Objective cough counting in clinical practice and public health: a scoping review

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Quantifying cough can offer value for respiratory disease assessment and monitoring. Traditionally, patient-reported outcomes have provided subjective insights into symptoms. Novel digital cough counting tools now enable objective assessments; however, their integration into clinical practice is limited. The aim of this scoping review was to address this gap in the literature by examining the use of automated and semiautomated cough counting tools in patient care and public health. A systematic search of six databases and preprint servers identified studies published up to Feb 12, 2025. From 6968 records found, 618 full-text articles were assessed for eligibility, and 77 were included. Five clinical use cases were identified—disease diagnosis, severity assessment, treatment monitoring, health outcome prediction, and syndromic surveillance—with scarce available evidence supporting each use case. Moderate correlations were found between objective cough frequency and patient-reported cough severity (median correlation coefficient of 0.42, IQR 0·38 to 0·59) and quality of life (median correlation coefficient of –0·49, –0·63 to –0·44), indicating a complex relationship between quantifiable measures and perceived symptoms. Feasibility challenges include device obtrusiveness, monitoring adherence, and addressing patient privacy concerns. Comprehensive studies are needed to validate these technologies in real-world settings and show their clinical value. Early feasibility and acceptability assessments are essential for successful integration.

Introduction

Cough has frequently signalled the need for care seeking, clinical evaluation, and diagnostic testing. Clinical evaluation of cough typically relies on patient-reported outcomes (PROs) using tools, such as the Leicester Cough Questionnaire to assess cough-related quality of life or the visual analogue scale to measure cough severity.[1,2] Although these PROs are practical and capture the patient's subjective experience,[3] a comprehensive cough assessment requires multiple complementary approaches. No single measure fully captures this complex symptom necessitating the incorporation of additional methods, such as cough diaries, numeric rating scales, verbal descriptive scales, and tussigenic challenges that assess cough reflex sensitivity.[4]

Digital cough monitoring tools and technologies offer objective methods for detecting cough and tracking changes in cough counts over time. Several cough counting technologies have been developed, including the Leicester Cough Monitor and VitaloJAK—two semiautonomous devices that have considerably contributed to the field of cough monitoring over the past 20 years for 24-h cough counting.[5–8] Advances in artificial intelligence (AI) and the heightened focus on respiratory symptoms during the COVID-19 pandemic have accelerated the field of digital cough counting.[9–11] This field has been termed acoustic epidemiology in reference to the use of technology to detect and analyse sounds produced by the body (eg, coughing and sneezing) to better understand and predict patient health outcomes.[12,13]

Despite these advances, digital cough tools are predominantly confined to clinical research trials and are used as an outcome measurement for evaluating new cough-suppressant treatments.[14–16] Objective cough counting is considered a viable outcome measure in cough guideline recommendations;[17] however, its use in clinical practice remains rare. This discrepancy between the rapid pace of technological advances in digital cough counting tools and their limited integration into clinical practice underscores a substantial gap between ideal standards and real-world application. Although existing commentaries have summarised the technical aspects and conceptual applications of these tools,[3,8,18–20] a systematic consolidation of their practical and clinical applications remains essential to advance the field of cough monitoring. Therefore, in this scoping review, we aim to synthesise the applications of objective cough monitoring tools in the clinical and public health management of respiratory diseases, with an emphasis on their real-world applicability and potential to transform patient care.

Methods

We conducted a scoping review to identify the applications of digital cough counting tools across various diseases, given their diverse implementations and technologies. Our aims were to identify and categorise objective cough counting tools used in clinical and public health contexts; analyse their clinical applications for diagnosis, monitoring, and management of respiratory diseases; and investigate factors affecting their adoption and integration into clinical practice and public health strategies.

A protocol was registered on the Open Science Framework on Oct 21, 2022.[21] This Review is reported in accordance with the PRISMA extension for scoping reviews guidelines (appendix pp 1–2).[22]

We defined digital cough counting tools as devices or systems that use automated or semiautomated methods to detect, quantify, and record cough sounds continuously

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See Online for appendix

over a duration ranging from hours to days. These tools are distinct from subjective measurements, which predominantly rely on PROs and personal recollections.

Search strategy and selection criteria

Our research was guided by a population, concept, and context[23] question: What are the current and emerging applications of digital cough counting tools in the clinical management of respiratory diseases and public health practice? We searched MEDLINE (Ovid), Embase (Ovid), CENTRAL (Cochrane Library), Web of Science Core Collection, IEEE Xplore, and preprints indexed in Europe PMC (eg, bioRxiv and medRxiv). The search terms combined "cough" or "tussis" with objective measurement descriptors, such as "automated", "biomarker", "monitor", and "frequency" (appendix pp 3–4), developed with input from the research team and a research librarian (GG). We limited the results to English, French, and Spanish articles. Publications in French and Spanish were translated by the authors AJZ and PEL. The initial search was performed for articles published from Jan 1, 2013, to Sep 9, 2023, and a second search was performed for articles published from Jan 1, 2013, to Feb 12, 2025. For multiple publications using the same dataset, we extracted data from a single source, prioritising peer-reviewed publications.

Studies were included if they used digital cough counting tools to assess cough patterns with clinical intent or addressed issues associated with clinical implementation. We included observational studies, case reports, and case series, without a minimum sample size requirement. Randomised trials were included when the primary investigation was the use of digital cough monitors as an intervention. No restrictions were applied on demographics, settings, locations, or cough treatments.

Studies were excluded if they focused on technical tool development (eg, developing a cough detection algorithm). Additionally, studies were excluded if they exclusively enrolled healthy individuals or involved non-human subjects. Experimental studies or clinical trials in controlled settings using cough monitoring as an outcome to evaluate the effectiveness of a novel therapeutic agent were also excluded. Studies using only subjective tools, such as questionnaires, surveys, or scores, were excluded. Reviews and editorials were omitted but scanned for relevant citations.

Screening was performed in two stages by two independent reviewers. Title and abstract screening (stage 1) were primarily conducted by AJZ, with RD, PEL, and VN serving as secondary screeners. Full-text screening (stage 2) was performed following the same process. Any discordance or uncertainty during either stage was resolved by consulting with SGL.

Data analysis

A structured data extraction form was used to capture publication data, study design, country, patient demographics, specific respiratory diseases, the cough counting tool used, clinical application, and implementation factors. Studies reporting correlation coefficients between objective cough counts and subjective scores or questionnaires were also documented. Primary extraction was performed by AJZ and verified by SGL.

