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Development of a miniaturized mechanoacoustic sensor for continuous, objective cough detection, characterization and physiologic monitoring in children with cystic fibrosis

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Abstract

Cough is an important symptom in children with acute and chronic respiratory disease. Daily cough is common in Cystic Fibrosis (CF) and increased cough is a symptom of pulmonary exacerbation. To date, cough assessment is primarily subjective in clinical practice and research. Attempts to develop objective, automatic cough counting tools have faced reliability issues in noisy environments and practical barriers limiting long-term use. This single-center pilot study evaluated usability, acceptability and performance of a mechanoacoustic sensor (MAS), previously used for cough classification in adults, in 36 children with CF over brief and multi-day periods in four cohorts. Children whose health was at baseline and who had symptoms of pulmonary exacerbation were included. We trained, validated, and deployed custom deep learning algorithms for accurate cough detection and classification from other vocalization or artifacts with an overall area under the receiver-operator characteristic curve (AUROC) of 0.96 and average precision (AP) of 0.93. Child and parent feedback led to a redesign of the MAS towards a smaller, more discreet device acceptable for daily use in children. Additional improvements optimized power efficiency and data management. The MAS's ability to objectively measure cough and other physiologic signals across clinic, hospital, and home settings is demonstrated, particularly aided by an AUROC of 0.97 and AP of 0.96 for motion artifact rejection. Examples of cough frequency and physiologic parameter correlations with participant-reported outcomes and clinical measurements for individual patients are presented. The MAS is a promising tool in objective longitudinal evaluation of cough in children with CF.

I. INTRODUCTION

Cystic fibrosis (CF) is a genetic disorder resulting in abnormal epithelial ion transport in multiple organs[1]. In the lung, dehydration of the airway mucus layer causes obstruction, infection, inflammation, progressive loss of lung function, and reduced life expectancy[2, 3]. Chronic cough is often a presenting symptom in CF in early childhood and reduces quality

of life[4, 5]. Increasing cough frequency or changes in cough character are sentinel signs of pulmonary exacerbation in CF, driving pulmonary function decline and mortality[3, 4, 6, 7].

While clinical assessment relies on specific cough characteristics, pediatric history-taking faces challenges due to intermittent parental observation and subjective interpretation [8–10]. Despite being used as a disease marker in clinical trials, validated diaries and existing devices for cough measurement are underutilized, poorly accepted[8], and have low association with objective lung function measurements[11]. There is significant unmet need to precisely measure the frequency, circadian timing, characteristics and severity of cough in children for acute and chronic disease management [9].

Acoustic analysis and cough recognition algorithms have been developed for use in CF and other lung diseases[9, 10, 12, 13]; state of the art techniques, limitations, and future directions are thoroughly reviewed[9]. Briefly, most methods involve recording cough sounds and analyzing the sound waveform to detect patterns or changes that may indicate increased airway secretions and/or airway obstruction. Existing devices generally include a microphone and include the Hull Automatic Cough Counter[14], PulmoTrack-CC[15], the Leicester Cough Monitor[16] and VitaloJak[17]. Limitations of free-field microphone techniques include difficulty distinguishing one individual's cough from that of others' and from ambient noise, leading to overcounting and high false-positive rate as demonstrated in external validation studies[9]. Several techniques have attempted to add additional sensors, such as a pneumogram belt (PulmoTrack-CC) or The LifeShirt[18] which combined many different sensors to increase specificity in the ambulatory setting but is no longer commercially available. The LifeShirt and other multi-contact approaches[19] have comfort and usability issues that require active device maintenance, interfering with normal activity. Only the PulmoTrack-CC and the Leicester Cough Monitor have achieved widespread use. Complicated data download tasks additionally reduced usability in these devices, a major barrier to their use in children.

Few cough monitoring approaches are specifically studied pediatric populations. One aimed at developing and assessing usability of an asthma monitoring device in adolescents[20] found that ambient sounds limited the reliability of their approach, and the wired microphone limited usability. Another approach achieved good performance using stationary microphones in a limited hospital setting but did not address ambulatory monitoring[21]. More recent work in pediatric cough detection using smartphone microphones had a significant decrease to their sensitivity during validation in clinical environments where proximity of the microphone to the patient could not be guaranteed[22].

Advances in materials science and biomedical engineering have enabled development of fully wireless, skin-like devices designed for high-quality, convenient, and continuous measurement of physiological signals[23–28]. Mechanoacoustic sensors (MAS) using a triaxial accelerometer can simultaneously measure physiological functions such as heart valve closure, skeletal muscle contraction, and vocal fold vibration, yielding mechanical waves and signals in the frequency of less than 1 Hz (body orientation, chest wall motion) to over 1,000 Hz (vocal and respiratory sounds). The direct skin interface reduces the effect of ambient noise on the measurements, greatly improving data quality and participant privacy.

We present initial studies of an MAS, repurposed from prior studies[23–26], for use in detecting and monitoring cough in children with CF. We describe how the sensor was studied, miniaturized and made more discreet to be acceptable to children and their parents. We report how custom machine learning algorithms to detect cough were trained, validated, and deployed on data collected from children with CF. Finally, we describe how the sensor was studied over multiple days in children with CF when health was at baseline or during pulmonary exacerbations, demonstrating the sensor's ability to objectively measure cough and other physiologic signals in the home and hospital setting. We also describe our experience monitoring cough with simultaneous collection of validated participant-reported outcome tools and clinical measurements.

II. METHODS

A. Study Design

This single-center pilot study was designed to determine if a small, wearable mechanoacoustic sensor 1) could detect cough and distinguish cough from other vocal and confounding signals at rest and during activities 2) required modification to be acceptable and usable to the children with CF and their parents/guardians and 3) could generate longitudinal cough and vital sign data in clinical, home and community settings. Children and teenagers with CF were studied under four clinical protocols to train a cough algorithm and study sensor performance under a variety of conditions. The study was performed at Ann & Robert H. Lurie Children's Hospital of Chicago. The Institutional Review Board at Ann & Robert H. Lurie Children's Hospital of Chicago approved the study protocol (IRB 2020–3743).

We recruited participants by telephone, secure electronic communication, or in-person in the clinic or hospital. Consent was obtained in-person or via an electronic consent platform after the study objectives, procedures, potential benefits and risks were described in a clear and understandable manner, and all questions were answered. Participants who were 18 years old, or parents or legal guardians, provided written informed consent. Children aged 12–17 years old provided written assent.

Inclusion criteria were a diagnosis of CF[5] and age 3–18 years and were otherwise cohort specific. Inclusion criteria intentionally remained broad (e.g. did not consider lung function measurements) in order to capture as much variety in disease states as possible for this pilot study. Exclusion criteria were limited to factors precluding placement of the device such as history of atopy, skin rash or breakdown involving the neck or upper chest, presence of tracheotomy, or factors preventing family ability to follow study procedures, physiologic instability requiring intensive care, or other factors identified based on discussion about and/or review of the study procedures outlined in the consent form.

