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RESEARCH ARTICLE

A feasibility study using radio-frequency sensors to collect respiratory metrics in patients with chronic obstructive pulmonary disease.

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ABSTRACT

Background: The symptom of dyspnea is commonly encountered in patients with underlying serious illness and can lead to distress and poor quality of life. In patients with chronic obstructive lung disease (COPD), the prevalence is reported in up to 95% of patients. With the growth in sensor technologies, continuous monitoring of respiratory metrics provides an opportunity to better understand the relationship between patient-reported dyspnea and objective respiratory measures.

Aims: To assess the feasibility of implementing a radio-frequency (RF) sensor in patients with COPD and describe the relationship between dyspnea and respiratory metrics in patients with COPD when compared to healthy controls.

Methods: A prospective cohort study was conducted to collect data on dyspnea scores and respiratory metrics in patients with COPD and healthy controls while conducting a walking test using a wearable RF sensor.

Results: Of the 12 COPD patients and 15 healthy controls recruited, all participants completed the modified incremental shuttle walking test while wearing the RF sensor; there was no attrition. For every one-point increase in the dyspnea score, there was a mean 1.94 increase in the respiratory rate per minute in the COPD group as compared to a 1.09 increase in respiratory rate in the healthy control group.

Conclusion: Preliminary data demonstrate the potential of using the RF sensors to track respiratory metrics in COPD patients and healthy adults. As this technology develops, it shows considerable promise and could provide significant implications regarding the use of non-invasive continuous monitoring for patients with lung disease.

Introduction

The symptom of dyspnea, defined as a "patient's subjective awareness of uncomfortable or distressing breathing[1]," can be caused by exertion, deficiency of ambient oxygen, high ambient CO_2, increased airway resistance, and insufficient cardiopulmonary outputs. Dyspnea is also commonly encountered in patients with underlying serious illness such as asthma, heart failure, COVID-19[2] and chronic obstructive pulmonary diseases (COPD)[3-5], and can lead to distress[6] and limited activities of daily living. In patients with COPD, the prevalence of dyspnea is reported in up to 95% of patients[3-5]. These patients can feel a sense of suffocation, distress, fear, and anxiety, resulting in a poor quality of life. Although physiological, psychological and social-demographic factors can all contribute to the dyspnea sensation[7,8], the mechanism around dyspnea remains incompletely understood. However, studies have hypothesized that dyspnea is partly due to an increase in inspiratory neural drive in the setting of decreased lung capacity or insufficient ventilation[9].

Exploring the relationship between self-reported dyspnea and objective respiratory metrics (e.g., respiratory rate, and inhalation/exhalation times) can provide important clinical information in identifying the multifactorial components (e.g., respiratory disease, cardiac disease, anxiety, and anemia) that can contribute to a patient's dyspnea. When dyspnea is resulted from physiological factors such as exertion and masking, the natural response often has been trained to increase the respiratory rate and volume with decreased variations to maximize ventilation[10]. However, the relationship between dyspnea and respiratory metrics have not been fully examined[10,11], and can potentially be different for healthy people and patients with various disorders[12]. Previous studies looking at these associations have been cross-sectional in nature[13-15] and required the use of cumbersome and uncomfortable instruments (e.g., diaphragm electromyogram (EMGdi) and body plethysmograph). While these studies showed certain correlations between dyspnea and pulmonary function measures, many of these cross-sectional studies were limited in the ability to capture continuous changes in respiration, which is important given that dyspnea can fluctuate over time.

With the growth in the use of non-invasive technologies (e.g., wearables, smartwatches[16], and bed sensors)[17], continuous monitoring of respiratory metrics provides an opportunity to better understand the relationship between self-reported dyspnea and objective respiratory measures. Continuous monitoring can potentially lead to earlier detection of changes in lung function that are associated with various contributors, which can lead to earlier assessment and management of dyspnea.

In particular, radio-frequency (RF) sensors have the potential to capture respiratory metrics in a non-invasive, comfortable and convenient manner. This technology has been successfully piloted in patients for detection and prediction of sleep apnea (via a bed sensor)[18], as well as in continuous monitoring of COVID-19 patients[12]. By the principle of near-field coherent sensing (NCS)[19,20], based on the strong near-field coupling of the ultra-high frequency (UHF) electromagnetic (EM) waves inside the body, the dielectric

boundary movement of internal organs and tissues is transduced as part of the antenna or channel characteristics, and can hence be directly evaluated to capture various respiratory metrics[10,21]. Thanks to the established wireless technology in the UHF band, the RF sensor can be readily integrated and miniaturized for commercial productization[22].