Inductive thematic analysis was used to categorise the studies into five categories: disease diagnosis, assessment of disease severity, treatment monitoring, prediction of health outcomes, and syndromic surveillance. A sixth category captured studies exploring cross-cutting themes, such as feasibility and acceptability. No additional qualitative coding methods were used.

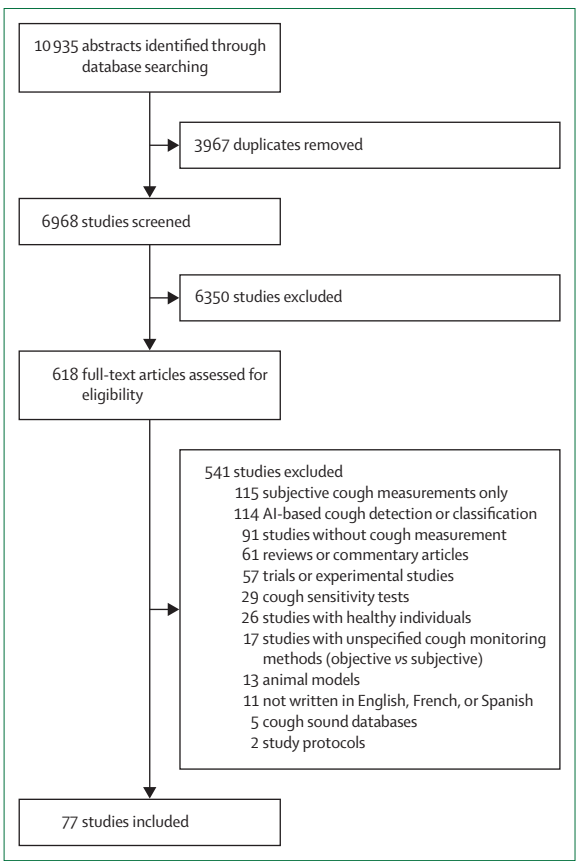

Figure 1: **PRISMA flow diagram on literature search and study inclusion**
AI=artificial intelligence.

Results

The search strategy identified 10 935 abstracts. After removing duplicates, 6968 were screened, of which 618 were selected for full-text assessment, and ultimately, 77 met the inclusion criteria (figure 1). Of the 77 studies included, the vast majority were prospective observational studies (74 studies; 96%). The remaining studies consisted of two case series (3%) and one case report (1%). No clinical trials were identified for inclusion in this review.

A total of 6350 studies were excluded during abstract screening, as they did not meet the inclusion criteria for

objectively measuring cough as a biomarker among humans. During full-text assessment, most exclusions occurred because the studies used only subjective cough assessment tools or focused on developing AI algorithms for cough detection without considering cough counts as a clinical marker. Additionally, 57 studies used objective cough monitoring to validate antitussive therapeutics, 29 studies investigated cough sensitivity reflex, and 26 studies examined the application of objective cough monitoring among healthy participants.

Study characteristics

The table summarises the included studies. Sample sizes ranged from one (case report) to 616 participants (median 41, IQR 25·5 to 71). Geographically, 52 (68%) of 77 studies were conducted in high-income countries, whereas seven (9%) were performed in low-income and middle-income countries and exclusively focused on tuberculosis. Eighteen studies (23%) did not specify a country.

Most studies, 52 (68%) of 77, investigated conditions linked to chronic cough. Seven studies (9%) investigated both chronic and acute respiratory ailments. 28 (36%) studies investigated asthma, making it the most frequently studied condition; 15 (19%) investigated chronic obstructive pulmonary disease (COPD), 12 (16%) focused on tuberculosis, and five (6%) focused on cystic fibrosis.

Digital cough counting tools were predominantly used in ambulatory settings, enabling remote monitoring. Most studies focused on adults, with only 15 (19%) of 77 studies assessing cough counting in paediatric populations younger than 15 years. Paediatric studies exclusively used contact-based devices, such as the LEOSound[31,100] and a custom cough monitoring system developed by Hirai and colleagues.[27,28,47]

Contact-based semiautomated systems—those requiring physical proximity or direct interaction with the patient—remained the most widely used. 15 (19%) of 77 studies used the Leicester Cough Monitor, seven (9%) used VitaloJAK, three (4%) used the Hull Automatic Cough Monitor, and three (4%) used the Cayetano Cough Monitor. The technical specifications of these devices have been well documented.[3,8] These systems typically use commercially available digital recorders (eg, MP3) with free-field microphones,[8] aside from VitaloJAK, which has a custom built-in microphone.[6] Several studies also deployed validated non-contact autonomous cough detection algorithms on smartphones, including Clara,[58] Coughy,[53,72,101] Hyfe Cough Tracker,[69,70,73,75,78,93,97] and CurieAI,[65] representing a shift towards more accessible solutions. 19 (25%) of 77 studies used custom recording devices lacking prior validation of their technical performance.

53 (68%) of 77 studies reported cough counts per unit of time (eg, per hour or per 24 h) as the primary outcome, whereas other studies used cough epoch or cough bout per hour, defined as a continuous coughing episode without a pause exceeding 2 s, proposed by the European Respiratory Society guidelines for cough evaluation.[17]

Clinical and public health applications

In line with the thematic analysis (figure 2), studies were categorised as follows: disease diagnosis (18 of 77, 23%); severity assessment (24 of 77, 31%); treatment monitoring (17 of 77, 22%); health outcome prediction (8 of 77, 10%); and syndromic surveillance (4 of 77, 5%). An additional six (8%) studies considered cross-cutting and feasibility applications of objective cough counting tools.

The potential of cough counts as a diagnostic biomarker lies in their ability to reveal disease-specific cough patterns, which can be examined over the course of a single day (circadian analysis) or across several days or weeks (longitudinal analysis).

Studies have shown differences in circadian cough count change between healthy individuals and those with pulmonary diseases.[26,33–35,38,41,54,81] However, distinguishing the rates and patterns between different diseases is difficult. Although some diseases show different absolute cough counts (eg, cystic fibrosis *vs* primary ciliary dyskinesia[33]) or unique cough patterns (eg, asthma *vs* acute bronchiolitis[27] and COPD *vs* asthma[32]), others do not.[37,39,41,45,62,81] Given the many illnesses that are characterised by cough as a symptom and the variability in cough patterns, using cough counts alone for diagnosis is challenging. Therefore, while increased cough counts might indicate the presence of disease, they are not consistently reliable for differential diagnosis.

