose accurately, underscoring the need for more objective, precise diagnostic methods —with cry analysis emerging as a potential indicator.

Several studies have demonstrated that the characteristics of an infant's cry can be correlated with specific clinical conditions, enabling the distinction between preterm and full-term infants, identification of pathologies or excessive crying such as infantile colic cries, and even early recognition of linguistic patterns.[17,18]

Colic cries are described in the literature as longer, louder, and higher-pitched than non-colic cries, with more significant pitch variability, broader spectral energy, and irregular rhythms.[19–21] Studies analyzing the acoustic characteristics of colic cries have reported higher fundamental frequency (F0), broader spectral energy, and prominent high-frequency components.[20,21] However, one study[22] has noted lower F0 in colic cries, potentially aligning with findings by Laguna et al.[23] and Bolfan-Stošić and Brestovci,[24] which suggest that F0 decreases in distress-related cries —common in colic—compared to crying linked to non-distress-related cries.[24]

Despite the numerous studies[14,22,25] published analyzing the cries of infants with colic in the last 20 years, most of the work conducted by neonatologists and pediatricians still relies on manual diaries and parents' reporting,[26] introducing limitations to the exhaustiveness and objectivity of the data analysis.[23,27] Moreover, until now, only one study[14] has trained a machine learning (ML) algorithm, associating colic cries with pain rather than with hunger or fussiness. Thus, colic cries exhibited a "73% pain" rating, indicating significant acoustic similarities with pain-related cries, such as those following medical procedures. This raises the possibility that infants experiencing colic might indeed be in pain or experiencing distress that is uncomfortable in nature. Another study[25] analyzed the correlation between the amplitude and frequency of newborn cries and pain intensity. The study aimed to assess differences in crying sound spectra, pitch, and sound pressure of cries of term newborns concerning different pain levels. Usually, a pain cry is characterized by a first cry unit at a high pitch, followed by the siren cry, with a sound level maintained near its maximum.[25] From a behavioral perspective, some studies also confirm that infantile colic induces discomfort, distress, and pain.[7] Therefore, infant cries acoustics are related to pain or discomfort, typically beginning as a high-pitched, intense wail, followed by very loud crying,[28] and may last longer than usual. The infant may also grunt or hold their breath.[29,30] In addition to the acoustic characteristics of the cry, changes in the infant's behavior, movements, or facial expression can also indicate pain or discomfort.[23,27,28]

Previous studies[23,31] identified associations between neonatal cry acoustics, neurophysiological signals, and behavioral features according to newborns' different cry distress levels, finding correlations between most of the features extracted from the signals (cry acoustics, brain activity, cerebral and body oxygenation, heart rate, facial expression, and body movement) depending on the infant's arousal state.[23,31,23] The study[23] found that distressed infant cries are more erratic, with fewer pauses, longer duration, and higher pitch with more variability and instability. The alertness state was evidenced not only by the distinct cry patterns but also by heightened brain activity, increased facial tension, notable body rigidity, and agitation.[23,27]

Table 1. Demographic characteristics of the sample.

Demographic information	Colic ($n = 11$)	Non-colic ($n = 11$)
Gestational age (weeks, mean ± SD)	39.45 ± 0.82	39.72 ± 0.46
Gender (M/F)	6/5	6/5
Type of feeding (breastfeeding/bottle feeding/mixed)	4/3/4	7/0/4
Gas-related discomfort (yes/no)	8/3	4/7
Feeding-induced sleep (yes/no)	6/5	8/3
Contact sleep (yes/no)	8/3	11/0
Home language exposure (Monolingual/bilingual/polyglot/NA)	7/1/1/2	5/4/1/1

Lastly, advanced signal processing techniques and ML methods can help understand infant cries and their association with pain, distress levels, and discomfort.[27,28] Infant cry signal analysis and classification include traditional processing approaches to extract diverse cry features to train artificial intelligence (AI) algorithms.[28,32–35]

Consequently, our work aims to analyze the cry patterns of infants with colic, comparing them to control vocalizations based on a non-elicited spontaneous infant cry database automatically and longitudinally collected in a home environment. Furthermore, the study aims to develop a user-friendly, non-invasive, and objective AI-based approach for the automatic identification of infants experiencing infantile colic. The detection will be based on the arousal states identified through their behavioral and acoustic cry patterns, in alignment with the criteria for infantile colic as defined in the literature. The implementation of home-based automatic monitoring tools for infantile colic, integrated with contextual information regarding the infant's behavior and symptomatology, has the potential to reduce the demand for emergency healthcare services. Additionally, such tools could provide critical and educational support to caregivers, alleviating stress and enhancing the overall well-being of both infants and their families.

Methods

Study design

This was an observational, prospective, longitudinal study conducted between 2021 and 2022. Data were collected in the natural home environments of participating families based in Spain, France, Hungary, Italy, Switzerland, Germany, and the United Kingdom. The study employed automatic and continuous audio monitoring using Zoundream's Cry Analysis Technology (AMSI v2.0, Zoundream Group, Spain) to capture spontaneous, non-elicited cry episodes (CEs).

