The Relationship Between Self-Reported Nocturnal Cough Symptoms and Acoustic Cough Monitoring[1]

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Abstract: Objective. This pilot investigation explored the relationship between self-reported clinical cough symptoms and objective acoustic cough data in individuals with nocturnal chronic cough.

Methods. Ten participants diagnosed with chronic cough with a nocturnal component underwent two study sessions, approximately 1 week apart. Participants completed questionnaires regarding cough severity and their perceptions of using a smartphone application (app) to audio record cough. Between sessions, participants utilized the continuous audio recorder while sleeping. The relationship between the number of coughs captured at night and the self-reported impact of cough awakening during sleep were analyzed.

Results. We found strong correlations ($\rho = -0.78, -0.87$) between formalized Leicester Cough Questionnaire scores and acoustically determined cough frequency. However, there were large differences between the average number of self-reported cough awakening events (0-3) and the number of acoustically recorded coughs (0-639). While users expressed comfort with recording and sharing acoustic data (4.8/5 Likert rating), concerns over confidentiality in daytime use were noted (4.1/5).

Conclusion. Formalized cough questionnaires provide insight into chronic cough at night but may fall short in quantifying the shear frequency of coughs patients are experiencing. Although continuous audio recordings via smartphone emerged as a comfortable means for patients to supply quantifiable data regarding the impact of chronic cough during sleep, future endeavors in cough acoustic monitoring should prioritize privacy considerations for daytime use and work to share information with health care providers.

Key Words: Acoustics—Technology—Upper airway disorders.

INTRODUCTION

Chronic cough is defined as a cough that persists longer than 8 weeks.[1] It can result from several different etiologies, including (but not limited to) respiratory diseases (eg, asthma[2]), respiratory infections (eg, COVID[3]), gastroesophageal reflux disease,[4] allergies and/or environmental irritants,[2] neurogenic,[5] as well as cases of unknown, or idiopathic, cause.[6] Chronic cough impacts ~11% of people in the United States[7] and has been well documented to adversely impact quality of life,[8,9] with a noted reduction in the ability to participate in daily activities related to communication and social interactions.[10] Although it can be managed by a variety of methods (eg, pharmacological, behavioral treatment[11,12]), ~20% of patients will continue to have persistent cough (ie, refractory cough) despite treatment.[13]

Approximately 80% of patients with chronic cough have a night-time, or nocturnal, component to their symptoms.[14] Data show those with nocturnal cough typically have fewer cough events at night compared to the day,[15-17] however, nocturnal cough has the additional negative impact on sleep duration and quality.[18] Disruptions to sleep have been associated with increased psychological disorders, such as depression[19] and negative impacts to overall health.[20] Subsequently, health care providers often inquire about the presence and degree of nocturnal cough using standard questionnaires and/or non-validated questions (eg, "How often does your cough awaken you at night?"). However, the ability for patients to self-report their nocturnal cough symptoms has not been tested as an accurate measure of nocturnal cough characteristics (frequency, severity), leading to a potential discrepancy between reported cough events and actual cough occurrences.

Clinical cough questionnaire

The Leicester Cough Questionnaire (LCQ) is a common patient-reported outcome measure and clinical assessment tool used to determine the frequency and impact of cough on daily life.[21] The LCQ consists of 19 questions with 7-point Likert scale response options, ranging from "1: All of the time" to "7: None of the time," for various cough symptoms over the previous two weeks. The tool is further divided into three domains—physical, psychological, and social—as a way to provide more specific information within each functional area as well as a total score across all domains. Birring[21] showed moderate concurrent validity with other clinical cough questionnaires.

LCQ question number 10 pertains to nocturnal cough, asking: "In the last two weeks, has your cough disturbed

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your sleep?" To our knowledge, there is no reported information on the relationship between the response to this specific question and objective measures of cough at night. This may be helpful for health providers who are already using this questionnaire as a clinical tool to assist with characterizing the frequency and severity of cough. More information is needed to assist clinicians in determining how helpful this specific question may be for patients with chronic cough who have a nocturnal component.

Digital cough monitoring

Cough monitoring through digital acquisition (acoustics, sensor signals) is an emerging area of healthcare. Modern health applications (apps) utilize smartphones and other devices to monitor various biological health patterns, offering potential benefits for patient biofeedback and informing clinical follow-up. There have been several recent apps to increase digital monitoring of chronic cough in real-life settings.[22-29]

Digital ambulatory cough monitoring devices first appeared in the literature in the 1990s and early 2000s.[30-32] One such device, the Leicester Cough Monitor (LCM[30])—an external microphone and recorder attached to a necklace that recorded acoustic signals—was developed by the same researcher who created the LCQ. One of the LCM validation studies assessed the relationship between the number of coughs patients experienced and the LCQ total score.[33] The authors found a significant, negative correlation ($r = -0.60$) indicating a moderate relationship between cough counts and the LCQ. However, this study was completed during the day (9 am-3 pm) and therefore did not have a nocturnal component to it.