To date, no studies have investigated the use of cough counting devices to monitor the onset of acute infectious diseases in healthy individuals following exposure. The use of cough counting devices for monitoring the onset of acute infectious diseases could have value for contacts of individuals with transmissible respiratory diseases, enabling early detection of disease acquisition and timely intervention in populations at high risk.

To assess disease severity of previously diagnosed conditions, longitudinal cough monitoring, which often involves repeated 24-h intervals, is used for observing trends and understanding the evolving nature of cough patterns and severity over time.[42,46,50,52,56–59] For example, Crooks and colleagues[42] reported a decline in cough counts from baseline to day 45 among individuals recovering from acute exacerbations of COPD, highlighting the natural trajectory of recovery. Similarly, Koehler and colleagues[50] examined nocturnal cough counts in children with bronchitis over three nights (baseline, night 5, and night 9) and showed how objective cough monitoring can track the evolution of acute respiratory diseases.

Both circadian and longitudinal cough trends provide valuable information on disease severity in individuals with established diagnoses. Asthma is the most extensively researched condition in this context. Reports suggest that nocturnal coughing among individuals with asthma can indicate severe asthma during an exacerbation.[48] Several

	Country	Setting	Age group	Disease	N*	Recording time	Cough monitoring tool	Unit of analysis
Clinical application: disease diagnosis								
Bisballe-Müller et al (2021)[24]	Australia	Inpatient	Paediatric	Asthma, bronchiolitis, pneumonia, acute respiratory infections	118	24 h	Sony ICD-PX470 Digital Voice Recorder	Cough cluster (explosive sounds with no more than 5 s between each sound) per hour
Fischer et al (2018)[25]	Germany	Ambulatory	Adults	COPD	30	2 nights (consecutive)	LEOSound	Cough epochs (continuous coughing without a 2-s pause) per recording period
Grosse-Onnebrink et al (2016)[26]	Germany	Inpatient	Adolescents, adults	Cystic fibrosis	21	7 h (night)	LEOSound	Cough counts per hour
Hirai et al (2019)[27]	Japan	Inpatient	Paediatric	Asthma, RSV-bronchiolitis	36	8 h (night)	Custom	Cough counts per 30 min
Hirai et al (2022)[28]	Japan	Inpatient	Paediatric	Asthma with and without post-nasal drip	8	8 h (night)	Custom	Cough counts per 30 min
Imai et al (2017)[29]	Japan	Inpatient	Paediatric	Psychogenic cough	2	8 h (night)	Custom	Cough counts per night
Key et al (2019)[30]	NA	Ambulatory	Adults	Bronchiectasis	6	24 h	NA	Cough counts per day or night
Lindenhofer et al (2020)[31]	Austria	Ambulatory and inpatient	Paediatric, adolescents	Asthma, cystic fibrosis, pneumonia, habit cough, chronic cough	39	8–10 h (night)	LEOSound	Cough episodes (30-s period in which at least one cough was registered) per night
Otto et al (2024)[32]	NA	Ambulatory	Adults	COPD, asthma, RCC, chronic bronchitis, other	241	3 days (consecutive)	NELA	Cough counts per hour
Radine et al (2019)[33]	Germany	Ambulatory	Paediatric, adolescents, adults	Cystic fibrosis, primary ciliary disease	49	2 nights (consecutive)	LEOSound	Cough counts and cough epochs (continuous coughing without a 2-s pause) per hour
Sinha et al (2016)[34]	UK	Ambulatory	Adults	Sarcoidosis	32	24 h	LCM	Cough counts per 24 h
Spinou et al (2017)[35]	UK	Ambulatory	Adults	Bronchiectasis	54	24 h	LCM	Cough counts per 24 h
Sumner et al (2013)[36]	NA	Ambulatory	Adults	COPD	68	24 h	VitaloJAK	Cough counts per hour
Turner et al (2013)[37]	NA	Inpatient	Adults	Asthma, COPD, lower respiratory tract infection	40	24 h	LCM	Cough counts per hour and cough counts (undefined) per 24 h
Vertigan et al (2018)[38]	Australia	Ambulatory	Adults	RCC, muscle tension dysphonia, vocal cord dysfunction	57	24 h	LCM	Cough counts per hour
Vertigan et al (2020)[39]	Australia	Ambulatory	Adults	Vocal cord dysfunction, chronic cough	90	24 h	LCM	Cough counts per hour
Wang et al (2014)[40]	UK	Ambulatory	Paediatric	Pertussis	6	24 h	LCM	Cough counts per 24 h
Yousaf et al (2013)[41]	UK	Ambulatory	Adults	Asthma, bronchitis, chronic cough, COPD	78	24 h	LCM	Cough counts per 24 h
Clinical application: disease severity assessment of previously diagnosed conditions								
Crooks et al (2016)[42]	NA	Ambulatory	Adults	COPD	18	24 h; baseline, day 5, day 20, day 45	Hull Automated Cough Counter	Cough counts per hour
Doenges et al (2020)[43]	Germany	Ambulatory	Adults	Asthma	55	5–9 h (night)	LEOSound	Cough counts per hour
Elghamoudi et al (2017)[44]	NA	NA	Paediatric, adolescents	Asthma	26	24 h; during exacerbation, when stable	VitaloJAK	Cough counts per 24 h, day and night
Fletcher et al (2017)[45]	NA	Ambulatory	NA	Asthma, RCC, gastro-oesophageal reflux disease, rhinosinusitis	320	24 h	LCM	Cough counts per hour
Harle et al (2019)[46]	NA	Ambulatory	Adults	Lung cancer	39	24 h; baseline, day 60	VitaloJAK	Cough counts per hour
Hirai et al (2016)[47]	Japan	Inpatient	Paediatric	Asthma	34	8 h (night)	Custom	Cough counts per 30 min
Holmes et al (2022)[48]	UK	Ambulatory	Adults	Asthma	61	24 h	LCM	Cough counts per hour
Kebbe et al (2024)[49]	USA, Europe	Ambulatory	Adults	Pulmonary fibrosis	27	24 h; baseline, week 2, week 4	VitaloJAK	Cough counts per hour
Koehler et al (2019)[50]	Germany	Ambulatory and inpatient	Paediatric	Acute bronchitis	36	10 h; night 1, night 5, night 9	LEOSound	Cough epochs (continuous coughing without a 2-s pause) per 10 min
Krönig et al (2017)[51]	NA	Ambulatory	Adults	COPD	48	2 nights (consecutive)	LEOSound	Cough period (cough events within an interval shorter than 15 s) per hour
Kulnik et al (2015)[52]	NA	Inpatient	Adults	Stroke	21	24 h; baseline, week 1, week 4	LCM	Cough counts per 24 h