We recruited participants into 4 cohorts to assess the device performance over a range of clinical conditions and outcomes. Participants could enroll in more than one cohort at different times. A priori, we anticipated device modifications may be needed based on participant and parent usability and acceptability feedback and planned limited tests using the cohort 1 protocol to assess form factors, placements, and adhesive types, prior

to using these devices for further studies. In summary, we planned to re-purpose a sensor used for adult cough monitoring[26] for initial data collection trials, collect usability and acceptability surveys, then pursue a MAS redesign based on patient and parent feedback for long-term monitoring.

B. Survey Assessments

1) Cystic Fibrosis Respiratory Symptom Diary (CFRSD)—The CFRSD[29] is a validated measure of the symptoms and impact of the pulmonary symptoms in adults and adolescents (>12 years) with CF and chronic respiratory infection. It is used to evaluate the effect of treatment on the severity of symptoms of a respiratory infection.

2) Revised Cystic Fibrosis Questionnaire (CFQ-R)—The Cystic Fibrosis Questionnaire-Revised (CFQ-R)[30–34] is a validated, disease-specific health-related quality of life (HRQOL) survey. It is completed by parents of children < 6 years, as separate child and parent surveys for child participants between 6–13 years of age, and directly to participants >13 years of age.

3) Sinonasal Outcome Test—The 22-item Sinonasal Outcome Test (SNOT-22) is a validated, participant rated outcome measure[35] considered the most suitable tool to evaluate nasal symptoms in terms of ease of use[36]. It queries key diagnostic symptoms included in the European Position Paper on Rhinosinusitis and Nasal Polyps[37] definition for chronic rhinosinusitis.

4) Acceptability and Usability—We designed a usability questionnaire for administration to participants and/or their parents/guardians. This 6-question survey was designed to generate feedback on overall comfort, effectiveness, efficiency, and satisfaction with the MAS system. Direct verbal and written feedback solicited by the study team supplemented information about device acceptability.

C. Clinical Metrics

The pulmonary exacerbation (PEx) score is a tool used at Lurie Children's CF Center during clinic visits and telephone encounters for illness to support standardization and quality of care in identifying pulmonary exacerbation[38, 39]. PEx scores were calculated at clinical encounters in accordance with usual practice at the Lurie CF Center (Supplementary Table 2). FEV1 was measured in accordance with American Thoracic Society standards[40] at the time of clinic or hospital encounters and recorded as percent predicted FEV1 (FEV1pp).

D. Cohorts

Cohort 1 included children during routine clinic visits to the Lurie Children's Hospital Cystic Fibrosis Center. Each participant had an MAS mounted at the suprasternal notch by a trained research coordinator and was instructed through a series of standardized vocalizations and activities. A research staff member observed the participant continuously in an exam room or virtually through a Health Insurance Portability and Accountability Act (HIPAA) compliant videoconferencing platform. Activities were time stamped by the staff member. Timestamps were electronically supplemented by notes on a source document

for use in algorithm training. The duration of the procedure was approximately 30 minutes following the protocol outlined in Supplementary Table 1.

Cohort 2 included children who were monitored during all procedures at a routine CF clinic visit. Procedures included spirometry or multiple breath washout tests, collection of expectorated sputum or oropharyngeal secretions for culture, and clinical assessments by members of the multidisciplinary CF team. A research staff member mounted the MAS at the suprasternal notch prior to clinical assessments and observed the visit, annotating times of activities and observed coughs on a study-specific document. The duration of the ambulatory evaluation was approximately 120 to 150 minutes.

Cohort 3 included participants who were stable during routine clinical care or at a screening visit, agnostic to baseline symptoms or FEV1pp. Clinical stability was defined as: (a) clinical PEx score < 2 and/or, as applicable, (b) absence of FEV1-indicated exacerbation[41]. Remote screening included home spirometry for participants who could perform spirometry, had a device at home, and had at least 3 prior measurements on separate days when clinically stable. Participants were shipped 2 MAS devices, adhesives, chargers, and tablets and guided through mounting the devices over HIPAA compliant videoconferencing calls. Participants wore the MAS for one week, changing devices either on their own or with parental assistance every 24 hours to allow for charging and data download. Participants and parents were instructed to complete the CFRSD daily and the CFQ-R on days 1 and 7.

Cohort 4 included participants with clinically diagnosed pulmonary exacerbation of any severity who were prescribed antibiotic therapy. They were identified at admission to Lurie Children's Hospital, during clinic visits, or after phone or electronic health record communication. Participants were enrolled as early as feasible, within 3 days of initiating treatment. Participants were trained to place the sensor and wore it for the duration of treatment or up to 14 days, changing and charging sensors daily for near-continuous data capture. Hospitalized participants who were discharged from the hospital to complete therapy continued monitoring at home. Disease specific quality of life and symptom questionnaires were administered similar to cohort 3, with addition of the sino-nasal outcome test (SNOT-22), administered at enrollment and on the final day of treatment. CFQ-R surveys were completed at enrollment, days 7 and 14, and/or on the final day of treatment. FEV1pp was also measured as ordered by the treating practitioner along with any available PEx scores. Site, duration of therapy, and specific treatment (antibiotics, airway clearance) was extracted from the medical record for descriptive purposes.

E. Mechanoacoustic Sensor Framework

The MAS (Fig. 1) includes two inertial measurement units (IMUs) capable of triaxial accelerometry and triaxial angular velocity measurements via a gyroscope. The primary IMU is mechanically isolated at an island, while the secondary IMU in the sensor body serves as a backup or for artifact cancellation[23]. For the purposes of this study, surface-normal (z-axis) acceleration is measured at 1.6kHz, while the x- and y- axes are resampled to 30Hz to provide low-frequency three-dimensional chest wall motion, activity, and body orientation measurements. 1.6kHz was chosen as the optimal sampling frequency as it

captures a majority of the energy in coughs[9, 42, 43] while limiting the amount of data required to be written to memory or transferred wirelessly. The internal temperature sensors in the IMUs and system-on-a-chip (SoC) provide skin temperature measurements. The SoC manages communication between device components and external data transfer through the Bluetooth Low-Energy (BLE) protocol.

Devices are encapsulated in medical grade silicone elastomer (Silbione 4420, Elkem) and charge wirelessly via power collection from an inductive coil tuned to 13.56MHz. Devices are attached to the skin using a custom laser cut, medical grade dual sided silicone-acrylate adhesive (2477p, 3M). Sensor mechanical characteristics, performance, and bandwidth are reviewed in previous work[23, 25], capabilities in cough and vocal characterization including association with droplet production (in adults) are presented[26]. All integrated components are soldered onto flexible polyimide printed circuit board (fPCB).

Data are streamed through BLE to a consumer mobile device running custom software nearby or stored in onboard memory when out of range or to save power. Independent power management circuitry isolates the battery from sensor components and coordinates power transfer. Data streamed to the mobile device is displayed and processed locally, and simultaneously securely uploaded to a timeseries database optimized for storage, retrieval, processing, and visualization of the data. Further improvements made to the sensor based on patient feedback during this study are reviewed in the Results section.

F. Cough Detection Strategy

1) Preprocessing—Coughing is a complex reflex response, can be voluntary or involuntary and is influenced by both behavior and pathologic processes[9]. Fig. 2 shows a segment of data from a natural coughing pattern collected from a participant in cohort 2 during spirometry (top panel). Coughs are followed by throat clearing and a vocalization, converted into a spectrogram using conventional Fourier analysis (Fig. 2 middle panel). Coughing exhibits spectrally distributed power, while throat clearing and vocalization show clear fundamental frequencies and harmonics, findings consistent with observations in other studies[9, 43].