In this brief report, we employed this RF sensor[11,12,19] [COVID-19] to capture respiratory metrics in patients with COPD while performing a series of walking exercises. Data obtained from patients with COPD were compared to a group of healthy controls consisting of young adults. The objectives of this study were to assess the feasibility of implementing such RF sensing in a wearable format and describe the relationship between dyspnea and respiratory metrics in COPD patients with healthy controls.

METHODS

We conducted a prospective cohort study to collect data on dyspnea scores and respiratory metrics in patients with COPD and healthy controls using a wearable RF sensor[22]. The Institutional Review Boards at Weill Cornell Medicine and Cornell University approved this study.

PARTICIPANTS

Recruitment of participants with COPD was conducted at Weill Cornell Medicine's pulmonary clinic, an academic clinical practice consisting of pulmonologists who provide care to over 1,200 patients suffering from COPD and other lung related illnesses. Eligible patients were identified from electronic medical records screening, and their providers were contacted to obtain approval on the appropriateness of enrolling the patient. Participant inclusion criteria include age 18 years or older, ability to self-report dyspnea, English speaking, and having a pulmonary function test (PFT) within the last 5 years on record indicating a ratio of forced expiration volume at the first second (FEV1) and forced vital capacity (FVC) <70%. Participants also had to have a FEV1 <50% predicted value on spirometry and/or a mMRC (Modified Medical Research Council)[23] dyspnea scale score of 2 or greater to qualify for the study. Exclusion criteria include inability to self-report dyspnea due to cognitive impairment, stroke, or other medical illness, and inability to walk 10 meters or more.

To compare the differences between the respiratory metrics (e.g., respiratory rate, inhalation/exhalation times) of COPD patients with healthy controls, we recruited healthy adults from Cornell University through posting on the college webpage. Inclusion criteria for the healthy control group include age 18 years or older and no known reported cardiopulmonary disorders. Written informed consent was obtained from all participants.

SENSOR DESIGN

To monitor the respiratory metrics in COPD patients, a wearable RF sensor was employed to retrieve continuous respiratory data with user comfort and convenience. NCS is based on the near-field coupling of the ultra-high frequency (UHF) electromagnetic (EM) waves inside the body to measure the dielectric boundary movement of internal organs and tissues[19,20]. In this study, we captured waveforms that originated from the respiratory diaphragm, providing data to derive

respiratory rate and the timing and degree of motion of inhalation and exhalation.

We built an all-in-one wearable RF NCS unit on a 4-layer printed circuit board (PCB)[22], as shown in Figure 1(a). The block diagram of the entire sensing unit is shown in Figure 1(b). An inertia-measuring unit (IMU) that captures acceleration with six degrees-of-freedom and a surface temperature sensor were also integrated with 1ms-level synchronization. The RF sensor captured internal lung motion while the IMU recorded chest movement. When a participant remains at rest, the RF and IMU outputs are highly correlated, which we used as a criterion of data integrity.

STUDY PROTOCOL

After written consent was obtained, the sensor (Figure 1) containing RF and IMU units was fitted on the participant to continuously track their respiratory measures as shown in Figure 1(c). Chest and shoulder belts were used to fix the stable position of the sensor.

Participants were seated for 5 minutes while wearing the sensor to collect baseline respiration waveforms to extract respiratory metrics (e.g., respiration rate, inhalation time, and exhalation time) and baseline self-reported dyspnea score using the Borg scale[24]. After being seated for 5 minutes, participants were guided to perform a modified incremental shuttle walking test[25], which is a validated exam[26] developed to simulate cardiopulmonary exercise in COPD patients, as shown in Figure 1(d). For this test, the participant is required to walk around two cones set 9 meters apart during a given period guided by auditory instructions. Initially, the walking speed as set by the auditory track is very slow, but after each track that lasts a minute, the walking speed progressively increases. Participants were asked to report their dyspnea score on the Borg scale after completion of each track for a total of 10 tracks, each followed by one minute of rest before the next track. Those who could not keep up with the walking speed set by each track were allowed to walk at their own pace or stop the activity. The measured walking speed, based on the distance traveled and the time taken, was then annotated on the record. After the last track was completed, participants were asked to sit in a chair for 6 minutes. The sensor was subsequently removed after the 6-minute rest. At the completion of the study, dyspnea scores were collected for up to 12 timepoints (e.g., before, during and after the incremental shuttle walking test) for each participant.

