

Title: Feasibility and Utility of a Smartphone Application-Based Longitudinal Cough Monitoring in Chronic Cough Patients in a Real-World Setting

Seung-Eun Lee¹, Matthew Rudd², Tae-Hwa Kim¹, Ji-Yoon Oh³, Ji-Hyang Lee³, Lola Jover⁴, Peter M. Small^{4,5}, Kian Fan Chung⁶, Woo-Jung Song³

¹Department of Internal Medicine, Pusan National University School of Medicine, Pusan National University Yangsan Hospital, Yangsan, Korea.

²Department of Mathematics and Computer Science, The University of the South, Sewanee, TN, USA.

³Department of Allergy and Clinical Immunology, Asan Medical Center, University of Ulsan College of Medicine, Seoul, Korea.

⁴Hyfe Inc, Wilmington, DE, USA.

⁵Department of Global Health, University of Washington, Seattle, WA, USA.

⁶National Heart and Lung Institute, Imperial College London, London, UK.

Corresponding author

Woo-Jung Song, MD, PhD

Department of Allergy and Clinical Immunology, Asan Medical Center, University of Ulsan College of Medicine, Seoul, Korea.

E-mail: swj0126@amc.seoul.kr; Tel: +82-2-3010-3288

Short title: Feasibility of Longitudinal Monitoring of Chronic Cough

Abstract word count: 246

Manuscript word count: 2,824

Number of Tables: 5

Number of Figures: 3

Source of Funding: None

Conflict of interest: SEL, THK, JYO, JHL, and WJS declare no related financial interests. MR, LJ, and PMS are employees of Hyfe Inc. KFC has received honoraria for participating in Advisory Board meetings of Roche, Merck, Novartis, GSK, Nacion, Shionogi and Rickett-Beckinson and has also been remunerated for speaking engagements for Novartis and AZ. No authors received financial compensation for participation in this work.

Author contributions:

WJS is the full guarantor of this manuscript. SEL, PMS, KFC, and WJS contributed to the study conception and design, and data interpretation. THK, JYO, JHL, and LJ have made contributions to the data acquisition. SEL and MR performed formal analysis. SEL and WJS drafted the first version of the manuscript. PMS, KFC, and WJS supervised and revised the manuscript. All authors approved this version of the manuscript for submission.

ABSTRACT

Purpose: This study evaluated the feasibility and utility of longitudinal cough frequency monitoring with the Hyfe Cough Tracker, a mobile application equipped with cough-counting artificial intelligence algorithms, in real-world patients with chronic cough.

Methods: Patients with chronic cough (>8 weeks duration) were monitored continuously for cough frequency with the Hyfe app for at least one week. Cough was also evaluated using the Leicester Cough Questionnaire (LCQ) and daily cough severity scoring (0-10). The study analyzed adherence rate, the correlation between objective cough frequency and subjective scores, day-to-day variability, and patient experience.

Results: Of 65 subjects consecutively recruited, 43 completed the study. The median cough monitoring duration was 13.9 days, with a median adherence of 91%. Study completion was associated with baseline cough severity, and the adherence rate was higher in younger subjects. Cross-sectional correlation analyses showed modest or weak correlations between objective and subjective cough measures at the group level. However, in time-series correlation analyses, correlations between objective and subjective measures widely varied across individuals. Cough frequency had greater day-to-day variability than daily cough severity scores in most subjects. A patient experience survey found that 70% of participants found the cough monitoring helpful, 86% considered it acceptable, and 84% felt it was easy-to-use.

Conclusion: Monitoring cough frequency longitudinally for at least one week may be feasible. The substantial day-to-day variability in objective cough frequency highlights the need for continuous monitoring. Grasping the implications of daily cough variability is crucial in both clinical practice and clinical trials.

Keywords: chronic cough, cough frequency, cough monitor, patient-reported outcome

INTRODUCTION

Cough is a forced expulsive maneuver against a closed glottis and has a characteristic sound, which can be used to measure cough frequency [1]. Cough frequency counting has potential applications in epidemic surveillance, monitoring treatment response, and predicting acute exacerbations of respiratory diseases [2-10]. Cough itself can also define a disease, particularly in patients with chronic cough [11]. Objective cough frequency serves as the primary endpoint in clinical trials of antitussive drugs and in guideline decision-making for chronic cough [12-15]. VitaloJAK and the Leicester Cough Monitor (LCM) are currently the leading tools for the objective measurement of cough frequency [16,17]. However, the utility for real-time analysis is limited since counting is not automated, and recordings are mostly restricted to a 24-hour period at specific time points in research setting. Individuals with chronic cough may have substantial day-to-day variability in cough frequency [18,19].