Potential cough events were isolated from the continuous data using a first-pass algorithm with high sensitivity but low specificity for cough-like events, a process described in detail in previous work[26]. Briefly, spectrally distributed “burst” events are identified as peaks in the time series power sum (10–800Hz range) exceeding a predetermined threshold of 2,000 times the noise floor power sum of the dataset. These burst events are collected into 0.32 second windows (512 samples), roughly the average cough sound length noted in the literature[43]. Events with clear periodic peaks in their power spectrum representing a harmonic series were removed from further analysis to limit the number of vocal events requiring classification[26]. The remaining segments of signal are then converted into wavelet scalograms with inversely scaled Morlet wavelets corresponding to 128 linearly spaced frequency bins with centers between 0.13Hz and 765Hz (Fig. 2 bottom panel). This accomplishes three crucial tasks: 1) improved representation of rapidly changing frequency components throughout time via wavelet analysis, 2) separation of low-frequency chest wall and throat motion (arrows in Fig. 2) which are not present in vocalization events

(dotted circle in Fig. 2), and 3) enhanced representation of higher frequencies expected to be generated by pediatric participants. The spacing of these frequency bins to highlight higher frequencies represents a departure from previous work[26].

2) Labeling—Burst events (marked events in Fig. 2) from participants in cohort 1 and cohort 2 were labeled as coughing, throat clearing, talking, laughing, and motion artifact by expert evaluation. Two independent experts combined visual inspection of known signal patterns[9, 43] with audio playback of the raw acceleration signal cross-referenced with research coordinator notes on participant activity to label the data. Disagreements were resolved by arbitration with a third expert. In many cases, especially with younger participants, elicited coughing and throat clearing on demand were difficult to distinguish from each other. This is likely due to both behavioral and motor differences and between younger and older children and milder disease in younger participants[44]. Children with CF and bronchiectasis are often taught to “huff” or cough in a stereotyped fashion to aid in airway clearance[45], leading to measurable physical differences[46]. Nevertheless, cough and throat clearing events were kept separate for model training purposes to attempt to separate true, involuntary, pathologic coughs from non-pathologic voluntary events. Events labeled as “talking” included a broad range of speech, singing, humming and interjections.

3) Model—The choice of the model used for the interpretation of the wavelet spectrogram representation and classification of cough events was based on previous success with a similar model used for adult vocal event classification, described in detail elsewhere[26]. Briefly, the model treats the 2D wavelet scalograms as an image. The model takes advantage of the convolutional neural network (CNN) architecture and the pre-trained and optimized ResNet50[47] architecture widely used in image classification approaches to identify unique combinations of features enabling accurate classification.

Fig. 3 outlines the model layers and training strategy. 512 × 128 scalograms are passed through a 3×3 kernel CNN, followed by a fully pre-trained ResNet50. This output undergoes global pooling, followed by two fully connected layers of 512 and 128 neurons, respectively, followed by the five-neuron output layer. Rectified linear unit activation, 50% dropout, and random initialization is used throughout non-ResNet layers. The adam optimizer and sparse categorical crossentropy loss is used. Data from cohort 1 was used to train and cross-validate the model, while data from cohort 2 was held out for testing.

G. Vital Sign Measurements from the MAS

1) Heart Rate—Heart Rate (HR) is calculated from the 20–50Hz zero-phase filtered z-axis acceleration signal. A Shannon energy envelope is calculated on this bandpassed signal, from which peaks are detected via automatic multi-scale peak detection[48]. Pairs of peaks corresponding to the first (S1) and second (S2) heart sounds are extracted, with the difference in time between subsequent S1 sounds used for HR and HR variability (HRV) calculations. HRV is calculated using the root-mean-square of successive differences definition.

2) Respiration Rate and Body Orientation—Respiration Rate (RR) is extracted from the 3-dimensional periodic motion of the chest wall. A modified algorithm[49] was used to estimate the dominant gravity vector in a 1-minute window, from which small deviations in the frequency range of 0.1–0.8Hz were assumed to arise from chest wall motion. The dominant gravity vector also determined the body orientation.

3) Activity—Relative activity measurements were estimated by a power density sum from 1–10Hz over a 15-second window expressed in decibels relative to a power sum of $1g^2$. An additional, high-frequency metric corresponding to a similar power sum from 10–100Hz aided in the identification of mechanical vest usage.

H. Bias, Study Size, and Statistical Analysis

This is a pragmatic pilot study to assess performance of the MAS and to test usability and acceptability. We did not aim to compare cough between individuals or cohorts. No sample size was calculated as this is a pilot study aimed at evaluating if sensor-measured coughs can be separated from other vocal events and artifacts without prior knowledge of the prevalence and variance of these events. A recent review[50] notes that a majority of studies on cough detection recruited fewer than 30 subjects. We therefore aimed to recruit a sample size of 50. We initiated the study with an older version of the MAS and used survey and participant feedback, ultimately redesigning the device for acceptability. These new devices then informed subsequent software and application updates. Quantitative variables from surveys and metrics derived from the MAS including vital sign measurements and cough metrics were compared only within individual subjects to reduce inter-subject variability and bias.

III. RESULTS

A. Participant Characteristics

A total number of 50 individuals were approached and consented for the study. Satisfactory data collection was accomplished for 36 individuals across 4 cohorts. Some participants contributed datasets to multiple cohorts. A flow diagram is shown in Fig. 4. Overall, over 2767 hours (111.7 days) of usable continuous sensor data was collected across all cohorts.

Those who consented but did not participate were simultaneously consented for enrollment in a clinical trial of alternative approaches to mild pulmonary exacerbation but never developed an exacerbation. Demographics (Table 1) of enrolled participants reflected the population of our pediatric CF program.

B. Mechanoacoustic Sensor Improvements and Data

Improvements to the sensor form factor and operating characteristics were made following analysis of the acceptability and usability survey responses. Participant/parent reports included comments on sensor size, visibility, difficulty adhering the device to skin, and color options (Supplementary Table 3). Furthermore, the demands of daily use required improving the robustness of device components, reducing overall power consumption and memory usage to allow for longer continuous recording periods. A schematic of the new

devices is presented in Fig. 5. Table 2 presents measurements of current consumption over one minute of steady-state operation for the old device and the new device compared under different conditions.

1) Hardware Improvements—Device size was reduced primarily by improving the power management circuitry for more efficient operation at lower voltages, therefore enabling selection of smaller battery sizes. The operating voltage of the device was lowered to 1.8V from 3.3V by implementing a power management integrated circuit (nPM1100, Nordic® Semiconductor) with a high efficiency buck regulator. Upgraded components include a low-power IMU (LSM6DSO, STMicroelectronics) and NAND memory (W25M02GVZEIG, Winbond). To maximize use of available memory, the NAND driver implemented a 16KiB buffering scheme that compresses and fragments payloads across NAND pages. The NAND packing scheme provided, on average, a 1.2x compression ratio at the cost of additional CPU usage overhead not represented in the old device firmware. These improvements are best represented as an overall ~170μA improvement to current draw when recording (Table 2).