All patients in the COPD group were unable to keep up with the speed of the incremental shuttle walking test after the fourth track and completed the remaining tracks walking at their own pace. To match the activity of the COPD patient group, the healthy control group followed the same protocol, where all participants have finished the incremental shuttle walking test according to the voice instructions.

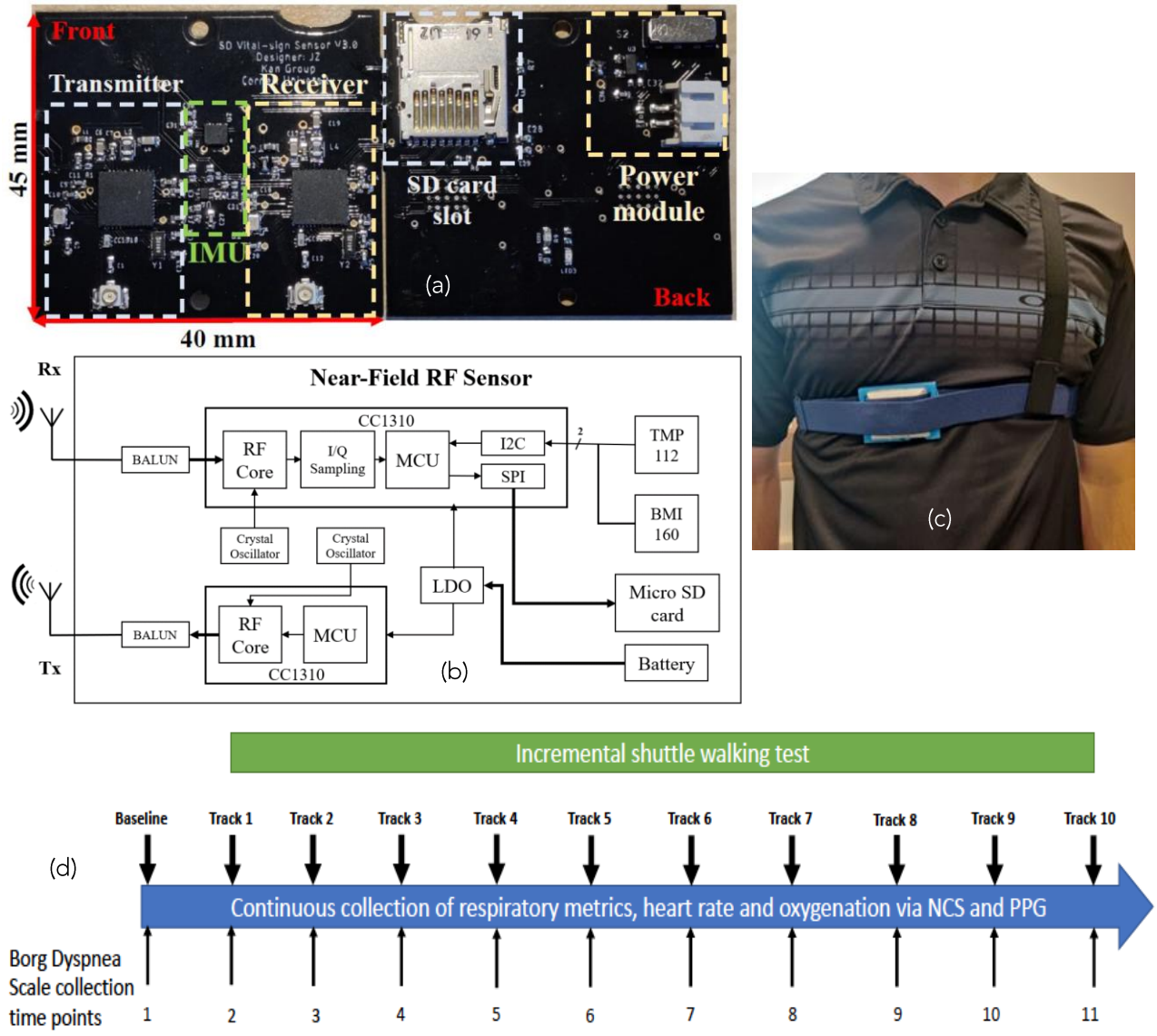

Figure 1. The experimental setup. (a) The front and back photos showing the all-in-one radio sensor PCB, including radio transmitters and receivers, the inertia measuring unit (IMU), secure data (SD) slot, and the power module on PCB; (b) The block diagram for the sensor transceiver; (c) Body deployment of the RF respiratory sensor by chest and shoulder belts; (d) The incremental shuttle walking test for COPD patients and healthy controls.

MEASUREMENTS

Self-reported baseline measures were collected prior to fitting the participant with the sensor. These measures included: age, gender, race/ethnicity, education level, and body mass index (BMI). Respiratory indicators (Breathlessness, Cough, and Sputum Scale (BCSS)[27], pain (Wong-Baker Faces Pain Rating Scale)[28], and shortness of breath (Borg dyspnea scale)[24] were also collected. The RF and IMU sensors used in the study captured continuous data on respiratory waveforms.

BORG DYSPNEA SCALE

The Borg dyspnea scale is a scale that ranges from 0 to 10 and has been used in multiple studies to evaluate dyspnea in patients with COPD[29-31]. It has been shown to have good validity[32] and reliability[24]. As an example, participants can report a score of 0 indicating