Other studies have also utilized audio recordings to capture and quantify cough. One study used smartphones to track nocturnal cough in the hospital setting at night,[22] with the ultimate aim of incorporating cough into vital sign monitoring to inform acute respiratory disease progression (eg, COVID-19; pneumonia). These authors determined that digital cough monitoring through a smartphone was possible in the hospital setting and comparable (though somewhat less sensitive) to formalized computer recordings. Other studies have been successful in completing acoustic recordings via smartphones in the home setting,[17,28] showing that they can capture nocturnal cough in those with chronic cough from respiratory diseases and/or idiopathic causes. However, many of these studies have utilized continuous acoustical recordings with manual-identification of cough events, a laborious process that would not be feasible for long-term monitoring and would not provide privacy for everyday use.[34]

One commercial system has attempted to address many of the ongoing monitoring issues using advanced acoustic cough detection and algorithmic cough estimation, known as Hyfe.[35] Hyfe uses a watch that can specifically detect an acoustic cough signature and subsequently minimize recordings of other acoustic events (ie, conversations), increasing privacy. It has been validated to differentiate cough from other sounds with 96.34% sensitivity and 96.54% specificity[36] and has shown promise for monitoring chronic cough from various etiologies during formalized clinical trials.[26,37]

Despite these efforts, many of the technologies described above are still under development and/or currently used for research purposes only. As such, technology has not yet been adopted as a primary means for quantifying chronic cough in the clinical setting. Consequently, health care providers generally rely on patient-reported information (such as the LCQ). However, self-reported information may not always be accurate, especially in terms of recalling previous health symptoms[38] and, more specifically, reporting cough information. For example, studies have demonstrated that individuals with chronic cough inaccurately assess their cough severity compared to digital monitoring, with only weak-to-moderate relationships between acoustically monitored nocturnal cough counts and subjective patient reports.[15-17,28]

It is first crucial to understand the relationships between clinical questionnaires used in otolaryngology and objective nocturnal cough measures and understand the potential limitations of these clinical tools. Subsequently, a deeper investigation into formal and informal clinical questionnaires and acoustic cough measures is required to ensure the ecological validity of cough monitoring tools. This research could offer clinicians valuable insights into the effectiveness of questionnaires and highlight the potential benefits of integrating health monitoring and smartphone apps for individuals managing chronic cough.

Purpose

The primary objective of this pilot study was to investigate the relationships between patient reported impacts of cough on sleep and objective acoustic measures of cough in those experiencing chronic cough with a nocturnal component. To achieve this, we collected acoustic recordings in a night-time sleeping environment over an extended monitoring period. First, we sought to understand the potential differences between subjects' reported cough awakenings during sleep and quantitative cough counts derived from continuous acoustic recordings. We hypothesized patients would report a lower number of incidences regarding when they were awoken by cough compared to their cough counts. Second, we aimed to determine the relationship between a standardized clinical cough questionnaire (LCQ total score, LCQ question #10 score) and the quantitative metric derived from acoustic recordings. We hypothesized that a weak relationship would exist between self-reported symptoms of cough impact on sleep and the objective cough data, due to known errors in patient self-reporting.[17,28,39] Finally, we aimed to elucidate the patient's perspective of cough impact on sleep using a continuous audio recording app at home during sleep. We hypothesized patients would respond positively to a health-monitoring app, providing further support toward the development of cough monitoring technology.

METHODS

Participants

Participants were recruited from the Robin Cotton and Rocco dal Vera Professional Voice, Swallowing, and Airway Center at the University of Cincinnati Medical Center from 2021 to 2023. Patients ≥ 18 years old diagnosed by a laryngologist with chronic cough (≥8 weeks in duration) including a nocturnal component were eligible to participate. Participants provided informed consent via the University of Cincinnati's Institutional Review Board approved protocol (#2020-0730).

A total of 10 participants (two cisgender males, eight cisgender females; Aged 44-71 years, Mean Age = 54.9, +/−12.3 years) completed the study. Nine participants identified as white and non-Hispanic, whereas one participant identified as two or more races and Hispanic. Participants reported a range of times they had experienced chronic cough, from as short as 3 months to as long as 44 years. See Table 1 for additional participant demographic information.