2) Data Compression—Compact integral time-series compression[51] leaning heavily on delta compression[52] is implemented on the SoC firmware. This leads to a significant reduction in the number of bits required to be written to memory or sent over BLE, drastically reducing the power consumption of these operations. The amount of compression achievable varies depending on the entropy of the incoming data, averaging around 4x compression. During typical operations, average current required to record to onboard memory is nearly halved (Table 2). The significant reduction in power consumption made feasible the real-time streaming of raw data over BLE to a local mobile device, when in range. This further reduces the amount of data required to be written to onboard memory, substantially extending recording intervals.

3) Mechanical Improvements—These improvements to power consumption and memory use overall enable a reduction to the size of the battery required to power the device from 75mAh to 50mAh. Device layout was optimized while maintaining a manufacturer-recommended 18mm keep-out-zone around the BLE antenna. Sections with integrated circuit components were reinforced while maintaining foldable areas and introducing a freely flexible umbilical.

The new device is 2cm × 3cm × 1cm with a 2.5cm narrow umbilical, shown in Fig. 6a-d. A comparison between old and new devices is shown in Supplementary Fig. 1. The smaller size represents a 40% decrease in area of the core electronics compared to the old device[23] and allows comfortable placement of the device on a smaller pediatric sternum. The umbilical design enables only a small part of the device to protrude into the visible suprasternal notch in response to participant feedback.

4) Example Data—Fig. 7 demonstrates data from a typical morning for a participant in cohort 4. Raw acceleration signals are shown alongside a normalized Fourier spectrogram, showing both time and frequency information. The background of the acceleration plot is shaded depending on the body orientation of the participant as they sleep, wake up, engage

with their routine mechanical vest therapy, eat breakfast, and walk to school. A 20 second segment of data from a quiet section showing the sinusoidal oscillations as the chest wall moves with every respiration and small, regular spikes originating from the opening and closing of heart valves (Fig. 7b). These are also seen as regular, low-frequency bumps on the corresponding spectrogram. A half hour of high frequency oscillatory vest therapy (Fig. 7c) appears as low-frequency vibrations applied at a periodic 5-minute interval of linearly increasing and decreasing frequency. Broad-spectrum spikes associated with coughs are near the peaks of these oscillations. Fig. 7d shows the participant walking around and performing activities of daily living.

C. Cough Detection Training and Performance

Labeled events from the protocolized recordings in cohort 1 were used for training and cross-validation. A leave-one-subject-out cross-validation strategy with 40% weighting on cough events was used, and the cross-validation was repeated 10 times. The model with best cross-validation performance was subsequently tested on never-before-seen data from clinical visits (cohort 2) to generate the results in Fig. 8 and Supplementary Fig. 2. This model was frozen and subsequently deployed on the long-term monitoring cohorts 3 and 4. The final model was implemented on the cloud.

As expected, there is inherent similarity between the cough and throat clearing classes, and the talking and laughing classes. This was also evident in the raw data during the process of expert labeling, and the model does not perform well separating these pairs of classes, as shown by the confusion matrix in Supplementary Fig. 2. While these labels were kept separate for training the model, throat clearing can be folded into cough (and laugh into talk) and treated as one physiologically related class. These combined classes are used to when presenting the final confusion matrix (Fig. 8a), receiver-operator characteristic (ROC) curves (Fig. 8b) and precision-recall curves (PRC) (Fig. 8c). This model is particularly capable of rejecting motion artifacts, with over 95% accuracy and total area under the ROC (AUROC) of 0.97 and average precision (AP) of 0.96. The overall micro-averaged AUROC is 0.96 and overall micro-averaged AP is 0.93.

D. Long-Term Monitoring of Pulmonary Exacerbation

Fig. 9 shows data from a single participant from cohort 4 enrolled by the study team on the second day of admission to the hospital for pulmonary exacerbation. Vital signs including HR, HRV, RR, activity, and skin temperature are calculated from sensor signals. Cough counts per hour were generated from cough events labeled by the machine learning model. Re-analysis of labelled events measured the total power, plotted as varying colors of the cough count bars.

Cough variability is defined as the root-mean-square of the time intervals between coughs in a 1-hour interval around each detected cough event. For this participant, self-reported symptom and quality of life surveys improved at discharge relative to the time of admission. Cough count and intensity was higher during admission, especially during mechanical vest therapy, frequently exceeding 25 coughs per hour. Coughs also occurred regularly, as indicated by low variability compared to the sparser coughing after discharge. HR often

peaked greater than 100 beats per minute during admission, and nighttime HR was higher than after discharge. The participant's temperature was generally higher during the hospital admission, however nighttime temperature appears to remain similar, indicating this may be an environmental effect rather than physiologic. Two additional examples of long-term cohort 4 monitoring are shared in Supplementary Fig. 3.

E. Acceptability and Usability

Acceptability and usability survey result responses are separated by cohort based on sensor wear time; cohorts 1 and 2 are grouped as short-term wear (Table 3), and cohorts 3 and 4 are grouped as long-term wear (Table 4). As shown in Fig. 4, the cohort 1 and 2 participants primarily used the original device whereas cohorts 3 and 4 primarily used the newer device.

Overall, there was a high level of acceptability for this sensor to pediatric participants and their families, which decreased slightly with wear time. Participants reported few problems using the sensor during the short-term wear. While 55% of participants in the long-term wear group reported problems using the sensor, 91% of long-term wear participants still reported the sensor was easy to use. Verbal feedback suggested most problems were associated with charging the MAS but were quickly resolved. Of note, the age of participants in the long-term wear cohorts were generally older (12.36+/−3.6 years old) than the short-term wear cohorts (9.44+/−5.4 years old), Table 5.

1) Symptom and quality of life survey completion rates—Overall, there were low rates of completing the SNOT-22, CFRSD, and CFQR surveys during 7 days of monitoring at home during a period of baseline health (Cohort 3) and during up to 14 days of monitoring during pulmonary exacerbation treatment (Cohort 4), shown in Supplementary Table 4.

IV. DISCUSSION

This study introduces a mechanoacoustic sensor for children, facilitating convenient and user-friendly multiparameter physiologic monitoring. Specifically, this is a unique device simultaneously able to capture cough in addition to physiologic signs such as HR(V), RR, activity, body orientation, and temperature among other physiologic parameters from a single wearable sensor acceptable to children over long-term (up to two weeks) monitoring periods. Coughs and throat clearing events detected by the device are distinguishable from other vocal events (talking and laughing) and other artifacts with an overall micro-averaged AUROC of 0.96 and overall micro-averaged AP of 0.93.

Improvements over existing automated cough detection techniques[9] include a reduction to the high false-positive rate often observed in free-field microphone approaches. This is accomplished by soft mechanical coupling of the accelerometer to the suprasternal notch, minimizing the effect of ambient sound and enabling introduction of low-frequency chest and throat motion into the model (Fig. 2). This work observed 95% accuracy, an AUROC of 0.97 and an AP of 0.96 in artifact identification by the cough classification algorithm. This observation is limited by a lack of external validation; other studies were able to evaluate algorithm performance on standardized audio datasets[9], which are not available

in the same form for accelerometer data or for pediatric patients. Direct comparison between studies is impeded by varying definitions, objectives, health conditions, and studied environments[9, 50]. Despite these limitations, the deployed MAS and model demonstrated cough counts trending with symptom surveys in several individual children in a variety of uncontrolled, natural settings – in clinic, the hospital, at home, or at school. Future research effort directed at establishing concrete relationships between these detected coughs and physiological states is warranted.