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	Country	Setting	Age group	Disease	N*	Recording time	Cough monitoring tool	Unit of analysis
(Continued from previous page)								
Kwon et al (2023)[53]	South Korea	Ambulatory	Adults	Pulmonary fibrosis, interstitial lung disease	18	7 days (consecutive)	Coughy app	Cough counts per hour
Lodhi et al (2019)[54]	NA	NA	Adults	Asthma	92	24 h	VitaloJAK	Cough counts per hour, per 4 h, and per 24 h
Mackay et al (2015)[55]	UK	Ambulatory	Adults	COPD	64	24 h	VitaloJAK	Cough counts per 24 h
Ovsyannikov et al (2019)[56]	Russia	Inpatient	Adults	COPD	110	12 h; baseline, day 10	Custom	Cough counts per 12 h
Proaño et al (2018)[57]	Peru	Ambulatory	Adults	Tuberculosis	41	2 weeks (consecutive), day 21, day 30, day 60	CayeCoM	Cough episode (continuous coughing without a 2-s pause) per hour
Rassouli et al (2020)[58]	Switzerland	Ambulatory	Adults	Asthma	79	29 nights (consecutive)	Clara smartphone app	Cough counts and cluster (a series of at least two coughs with a maximum time of 2 s in between their expulsive phases) per night and per hour
Rhee et al (2015)[59]	USA	Ambulatory	Adolescents	Asthma	42	7 days (consecutive)	Automated device for asthma monitoring	Cough counts per 6 s
Schwarz et al (2021)[60]	Germany	Ambulatory	Adults	COPD	40	24 h	LEOSound	Cough epochs (amount of coughing during 30 s) per day and night
Turner et al (2014)[61]	NA	NA	NA	Tuberculosis	30	24 h	LCM	Cough counts per 24 h
Turner et al (2015)[62]	NA	Ambulatory	NA	Chronic cough, COPD, tuberculosis	69	24 h	LCM	Cough episodes (a lone cough or bout of multiple coughs separated by 2 s of no cough) per 24 h
Turner et al (2018)[63]	UK	Ambulatory and inpatient	Adolescents, adults	Tuberculosis	61	24 h	LCM	Cough counts per hour and 24 h
Weisser et al (2022)[64]	NA	NA	Paediatric	Asthma	94	2 nights (consecutive)	LEOSound	Cough episodes (undefined) per night
Winders et al (2023)[65]	NA	Ambulatory	Adults	Asthma	108	9 h (night)	Tablet with CurieAI algorithm	Cough episodes (all coughs within 10 min after an initial cough) per 2 h
Clinical application: treatment monitoring of previously diagnosed conditions								
Faruqi et al (2016)[66]	NA	Ambulatory	Adults	Cystic fibrosis	2	24 h; pre-treatment, post-treatment	Hull Automated Cough Counter	Cough counts per hour
Faruqi et al (2020)[67]	UK	Ambulatory	Adults	Severe eosinophilic asthma	11	24 h; baseline, 1, 3, 6 months	Hull Automated Cough Counter	Cough counts per 24 h
Fukuhara et al (2020)[68]	Japan	Ambulatory	Adults	Asthma	73	24 h; pre-treatment, post-treatment	MP3 sound recorder with a free-field microphone	Cough counts per hour
Griffith et al (2024)[69]	USA	Inpatient	Adults	Bronchiectasis	9	4 days (consecutive)	Hyfe Cough Tracker app	Cough counts per 24 h
Huddart et al (2023)[70]	India, Philippines, South Africa, Uganda, Viet Nam	Ambulatory	Adults	Tuberculosis	144	14 days (consecutive)	Hyfe Cough Tracker app	Median cough counts per hour
Janssen et al (2023)[71]	South Africa	Ambulatory	Adults	Tuberculosis	8	14 days (consecutive)	Smartphone (app not specified)	Cough counts per 24 h
Jung et al (2023)[72]	South Korea	Ambulatory	NA	Asthma, interstitial lung disease	45	Asthma: 7 days (consecutive) 2 h during the day and 5 h during the night; interstitial lung disease: baseline, 3 months, 2 h during the day, and 5 h during the night	Coughy app	Cough epochs (undefined) and cough counts per recording period
Kang et al (2022)[73]	South Korea	Ambulatory	Adults	Post-COVID-19 condition refractory cough	1	42 days (consecutive)	Hyfe Cough Tracker app	Cough counts per 24 h
Lee et al (2020)[74]	Peru	Ambulatory	Adults	Tuberculosis	69	4 h; baseline, day 3, day 7, day 30, day 60	CayeCoM	Cough episodes (series of coughs separated by less than 2 s between each cough) per hour
Lee et al (2023)[75]	South Korea	Ambulatory	Adults	Chronic cough	43	Up to 14 days (consecutive)	Hyfe Cough Tracker app	Cough counts per hour