With advances in digital technology, real-time continuous cough frequency monitoring may be realized using mobile applications with cough-counting artificial intelligence (AI) algorithms. There are several smartphone apps and wearable device technologies for cough detection [20-26]. Given that smartphones and wearable devices are widely utilized, the combination of such technologies with AI has the potential for integration into routine clinical practice for patients with chronic cough. Continuous cough monitoring may provide comprehensive information on cough patterns and changes over time.

In the present study, we hypothesized that continuous cough frequency monitoring (≥ 1 week) based on a smartphone app is feasible and useful for the clinical management of patients with chronic cough who are attending cough clinics. We utilized the Hyfe Cough Tracker smartphone application, which uses AI algorithms to measure cough frequency [6-8,27], and evaluated data for the following outcomes: i) adherence to continuous cough frequency monitoring, ii) correlations of objective cough frequency with subjective cough scores and iii) patient experience.

METHODS

Participants

Patients with chronic cough (>8 weeks in duration) were recruited consecutively from two referral clinics in South Korea. Eligible patients were 19- to 80-years-old, used a smartphone, had active coughs, and did not have any red flag signs, such as hemoptysis, severe dyspnea, fever, weight loss, peripheral edema, dysphagia, vomiting, a history of recurrent pneumonia, or a medically significant abnormal finding on physical examination or chest radiography. During the initial study visit (V1), patients' baseline clinical characteristics were evaluated, including cough duration and comorbid conditions. Participants received the usual care recommended by international and national cough guidelines [12,28]. The follow-up visit day (V2) aligned with clinical appointment schedules. The institutional review boards (IRB) of the two institutions approved the study, and all patients provided written informed consent [IRB No. 2021-1632 and IRB No. 05-2021-281].

Cough frequency monitoring

The hourly cough rate was calculated for each day throughout the monitoring period, using the Hyfe Cough Research App (Wilmington, DE, USA, <https://www.hyfeapp.com>). It is a smartphone application that measures the frequency of coughs using AI algorithms to distinguish cough sounds from ambient noise. It operates as a smartphone background application, monitors ambient sound levels, and records short snippets of "explosive" sounds (<0.5 s) [7]. The half-seconds containing at least one explosive sound are transferred to a server and analyzed on a server-based convolutional neural network (CNN) AI model, which differentiates cough sounds from non-cough sounds. The CNN model was demonstrated to have greater than 96.0% sensitivity and specificity [8,27,29].

Cough frequency monitoring set-up

At V1, participants were provided with research smartphones or were allowed to use their personal

smartphones with the application installed. Research coordinators instructed the participants on how to install and use the application. The training covered the following content: (1) the smartphone must be carried within a 1.5-m distance of the subject for cough monitoring, including during the nighttime, (2) the battery should be frequently charged to avoid complete discharge, (3) the application should be reactivated when the microphone was commandeered by another application using an audio system, and (4) the smartphone should be connected to Wi-Fi at least once every three days so that the measured cough data are automatically transmitted to the server. Participants were provided with a small pouch to carry their phone during the study period. Monitoring continued for a full 24-hour cycle, including nighttime. Instructions were also provided as a single-page leaflet. The time spent on the set-up and training was measured. Patients were not aware of cough frequency data during the monitoring period.

Subjective cough measures

At V1, the participants recorded their cough severity using the numerical rating scale (NRS) (0-10), Leicester Cough Questionnaire (LCQ), and Cough Hypersensitivity Questionnaire (CHQ). The NRS score for daily cough severity was also recorded in a paper diary every evening of the monitoring period. At the follow-up visit day (V2), the participants indicated their cough status by responding to the severity NRS and LCQ.

Adherence to continuous cough monitoring

We determined the actual recording time of the application from the monitoring record. Adherence, which indicates application usage, was defined as the percentage of actual operation to the monitoring period. For analysis, we categorized adherence as "good" ($\geq 75\%$) and "excellent" ($\geq 85\%$).

Correlations between objective cough frequency and subjective cough scores

In subjects with excellent adherence to continuous cough monitoring, the relevance of objective cough frequency was explored using correlation analyses of objective cough frequency and subjective cough scores, as indicated by cough severity NRS and LCQ scores.

Day-to-day variability of cough

The changing patterns of objective cough frequency and cough severity score were initially assessed through visual inspection of daily changes and subsequently analyzed using time-series correlation analyses. To measure day-to-day variability of objective cough frequency and cough severity score, the variance index was calculated by dividing the standard deviation by the mean daily cough frequency (or severity score) for each subject.