Participants

A total of 136 families enrolled in the study and completed the parental reports regarding the presence or absence of infantile colic. Data from all participants were evaluated using the same eligibility and data-quality criteria.

Data-quality selection criteria. Before classifying infants into colic or non-colic groups, data-quality selection criteria were applied equally to all subjects. Thus, all recordings were screened according to the following requirements:

1. Successful activation of the Zoundream Cry Analysis Technology - Acoustic MultiStage Interpreter (*AMSI v2.0 - Zoundream Group, Spain*) to monitor and support the interpretation of their infants' cries. This tool automatically recorded every cry episode (CE - the amount of time the infant cries in each audio recording divided by silence periods) when it detected crying within its range, ensuring a continuous 24/7 recording of crying episodes.
2. Recording consistency
   - A minimum of 80% of the required monitoring days was needed after the caregiver-reported colic onset date (for infants with colic) or during an age-matched reference period (for infants without colic).
3. Sufficient amount of cry data
   - A minimum number of 10 cry events per subject was required to allow robust acoustic analysis.
4. Minimum audio quality

- Infants were excluded if recordings were affected by:
  1. excessively loud environments,
  2. incorrect device placement (too far/too close),
  3. obstructed or degraded audio, or
  4. any condition preventing reliable feature extraction.
5. Completion of parental reports, including questions related to basic demographics, type of feeding, sleep, digestive discomfort, demand level of the infant, or confirmed medical conditions (see Table 1).

Following data-quality assessment, eligibility was further determined using clinical inclusion and exclusion criteria for both groups.

Inclusion criteria. The inclusion criteria for the infants with colic were based on established literature regarding infantile colic, specifically:

(a) Infantile colic typically occurs in infants aged 0–4 months.[9] Symptoms often begin around 2 to 3 weeks of age and peak between 6 and 8 weeks.[36] Therefore, the selection criteria for our study focused on infants aged 12–54 days, ensuring cry data were collected within the critical period of 2–8 weeks.

(b) Caregivers reported recurring, prolonged periods of crying, fussing, or irritability that suddenly and abruptly began and ended spontaneously and without an obvious cause, typically occurring in the afternoon or evening. Caregivers could not prevent or resolve these episodes, and there was no evidence of failure to thrive, fever, or illness.[16]

(c) According to the modified Wessel criteria[37] and the new Rome IV criteria,[9] colic was defined as episodes of crying or fussing lasting for 3 or more hours per day on at least 3 days in the preceding week.

(d) In the literature, parents were required to keep a 24-h behavior diary to confirm that the total crying and fussing exceeded 3 h within any 24-h period.[9] Instead of a manual diary, parents joined the study voluntarily and agreed to use Zoundream's Cry Analysis Technology to monitor and record 24/7 their infant's cries.

For infants without colic, the selection criteria included infants aged 0–4 months whose crying was recorded between 2 and 8 weeks of age, the same period of time as the colic group. Caregivers also needed to report the absence of recurring, prolonged periods of crying, fussing, or irritability that started and stopped without an obvious cause. Additionally, these caregivers were required to use Zoundream's Cry Analysis Technology to automatically record their infants' cries.

For both groups, the exclusion criteria included twins and any infant diagnosed with a medical condition other than infantile colic (e.g. respiratory, neurological, or metabolic disorders, congenital anomalies).

Participants selection. Based on the data-quality requirements and inclusion criteria described above, the following participant flow and proportions were obtained:

- Caregivers reported colic and completed the parental report ($n = 49$): Of these, 37 caregivers provided the colic onset date. After applying the recording-consistency, audio-quality, and minimum-data thresholds, 11 infants met all criteria and were included in the *colic* group.
- Caregivers reported no colic and completed the parental report ($n = 86$): Within this subset, 59 infants had audio recordings available within the target age window (2–8 weeks). Applying the same data-quality criteria as above, 11 infants fulfilling all requirements were selected to match the *non-colic* group and balance the data set.

Only infants who satisfied all eligibility and data-quality conditions were retained for analysis.

Thus, the final data set consisted of **22 healthy, full-term infants** divided into two groups: 11 infants with diagnostic criteria for infantile colic,[9,37] as reported by their parents (*colic group*), and 11 infants without diagnostic criteria for infantile colic (*non-colic group).* Both groups recorded an average of 12 CEs per day, with minimum usage sustained over at least seven consecutive days, consistent with Rome IV criteria. Table 1 displays the demographic information for both groups.

Ethical considerations

The study followed the Institutional Research Ethics and the Declaration of Helsinki. Formal ethical approval was granted by the Research Ethical Committee—CEI de la Universidad Nebrija, Madrid, Spain (Ref: UNNE-2023–0033). The consent form documented the study's aims, nature, and data acquisition procedures. Anonymization and data confidentiality were maintained throughout the study, and all parents agreed and signed the informed consent prior to participation.