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	Country	Setting	Age group	Disease	N*	Recording time	Cough monitoring tool	Unit of analysis
(Continued from previous page)								
Marsden et al (2016)[76]	UK	Ambulatory	Adolescents, adults	Asthma	89	24 h	VitaloJAK	Cough counts per hour
Proaño et al (2017)[77]	Peru	Ambulatory	Adults	Tuberculosis	64	24 h; pre-treatment, day 3, day 7, day 14, day 21, day 30, day 60	CayeCoM	Cough episodes (series of coughs separated by less than 2 s between each cough) per hour
Raberahona et al (2025)[78]	Madagascar	Ambulatory	Adults	Tuberculosis	22	6 months	Hyfe Cough Tracker app	Cough counts per hour
Shim et al (2023)[79]	South Korea	Ambulatory	NA	Asthma	24	7 days (consecutive); 2 h during the day and 5 h during the night	Coughy app	Cough counts per hour
Turner et al (2015)[80]	NA	Ambulatory and inpatient	NA	Tuberculosis	44	24 h; baseline, day 1, days 2–4, days 5–8, week 2, week 8, week 26	LCM	Cough counts per hour
Vertigan et al (2021)[81]	Australia	Ambulatory	Adults	Asthma, RCC, laryngeal obstruction	174	24 h; pre-intervention, post-intervention	LCM	Cough counts per 24 h, day, and night
Zhang et al (2022)[82]	UK	Ambulatory	Adults	Cystic fibrosis	16	24 h; pre-treatment, 1 month	Philips Digital Record	Cough counts per 24 h, day, and night
Clinical application: predicting health outcome								
Altshuler et al (2023)[83]	Canada, USA	Inpatient	Adults	COVID-19	123	Until discharge or death	Hyfe Cough Tracker app	Cough counts per hour
Boesch et al (2023)[84]	Switzerland	Inpatient	Adults	COVID-19, pneumonia	46	Until discharge or death	Cough detection app (unspecified)	Cough counts per hour and 6 h; mean coughs per hour
Crooks et al (2021)[85]	UK	Ambulatory	Adults	COPD	25	8 days before and 8 days after acute exacerbation of COPD (consecutive)	Stationary microphone with laptop	Cough counts per 24 h
den Brinker et al (2021)[86]	UK	Ambulatory	Adults	COPD	28	90 days (consecutive)	Custom	Cough counts per hour
den Brinker et al (2025)[87]	UK	Ambulatory	Adults	COPD	38	50–150 nights (consecutive)	Custom, stationary	Cough counts per hour
Nagakumar et al (2024)[88]	UK	Ambulatory	Paediatric	Asthma	18	12 months (night)	Albus Home Research Device	Cough counts per hour
Pekacka-Egli et al (2021)[89]	Switzerland	Inpatient	Adults	Post-stroke pneumonia	30	8 h (night)	LEOSound	Cough counts per hour
Tinschert et al (2020)[90]	Switzerland	Ambulatory	Adults	Asthma	79	29 nights (consecutive)	Smartphone app	Cough counts during first 30 min of sleep; cough counts per night
Public health application: syndromic surveillance								
Al Hossain et al (2020)[91]	USA	Waiting room	All ages	Influenza, influenza-like illness	NA	Day	FluSense	Average cough counts per hour per day; total cough epoch (coughs occurring with less than 3-s difference)
Al Hossain et al (2024)[92]	USA	Waiting room	Adults	COVID-19, Influenza, RSV	NA	24 h over 4 months	Syndromic Logger	Cough counts per 24 h
Gabaldón-Figueira et al (2022)[93]	Spain	Ambulatory	Adolescents, adults	COVID-19	616	24 h: until discontinuation	Hyfe Cough Tracker app	Cough counts per hour
Zürcher et al (2022)[94]	South Africa	Waiting room	Adolescents, adults	Tuberculosis	NA	Day	CoughSense	Cough counts per 24 h
Cross-cutting and feasibility studies								
Elghamoudi et al (2015)[95]	NA	Ambulatory and inpatient	Paediatric, adolescents	Acute cough, chronic cough	40	24 h	VitaloJAK	NA
Fletcher et al (2024)[96]	USA	Ambulatory	Adults	Chronic cough	10	2–7 nights (consecutive)	Android and iPhone app	Cough counts per night
Huddart et al (2022)[97]	India, Philippines, South Africa, Uganda, Viet Nam	Ambulatory	Adults	Tuberculosis	144	14 days (consecutive)	Hyfe Cough Tracker app	Cough counts per hour, maximum cough counts per hour per day, median cough counts per hour per day
Kuhn et al (2023)[98]	Switzerland	Ambulatory	Adults	Chronic cough, COPD, asthma, interstitial lung disease	27	8 days (consecutive)	SIVA-P3	Cough epochs per 24 h

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	Country	Setting	Age group	Disease	N*	Recording time	Cough monitoring tool	Unit of analysis
(Continued from previous page)								
Rhee et al (2014)[99]	USA	Ambulatory	Adolescents	Asthma	42	7 days (consecutive)	Automated device for asthma monitoring	NA
Urban et al (2022)[100]	Germany	Inpatient	Paediatric, adolescents	Asthma, bronchitis, pneumonia	86	8 h (night)	LEOSound	Cough epochs (coughs during 30 s) per hour

*N does not include healthy individuals. CayeCoM=Cayetano Cough Monitor. COPD=chronic obstructive pulmonary disease. LCM=Leicester Cough Monitor. NA=not available. RCC=refractory chronic cough. RSV=respiratory syncytial virus.

Table: **Summary of studies examining the use of digital cough monitoring tools in a clinical or public health context**

studies on single-night nocturnal cough patterns discerned variations in cough counts among individuals with varying levels of asthma severity. Notably, people with more severe, less controlled asthma showed heightened nocturnal cough episodes.[43,44,47,48,54,64,65,76]

Studies have also examined circadian and nocturnal cough patterns in individuals with COPD. Unlike asthma, no considerable differences in circadian and nocturnal cough counts were observed when individuals with stable COPD were compared with those with acute exacerbations of COPD.[55,60] Additionally, individuals in advanced stages of COPD coughed less frequently than those in the moderate stage and showed a more uniform pattern of nocturnal coughing, with less variation throughout the night compared with individuals in the earlier stages of the disease.[25,51]

A correlation between tuberculosis severity and cough counts has been observed, with individuals having positive sputum smear results (indicative of a high bacterial load) showing increased cough counts.[61,63] Proaño and colleagues[57] further supported this finding by reporting a positive association between the severity of pulmonary cavitation and a heightened cough rate. This association underscores cough counts as a potential marker for assessing the severity, activity, and progression of tuberculosis. Additionally, increased disease severity resulting in high cough counts in transmissible respiratory diseases, such as tuberculosis, might correlate with greater infectiousness, with implications for contact screening and infection control measures in households and health-care settings.[63]

Typically, treatment response monitoring uses a range of indicators, from PROs to objective clinical markers, such as laboratory results or imaging. Amid various tools and biomarkers, objective cough monitoring could offer real-time, non-invasive insights into treatment effectiveness. Instead of assessing novel treatment effectiveness in controlled trials, the studies included primarily evaluated patient treatment outcomes in routine clinical practice settings.