Self-reported cough and sleep measures

The formalized LCQ[21] was completed by each participant. The LCQ is a 19-question, 7-point Likert scale that assesses the impact of cough on quality of life across physical, psychological, and social domains. Each domain is averaged and summed together for a total score ranging from as high as 21 to as low as 3. A higher score indicates a better quality of life, whereas a lower score reflects a greater impact of cough on daily living. The LCQ question 10 specifically asks about the impact of cough on sleep, with the question, "In the last two weeks, has your cough disturbed your sleep?"

Additionally, informal 5-point Likert scale questions were collected to further describe the participants' experiences with cough and sleep (see Figure 1 for the list of questions and responses). These questionnaires collectively provide valuable insights into the patient characteristics and the impact of chronic cough on the quality of life and sleep patterns of the study participants.

Protocol

The study involved 2 sessions, each lasting approximately half an hour, where participants had the option to attend either in-person or through a virtual online platform due to the constraints posed by the COVID-19 pandemic. During the initial session (Session 1), participants provided demographic information, completed the LCQ, and installed a designated, publicly available continuous audio recording app on their smartphones for at-home acoustic recordings. The chosen apps for Android included RecForge or Voice Recorder Pro, while iPhone users utilized Voice Memo. All recordings were standardized with a minimum sampling rate of 44,100 Hz and were subsequently converted to either .mp4 or .wav file formats for further analysis.

Between Session 1 and Session 2, participants were tasked with recording their sleep in their home environment. They were instructed to activate the acoustic recorder and leave their phones on their bedside tables. No formalized distance parameters were provided. Although 3 of the 10 study participants were diagnosed with sleep apnea, none wore a continuous positive airway pressure machine during the study recordings. While participants were encouraged to record for up to three nights, they had the flexibility to extend this period if they desired. Participants were allowed to sleep next to a bed partner during the study. None of the participants reported that their bed partner had issues with cough, snoring, or sleep disorders (ie, sleep apnea) that may add audio interference to the audio recordings.

To enhance data collection, participants were provided with a Cough Monitoring Log to document the number of hours slept each night and the instances of awakening due to coughing. This approach aimed to capture both subjective and objective data related to participants' sleep patterns and cough episodes and mirrored questions asked

TABLE 1.
Participant Demographic Information

ID	Age (Yrs)	Sex	Leicester cough questionnaire total score*	Cough duration (Yrs)	Respiratory disease	Hx of smoking	Hx of second-hand smoke exposure	Reflux	Sleep apnea
P_01	71	M	16.87	3	Yes	Yes	No	No	No
P_02	47	F	9.86	10	Yes	Yes	Yes	No	No
P_03	75	F	9.89	0.9	Yes	No	No	No	No
P_04	62	F	8.59	30	No	Yes	Yes	No	Yes
P_05	44	F	8.11	0.75	No	Yes	Yes	No	No
P_06	44	M	13.13	1.5	No	Yes	Yes	Yes	Yes
P_07	46	F	11.59	1	No	No	No	Yes	No
P_08	44	F	6.73	0.33	Yes	No	Yes	Yes	Yes
P_09	70	F	12.68	44	Yes	No	Yes	Yes	No
P_10	46	F	16.02	10	No	Yes	No	No	No

Notes: M = male; F = female; Hx = History; * = ranges from 3 (maximum severity) to 21 (minimum severity).

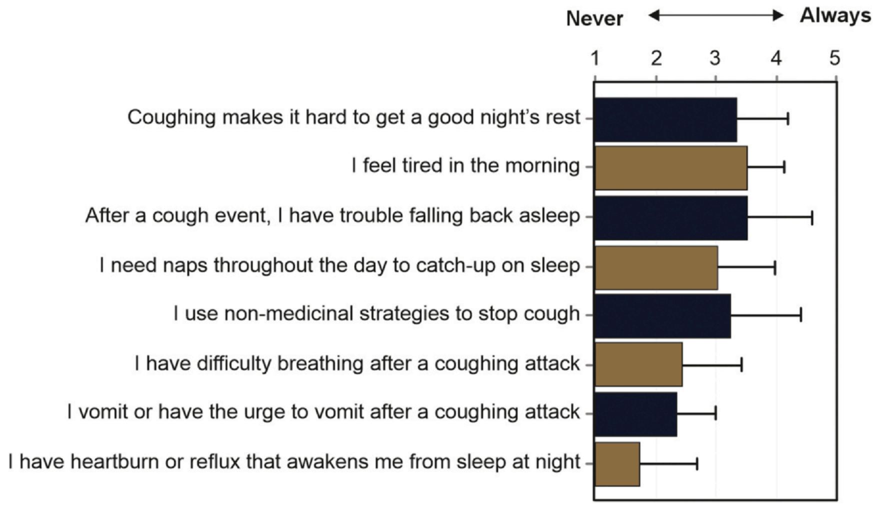

FIGURE 1. Mean and 95% confidence interval of self-reported cough and sleep difficulties. All answers were on a 5-point Likert scale, in which 1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Almost Always, 5 = Always.