Data collection

Infant cries were recorded and preprocessed using Zoundream's Cry Analysis Technology, which utilizes the AMSI system,[27,38] an audio deep learning (DL) algorithm that performs the automatic detection and segmentation of audio recordings into CEs and cry units (CUs - individual cry patterns within a CE separated by an expiration phase). Additionally, this algorithm identifies the potential reasons for different cry types characterization. Based on previous research,[27] the following are the main cry types identified by AMSI: The hungry cry, occurring pre-feeding, features short cry units, constant, rhythmic, and harmonic CEs. The sleepy cry, often post-feeding, is softer with a falling melody and prolonged duration cry units. The fussy cry is monotonous and involves low-level intermittent whimpering separated by unvoiced periods. The burp cry, during or after feeding, denotes effort and indicates the need to expel something. The distress cry, from an irritated infant, is more urgent and intense with high spectral content and instability.[27]

Families who proactively volunteered for the study were given a hardware device (e.g. smartphone) with Zoundream's Cry Analysis Technology integrated to be placed 1–3 m away from their infants in their natural environment (i.e. at home). The device activates automatically upon detecting an infant's cry and records the sound. All audio data was pseudo-anonymized and encrypted during transfer and storage.

Data analysis

Behavioral cry pattern analysis

Using the AMSI algorithm, raw audio recordings were automatically segmented into CEs. The audio preprocessing within the AMSI system includes a filtering process that removes background noise and false-positive sounds to retain only the highest-quality CEs for subsequent analysis.

After the automatic audio preprocessing, the following information related to each CE was estimated:

- Duration of each CE in seconds.
- Timestamps of each CE (based on the Coordinated Universal Time (UTC+2)).
- The frequency distribution of CEs is defined as the number of CEs occurring within each time interval across 24 h. Four time-of-day intervals were also defined[21]: (1) *morning*: 10–13 h, (2) *afternoon*: 13–19 h, (3) *evening:* 19–22 h, and (4) *night:* 22–10 h.
- Cry types characterization of CEs. The AMSI algorithm was applied to automatically detect and identify different cry types within all segmented CEs, including *hungry, sleepy, burp, fussy,* and *distress*, based on established cry interpretation criteria.[27]

The variables described above were derived as aggregated features based on specific data points and intrinsic audio characteristics from each participant's audio files and corresponding time points. This aggregation was performed to reduce dimensionality, enhance computational efficiency, and simplify interpretation.[39]

Based on these variables, we analyzed the amount of crying by measuring the average frequency and duration of CEs per day, calculated from the timestamps. This analysis and its corresponding model are henceforth referred to as the Behavioral Cry Pattern Analysis/Model. Frequency and time variables were employed in this analysis to evaluate cry patterns across groups, as specified by the inclusion criteria and aligned with existing literature defining infantile colic.[9]

Acoustic cry pattern analysis

Audio processing for each CE was performed using Praat software,[40] employing a band-pass filter ranging from 200 to 1200 Hz to compute F0 and a low-pass filter set at 10,000 Hz to analyze the spectrum.[41] Subsequently, relevant phonation parameters, including jitter, shimmer, and harmonic-to-noise ratio (HNR), were extracted using the "parselmouth" Python library v.0.4.3 (https://parselmouth.readthedocs.io/en/stable/). Descriptive statistics of F0 (maximum, minimum, mean, and standard deviation), the percentage of the pitch above 800 Hz (high-pitched cries),[42] and hyper-phonation ($F0 \geq 1000$ HZ)[43] were also calculated. Furthermore, mel-frequency cepstrum coefficients (MFCC) ranging from 1 to 13 were computed and utilized as cepstral features. Therefore, the analysis performed using these features and its corresponding ML models are henceforth referred to as the Acoustical Cry Pattern Analysis/Models.

Statistical analysis. Statistical analyses were conducted using GraphPad Prism v8.0.2 (San Diego, USA) and MATLAB R2023b (MathWorks, USA). Data normality was assessed with the Kolmogorov-Smirnov test. For normally distributed data—such as the analysis of behavioral cry patterns—an unpaired t-test was employed to compare the non-colic and colic groups. For non-normally distributed data—such as the analysis of acoustic cry patterns—a non-parametric permutation test[44,45] was used to evaluate differences in means between the groups. This test utilized 10,000 permutations, with significance determined at a non-parametric p-value threshold of <.05.

To account for multiple comparisons in both approaches, the false discovery rate was controlled using the two-stage step-up method by Benjamini, Krieger, and Yekutieli, with the q-value set at 1%.

Classification analysis. Given the distinctive nature of the two data analyses, models were trained separately for behavioral and acoustic cry patterns.

Behavioral cry pattern classification

The inputs to the behavioral cry pattern model (Model 1) are derived from the prior statistical analysis that guided feature selection based on statistical significance. The most relevant aggregated features include the cry frequency percentage of CEs during three specific times of day (morning from 10 to 13 h, evening from 19 to 22 h, and night from 22 to 10 h next day), yielding three time-based features. Additionally, this model includes three cry types characterization of CEs expressed as percentages over a day (hungry, sleepy, and burp), resulting in a total of six input features.

Once aggregated, the data set accounts for a total of 812 instances (non-colic = 498 and colic = 314). For this study, 80% of the available data was used for training the algorithm, while the remaining 20% was reserved for evaluating the model's performance using 10-fold cross-validation. To minimize bias, a stratification technique was applied across users and CEs for the training and validation data sets. The data was preprocessed to normalize the input features and ensure consistency across all data points.