Most studies (11 of 17, 65%) have explored cough as a potential biomarker for monitoring treatment in chronic respiratory diseases, including asthma,[67,68,76,81,101] bronchiectasis,[69] interstitial lung disease,[72] cystic and pulmonary fibrosis,[66,82] chronic cough,[75] and refractory cough related to post-COVID-19 condition.[73] These studies consistently observed reductions in cough counts during treatment that correlated with clinical improvement markers. For example, Fukuhara and colleagues[68] observed weak but significant correlation between bronchial hyperresponsiveness (derived from the methacholine challenge test) and cough counts (correlation coefficient [*r*]=0·38; p=0·04) during asthma treatment. Marsden and colleagues[76] reported a correlation of 0·40 (p<0·001) between cough frequency and asthma control, proposing that quantitative cough monitoring can reveal aspects of disease activity not adequately reflected in conventional pulmonary function measurements, such as spirometry.

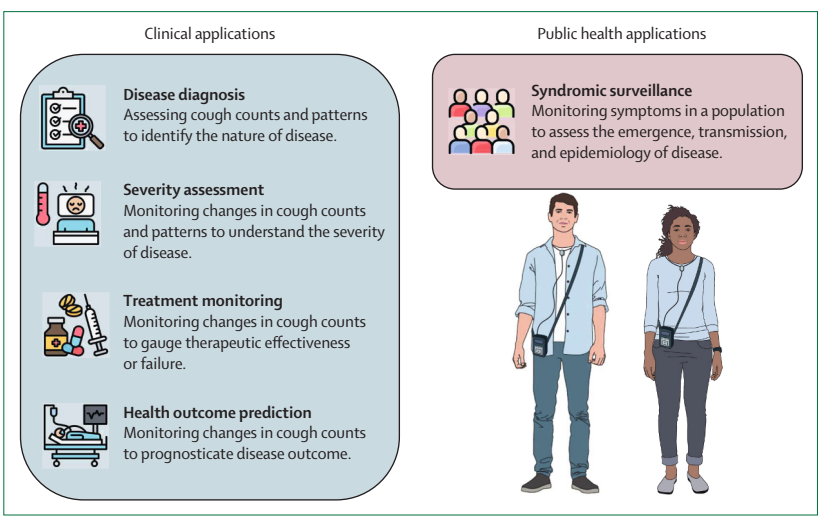

Figure 2: **Potential clinical and public health applications of digital cough counting tools**

For infectious respiratory diseases, cough monitoring has primarily been examined as a biomarker for tuberculosis treatment response.[70,71,74,77,78,80] Studies have reported a decline in tuberculosis cough counts, typically within the first 1–2 weeks of treatment, correlating with reduced bacterial load. Raberahona and colleagues recently observed that cough counts continued to decrease over the course of 6 months of treatment in a cohort of 22 tuberculosis-positive individuals.[78] The current standard for tuberculosis treatment monitoring relies on sputum production, which can be difficult for some populations—particularly during later stages of treatment or in individuals with airway hypersensitivity.[102] Several studies have shown that objective cough monitoring provides an

immediate and non-invasive measure of tuberculosis treatment response, with cough frequency showing an association with bacterial load (measured by time to culture positivity) and declining rapidly during early treatment, even before microbiological conversion was achieved in many individuals.[74,77]

As cough counts are contingent on various demographic and clinical factors, they might not manifest consistently across individuals. For example, Proaño and colleagues[77] found that some of the participants who were diagnosed with tuberculosis did not cough, whereas Lee and colleagues[74] observed that 21% of patients with tuberculosis had pre-treatment cough rates similar to those of healthy individuals. Additionally, Lee and colleagues[74] highlighted the difficulty of applying a universal threshold for assessing tuberculosis treatment response using cough counts.

Health outcome prediction through telemonitoring enables real-time tracking of patient health metrics and facilitates timely interventions. However, evidence of the role of telemonitoring in reducing admissions to hospitals is inconsistent,[103] partly owing to the generation of false alerts.[104] A growing body of research is exploring the potential of monitoring cough counts and patterns as a more precise tool for remotely monitoring patient health and predicting clinical outcomes.[83–86,89,90]

Passive cough alert systems have been evaluated for monitoring exacerbations in chronic pulmonary diseases, such as COPD and asthma.[85–89] den Brinker and colleagues[87] reported that individuals with COPD show highly individualised night-time cough density profiles. Further, they normalised cough counts across participants with different baseline frequencies, enabling their alert system to identify considerable deviations in both cough quantity and timing distribution as indicators of respiratory deterioration. Similarly, the Albus Home Research Device detected changes in nocturnal cough counts in the week preceding asthma attacks among paediatric participants.[88]

All studies using cough alert systems found that cough monitoring for exacerbations is more specific than sensitive. For example, Crooks and colleagues[85] reported that symptom questionnaires captured 88% of acute COPD exacerbations but generated one false alert every ten days, whereas a cough monitor identified only 45%, but detected false alerts once every 100 days. Similarly, Tinschert and colleagues[90] observed that nocturnal cough events were more specific than sensitive in forecasting asthma attacks. They proposed that integrating cough monitoring with additional markers, such as sleep quality, could enhance predictive accuracy.

In hospital settings, there is a growing interest in leveraging cough counts for immediate clinical decision making. This non-invasive approach might avoid more invasive techniques (eg, bronchoscopy for direct airway visualisation) and enable quick responses to disease fluctuations. Several studies have investigated the relationship between cough rates and outcomes. For example, Pekacka-Egli and colleagues[89] linked frequent protective coughs to a high risk of post-stroke pneumonia. Boesch and colleagues[84] found a positive correlation between cough counts and markers indicative of disease progression among individuals with COVID-19 or pneumonia, suggesting that increased cough counts indicates heightened disease activity. By contrast, Altshuler and colleagues[83] found an inverse relationship between cough counts and severe COVID-19 outcomes, implying that a high cough rate was linked to decreased adverse outcomes. Compared with the findings of Boesch and colleagues,[84] the findings of Altshuler and colleagues[83] highlight the complexities of interpreting cough dynamics in acute care settings. The variability in cough counts at different disease stages adds another layer of complexity. The study by Altshuler and colleagues[83] highlighted disparities in cough counts between individuals in Florida in the USA and Montreal in Canada, attributing these differences to the disease stage. Participants in Montreal were typically at an earlier stage of COVID-19, which was associated with more frequent coughing compared with those in Florida.[83]

Syndromic surveillance is crucial for the early detection of and response to infectious respiratory disease outbreaks by monitoring symptom patterns within populations. Traditionally, syndromic surveillance involves analysing health-care data, such as emergency department visits or pharmacy sales, to predict disease activity. Researchers are beginning to uncover how monitoring of population-level changes in cough counts—an unobtrusive measure—might serve as a proxy for the emergence of infectious respiratory diseases.