Patient experience survey

At V2, study participants were provided with a paper report on daily cough frequency between V1 and V2. Physicians and patients discussed the cough report and their clinical course. Then, patients were presented with 14 questions about their user experience, including the convenience, usefulness, and acceptability of the tool. Responses were recorded as answers to open-ended questions and on a 5-point Likert scale.

Statistical analysis

Descriptive data were expressed as means \pm standard deviations, medians (interquartile range [IQR]), or percentages. Subject characteristics were compared according to study completion or adherence rate. Categorical variables were analyzed using the chi-square test, and continuous variables were analyzed using the t-test, Mann-Whitney U-test, or Wilcoxon signed-rank test. The correlation between the variables was evaluated using the Spearman or Pearson correlation coefficient, depending on the variable distribution. Data were analyzed using the R software version 4.2.2 (R Core

165 Team, 2022) and the Stata/SE 17.0 software package (Stata Corporation, College Station, TX, USA). All
166 tests were two-sided, and p values were significant at <0.05 .
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RESULTS

Baseline characteristics

A total of 65 subjects with chronic cough were recruited consecutively for the study. Their median age was 47.0 years (IQR: 36.0 to 59.0), and 70.8% of them were female. The median duration of cough was 30 months (IQR: 4.0 to 120.0). Of the patients recruited, 13 missed the follow-up visit (V2). For another nine subjects, the operating time of the cough monitoring device did not align with the study period (e.g., due to delayed initiation or early termination of cough monitoring by the subjects). Therefore, 43 participants (66.2%) were deemed to have completed the study and provided reliable cough monitoring data for comprehensive quantitative analysis.

The baseline characteristics of subjects according to study completion are summarized in Table 1. Subjects who completed the study (n=43) had significantly higher baseline cough severity NRS scores. There were no significant differences in other baseline parameters, such as age, sex, body mass index, cough duration, smoking history, comorbid conditions, pulmonary function, LCQ scores, and CHQ scores. The average setup time was 191 s, and setup took longer in the group that completed the study—a median of 206.0 s (IQR: 170 to 230) vs. a median of 185 s (IQR: 170 to 191; Table 1).

Adherence to continuous cough monitoring

Adherence, defined as the percentage of actual app operation duration in relation to the monitoring period (V2-V1), was calculated in 43 subjects who completed the study (Table 2). Median cough monitoring duration, calculated based on the time elapsed between the initiation and termination of the app usage, was 13.9 days (IQR: 7.3 to 14.3). The overall adherence rate for monitoring was 91% (IQR: 74 to 100). Adherence was categorized as good ($\geq 75\%$) for 74.5% of participants (n=32) and as excellent ($\geq 85\%$) for 60.5% of participants (n=26). Table 3 compares subjects' baseline characteristics according to their adherence rate. Subjects with adherence $\geq 85\%$ (n=26) were significantly younger (median 36.5 [IQR: 29.0 to 53.0] vs. 62.0 [IQR: 47.0 to 65.0]; $p=0.001$), compared with those whose

adherence was <85% (n=17). However, there were no significant differences in hourly cough rates or in baseline cough severity NRS, CHQ, or LCQ scores. At V2, subjects with adherence \geq 85% had lower LCQ scores than did those with poor adherence, but the difference was not statistically significant (median 12.4 [IQR: 9.1 to 14.9] vs. 15.3 [IQR: 12.2 to 18.5]; $p=0.071$; Table 3).

Correlations between hourly cough rates and subjective cough scores

Correlations of continuous cough frequency with PRO scores were examined in 25 subjects with adherence \geq 85% (V1 and V2 data combined). The hourly cough rate showed a moderate correlation with the LCQ score ($r=-0.566$, $p<0.001$) and with the cough severity NRS score ($r=0.609$, $p<0.001$; Figures 1A and 1B).

Day-to-day variability of cough

Longitudinal changes in hourly cough rate and daily cough severity NRS score were plotted in Figure 2. Time-series correlations between hourly cough rate and subjective cough severity were summarized in Table 4; and the degree of correlations between objective and subjective measures varied widely between individuals, and the degree did not correlate with adherence ($r=-0.100$, $p=0.646$). The variance index of hourly cough rates was higher than that of cough severity scores in most subjects (19 of 25) (Figure 3).