in clinical visits (ie, "How many times, on average, do you awaken at night from cough?").

Session 2, occurring approximately 1 week after Session 1, focused on participants' Likert-based responses regarding their experiences and perceptions of using at-home health monitoring tools (See Table 2). Additionally, during this session, all acoustic recordings were transferred to the researchers for subsequent analysis. Recordings < 4 hours in duration were not deemed long enough and excluded from further analysis. These sessions and data collection methods were designed to provide a comprehensive understanding of participants' interactions with the health monitoring tools and their perceptions of the overall experience.

Data processing

Answers from the formal questionnaire and Likert-based questions were placed into a spreadsheet (Microsoft Excel, Microsoft Office Professional) for further summary and analysis. Data were re-checked to ensure accuracy. Next, acoustic recordings were manually analyzed using Audacity (version 3.4.2[40]), a freely available acoustic processing software. Coughs were defined as a 2-phase or 3-phase acoustic signature event that includes an explosive phase, an intermediate phase, and often a subsequent voiced segment (in the 3-phase signature[41]). For extraction, acoustic recordings were first segmented into silent and non-silent parts when the signal amplitude was plotted against the time domain in Audacity. Next, trained undergraduate and graduate student technicians manually extracted cough events based on the 2- or 3-phase cough signatures via visual displays and listened to the non-silent parts. Cough counts were re-checked by a second, trained technician to ensure accurate extractions.

Statistical plan

To understand the relationship between subjective and objective cough data (aim 1), we provided a table to visualize self-reported symptoms of cough impact on sleep that caused the participant to awaken each night and the number of coughs captured in the acoustic recordings. To determine the relationship between the standardized clinical cough questions and the quantitative metric derived from acoustic recordings (aim 2), we calculated correlations between the average number of coughs of the participant's acoustic recordings with the LCQ total score as well as the LCQ question #10 specific to cough and sleep at night. Prior to analyzing correlations, we assessed the data for

TABLE 2.
Perceptions of Comfort With Using Health Tracking Apps and Sensors

Question	Mean	Median	Min	Max
In the future, I would consider using an app to track information on my **sleep** at **night**	4.8	5	4	5
In the future, I would consider using an app to track information on my **cough** at **night**	4.9	5	4	5
In the future, I would consider using an app to track information on my **cough** during the **day**	4.1	5	1	5
I would like an app that can send information to my medical provider (doctor)	4.8	5	4	5
I would like to use additional devices/sensors (like audio recorders built-into necklaces or watches, such as Apple Watch or Fitbit, or small sensor devices placed on the neck), if that could increase the **accuracy** of cough detection	4.6	5	2	5

Notes: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

normality using an Anderson-Darling test, finding that the average number of coughs violated the normality assumption ($P < 0.05$). Therefore, we calculated non-parametric Spearman's rank-order correlations with significance set to $P < 0.05$. To assess the perception of using an app to monitor night-time cough at home (aim 3), we compiled and reported responses to the 5-point Likert scale questions on comfortability and concerns. We included descriptive statistics and visual displays. Statistical analyses were completed in Minitab software (version 20.3).

RESULTS

The 10 participants completed an average of 3.5 night-time acoustic recordings (range of 2-7 nights). Seven participants used Apple iPhones and three used Android-based phones to make their recordings.

The average score on the LCQ was 11.35 +/- 3.18 (range = 6.73−16.87), with all scores falling below the established normative cut-off score of 17.68,[42] indicating impacted quality of life due to cough. Specifically, in response to question #10 of the LCQ regarding the disturbance of sleep due to cough in the last 2 weeks, participants reported an average score of 3.3, indicating their sleep was impacted "a good bit of the time." The scores ranged from "1: All of the time" to "6: Hardly any of the time."