Gabaldón-Figueira and colleagues[93] leveraged the widespread availability of smartphones to deploy the Hyfe Cough Tracker app to 616 residents in northern Spain over a 10-month period in 2021. The portability and ubiquity of smartphones streamlined the community-wide deployment. However, the study faced challenges with adherence, with retention gradually declining. The data suggested higher adoption rates among individuals with chronic respiratory diseases as opposed to individuals without a chronic condition, as the former group naturally cough more frequently and thus these data might introduce bias. Additionally, the study covered only 1·7% of the intended population, which might not be sufficient to reflect population-wide cough dynamics.

Other studies explored stationary approaches to monitoring respiratory health. Al Hossain and colleagues[91] introduced FluSense, a multimodal platform (including cough detection) designed to assess the influenza burden within a university setting. FluSense—installed in four clinic waiting rooms—detected a correlation between cough counts and the number of positive influenza tests, with a correlation coefficient (r) of 0·40. Rahman and colleagues[105] also deployed the Syndromic Logger in the emergency department waiting room of a tertiary hospital to track respiratory pathogens, including SARS-CoV-2, influenza virus, and respiratory syncytial virus. The daily cough counts

showed moderate correlation with positive COVID-19 (r=0·40) and respiratory syncytial virus infection (r=0·27) cases, but no association was observed for influenza.

A fundamental limitation of stationary systems is their confinement to specific settings. The studies investigating stationary systems primarily captured cough sounds from patients seeking care, which might exaggerate the perceived severity of respiratory conditions in the broader community. Mobile systems, such as the Hyfe Cough Tracker, can potentially capture cough dynamics in the broader community, provided challenges with uptake and retention are addressed. Stationary systems, including FluSense and the Syndromic Logger, offer insights in health-care environments, and understanding disease burden is crucial in these settings.

Cross-cutting themes

Continuous cough recording tools, which constantly monitor and record cough sounds, raise privacy concerns that could lead to user distrust. Al Hossain and colleagues[91] highlighted privacy concerns in the context of cough surveillance. This privacy concern was also reflected in the usability study by Fletcher and colleagues,[96] in which Likert scale responses indicated varying levels of privacy concerns among individuals. A potential solution is to refine cough detection algorithms to selectively record cough sounds, minimising the risk of recording conversations.[85,93]

Portable cough monitors can be obtrusive, often requiring both a recorder and an external microphone, which can be burdensome for individuals in ambulatory settings.[50,70,82,95,100] Even small cough counting devices that are intended to be worn around the neck, such as the SIVA-P3 developed by Kuhn and colleagues,[98] resulted in some discomfort among participants. Prioritising night-time monitoring using stationary devices might help to overcome the issue of having to wear devices around the neck[96] and remains clinically relevant, as studies have shown a correlation between night-time and daytime cough counts.[87,106] There is also a trend towards developing user-friendly, less obtrusive solutions, such as smartphone-based applications. Although these applications could overcome the limitations of wearable devices, they introduce new challenges, including battery consumption, potential interference from other applications, and user compliance. Individuals might need to actively engage with the app, leading to gaps in data collection. Lee and colleagues[75] found that only 43 (66%) of 65 participants adhered to smartphone-based cough monitoring over 1 week, with lower adherence observed among older participants. The study by Lee and colleagues[75] further highlighted issues affecting ease of use, including the inconvenience of having to carry the device. Further studies are needed to understand the emerging challenges related to smartphone-based solutions and how they might affect the widespread adoption of smartphone-based solutions.

Environmental factors influencing cough detection accuracy remain a pertinent issue, as current algorithms do not differentiate between individuals. In crowded spaces or shared living environments, cough sounds from others could be inadvertently recorded, skewing a patient's cough data and limiting its clinical utility. This problem is particularly relevant in shared domestic settings or public spaces, where multiple cough sources coexist.[31,42,77,84,86,93,100] The development of sophisticated AI models capable of recognising individual cough signatures, an approach known as diarisation in audio data analysis,[107] holds promise for enhancing the precision and personalisation of cough tracking. Until such advancements are realised, the indiscriminate nature of cough recording remains a limitation in the field of objective cough monitoring, underscoring the need for further refinement in cough detection technology.

Several studies evaluated the relationship between cough counts and PROs. Studies reported moderate correlations with cough severity PROs, with median unweighted correlation coefficients of 0·42 (IQR 0·38–0·59) for the visual analogue scale and 0·43 (0·34–0·46) for the verbal category descriptive scale. These correlations were maintained across day and night assessments (appendix pp 5–6). In terms of quality-of-life scales, the Leicester Cough Questionnaire similarly displayed a moderate negative correlation with a median of –0·49 (IQR –0·63 to –0·44). Notably, the association between cough counts and the Parental Cough-Specific Quality of Life questionnaire—a standardised tool for assessing cough in young children, with parents serving as proxy assessors—was weak, with a median correlation coefficient of –0·26 (IQR –0·29 to –0·08).[24,31,50]

The moderate to weak associations between cough counts and PROs observed across different studies, each investigating different diseases and utilising different cough measuring tools (appendix pp 5–6), underscore the complex relationship between an individual's subjective perception and empirically quantified cough counts. The discrepancies between subjective and objective assessments of cough highlight the complementary roles of both assessment approaches in clinical practice—objective measurements can identify cough patterns that might go unrecognised in subjective reporting, whereas PROs capture the patient's experience of cough burden that devices cannot measure. One hypothesis advocates for the primacy of the subjective experience, suggesting that cough count is only one aspect contributing to an individual's overall experience and quality of life.[18] Another hypothesis highlights the importance of objective measurements, proposing that individuals might not fully recognise the frequency of their coughing and thus underestimate its severity. Such underestimation is particularly true for proxy tools, such as the Parental Cough-Specific Quality of Life questionnaire, in which reporting is based on a third-party observer. Conversely, Ovsyannikov and colleagues[56] reported that individuals with anxiety might exaggerate their symptoms, showing an inverse correlation between visual analogue scale and cough count (r=–0·38 for individuals with healthy

weight having anxiety, r=0·42 for individuals with healthy weight without anxiety, r=–0·40 for individuals with obesity having anxiety, and r=0·44 for individuals with obesity without anxiety).[56] These hypotheses underscore the need to comprehensively document various dimensions of cough to ensure a holistic understanding and management within the greater context of the patient's health profile.