While an attempt was made to separate pathologic coughs from non-pathologic throat clearing, the trained model ultimately failed to distinguish these classes. Model training data was collected on children with CF who performed coughing, throat clearing, and other activities during routine clinic visits (i.e. without concurrent pulmonary exacerbation). As cough has both behavioral and functional components[53], some younger participants in the training cohort had difficulty mimicking pathologic coughing which precluded finer classification of respiratory mechanics. Indeed, it was often difficult for the trained experts labeling the data to agree on the labeling of these events, a commonly observed interrater reliability issue[17].

This pilot and feasibility study was not designed to perform inter-individual comparisons, or comparisons between pathologic coughs that arise during exacerbation compared to those that occur (e.g. for mucus clearance) at the baseline state. While PEx scores and lung function measurements (FEV1) were collected, these were only used to determine cohort assignments rather than characterize cough. The definition used for coughs and the respiratory status of patients selected for this study were purposely kept broad to observe a realistic distribution of measurements. Future work may benefit from characterizing coughs based on physiologic or radiologic criteria[54].

The additional physiologic variables measured by the MAS were not used to influence the cough detection or classification algorithm in the current study. While extensive analysis of these other variables is not a core aim of the current study, their availability to subsequent researchers through the convenient, acceptable, single-sensor format presented here adds important variables to future research efforts. For instance, respiratory phase measurement, concurrent tachypnea, activity, temperature and other values used to calculate clinical PEx scores[39] may allow for finer delineation of pathologic cough.

An increased duration of cough monitoring is desirable due to the objective data gained through diurnal and inter-day variations in cough frequency during natural tasks, when the wearer has become accustomed to the monitoring device and does not adapt behavior to being monitored[9]. In this work, hardware upgrades, firmware optimizations, and compression implementation aimed at reducing power-intensive operations such as data bus usage, BLE radio usage, and writing data to memory reduced power consumption compared to previous designs by over 60% while recording. The same advancements enable real-time raw data streaming, reduce reliance on limited device memory, and result in continuous monitoring intervals of >24h for a single device; long-term monitoring up to 2 weeks is demonstrated with patients switching devices daily. User comfort, ease of use, and

compliance reported on surveys by 91% of long-term users supports the use of the MAS in this regard.

Model selection was based on previous success with similar architectures[26]. Model size optimization such as parameter pruning and layer trimming were not performed. With full access to continuous raw sensor data provided by the MAS, future work may be able to iterate and improve on any aspect from pre-processing and feature selection, to model architecture and optimization, enabling deployment of the model to the mobile device or onboard the sensor itself as desired.

A barrier to further analysis of the data collected was that many of the patients screened into cohort 4 had only minor exacerbations or were treated with antibiotics for lung-related complications where an increase in cough frequency or change in cough character was not a significant presenting symptom. The study was conducted during the first years of the COVID-19 pandemic, when viral respiratory tract infections decreased in children due to community masking and restrictions[55]. It is proposed that future work pursue long-term home monitoring with the aim of establishing individualized baseline cough counts in order to better recognize changes in these values when a pulmonary exacerbation is encountered, similar to a recent study performed in chronic obstructive pulmonary disease[12].

There was also poor adherence with participant reported outcome surveys in cohorts 3 and 4, which has been reported in other studies using these measures[9, 56]. The relative patient adherence with the MAS supports the argument that objective tools acceptable to pediatric patients such as the MAS could be valuable as an outcome measure for future observational and interventional studies as well as to monitor symptoms for early detection, progression, and resolution of pulmonary exacerbation after further work.

In summary, we evaluated, redesigned and demonstrated the performance of a mechanoacoustic sensor for noninvasive, continuous monitoring of cough and vital signs. Further development may lead to an effective, objective way to monitor symptoms in CF and other childhood respiratory diseases, for research and in clinical practice.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

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The Institutional Review Board at Ann & Robert H. Lurie Children’s Hospital of Chicago approved the study protocol (IRB 2020–3743).

DATA AND CODE AVAILABILITY

All data required to evaluate the conclusions are present in the paper or in the supplementary materials, and code used in analysis is based on open-source, publicly available resources. Additional data and materials may be requested from one of the corresponding authors.

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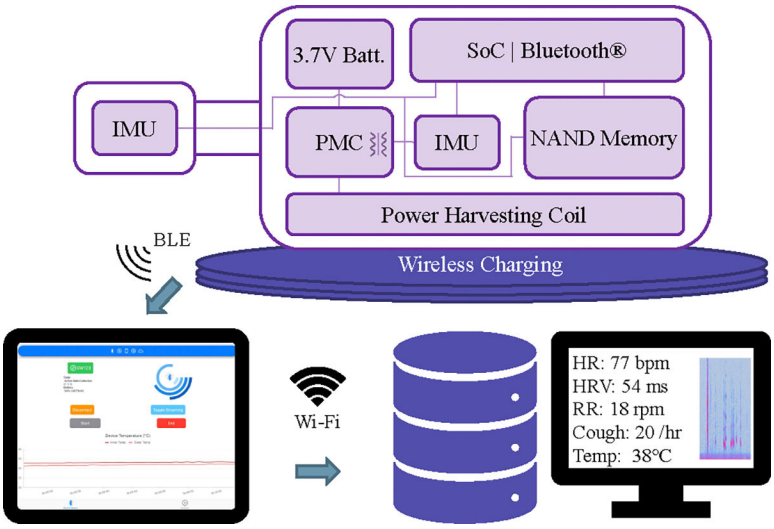

Fig. 1.

A schematic view of key sensor components and data flow. The device stores raw data locally on onboard memory for low-power operation or streams to a mobile device through BLE. The mobile device is able to display data and run pre-defined signal processing locally. All raw data are securely uploaded to cloud storage from which retrospective analyses are performed and larger models can be trained.

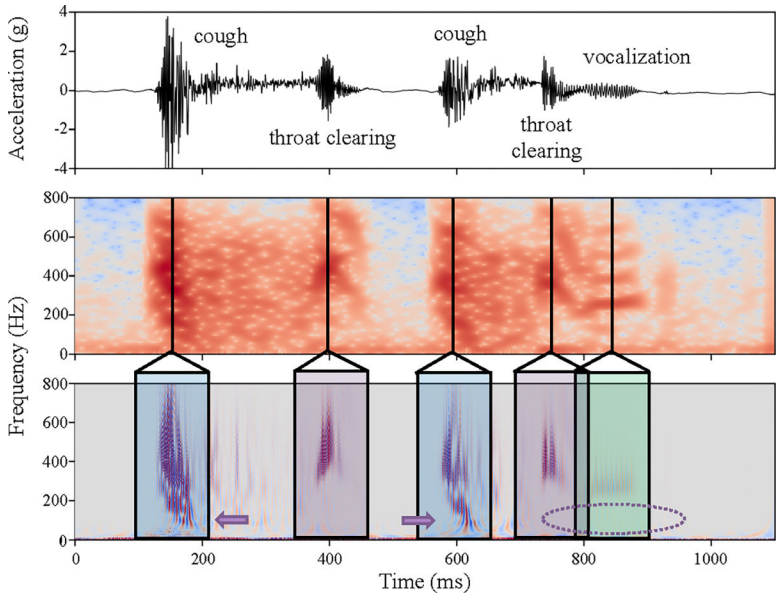

Fig. 2.