Self-perceived cough and acoustic recordings

A total of eight out of 10 subjects completed the at-home Cough Monitoring Log, with two of these participants filling out the log at Session 2. On average, participants reported 1.3 instances of awakening from sleep due to cough, with a range of 0-3 times awakening per night. Quantitative analysis of acoustic signals showed wide variation of coughs per night from 0 to 639 coughs ($M = 149.4$, +/-189.0 coughs) each night. See Table 3 for a complete list of the number of recordings, number of awakenings, and number of total coughs for each participant. See Figure 2 for a visual comparison of self-reported awakenings and acoustically determined coughs across all nights for the eight participants who completed the Cough Monitoring Log.

Spearman's rank-order correlation analysis was calculated to assess the relationship between the LCQ total score and the average number of acoustically determined coughs at night. We found a strong negative relationship ($\rho = -0.78$; $P = 0.008$), in which lower total scores (indicating a greater degree of impairment) resulted in a higher number of coughs (Figure 3A). Further, a Spearman correlation was calculated between the score on the LCQ question #10 about the impact of cough on sleep and the average number of coughs for each participant. Once again, the relationship was deemed significant ($P = 0.001$) with a strong, negative relationship between variables ($\rho = -0.87$). Figure 3B provides a scatterplot of these data.

Comfortability and concerns of using health technology

The results from Table 2 list perceptual ratings regarding comfort with using the continuous audio recording app. Participants expressed strong agreement when considering the use of an app to track information on their sleep and cough at night, with Likert scores of 4.8/5 and 4.9/5, respectively. The average score decreased slightly to 4.1 when asked about comfort tracking cough during the day, with an increase in the overall range of scores from as low as 1 to as high as 5. The desire for seamless integration with medical providers was evident, as indicated by the mean score of 4.8/5, and participants expressed openness to incorporating additional devices or sensors, such as audio recorders in accessories like necklaces or smartwatches (4.6/5). Concerns over privacy were evidenced with an average rating of 3.2 and large variation across subjects (see Figure 4 for dot plot of participant concerns).

DISCUSSION

The overarching purpose of this study was to investigate the relationship between self-reported symptoms of cough impact on sleep and acoustically determined cough quantities, as well as to understand perceptions of health technology in those with nocturnal chronic cough. To answer these questions, participants acoustically recorded their sleep at night to capture any cough events and answered formal and informal questions about cough and sleep.

All participants exhibited coughing across all nights of recordings except for one who had one night with 0 coughs captured. Therefore, the overall range was found to be 0-639 coughs per night with an average of 149 coughs per night. The range of individual averages were from 1 to 524 coughs when averaged within each participant's recordings. This finding was somewhat consistent with previous studies on those with chronic cough due to chronic obstructive pulmonary disease reporting a range of 0-326 coughs per patient.[14] Another study that enrolled patients with asthma reported an average of 0-90 coughs per patient.[28] However, both studies reported a wide range of variability across patients, which was also observed here.

Supporting our first hypothesis, we observed a lower number of awakening events compared to the number of coughs recorded at night. That is, the average number of times patients awakened each night was 1.3, while the average number of coughs each night varied widely from 1 to over 600. The greater number of cough events compared to awakening events could be due to only 8 out of 10 participants who completed the Cough Monitoring Log reported their awakening events, with two filling it out at Session 2, based on memory. The accuracy of recall was likely impacted by the delay, which occurred between the cough events and reporting their measures.[43] Additionally, remembering awakening events can also be impacted by sleep phases, which have known effects on immediate memory consolidation and delayed recall,[44] or due to the

TABLE 3.
Self-Reported Cough Awakening Home Monitoring Log and Acoustical Data

ID	Leicester cough questionnaire question #10 Response*	Sleep recording	Duration of recording (Hrs)	Number of self-reported cough awakening events	Number of coughs from acoustic recording	Average number of coughs over nights of recording
P_01	6	1	7	1	10	11.34
		2	7	0	12	
		3	9	0	12	
P_02	3	1	8	3	52	60.5
		2	6	0	18	
		3	6	2	141	
		4	7.5	3	31	
P_03	1	1	8	3	522	524.33
		2	9	3	561	
		3	9	3	490	
P_04	3	1	10.5	2	445	296.5
		2	7	1	146	
		3	4	3	137	
		4	7	3	458	
P_05	1	1	5	NR	49	94.5
		2	8	NR	140	
P_06	6	1	7.5	0	38	28.67
		2	7.5	0	32	
		3	7.5	0	16	
P_07	4	1	7.5	3	39	25.67
		2	7	0	17	
		3	7	2	21	
P_08	1	1	7	NR	639	408.33
		2	5	NR	467	
		3	5.5	NR	119	
P_09	3	1	7	3	125	87.71
		2	5.5	0	30	
		3	6	1	132	
		4	4.5	0	40	
		5	5	1	69	
		6	6	NR	105	
		7	7	0	113	
P_10	5	1	7.5	0	0	1
		2	7	0	1	
		3	7.5	1	2	