no shortness of breath, 5 indicating severe shortness of breath, or 10, indicating maximal shortness of breath.

STATISTICAL ANALYSIS

After gathering data from COPD patients and healthy controls, we pre-processed our waveform datasets, and extracted respiratory metrics from participants when they were at rest and during each stage of the incremental shuttle walking test. Respiratory waveforms were down sampled and filtered to reduce high-frequency noises that can degrade the peak detection accuracy in later feature extraction. We divided the waveforms into short segments of T_{seg} = 30 seconds with a sliding window of T_{slide} = 30 seconds for waveform processing. For example, the baseline 5-minute rest is divided into 10 segments of 30 seconds for feature extraction. For our descriptive analysis, we detected waveform peaks and calculated respiratory metrics. Figure 2 is an example of the feature extraction process.

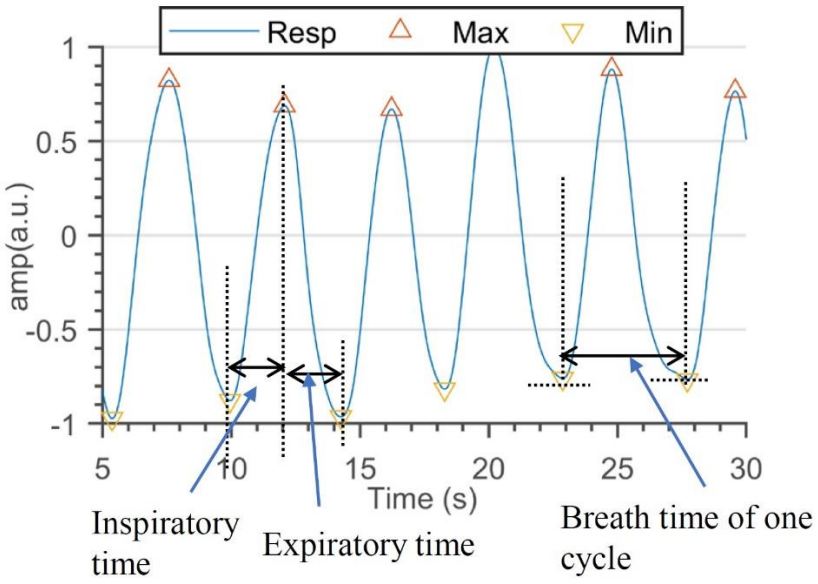

Figure 2. An example of feature extraction using respiratory waveforms.

Feasibility for this study was assessed by analyzing recorded RF data and identifying participants with good signal quality. During our analysis, we encountered poor signal quality due to uncontrollable variations such as ambient movement, patient talking, and excessive coughing which led to signal-to-noise ratio (SNR) degradation. Finally, we accumulated all selected time segments with acceptable SNR and estimated averaged respiratory metrics over all selected time segments. In addition, we documented whether participants undergoing the walking activity were able to wear the RF sensor for the entire protocol.