Patient experience

Patient experience is summarized in Table 5. More than 80% of the participants responded that the measurement of cough frequency was important to and helpful for cough treatment. In addition, 70% responded that the monitoring was helpful, 86% reported that the tool's use was acceptable, and 84% found the app easy to use. The most common reason for characterizing the tool as unacceptable was the inconvenience of continuously carrying the device (n=14). Additional technical issues included

218 difficulty with using other audio-enabled apps simultaneously (n=3), increased battery usage (n=2),
219 and application freezing (n=2). Two subjects also expressed concern about confounding by ambient
220 noise or another person's coughs.

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DISCUSSION

In this feasibility study, we used the Hyfe Cough Tracker, a smartphone application for longitudinal monitoring of cough frequency in patients with chronic cough as they go about their daily lives. Of the 65 subjects recruited, 43 (66.2%) completed the study visits and were considered to have reliable cough frequency data suitable for full quantitative analysis. The median duration of continuous cough monitoring was 13.9 days (IQR: 7.3 to 14.3), and the adherence rate during the study period was a median of 0.93 (IQR: 0.74 to 1.0).

Very few studies have reported the feasibility and utility of monitoring cough frequency longitudinally over several days in real-world practice. In a retrospective analysis examining the feasibility of using the LCM, Vertigan and colleagues found that 75% of participants used the monitors correctly, most cough recordings (93%) were interpretable, and the set-up time was between 10 and 20 minutes, suggesting that such monitoring is potentially feasible [30]. However, this analysis was limited to only 24 hours of monitoring experience. Kuhn et. al evaluated the 7-day performance and wearability of a novel, small, wearable cough detector (SIVA-P3) in 27 patients with chronic cough [26]. Using cough epochs collected in the first 24 hours (compared against a human operator), they reported the algorithm's sensitivity and specificity to be approximately 85% and 99%, respectively. The monitor was comfortable for most participants to wear. However, the researchers did not report the feasibility and utility of continuous cough monitoring over multiple days.

In this study, of the 65 subjects recruited, only 66.2% (43 subjects) completed the study visits. Among those, 60.5% achieved an adherence rate of $\geq 85\%$. The reasons behind the relatively high rate of study incompleteness are presently ambiguous and might be diverse. In our baseline comparison, no specific characteristic linked to study incompleteness was identified. Nonetheless, given the relatively long duration of monitoring (a median of 13.9 days [IQR: 7.3 to 14.3]), the adherence rate may not be considered poor. The finding that the adherence rate was significantly associated with younger age underscores the practical challenges of implementing these technologies in current practice. We

anticipate that adherence will improve with enhanced device wearability, such as the adoption of smart watches.

We examined the correlations of objective cough frequency with subjective cough PRO scores in a group of subjects with adherence $\geq 85\%$. The cross-sectional correlations were found to be modest, which aligns with observations made for the VitaloJAK, LCM, and Hull Automatic Cough Counter [31-33]. However, upon visual inspection of longitudinal changes, it was observed that subjective daily cough scores often did not respond to changes in cough frequency in some subjects. This reaffirms the idea that cough severity might be an overarching concept that encompasses various dimensions of cough, including its frequency [34,35]. The pattern of daily changes also varied between individuals (Figure 2). In time-series correlation analyses, the degree of correlations varied widely between individuals (Table 4). Furthermore, cough frequency exhibited greater day-to-day variability compared to daily cough severity scores in most subjects (Figure 3). These findings suggest that daily cough severity scoring may not be well responsive to actual changes of daily cough frequency. Continuous measurements spanning several days or longer may be preferable to single-day measurements to address the variability of cough.

In our user experience survey, more than half of the participants responded that the measurement of cough frequency was relevant, acceptable, and easy to use. However, approximately 10 to 20% of participants responded negatively. Some respondents mentioned that they perceived low importance in measuring the frequency of coughs, primarily because the cough symptoms improved rapidly. Additionally, individuals with low adherence often expressed concerns about its usefulness and convenience. Notably, the most frequent complaint was the inconvenience of carrying the device. Additional issues included difficulty with using other audio-enabled apps, battery usage, and the application freezing. These issues indicate the need for improving the wearability of the tool or developing a dedicated unobtrusive device for long-term continuous monitoring.