Discussion

Although digital cough counting tools are commonly used in clinical trials to evaluate cough suppressants, their integration into clinical practice and public health remains underexplored. This Review bridges the gap between rapid technological innovation in digital cough counting tools and their practical clinical implementation.

Across all applications, there is insufficient evidence to support the use of cough as a standalone marker. Although cough patterns vary with disease cause, severity, and treatment response, relying solely on this marker could lead to inaccuracies due to interindividual and intraindividual variabilities.[108,109] Monitoring over several days or weeks provides a better understanding of cough status or treatment response compared with short-term (24 h) or intermittent monitoring, although this long-term monitoring poses feasibility challenges.[109,110] Nevertheless, cough monitoring holds value as part of a comprehensive suite of biomarkers that capture the complete disease status. Personalised approaches can enhance the diagnostic value of cough monitoring, making it most effective when correlated with additional patient-specific health indicators. Moreover, PROs remain essential for capturing subjective experiences. The moderate correlations observed between objective cough measurements and PROs in some studies[111,112] show that these methods capture distinct aspects of patient experience. Other aspects, such as cough intensity (measured using electromyography, acoustics, or effort metrics), might provide complementary information not reflected in cough counts.

Although cough patterns can signal disease presence, their standalone diagnostic utility is poor, and existing literature does not quantify the potential incremental value of this approach over the standard of care. Combining cough patterns with other cough characteristics (eg, wet *vs* dry cough) could enhance diagnostic accuracy. The development of AI algorithms for detecting underlying diseases from cough sounds (cough classification) could advance the application of using cough as a biomarker for disease screening and diagnosis. Cough classification studies frequently adopt a diagnostic accuracy design, allowing to objectively measure the performance of cough-based tools relative to standard of care diagnostics.[113]

Cough monitors for public health surveillance represent an emerging opportunity for improved outbreak management and understanding of transmission dynamics. An expanding field of research is examining the role of physiological markers gathered from wearable devices to support outbreak response,[114] although the reliability and accuracy of this approach requires further validation. Integrating personalised monitoring data presents challenges, including data privacy, ownership concerns, and regional variations in health-care regulations. Addressing these issues is essential for leveraging cough monitors and other wearable devices as effective tools in disease surveillance.

Clinical performance data on cough monitoring tools are scarce, with even fewer insights into their implementation, feasibility, and societal acceptance. Technologies that record patient data raise social and ethical concerns that could affect adoption, regardless of their performance. Few studies have addressed the patient perspectives or health equity considerations surrounding the implementation of these tools. Most studies were conducted in high-income countries, raising concerns about the generalisability of the findings. Barriers, including cost, internet connectivity, smartphone access, and digital health literacy, could limit adoption in resource-constrained settings and exacerbate health-care disparities. The American Thoracic Society framework for home-based monitoring tools highlights some of these gaps across all emerging digital tools.[115] As clinical validation advances, qualitative research should explore patient experiences, ethical considerations, data governance, and the balance between societal values and innovation[116] to ensure that these tools are clinically effective, socially responsible, equitable, and aligned with diverse patient expectations.

The ideal cough monitoring system ultimately depends on its intended application. For short-term clinical assessment requiring accurate tracking of individualised cough counts, portable wearable devices, such as smartphones or smartwatches, offer practicality and convenience. App-based solutions might also provide user-friendly interfaces that allow patients to self-monitor their coughs in real time. However, long-term monitoring, particularly for chronic conditions or nocturnal cough patterns, could benefit from stationary systems installed within a patient's home environment, which can continuously capture data without burdening the user. Similarly, public health surveillance applications would likely require stationary monitoring systems strategically positioned in public spaces or health-care facilities. These application-specific design considerations highlight the importance of aligning technological capabilities with clinical or surveillance objectives while addressing patient acceptability and data privacy concerns.

This scoping review has some limitations. The clinical applications of digital cough monitoring tools remain speculative, as they are based on findings from clinical studies rather than established through the deployment of these tools in routine practice. We did not evaluate the technical performance of individual tools, which varied considerably from rigorously validated systems to those with poor validation. This variability might affect the interpretation of quantitative findings, particularly correlations with PROs. Study quality was another limitation. Although we did not formally assess study quality, most

studies had small sample sizes and short monitoring periods, which might be insufficient for evaluating treatment response or predicting outcomes in chronic conditions. Of the 78 studies included, 20 (26%) were preprints. Additionally, considerable diversity in the diseases studied, technologies used, and clinical contexts limits the ability to make direct comparison across studies.

This Review represents an initial effort to summarise how digital cough monitoring could enhance clinical and public health outcomes for respiratory conditions. These tools are not currently integrated into standard clinical or public health practice. Although innovation remains crucial for addressing challenges in cough detection accuracy and device ergonomics, extensive evaluation of clinical effectiveness is needed. Technological innovations have outpaced clinical validation, and reliable digital cough data are not guiding clinical decision making. Effective adoption requires both understanding end-user acceptability and conducting rigorous validation studies that provide clinicians with actionable information.

Contributors

AJZ and SGL conceived the study and interpreted the data. AJZ and GG acquired the data. AJZ, RD, PEL, VN, and SGL performed the data analysis. AJZ drafted the manuscript. RD, PEL, VN, GG, CU-G, KFC, W-JS, MP, and SGL critically reviewed the manuscript and approved the final version for publication. AJZ and SGL agreed to be accountable for all aspects of the work, ensuring that any questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. All authors had full access to all the data in the study and had final responsibility for the decision to submit for publication.

Declaration of interests

KFC received payment or honoraria from GlaxoSmithKline, Novartis, and AstraZeneca and serves on advisory boards for GlaxoSmithKline, AstraZeneca, Novartis, Roche, Merck, Trevi, Rickett-Beckinson, Nocion, and Shionogi, focusing on asthma, chronic obstructive pulmonary disease, and chronic cough. KFC also serves on the scientific advisory board of the Clean Breathing Institute supported by Haleon. PEL received an International Development Research Centre grant and is a subgrantee on household cough monitoring. All other authors declare no competing interests.

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