Example segment of raw, surface-normal acceleration data during a coughing fit. The raw acceleration data (top panel) is converted into a Fourier power spectrogram (middle panel), from which “burst” events are detected via power-sum peaks of spectrally wide-band data. These events are further converted into wavelet scalograms (bottom panel), which better represent dynamic frequency changes and can simultaneously capture relationships between low frequency components (throat and chest wall motion) which are present in cough events (purple arrows) and not in simple vocalizations or throat clearing (dotted circle).

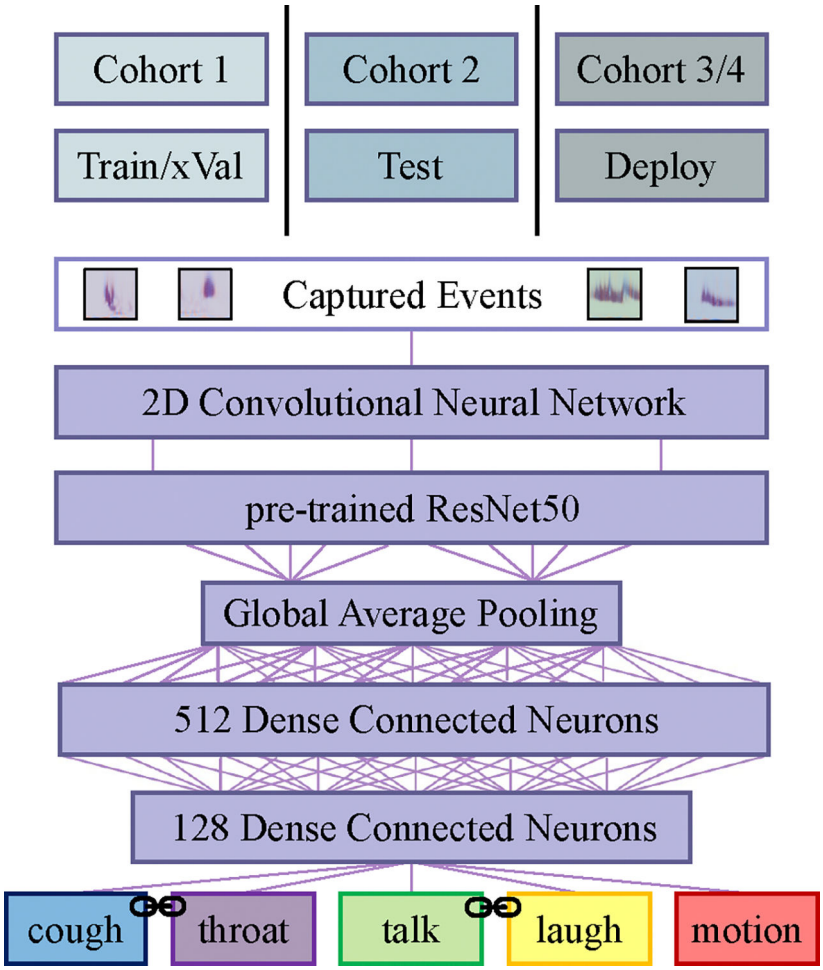

Fig. 3.
Overview of the CNN-based Cough Classifier Model

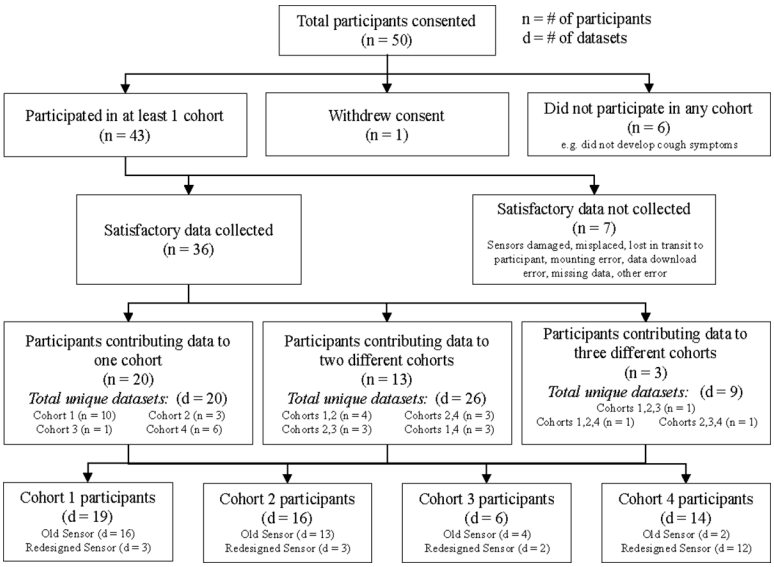

Fig. 4.
Recruitment flow diagram

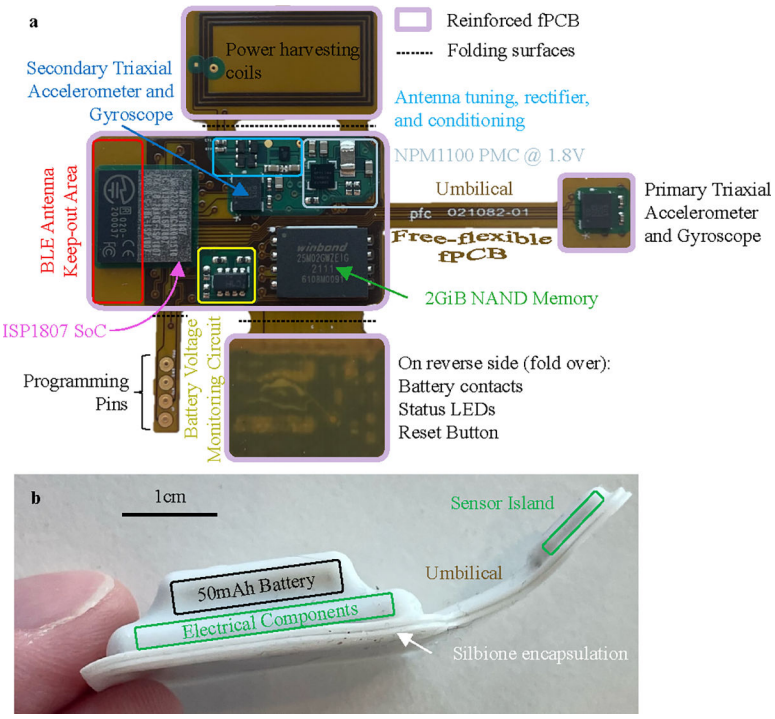

Fig. 5.

New Device Schematic, **a** top-down circuit view with key components highlighted, **b** fully encapsulated side view with annotations.