The study employs a classification approach utilizing a feedforward neural network to analyze frequency and cry types characterization among two groups: infants with and without colic. This approach has been reported by previous cry analysis studies that have addressed comparable feature sets, sample sizes, and model architectures.[35,46–48]

Model 1 employed a multilayer perceptron (MLP) implemented using PyTorch. The MLP consisted of four fully connected layers, with an input layer of six selected features representing the frequency of crying across the three times of day and three cry types characterization measures. The hidden layers used the Rectified Linear Unit activation function, while the output layer applied a sigmoid activation function to predict the binary outcome[49] (colic or non-colic). A dropout rate of 0.3 was implemented during training to prevent overfitting.

Model 1 was trained using the Binary Cross-Entropy (BCE) loss function, suitable for binary classification models.[50] The Adam optimizer was employed with a learning rate of 0.001 to optimize the model's parameters. The model was trained for 2000 epochs with an early stopping criterion to prevent overfitting, where training was halted if the validation loss did not improve for a predefined number of epochs. ML performance metrics were reported in terms of accuracy (the proportion of true results — both true positives and true negatives— among the total number of cases examined), sensitivity (number of colic instances, the proportion of true positives correctly identified by the model) and specificity (number of non-colic instances, the proportion of true negatives correctly identified by the model).

Acoustic cry pattern classification

For the acoustic model, we analyzed 2239 CEs from the non-colic group and 1179 CEs from the colic group, extracting 26 acoustic features. The analyzed features encompassed a combination of time-frequency characteristics, including duration, F0 and its descriptive statistics (minimum F0, maximum F0, and F0 standard deviation), HNR, jitter, shimmer, and resonance frequencies (F1, F2, and F3). Additionally, the feature set included the proportions of F0 exceeding 800 and 1000 Hz, as well as cepstral characteristics, specifically the 13 MFCC.

Three distinct models were trained: (Model 2) a model using all 26 acoustic features, (Model 3) a model using only the cepstral features (13 MFCC), and (Model 4) a model using only time-frequency features.

A support vector machine (SVM) classifier with a Medium Gaussian radial basis function (RBF) and adaptive kernel scale was used to classify infantile colic cry utterances based on the specific features. The data set was divided into an 80% training set and a 20% validation set, with 10-fold cross-validation employed to assess model performance. A stratification technique across users and CEs for training and validation sets was applied to ensure balanced data distribution, minimizing the risk of bias. Feature normalization was applied within each fold to standardize training and validation sets. We calculated key performance metrics such as accuracy, sensitivity, specificity, precision, and F-score for each fold, yielding an overall measure of the model's effectiveness.

Various ML techniques were tested, including neural networks, decision trees, discriminant analysis, and logistic regression.[51] Here, we report only the model with the best performance for infantile colic classification.

Results

To contextualize our analysis, we first examined the demographic characteristics of the sample (Table 1). The trends are consistent with prior literature,[52] with bottle-fed infants more frequently exhibiting colic-related behaviors (4/11 vs. 7/11; Table 1) and gas discomfort (8/11 vs. 4/11; Table 1), while breastfed infants —particularly in the non-colic group— showed slightly greater contact-dependent and sleep needs, a factor that may help contextualize variations in cry types across feeding groups.

From a behavioral cry perspective, we analyzed cry characteristics, including frequency, duration, and time intervals throughout the day, to identify and characterize differences between cries from infants with and without colic, both generally and for specific cry types. Regarding acoustics cry patterns, we conducted a statistical analysis of time-frequency features for both groups.

Behavioral cry colic patterns: when, how, and why do infants with colic cry within a 24-h schedule?

Given the importance of comprehending crying patterns and triggers in infants with colic for optimal caregiving and intervention, we analyzed the frequency of CEs over

