Supplementary Material

Artificial intelligence and wheezing in children: where are we at?

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# Supplementary Table 1 Studies on digital auscultation published in the last decade

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| **Study (year)** | **Country** | **Type of study** | **Aim of the study** | **Methods** | **Study population (male%)** | **Study population’s age** | **Main findings** | **Parents satisfaction**  | **Quality of life** | **Performance****Sensitivity specificity accuracy** |
| Do et al. (2024)(1) | Germany, Turkey and United Kingdom | Multicentre randomised controlled open-label trial | Assess if a digital support tool for wheeze recognition improves symptom control | Digital wheeze detector WheezeScan™ with a mobile application WheezeMonitor™ | 167 children; 87 intervention group (69.5%) | Mean 3.2 years (SD 1.6) | No statistically significant difference in wheeze control assessed by TRACK | PACQLQ and PAMSES improved without statistical difference between the groups | TAPQOL improved without statistical difference between the groups | Sensitivity 100%\*Specificity 95.7%\* |
| Dramburg et al. (2021)(2) | Germany | Single-armed pilot study | Assess the feasibility of a digital support tool for wheezing recognition | Digital wheeze detector WheezeScan™ with a mobile application WheezeMonitor™ | 20 (85%)  | Mean 39.5 months (q1:24.3 months; q3: 60 months)  | Improvement of ACT in 64% | Improvement of PAMSES | NI | PPV of 83.3% and NPV of 87.3% compared to the doctors’s judgement. |
| Habukawa et al. (2020)(3) | Japan | Case control study | Develop an algorithm for automatic wheeze recognition | Digital wheeze detector (future WheezeScan™) | 214 (64.5%)  | Mean 57.5 months (SD 43.1 months) | Development of an accurate algorithm for wheezing recognition | NI | NI | Sensitivity 100%, specificity 95.7%, PPV 90.3%,NPV 100%. |
| Kim et al. (2022) (4) | Korea | Prospective study  | Develop an improved deep-learning model learning to detect wheezing in children | Electronic stethoscope (Jabes, GSTechnology, Seoul, Korea) | 76 (\*\*) | (\*\*) | 34-layers ResNet with CBAM + TabularData enhibited the highest performance when compared to other models | NI | NI | Accuracy 91.2%, AUC 89.1%, precision 94.4%, recall of 81%,F1-score of 87.2%. |
| Porter et al. (2019)(5) | Australia and New Zealand | Prospective, multi-centre study | Compare diagnoses made by the algorithm to those froma clinical adjudication panel | Automaticcough detector using Time Delay Neural (TDNN) Networkoperating and identifying Mel Frequency CepstralCoefficients (MFCC) | 585 (59%) | Mean 53 months (SD 37 months) | The analyserwas able to diagnose reactive airway disease at a high-performancelevel without the need for bronchodilator-response testing | NI | NI | Focusing on asthma and reactive airways diseases, thealgorithm achieved excellent agreement results (PPA97%, NPA 91%) |
| Kruizinga et al. (2022)(6) | The Netherlands | Prospective validation study | Develop a smartphone-based algorithm that objectively and automatically counts cough sounds of children | CHDR MORE® application on a smartphone | 21 children (\*\*) | 0–16 years (\*\*) | Good accuracy on detection of cough sounds | NI | NI | Accuracy 99.7%, Sensitivity 47.6%Specificity 99.96%PPV 82.2% NPV 99.8% |
| Liao et al (2022)(7) | China | Validation study | Classify bronchitis and pneumonia in children byanalyzing cough sounds | Classification Framework based on Cough Sounds (CFCS) adopting Support Vector Machine (SVM) and t Long Short-Term Memory Network (LSTM) | 173 children (54%)  | 0-11 years (\*\*) | CFCS caneffectively classify children into bronchitis and pneumonia in children | NI | NI | SVM: accuracy of 86.04% Precision and recall of bronchitis: 93.75%, 88.24%Precision and recall of pneumonia: 87.5%, 93.33%. AUC of SVM: 0.92 AUC of LSTM: 0.93  |
| Kevat et al. (2020)(8) | Australia | Prospective study | Test an AI algorithm to detect crackles and wheeze in children | Recordings collected using two digital stethoscopes (Clinicloud™ and Littman™) submitted for analysis by a blinded AI algorithm (stethome AI) | 25 (72%)  | Median age 6.7 years (interquartile range 3.4) | AI can detect wheeze with good accuracy  | NI | NI | Focusing on wheeze detection: PPA 0.90 (Clinicloud), and 0.80 (Littman)NPA 0.97 (Clinicloud),and 0.95 (Littman) |
| Arjoune et al. (2023) (9)  | USA | Multicenter Prospective Study | Validation of StethAid (a digital platform for AI-assisted auscultation and telehealth) | StethAid, consisting of a wireless digital stethoscope, mobile applications, customized patient-provider portals, and deep learning algorithms | NS (\*\*) | 2-18 years (\*\*) | Accurate detection of wheezing | NI | NI | Focusing on wheeze detection: Harmonic Networkssensitivity 83.7% specificity of 84.4%accuracy of 84.0%.ResNet18: sensitivity 77.0%, specificity of 70.1%, accuracy of 73.9% |