RESULTS

We recruited 12 patients with COPD and 15 healthy controls for the study. Representative data reported in this paper stems from 5 (42%) COPD patients and 7 (47%) healthy controls. Data collected from patients that were unable to be analyzed were due to battery issues (n = 3), from excessive talking or coughing during the procedure (n = 5), and SNR degradation from sensor positioning or unknown reasons

(n = 7). Table 1 shows the demographic data for the COPD group and the healthy control group. Of note, all participants were able to complete the modified incremental shuttle walking test with the sensor attached; there was no attrition.

Table 1. Demographic data.

	COPD patients (n = 5)	Healthy controls (n = 7)
Age (mean ± SD)	80.4 ± 5.68	30.6 ± 13.10
Gender (n (%))		
Female	3 (60.0)	3 (42.9)
Male	2 (40.0)	4 (57.1)
Race/Ethnicity (n (%))		
White	4 (80.0)	2 (28.6)
American Indian or Alaska Native	1 (20.0)	0 (0.0)
Asian	0 (0.0)	5 (71.4)
Body mass index (mean ± SD)	24.0 ± 6.63	22.4 ± 3.95
Respiratory Symptoms (BCSS[1]) (mean ± SD)	3.0 ± 2.12	0.4 ± 0.53
Difficulty breathing	1.0 ±1.00	0.3 ± 0.49
Cough	0.6 ±1.34	0.1 ± 0.38
Sputum	1.4 ±1.14	0.0 ± 0.00
Pain (Wong-Baker Faces Scale) (mean ± SD)	0.0 ± 0.00	0.3 ± 0.76

[1]*BCSS: Breathlessness, Cough, and Sputum Scale*

Table 2 displays the average respiratory rate, inspiratory time, expiratory time, sensor signal magnitude representing the lung volume, and dyspnea score for participants in both groups at rest and after completing each track of the incremental shuttle walking test. Of note, the average respiratory rate is not equal the inverse of the sum of inspiratory and expiratory times, not only because of the nonlinearity in the inverse calculation, but also because of a possible breath hold period between the inspiratory and expiratory phases. Table 3 shows the overall average respiratory rate, inspiratory time, expiratory time, sensor signal magnitude, and dyspnea score for participants along with the mean change in respiratory metrics to mean change in the dyspnea score. In data collected from COPD patients, for every one-point increase in the dyspnea score, there was a mean 1.94 increase per minute in the respiratory rate. This compares to a 1.09 increase in the healthy group. For inspiratory time, for every one-point increase in the dyspnea score, the mean inspiratory time decreased by 0.07 second in the COPD group while it increased by 0.18 second in the healthy group. As for the expiratory time, for every one-point increase in the dyspnea score, the mean expiratory phase decreased by 0.21 second in the COPD group, while it decreased by 0.32 seconds in the healthy group.

Table 2. Average respiratory rate, inspiratory and expiratory times, dyspnea score for COPD patients and healthy controls (HC) performing the incremental shuttle walking test.

Activities	Respiratory rate (breaths/min)		Inspiratory time (sec)		Expiratory time (sec)		Dyspnea score	
	COPD	HC	COPD	HC	COPD	HC	COPD	HC
Baseline (5-min rest)	19.5	16.9	1.50	1.38	2.05	2.30	0.3	0.0
Incremental track 1	23.7	19.9	1.26	1.42	1.46	1.68	0.6	0.21
Incremental track 2	22.2	21.3	1.04	1.61	2.17	1.42	2.3	0.42
Incremental track 3	26.0	18.6	1.19	1.64	1.26	1.79	3.5	0.71
Incremental track 4	24.1	17.8	1.33	1.71	1.32	1.77	4.0	1.4
Incremental track 5	22.3	17.6	1.52	1.63	1.30	1.98	4.5	1.3
Incremental track 6	24.1	17.6	1.37	1.76	1.34	1.84	4.8	2.0
Incremental track 7	24.1	17.9	1.34	1.65	1.40	1.86	5.3	2.5
Incremental track 8	27.6	18.9	1.11	1.76	1.17	1.56	5.3	2.7
Incremental track 9	26.2	18.2	1.14	1.7	1.29	1.72	6.3	3.2
Incremental track 10	28.5	19.3	1.11	1.38	1.11	1.83	2.7	0.79
1st rest – 3 minutes	22.9	18.8	1.21	1.31	1.87	1.99	0.50	0.79
2nd rest – 3 minutes	21.8	19.3	1.50	1.52	1.51	1.69	0.33	0.21

Table 3. Average change in respiratory metrics corresponding to the change in dyspnea score.