Notes: * = Leicester Cough Questionnaire Question #10: "In the last two weeks, has your cough disturbed your sleep?" is rated on a 1-7 Likert scale in which a score of 1 indicates the participant is impacted "All of the time," and a score of seven indicates they are impacted "None of the time." NR = not reported; "Duration of recordings" have been rounded to the nearest half hour.

nature of the question at hand. The question related to the number of times they awakened (instead of the total number of coughs occurring at night) is a common clinical question used by clinicians to understand the impact of cough on sleep and thus was investigated here with the intent of understand this relationship. Still, asking patients how many times they coughed each night is also unlikely to produce accurate responses due to known confusion during wake/sleep cycles and difficulty quantifying the number of coughs over a long period of time to begin with. Based on these reasons, discrepancies could be observed in instances where there was a stark contrast between the awakening and cough events (eg, 1.3 awakening events and 400 coughs). Therefore, this clinical question may hold meaning for the quality of sleep but may not be representative of the frequency of coughs for patients. Instead, cough metrics related to the duration of night-time cough events, or perhaps the number or duration of pauses between cough events, could be helpful to further align this clinical question with quantitative cough measures.

Contrary to our second hypothesis, the number of acoustically determined coughs were significantly correlated with both the LCQ total score, as well as the rating on question #10 specific to the impact of cough on their sleep. Birring et al,[33] reported a moderate correlation of $r = -0.60$ between daily cough frequency and LCQ score, whereas our results indicated a slightly stronger relationship between nocturnal cough frequency and LCQ score of

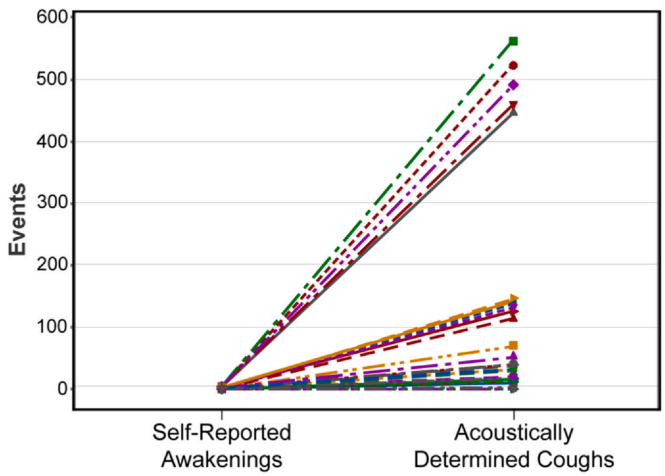

FIGURE 2. Line plot depicting the difference between self-reported awakening events at night and acoustically determined coughs for the eight participants who completed the Cough Monitoring Log.

$\rho = -0.78$. Likewise, the relationship between acoustically determined cough duration (time spent coughing) and LCQ in nocturnal monitoring of 58 patients with chronic cough also yielded a moderate correlation of $r = -0.62$.[15] The difference with our results and the latter study may have been due to the discrepancy between measurement techniques (ie, raw number of coughs vs. total duration of coughs).

Further, our results provide quantitative evidence supporting the accuracy and clinical usefulness of the LCQ question #10 as a measure related to the frequency of nocturnal cough events with a strong, negative relationship of $\rho = -0.87$. To our knowledge, we are the first study to report on the relationship between objective cough measures and this individual LCQ question. Still, a larger data set should be analyzed to understand the nature of that relationship. That is, a non-linear relationship was evidenced in this participant set, yet this was only a small sample of 10 participants. A larger sample may show smaller nuances, linear relationships, or continued non-linear (eg, exponential, curvilinear) relationships between self-reported cough awakening scores and number of total coughs.