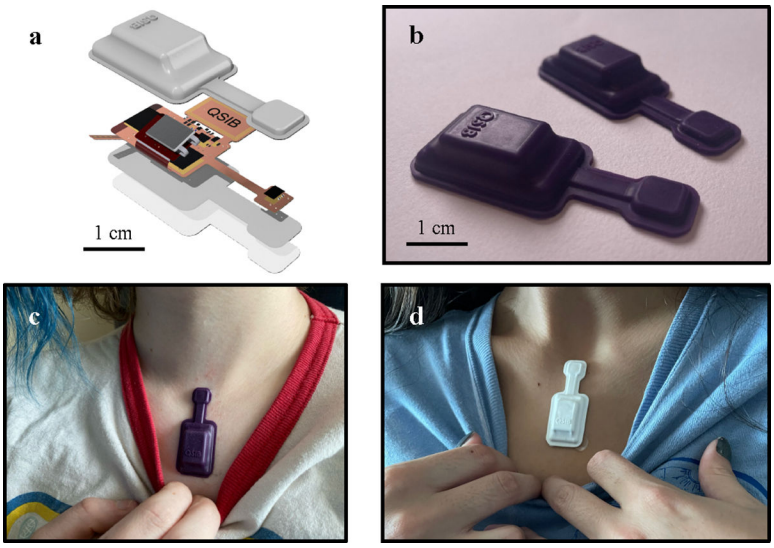

Fig. 6.

Mechanoacoustic Cough Sensor, **a,** exploded view of the pediatric optimized device, **b,** a pair of fully encapsulated devices, **c-d,** multi-colored devices mounted on the suprasternal notch. Note the subjects must lower their shirt collar to fully display the device.

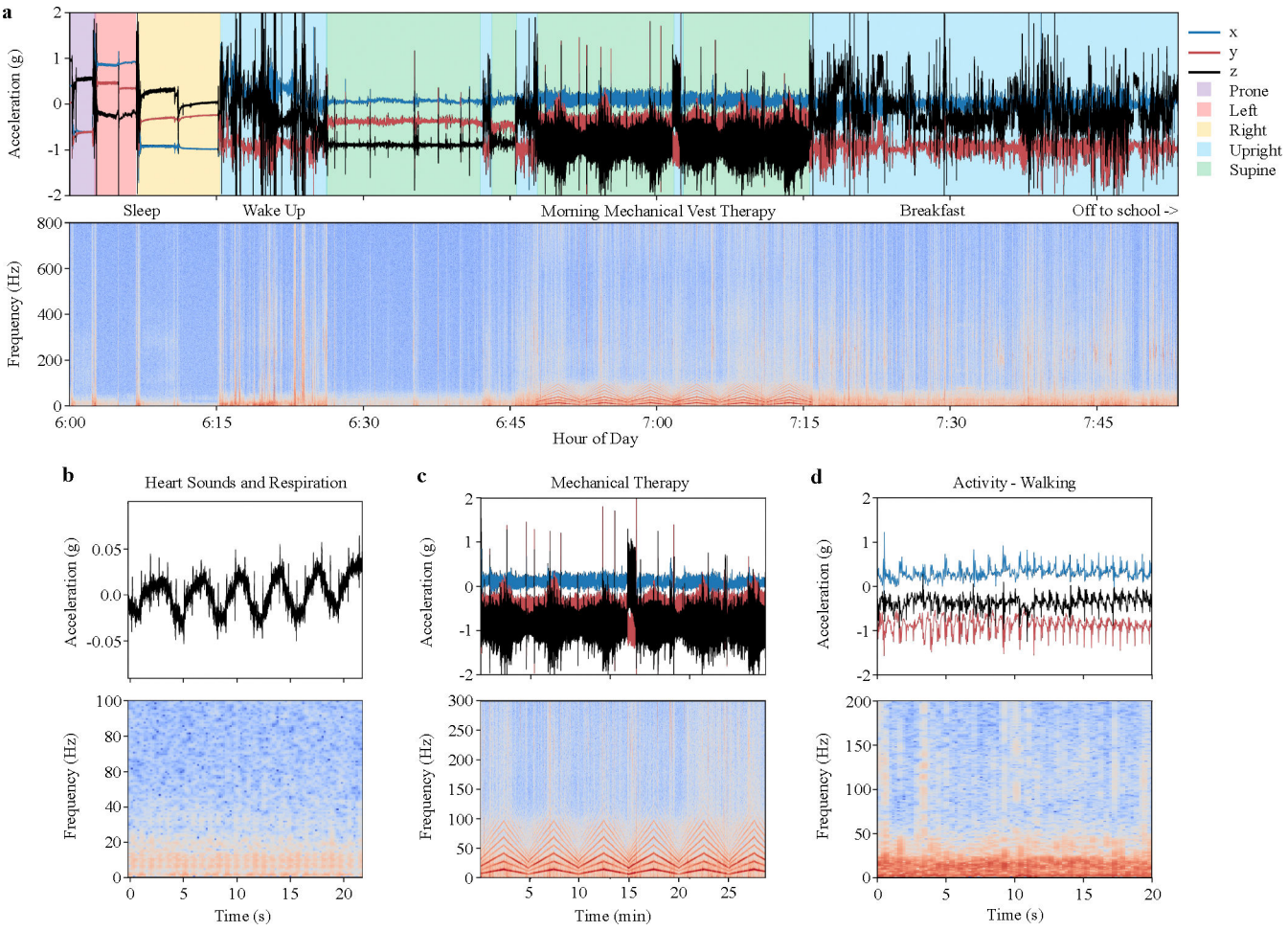

Fig. 7.

Raw Data and Spectrograms in Free-living Environments. Raw triaxial accelerometer data are shown above the corresponding Fourier power spectrogram with colors normalized for clarity, red corresponds to higher power, blue to lower power. (**a**) shows a typical morning routine for a CF patient while wearing the device. Examples of events captured, ranging from subtle oscillations of heart valves opening/closing and chest wall motion (**b**), CF-related mechanical vest therapy and superimposed coughing (**c**), and physical activity (**d**) are shown.

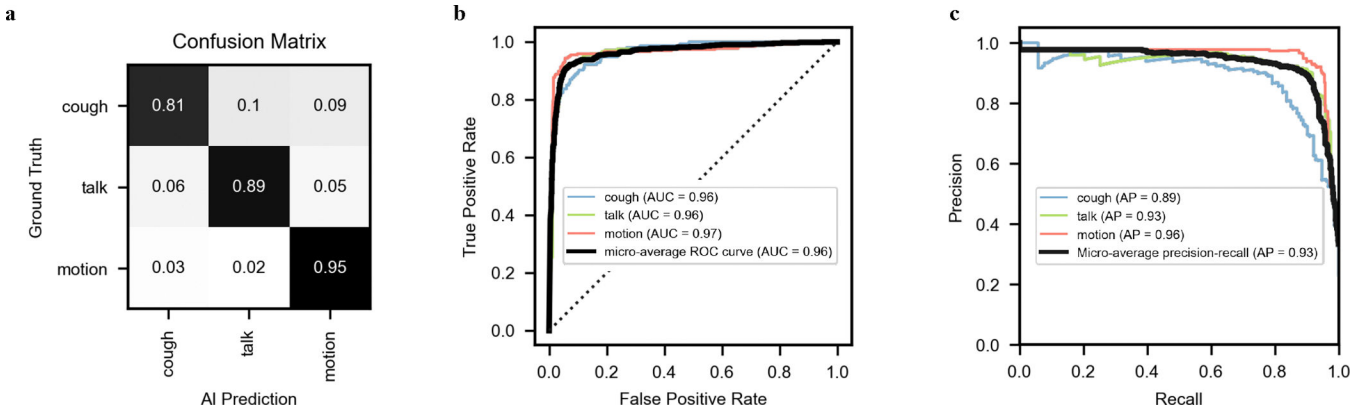

Fig. 8.