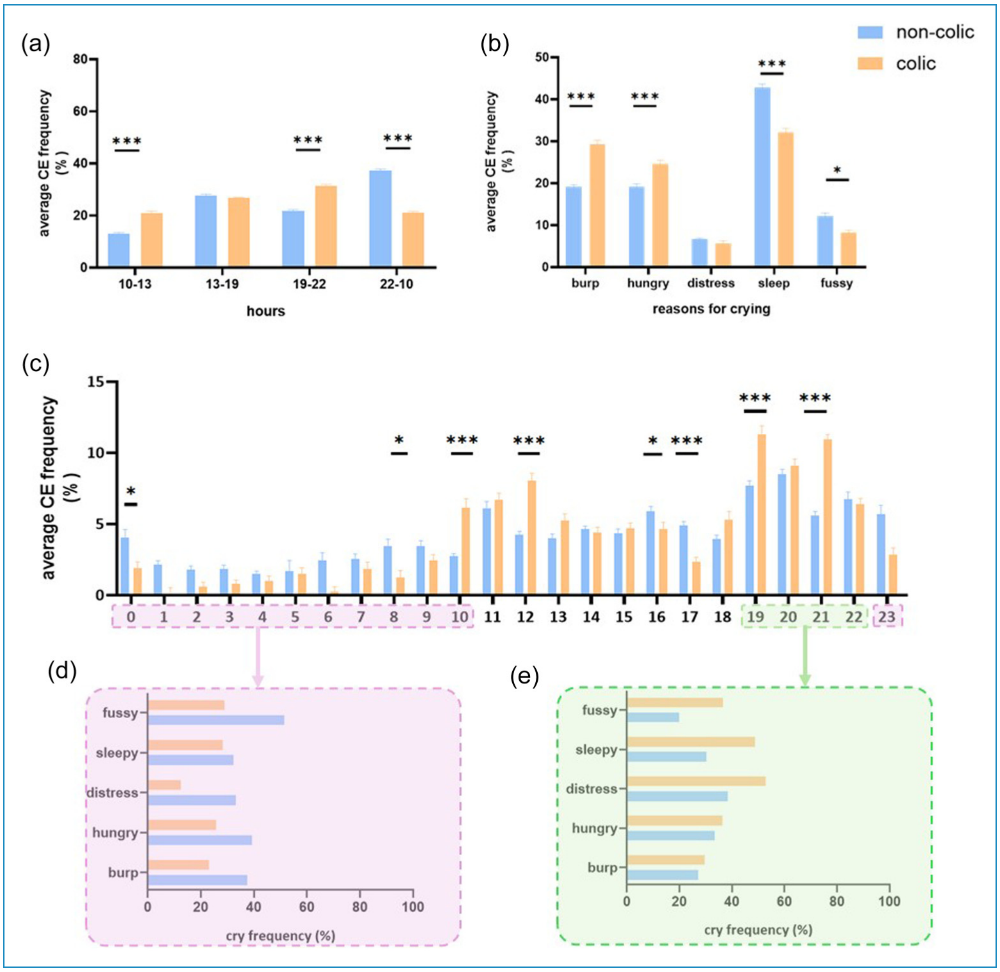

Figure 1. Time interval cry frequency and cry types characterization for colic (orange) and non-colic (blue) groups. (a) Average cry frequency of CEs over a day by time intervals (percentage) (b) Cry types characterization of CEs over a day (percentage) (c) Cry frequency of CEs over a day by hour (percentage) (d) Cry types characterization of the time interval corresponding to the 22-10 h and (e) Cry types characterization of the time interval corresponding to the 19–22 h. An unpaired *t*-test was employed to compare the non-colic and colic groups and to account for multiple comparisons of the FDR two-stage step-up method by Benjamini, Krieger, and Yekutieli, with the FDR (Q) set at 1%. Data are presented as the mean ± standard error of the mean (sem), and statistically significant *p*-values are coded as follows: ∗ $p < .05$, ∗∗ $p < .01$, and ∗∗∗ $p \leq .001$.

the day alongside cry types characterization of the CEs over a day and during the late afternoon/evening (Figure 1). Additionally, we analyzed the average duration of those CEs along the day (Figure 2).

Figures 1(a) and (c) both present data on the frequency of CEs, with Figure 1(a) showing frequencies by time intervals and Figure 1(c) displaying an hourly breakdown. Both figures demonstrate the same tendency in cry frequency across these different levels of aggregation. In general, we can observe that infants cry more frequently at the end of the day. However, infants with colic tend to experience a distinct peak of crying episodes in the morning and more pronounced in the late afternoon and evening, typically between 19 and 22 h, often referred to as the *witching hour*.[53]

When analyzing the acoustic cry types characterization over the whole day, Figure 1(b) shows that burp and hungry are the categories with a higher density over the day for infants with colic compared to non-colic infants.

As for infants without colic, they complained more about sleep over all day (Figure 1(b)) than those with colic, accounting for more than half of the cries for the fussy category occurring during the night 22–10 h time interval (51.4%) (Figure 1(d)).

When analyzing the cries during the *witching hour*, distress seems the highest condition for both groups during the evening time interval. Nevertheless, in infants with colic (Figure 1(e)), we observe that over half of the cries classified as distress (52.8%) occurred during the 19–22 h window. Sleepy cries followed closely, with nearly half

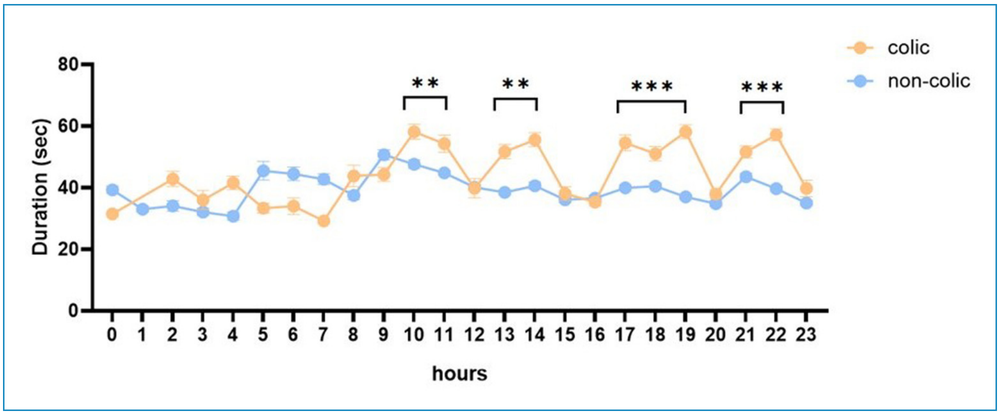

Figure 2. Duration of CEs in seconds per hour for colic (orange) and non-colic (blue) groups. An unpaired *t*-test was employed to compare the non-colic and colic groups and to account for multiple comparisons of the FDR two-stage step-up method by Benjamini, Krieger, and Yekutieli, with the FDR (Q) set at 1%. Data are presented as the mean ± standard error of the mean (sem), and statistically significant p-values are coded as follows: ∗ $p < .05$, ∗∗ $p < .01$, and ∗∗∗ $p \leq .001$.