Of interest, the strong relationships reported here are in opposition with previous reports yielding only weak-to-moderate relationships between acoustic cough measures and patient-reported outcome measures. Specifically, Rassouli et al[28] and Kelsall et al[16] reported correlations $r = 0.25\text{-}0.43$ between nocturnal acoustic cough counts and immediate ratings of cough severity on a visual analog scale that day. Moreover, Marsden et al[17] found a positive, but not very strong, correlation ($r = 0.30$) between nocturnal acoustic cough counts and the formalized Asthma Control Questionnaire, often used to quantify asthma severity.[45] The discrepancy between our results and these could have been due to the nature of the patient-reported questionnaires as well as the patient population enrolled. Marsden et al[17] and Rassouli et al[28] focused solely on patients with asthma, whereas Kelsall et al[16] took a broader approach (much like our study), enrolling across various etiologies and reporting a stronger correlation ($r = 0.43$) compared to the other two studies. It is not known how etiology may influence self-reported severity of cough, but this may be a factor in the outcomes reported here.

Our findings support the use of clinical questionnaires; however, it seems that they are not providing a complete picture of the impact of cough for patients, nor the sheer number of coughs each patient is experiencing. That is, there is likely a difference in the patient who coughs only 50 times a night compared to one who coughs 500 times per night. Our data show that the change in those individuals was only represented by a change in the Likert questionnaire scaling of 1-to-2 points. A larger analysis would

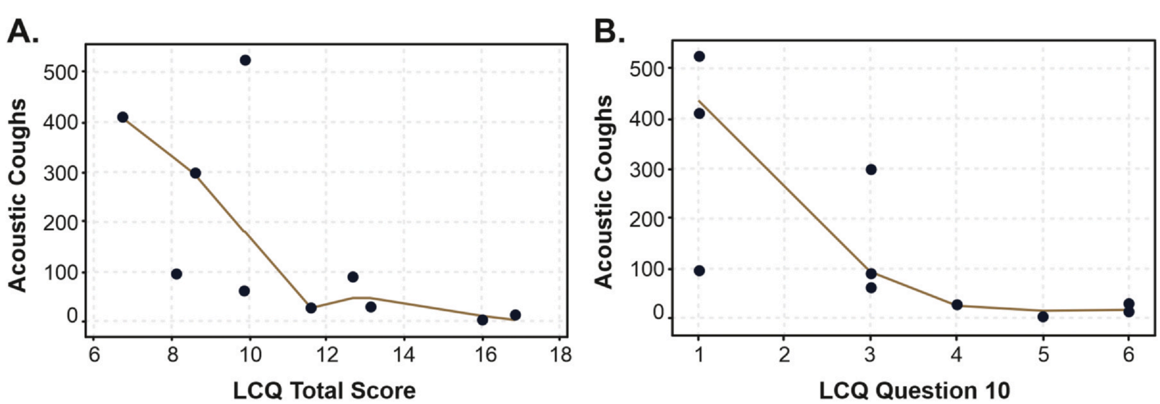

FIGURE 3. Scatterplots with locally weighted scatterplot smoothing (lowess) to show trends in the non-linear data. (**A**) Scatterplot depicting Leicester Cough Questionnaire (LCQ) total score and average cough events determined from acoustic recordings at night. Higher LCQ scores indicate a lower impact of cough on daily life. (**B**) Scatterplot depicting LCQ question #10 ("the disturbance of sleep due to cough in the last 2 weeks") and average cough events determined from acoustic recordings at night. Higher LCQ question #10 scores indicate a lower impact of cough on sleep.

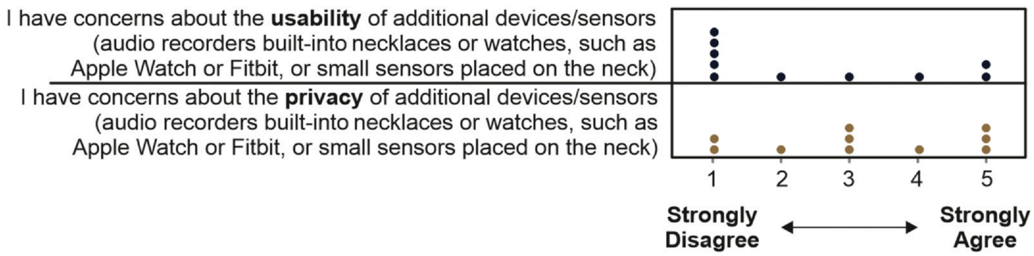

FIGURE 4. Dot plot of participant concerns about health technology comfortability and privacy concerns. 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

provide a means to identify relevant clinical cut-off scores for cough severity and has the potential to relate that to further patient characteristics and treatment options. Moreover, longitudinal studies tracking changes in the quantitative cough counts and LCQ ratings would aid in assessing the sensitivity of the formalized cough questionnaire to internal changes occurring within a patient's treatment process.