Cough Classification Testing Set Results. **a,** confusion Matrix, **b,** receiver-operator characteristic curves and **c**, precision-recall curves

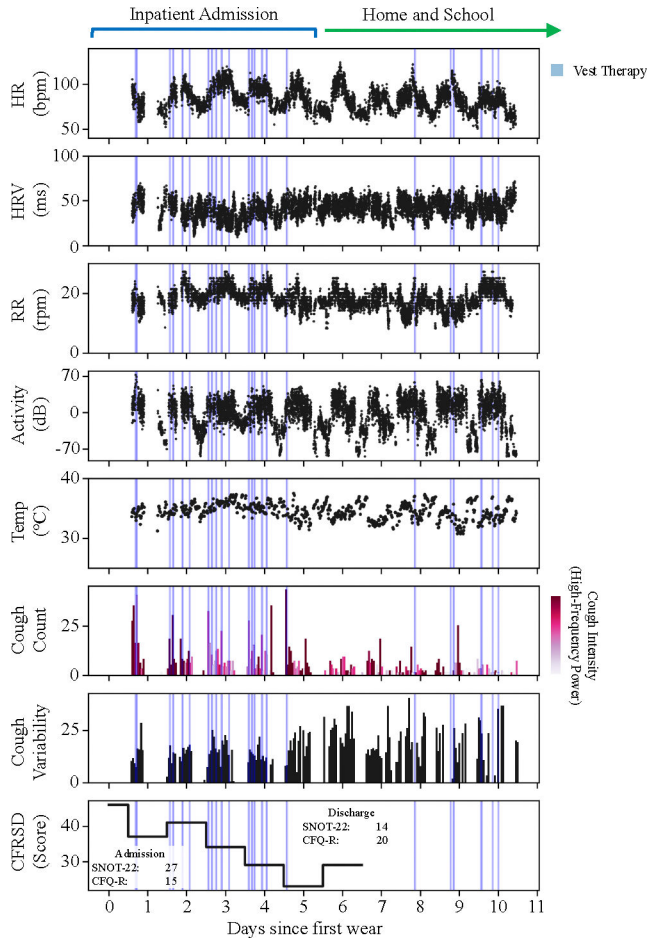

Fig. 9.

Multi-day Continuous Vital Signs and Cough Tracking. A patient's clinical course is continuously monitored from admission to discharge and resumption of daily activities. Average daily HR, RR, skin temperature, cough frequency and intensity decrease as survey-based symptom assessments improve, mechanical vest therapy is spaced, and the patient is clinically cleared to discharge home.

TABLE 1

PARTICIPANT DEMOGRAPHICS BY COHORT

	Cohort				
	1	**2**	**3**	**4**	***Unique participants***
Total Count					
(New Sensor, Old Sensor)	19 (3, 16)	16 (3, 13)	6 (2, 4)	14 (12, 2)	36
Gender					
Male	9	10	4	9	19
Female	10	6	2	5	17
Race					
White	17	11	5	11	30
Asian	0	0	0	0	0
Black	1	1	0	0	1
Other	1	4	1	3	5
Hispanic ethnicity	0	4	1	4	5
Age (yrs)	8.68 +/− 4.62	12.06 +/− 6.37	12 +/− 3.79	13.36 +/− 4.63	11.53 +/− 5.85
Height Percentile	55 [32, 78]	49 [31, 69]	58 [52, 71]	40 [36, 65]	55 [31, 75]
Weight Percentile	71 [59, 87]	72 [46, 78]	63 [55, 78]	68 [52, 69]	68 [53, 88]
BMI Percentile	83 [68, 88]	75 [65, 83]	77 [62, 82]	61 [53, 82]	76 [59, 88]
Baseline FEV1pp	110 [96, 112]	97 [77, 117]	95 [65, 117]	115 [62, 118]	103 [84, 114]

Race and ethnicity were documented in accordance with US Census categories and confirmed by participants or their parents. Age is reported as Mean +/− S.D. All other variables are reported as median [Interquartile range]

TABLE 2

Average Steady-State Current Consumption

	Recording to Onboard Memory	Full Raw Data Streaming over BLE	Exporting Onboard Memory over BLE
Old Device	577	-	2934
New Device (tsz compression disabled)	405	1206	5212
New Device (tsz compression enabled) typical - high entropy	216 – 243	689 – 995	3416

All values represent average μA current at steady-state operation over 1 minute.

tsz - Compact Integral Time-Series Compression

Only the new device is capable of real-time full raw data streaming.

TABLE 3

Cohorts 1 & 2 (Short-term wear) Survey Responses

	Strongly Agree n (%)	Agree n (%)	Disagree n (%)	Strongly Disagree n (%)	Total
I (or my child) likes wearing the cough sensor.	13 (38.2%)	21 (61.7%)			34
I (or my child) is embarrassed to wear the cough sensor.		2 (5.8%)	14 (41.1%)	18 (52.9%)	34
I (or my child) finds the sensor comfortable to wear.	19 (55.8%)	12 (35.3%)	3 (8.8%)		34
The cough sensor is easy to use.	24 (70.6%)	8 (23.5%)		2 (5.8%)	34
I (or my child) experienced problems using the sensor.	1 (2.9%)	3 (8.8%)	9 (26.4%)	21 (61.7%)	34
I (or my child) had trouble remembering to put on or change the cough sensor.		6 (20.7%)	12 (41.3%)	11 (37.9%)	29

TABLE 4

Cohorts 3 & 4 (Long-term wear) Survey Responses

	Strongly Agree n (%)	Agree n (%)	Disagree n (%)	Strongly Disagree n (%)	Total
I (or my child) likes wearing the cough sensor.	1 (9%)	7 (63.6%)	2 (18.1%)	1 (9%)	11
I (or my child) is embarrassed to wear the cough sensor.		2 (18.1%)	7 63.6%)	2 (18.1%)	11
I (or my child) finds the sensor comfortable to wear.	1 (9%)	5 (45.4%)	5 (45.4%)		11
The cough sensor is easy to use.	3 (27.2%)	7 (63.6%)	1 (9%)		11
I (or my child) experienced problems using the sensor.		6 (54.5%)	436.3%)	1 (9%)	11
I (or my child) had trouble remembering to put on or change the cough sensor.		1 (9%)	7 (63.6%)	3 (27.2%)	11

TABLE 5

Survey Response Age and Gender Characteristics

	Short term Cohorts 1 & 2	**Long Term Cohorts 3 & 4**
Age Mean (+/− SD)	9.44 (+/− 5.4)	12.36 (+/− 3.6)
Gender (M)	18	7
Gender (F)	16	4