	COPD group (n = 5)	Healthy control group (n = 7)
Respiratory rate (breaths/minute)	24.28	18.54
Borg dyspnea score	3.25	1.24
Mean Δrespiratory rate / Δdyspnea score	1.94	1.09
Mean Δinhalation time (seconds) / Δdyspnea score	-0.07	0.18
Mean Δexhalation time (seconds) / Δdyspnea score	-0.21	-0.32

DISCUSSION

Our study examined the feasibility of collecting respiratory metrics using a wearable RF sensor and the descriptive comparison of dyspnea scores and respiratory metrics (i.e., respiratory rate, and inspiratory/expiratory times) in COPD patients and healthy controls.

While all participants were able to complete the study protocol while wearing the RF sensor, we encountered some challenges in SNR degradation using this sensor implementation. Previous work conducted by our team showed less SNR degradation in patients undergoing sleep apnea assessments when using a RF bed sensor[18]; however, these patients were sleeping with minimal motion. In this study, the deployment of the RF sensor was under ambulatory conditions using a wearable sensor. As a result, data quality was poorer in this setting. We were able to identify various factors (e.g., talking, coughing, ambient interference, and sensor position shifts) that impacted the data quality. Future work will focus on identifying ways to mitigate

SNR degradation so that interpretable data can be more consistently captured in most participants performing various activities and in different positions.

On average, the COPD group reported higher dyspnea scores at baseline and during the walking activity. The COPD group's average respiration rate was higher than that of the healthy control group, consistent with findings described in the literature.[33] Altered respiratory mechanics such as differences in lung compliance and respiratory center drive contribute to the elevated respiratory rate in individuals with COPD. We found that for every change in 1 point on the Borg dyspnea scale, the change in respiratory rate was almost doubled in the COPD group (1.94) in comparison with the healthy control group (1.09). We hypothesize that COPD patients might be conditioned to feeling dyspneic that it takes more respiratory exertion for them to perceive a change in dyspnea reflected in the Borg scale. Alternatively, patients with COPD may be increasing their respiratory drive more in response to feeling air hunger. The decrease in Borg-scale dyspnea sensitivity and the increase in respiratory efforts for COPD patients may have implications to drug dosage and assisted ventilation parameters. Further studies with greater sample size are needed to understand whether this is more generalizable or mediated by other factors.

COPD is related to alveolar fibrosis, while pneumonia has stages of alveolar exudation, red hepatization and grey hepatization[34]. However, our COPD dyspnea study and the previous COVID-19 dyspnea study[12] both indicated similar correlation to respiratory parameters when compared to dyspnea induced by exertion and airway blockage in healthy persons. This observation suggests that the subjective dyspneic discomfort can be potentially evaluated with objective respiratory parameters in a broad population when the contributors are physiological in nature.

There were limitations in our study to report. While we looked at feasibility through data quality captured and whether participants completed the study protocol, additional data from participants about the sensor's comfort and its usability use could provide further information on its practicality. Furthermore, in our descriptive statistics comparing COPD patients to healthy controls, age was significantly different between the two groups. In future studies, selecting healthy controls that are of similar age can address this bias. Lastly, while our focus was on patients with COPD, understanding the respiratory metrics of other disease that commonly contribute to dyspnea is an area for future study.

CONCLUSIONS

The preliminary data of this study demonstrate the potential of using the RF sensors to track respiratory metrics in COPD patients and healthy adults. As this technology develops and matures, it could provide a method for non-invasive continuous monitoring for patients with lung disease. Additional testing still needs to be conducted to address challenges regarding SNR degradation before it can be used in a clinical setting. However, if implemented appropriately, it can provide a window of opportunity for capturing and analyzing respiratory data in a practical setting to better understand the patient experience and mechanisms of dyspnea.

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Conflicts of Interest Statement:

The authors have no conflicts of interest to declare.

Acknowledgements Statement:

None

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