| Puder et al (2016)(10) | Germany | Retrospective study | Evaluate the quality of respiratory sound recordings in young infants and determine whether the position of the sensor affected computerized wheeze detection. | PulmoTrack® Model 2020 | 112 (57%) | Median age 144 days (100–203) | TR sensor was less often affected by disturbances than the CW sensor, with a better quality of respiratory sound recordings. | NI | NI | Sounds from the chest wall were more oftenaffected by disturbances than sounds from the trachea (23% versus 6%, p < 0.001). |
| Puder et al (2014) (11) | Germany/Israel | Prospective study  | To determine and validate optimal cut-off values for computerized wheezedetection, based on the assessment by trained clinicians of stored records of lung sounds, in infants aged <1 year | PulmoTrack® Model 2020  | 120 (70%) | Median age 153 days (107–273) | PulmoTrack® can detect wheezing in neonates, with good values of sensitivity and specificity forinspiratory and expiratory wheezes. Computerized wheeze detection reliably detectseven short periods of wheezing. | NI | NI | Sensitivity 85.7% for inspiratory wheezes and 84.6% for expiratory wheezes. Specificity of 80.7% for inspiratory wheezes and 82.5% (expiratory wheezes.  |
| Zhang et al (2021)(12) | China | Prospective study  |  Evaluate the use of AI algorithm for detecting breath sounds in children with pulmonary diseases. | Class II CE-marked electronicstethoscope (Yunting model II, Tuoxiao, Shanghai, China) | 112 (73.2%)  | Median age 12.5 months (q 25% 5.0, q 75% 41.8) | The precision, the specificity and the F1 score in the detection of wheezing of the AI were significantly higher when compared to general pediatrician, with the highest accuracy in younger than 12 months   | NI | NI | Sensitivity 86.4%Specificity 83.0%Precision 76% F1 score 80.9% |
| Yu et al (2020) (13) | China | Retrospective | Compare machine learning–based models developed to identify asthma  | CatBoost, Logistic Regression, Naïve Bayes, and Support Vector Machines (SVM)  | DataSet-1   3,761 cases, DataSet-2   2,123 cases(\*\*) | 0-14 yearsDataSet-1 positive group mean ± SD, 3.680 ±2.6891 DataSet-1 negative group mean ± SD 2.176±2.8111DataSet-2 positive group mean ± SD 3.605±2.7956. DataSet-2 negative group mean ± SD 4.975±4.0442 | CatBoost model outperformed other models. AI model could rapidly and accurately identify asthma in general medical wards of children, and may aid primary pediatricians in the correct diagnosis of asthma | NI | NI | Accuracy of 84.7% and an area under the curve (AUC) of 90.9% on TestSet-1Accuracy of 96.7% and an AUC of 98.1% on TestSet-2 |
| Habukawa et al (2023) (14) | Japan | Prospective study | To validate the developed automatic wheeze recognition algorithm as a clinical medical device in children at different institutions | HWZ-1000T, Omron Healthcare Corporation, Kyoto, Japan | 374 (64.4%) | Mean 44.3 months, (SD 31.6) | The wheeze recognition algorithm was verified to identify wheezing with high accuracy; and, it might be useful in the practical implementation of asthma management at home. It will be useful for wheezing management at home and in remote medical care. | NI | NI | Sensitivity 96.6% Specificity 98.5% Positive Predictive Value 98.3%Negative Predictive Value 97.0% of the wheeze recognition algorithm  |
| [Emeryk](https://pubmed.ncbi.nlm.nih.gov/?term=Emeryk%20A%5BAuthor%5D) et al (2023)(15) | Poland | Observational study | Determine which devices and parameters work better in detecting asthma exacerbations | Home stethoscope, peak flow meter, pulse oximeter and subjective breathing quality | 90 children and 59 adults | 52 children aged 0-5 years: mean 3.0 years (q1 3.0, q3 4.25)38 children aged 6-17 years:mean 8.5 years (q1 7.0, q3 10.0)59 adults, mean 38.0 years(q1 32.5, q3 43.0) | A set of parameters measured by an AI-aided home stethoscope allows for the detection of asthma exacerbations without the need for performing PEF measurements.  | NI | NI | AUC 84% [95% CI, 82%-85%] |

*\* Parameters derived from a previous study (Habukawa C, Ohgami N, Matsumoto N, Hashino K, Asai K, Sato T, Murakami K. A wheeze recognition algorithm for practical implementation in children. PLoS One. 2020 Oct 8;15(10):e0240048. doi: 10.1371/journal.pone.0240048. PMID: 33031408; PMCID: PMC7544038.)*

*\*\* Sex and/or age are not clearly explicated in the text*

***TRACK****: Test for Respiratory and Asthma Control in Kids;* ***TAPQOL****: disease-specific quality of life;* ***PACQLQ****: parental quality of life;* ***PAMSES****: parental asthma management self-efficacy;* ***PPV****: positive predictive values;* ***NPV****: negative predictive values;* ***ACT****: asthma control test;* ***NI****: not investigated;* ***SD****: standard deviation;* ***PPA*** *Positive Percent Agreement;* ***NPA*** *Negative Percent Agreement;* ***AI*** *artificial intelligence;* ***NS*** *not specified;* ***F1 score***

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