(48.7%) of this category also occurring during the same interval.

Moreover, Figure 2 illustrates that the cry duration remains relatively consistent throughout the day for the non-colic group. However, there is a noticeable increase in cry duration throughout the day, also interestingly around the *witching hour* for the colic group. On average, the CEs of infants with colic are 15 s longer than the cry utterances from non-colic infants.

Acoustic cry patterns characterizing infantile colic

We observed statistically significant differences in several acoustic features between cries from infants with and without colic. Table 2 highlights these differences across the time-frequency acoustic metrics analyzed. The non-colic group demonstrated an increase in F0 alongside its associated descriptive statistics, F1, F0 ≥ 800 Hz, and F0 ≥ 1000 Hz compared to the colic group ($p < .0001$). The quality voice measures and the rest of the formants did not present significant differences.

Automatic infantile colic detection based on cry analysis using ML

Model 1, based on behavioral cry features using an MLP for the classification into distinct groups, that is, *colic* vs. *non-colic*, achieved a test accuracy of 92%. The best performing acoustic models (Model 2 and Model 3) trained with an SVM yielded a test accuracy of 88%. Model 3 used only 13 cepstral features (MFCC) while Model 2 used cepstral and time-frequency characteristics, accounting for a total of 26 features. Model 4, using only 13 time-frequency features, was the model with the lowest performance, obtaining 78% accuracy. Additional metrics can be found in Table 3. Performance metrics are reported in terms of accuracy, sensitivity, specificity, precision, and F-score.

Discussion

The present study investigated the efficacy of cry analysis in supporting the early detection of crying episodes associated with infantile colic, contributing to the existing literature on AI and colic cries through automatic cry data collection and analysis.

The study aimed to compare cry patterns in infants with and without colic, confirmed by parental observations consistent with the Rome IV criteria for infantile colic.[9] Cry data was automatically and longitudinally collected at home using Zoundream Cry Analysis Technology. This continuous monitoring system ensures the massive collection of non-elicited and spontaneous cry vocalizations from diverse and varied contextual scenarios part of the routine day of the infant (e.g. pre-feeding, post-feeding, distress, diaper change, boredom, and others).

The findings provided objective and quantitative information to reinforce the literature and previous research on infantile colic. From a cry behavioral perspective, our results revealed that infants generally tend to cry more frequently at the end of the day, likely due to physical or emotional fatigue. However, infants with colic showed an increase in cry frequency in the morning, and a pronounced peak during the well-known *witching hour* (19–22 h). Cries associated with infantile colic were, in general, also accompanied by longer-voiced vocalizations. These findings suggest that the frequency and duration of crying in infants with colic indicate a greater demand for attention, particularly in the late afternoon and evening,[36] with infants with colic being slightly more challenging to soothe[54] compared to infants without colic.

In characterizing cry types, burp and hungry cries were the most frequent categories observed throughout the day in infants with colic. Based on the existing literature, the need to burp condition reflects a gastrointestinal physiological need to be expelled, and it sounds similar to an effort

Table 2. Time-frequency audio features characteristics and statistically significant group differences.

Feature	Non-colic	Colic	p-value
Total Number of CEs	2239	1179	–
Number of hungry CEs	500	244	–
Number of sleepy CEs	960	350	–
Number of fussy CEs	219	133	–
Number of burp CEs	419	378	–
Number of distress CEs	141	74	–
Acoustic features			
F0 (mean)	448.166 ± 83.340	420.224 ± 87.384	<.0001
F0 (min)	259.177 ± 63.331	246.594 ± 65.332	<.0001
F0 (max)	762.563 ± 203.179	705.220 ± 197.844	<.0001
F0 (std)	117.971 ± 56.898	105.148 ± 50.369	<.0001
F1 (mean)	1034.715 ± 149.873	948.043 ± 141.783	<.0001
F2 (mean)	2019.577 ± 151.391	2026.324 ± 153.839	.2488
F3 (mean)	3037.280 ± 141.315	3049.019 ± 139.645	.0110
High-pitch	0.050 ± 0.079	0.037 ± 0.074	<.0001
Hyper-phonation	0.015 ± 0.037	0.009 ± 0.034	<.0001
HNR	9.667 ± 3.477	9.864 ± 4.399	.1628
Jitter	0.029 ± 0.012	0.028 ± 0.011	.0040
Shimmer	0.157 ± 0.031	0.157 ± 0.038	.8192

CE: cry episode; F0: fundamental frequency; F1, F2, and F3: resonance frequencies; HNR: harmonic-noise-to-ratio; Hyper-phonation: F0 ≥ 1000 Hz; High-pitch: F0 ≥ 800 Hz.

noise. Infants with gastrointestinal issues tend to produce longer cries with more variable pitch and intensity together with more irregularities and noise in the cry signal. These cries are often marked by higher muscle tone or body tension, reflected in facial rigidity and muscular contraction. In the case of hunger, a physiological need critical to survival, the cry is typically described[27] as urgent, constant, rhythmic, intense, and loud, accompanied by sharp and jerky movements indicating an increased state of arousal or urgency.