Our third hypothesis was partially supported when participants reported positive impressions about using smartphones, sensors, and technology to assist in monitoring their cough at home. Specifically, the average Likert-rating scores on questions related to the comfortability of app usage ranged between 4.1 and 4.9/5. This is unsurprising, as other studies have reported that 58.23% of people have health-related apps on their smartphones and that patients report that they trust in app accuracy, data safety, and health improvement.[46]

However, responses were mixed when asked whether they felt comfortable with smartphone recordings during the day, with a slight reduction in Likert rating to 4.1/5. This is where concerns of privacy arose. When asked to explain their reasoning for their response to the statement "I have concerns about the privacy of additional sensors…," one participant who reported strong concerns (rating of 5/5) stated she was concerned for the privacy of others, as her work included personal information about students. Another participant who gave a rating of "3: Neutral" to concerns about privacy, said, "I feel like we are being recorded all of the time anyway." The variability in responses (1-5 across the entire scale) suggests strong concerns for privacy, but only for some users.

Sensor technology encompasses a variety of tools to gather information about the health status of patients. An example is the accelerometer, which can capture acoustic markers through vibrations on the skin of the neck that do not include specific information about what was said.[47] This may be a more viable alternative to long-term acoustic monitoring, although acoustic monitoring has served as an important stepping stone to more advanced acquisition and processing strategies. Recent speech technology platforms (Google, etc) use acoustic signatures to detect timepoints to listen and record (eg, "Hey Siri"). Given that a cough signal has a unique acoustic pattern, it has the potential to be a marker that could signal recordings and reduce intrusive recording practices. For example, one commercial company has reported using acoustic cough signature detection to reduce concerns of privacy and confidentiality.[35] Our patients had positive perceptions (4.6/5 average Likert rating) about potentially using other sensors, making the market open to alternative sensors that may mitigate privacy concerns.

Nevertheless, all patients reported that they would like to gather health information to send to their physician (range of 4-5/5). Chronic cough, itself, is a frustrating diagnosis that can persist even after all treatments have been exhausted, and some patients experience symptoms indefinitely.[6,13] Current treatments could include cough desensitization,[48] behavioral replacements for cough,[49] and emerging pharmacological approaches (eg, P2X3 inhibitors[50]). Deciding which treatment is correct for which person, at present, is primarily based on self-reported information, and quantitatively tracking metrics over the course of treatment may be helpful when making decisions to start, stop, or continue treatment.

Limitations and future directions

The relatively small sample size of 10 participants is one limitation of this study. While the insights gained provide valuable initial perspectives, a larger participant pool would allow for the development of critical clinical cut-off metrics to identify patients with a higher volume of coughs (ie, > 100 per night) compared to those with lower amounts. The reported results, with correlation values ranging from −0.78 to −0.87, indicate strong associations between self-reported cough awakening during sleep and objective cough data. However, no additional factors (age, duration of cough, underlying etiology, etc) were examined as predictors in our study. To gain a more comprehensive understanding of the dynamics influencing participants' perceptions and experiences, future studies should employ mixed methods and longitudinal studies to explore the interplay of various factors.

Further, to identify objective measures that provide clinically relevant information to clinicians, it is essential to investigate both cough and sleep-related measures that could correlate with clinically significant questions, such as LCQ question #10. Future research should investigate the relationships between self-reported measures and objective metrics, such as sleep tracking data, cough duration, and intervals between coughing events. This, in turn, could identify an objective measure (or combination of measures) that correlates with self-reported awakenings to accurately quantify chronic cough severity and its effect on quality of life.

Future investigations should also prioritize the development of algorithms capable of accurately detecting cough events while distinguishing them from other signal types, such as speech and snoring.[41,51–54] Exploring alternative sensors, such as accelerometers, which may be less susceptible to background noise compared to microphones,[47] could improve the accuracy of cough detection as well. Additionally, these sensor approaches address concerns related to privacy and confidentiality, enhancing the ability for technology to adapt to ethical concerns.

CONCLUSION

Strong relationships were observed between participants' self-perceived cough and sleep symptoms and the objective cough data. This suggests some alignment between subjective perceptions of cough severity at night and objective acoustic measurements. Participants were comfortable using smartphone-based health apps, though concerns about privacy emerged, particularly when collecting continuous acoustic data during the daytime. To advance the state of technology in health monitoring, future efforts should focus on refining algorithms for accurate cough detection, addressing privacy concerns through transparent data practices, and incorporating user feedback to optimize app comfortability and user experience.

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Data Availability Statement

Data will be made available upon reasonable request to the authors.

Declaration of Competing Interest

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

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