During the late afternoon and evening (*witching hour)*, distress cries became more prominent in both groups, especially among infants with colic. For these infants, over half of the distress cries (52.8%) occurred between 19 and 22 h, with sleepy cries being the second most common condition (48.7%) during the same time interval. As described in the literature,[27] distress cries indicate a state of physical discomfort (e.g. pain) or emotional distress (e.g. overstimulation). Acoustically, these cries are more erratic, longer, and higher-pitched, with increased instability and signs of stress. They are often accompanied by increased motor activity, expressed as discomfort or emotional distress through body language, including facial grimaces, flailing limbs, back arching, clenched fists, red faces, leg drawing, and abdominal tension.[16,53]

These results suggest that, within the colic group, infants appeared more settled and exhibited fewer distress-related cry patterns during the day compared to the evening period. This diurnal variation may reflect increased caregiver interaction and environmental stimulation during daytime hours,

Table 3. Metrics obtained in the ML classification for the behavioral and acoustic cry patterns approach for both groups. Performance metrics are reported in terms of accuracy, sensitivity (true positives, number of colic instances), specificity (true negatives, number of non-colic instances), and F-score.

Performance metrics	Accuracy	Sensitivity	Specificity	Precision	*F*-score
Model 1—behavioral cry patterns	92.0	91.94	95.40	92.05	91.82
Model 2—acoustic cry patterns (cepstral and time-frequency features)	88.0	77.0	94.0	88.0	82.0
Model 3—acoustic cry patterns (cepstral features)	88.0	77.0	93.0	87.0	82.0
Model 4—acoustic cry patterns (time-frequency features)	78.0	52.0	91.0	76.0	62.0

or emerging patterns of behavioral regulation. By evening, infants may experience heightened irritation, potentially due to accumulated discomfort, tiredness, or overstimulation. Overall, when compared to infants without colic, infants with colic displayed higher arousal levels both during the day and evening, indicating a generally elevated state of distress throughout the day. Additionally, infants without colic presented a lower alertness level compared to the colic group, with more sleepy cries during the day and fussy cries during the night. According to literature,[23] both types of cries are typically less urgent, more monotonous, and contain more unvoiced segments. Overall, these findings suggest that infants without colic are generally calmer and more relaxed both day and night, likely experiencing fewer gastrointestinal issues, discomfort, or irritability than infants with colic.

Our demographic patterns also aligned with prior literature reporting higher colic prevalence among bottle-fed infants.[52] In the colic group, fewer infants were exclusively breastfed compared with the non-colic group. Moreover, gas-related discomfort was also more frequent in the colic group, aligning with colic's classification as a FGID[9]. Although our sample size is limited, breastfed infants—particularly in the non-colic group—displayed slightly higher levels of contact-dependent sleep, a pattern previously associated with increased proximity and regulatory needs in breastfed infants,[55,56] reason why cry types such as sleep and fussy could be more relevant within non-colic breastfed infants.

From a cry acoustic perspective, we observed that the most studied acoustic feature F0 presents a statistically significant decrease for colic cries, which may align with findings by[23,24] suggesting that F0 tends to be lower in cries associated with irritated infants. However, the rest of the F0 descriptives, resonance frequencies, and high cepstral content features do not always follow the same tendency or significance compared to Laguna et al.,[23] where the focus was specifically on distress vocalizations. At the same time, in this infantile colic study, there is a more ample variety of cry types characterization during the 24-h schedule that confirms that the infants are not constantly agitated, but on specific time intervals commonly associated with infantile colic. Additionally, voice quality parameters related to vocalization phonation are frequently analyzed in studies of infants with pathologies.[57–59] However, in our analysis, measures such as jitter, shimmer, and HNR did not effectively characterize colic cries, underscoring the notion that colic is not an organic but a functional condition.

Despite all the existing evidence described in the literature, many concerned parents usually consult clinicians who typically conduct a thorough history and physical examination to rule out organic causes for excessive crying, alleviating parental concerns and facilitating the diagnosis of infantile colic.[1] For a proper assessment, physicians usually gather details about the infant's behavior, including the timing, duration, and frequency of crying episodes. At this point, objective automated tools can greatly enhance this evaluation by providing quantitative and continuous data. Therefore, we introduced a novel approach for automatic and longitudinal collection of infant crying episodes in a home environment, potentially replacing traditional manual diaries. This innovative method enables us to massively monitor relevant cry features longitudinally, facilitating an extensive evaluation of the infant's cry patterns based on established criteria for infantile colic. Notwithstanding, the best-performing AI algorithm demonstrated a high accuracy (92%) in detecting subtle, objective behavioral cry differences between cry utterances associated with and without colic, surpassing previous studies.[14] Among the models leveraging acoustic cry patterns, those with cepstral features (Models 3 and 2) achieved high performances of 88%, while the model using time-frequency features alone (Model 4) performed less effectively at 78%. This underscores the superior predictive power of cepstral features in analyzing acoustic cry patterns. Nevertheless, the cry behavioral model still outperformed the cry acoustic approach, emphasizing the crucial role of crying infant behavior monitoring for infantile colic assessment. Previous studies, such as Parga et al.,[14] investigated ML applications for identifying infantile colic through acoustical cry patterns.[14,19,60] Using the ChatterBaby™ app, they achieved a 90.7% accuracy in detecting pain-related cries. In Parga et al.,[14] colic cries were most associated with pain, showing an average pain score of 73%, significantly higher than for fussiness or hunger. This suggests a distinct pattern in colic-related crying, which may explain why colic bouts are often perceived as “painful-sounding” by parents.[21]

Our ML analysis identifies behavioral and acoustic cry features frequently associated with infantile colic symptomatology, as perceived by parents in previous studies.[21] The cry behavioral approach highlights cry frequency, time of day, and cry type characterization as key factors in identifying crying episodes associated with infantile colic. Notably, the prolonged, inconsolable, and unexplained nature of colic cries implicit in this model, and often described in the literature,[19–21] are reliably confirmed through objective methods. Similarly, the cry acoustic approach underscores the importance of features such as high spectral content and F0, reflecting the “distinct sounding” quality of colic cries noted by caregivers too.[21] These findings demonstrate that infantile colic cries convey both observable, behavioral, and audible acoustic signals of high arousal or distress in infants, which can be objectively detected through cry analysis.

Hence, our approach to infantile colic detection offers quantitative support closely aligned with established infantile colic criteria,[9] integrating cry pattern analysis with essential infant data, such as age, longitudinal records, auditory, and cry behavioral data. Therefore, the algorithm is designed specifically for infants aged 0–4 months and identifies a likelihood of infantile colic only when the observed cry pattern persists for at least 3 days within a week. This multimodal approach offers a promising strategy to reduce emergency room visits by empowering parents to identify and manage infantile colic patterns more effectively. Additionally, it provides clinicians with comprehensive data to support the diagnosis and intervention of infantile colic.

Despite the promising results, it is important to acknowledge the limitations of this study. The data set used for model development may not capture the full range of variability and age in cry patterns among infants with colic. Most studies in the literature focus on analyzing specific cry samples or segments from the most audibly intense or distinctive colic bouts.[21] In contrast, our study examined sequential and varied segments, which may yield different findings compared to previous research.[21] Future research involves increasing the sample size of patients in the data set and optimizing and testing the algorithm in a clinical setting.

Conclusion

This study demonstrated the feasibility of using AI-based cry analysis to automatically detect and characterize crying episodes associated with infantile colic in natural home environments. The implications of the results are significant, holding promise for developing early intervention strategies and improved parental education and clinical management approaches for infantile colic during the critical early stages of infancy. Early identification of infantile colic can facilitate timely support and guidance for parents, leading to enhanced infant care and reduced parental stress and emergency room visits. Additionally, the potential for home-based, non-invasive, objective tools supporting infantile colic detection, combined with other infant symptomatology, may contribute to more proactive management. This could empower and promote parental education and enable healthcare professionals to implement timely interventions, improving the overall well-being and health of infants with colic and their caregivers.

ORCID iDs

Ana Laguna https://orcid.org/0000-0002-6829-4565
Sandra Pusil https://orcid.org/0000-0002-8395-1113
Paolo Piras https://orcid.org/0009-0003-3524-9674
Paolo Ingraito https://orcid.org/0009-0000-8975-2089
Helena Cuesta https://orcid.org/0000-0001-8531-4487
Jonathan Adrián Zegarra-Valdivia https://orcid.org/0000-0003-0497-5270
Anna Lucia Paltrinieri https://orcid.org/0000-0002-4560-6917
Silvia Orlandi https://orcid.org/0000-0003-2733-8450

Author contributions

Ana Laguna: conceptualization, funding acquisition, methodology, data processing, formal analysis, and manuscript–original draft preparation. Sandra Pusil: conceptualization, methodology, data processing, formal analysis, manuscript–original draft preparation, and preparing figures. Paolo Piras: methodology, data processing, and manuscript–original draft preparation. Paolo Ingraito: model training. Helena Cuesta: review and editing. Jonathan Adrián Zegarra-Valdivia: advice on data processing, and manuscript–review and editing. Anna Lucia Paltrinieri: conceptualization, advice on neonatology, and manuscript–review and editing. Silvia Orlandi: advice on data analysis pipeline and result discussion and manuscript–review and editing. All present authors contributed to the article and approved the submitted version.

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Data availability statement

The data set presented in this article is not readily available because the data supporting this study's findings are available from Zoundream Group. Data can be available from the authors upon reasonable request and with the written permission of Zoundream Group. Requests to access the data sets should be directed to ana.laguna@zoundream.com.

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