The present study has several limitations. First, its aim was not validation, but to evaluate the feasibility in a routine practice setting. The accuracy has not been fully assessed, and its real-world validity requires further investigation. Second, we limited our quantitative analysis to subjects with an adherence rate $\geq 85\%$, as the cough frequency data obtained from those with poor adherence group might be unreliable. Nevertheless, there is a potential risk of selection bias that needs to be acknowledged. Third, while we confirmed that the app was active and patients received verbal and written instructions to constantly keep their phones nearby, we did not ensure the actual patient's proximity to the phone, potentially leading to some undercounting of coughs or overcounting from external sources. Although we recommended using a small pouch, the carrying method was not strictly controlled. We calculated adherence (as the percentage of actual operation per the monitoring period) to assess potential operational interruptions of the app during the study. Nevertheless, we recognize this as an indirect measure of adherence. Fourth, there might be sex differences in the manner of carrying the phone. Investigation of the impact on adherence and cough frequency is warranted. Fifth, the current version of the application relies solely on acoustic signals. Incorporating the accelerometer present in smartphones could help address the limitations of the acoustic signal-based cough counting algorithm. Finally, if other individuals coughed within the 1.5-meter operational range of the phone, their coughs could have been mistakenly attributed to the study participant. While we acknowledge these factors might contribute to the day-to-day variability of cough frequency, we also believe that there is an inherent variability that requires consideration. This suggests the need for measuring cough frequency over an extended period of several days.

Despite these limitations, this study represents the first effort to evaluate the feasibility and potential value of a smartphone application-based, longitudinal, continuous cough monitoring (for a duration of ≥ 1 week) in patients with chronic cough receiving care in the real world. The analysis of the adherence rate points to the practical challenges of implementing such technologies in current practices. However, we anticipate that adherence will improve as device wearability advances. The

296 day-to-day variability in objective cough frequency, combined with the limited responsiveness of daily
297 subjective scoring, underscores the importance of introducing continuous cough frequency
298 monitoring. Furthermore, understanding the significance of day-to-day cough variability is essential
299 for both clinical practice and in clinical trials.
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407 **Table 1.** Baseline patient characteristics according to study completion

Characteristic	Subjects who completed study protocols (n=43)	Subjects who did not complete study protocols (n=22)	P-value
Age, years [†]	47.0 [34.0 to 61.5]	46.5 [38.0 to 56.0]	0.967
Female sex (%)	33 (76.7)	13 (59.1)	0.233
BMI, kg/m ^{2†}	23.6 [22.3 to 25.9]	23.9 [22.5 to 25.6]	0.857
Cough duration, months [†]	30.0 [4.0 to 120.0]	30.0 [4.0 to 120.0]	0.819
Previous diagnosis			
Asthma, n (%)	12 (27.9)	3 (13.6)	0.327
AR or CRS, n (%)	15 (34.9)	10 (45.5)	0.576
GERD, n (%)	8 (18.6)	6 (27.3)	0.627
Hypertension, n (%)	9 (20.9)	4 (18.2)	1.000
Never smoker, n (%)	33 (76.7)	17 (77.3)	0.999
FEV1/FVC, % [†]	82.0 [78.0 to 87.0]	82.0 [75.5 to 87.5]	0.764
FEV1% of predicted [†]	90.0 [83.0 to 95.0]	92.0 [85.5 to 100.0]	0.712
FVC% of predicted [†]	89.0 [82.0 to 98.0]	98.0 [82.5 to 104.5]	0.243
Abnormal chest X-ray, n (%)	7 (20.0)	6 (28.6)	0.683
FeNO, ppb [†]	17.0 [13.0 to 30.0]	11.0 [8.0 to 19.0]	0.011
CHQ [†]	10.0 [7.5 to 12.5]	10.0 [6.0 to 11.0]	0.573
Cough severity NRS [†]	7.0 [5.0 to 7.5]	5.0 [3.0 to 6.0]	0.015
LCQ [†]	9.7 [8.0;12.7]	11.4 [9.8 to 12.6]	0.238
Set-up time, seconds [†]	206 [170 to 230]	185 [170 to 191]	0.020

408 [†]Median [IQR]; AR, allergic rhinitis; BMI, body mass index; CHQ, Cough Hypersensitivity Questionnaire;

409 CRS, chronic rhinosinusitis; FeNO, fractional exhaled nitric oxide; FEV1, forced expiratory volume in

- 410 the first second; FVC, forced vital capacity; GERD, gastroesophageal reflux disease; LCQ, Leicester
- 411 Cough Questionnaire; NRS, numeric rating scale.
- 412

413 **Table 2.** Adherence to continuous cough monitoring using the Hyfe Cough Tracker*

Subjects, n	43
Monitoring period in days, median [IQR]	13.9 [7.3 to 14.3]
Participants who continued recording for at least 5 days, n (%)	37 (86.0)
Adherence (%), median [IQR]	91 [74 to 100]
Adherence<50, n (%)	5 (11.6)
Adherence≥50, <75, n (%)	6 (14.0)
Adherence≥75, <85, n (%)	6 (14.0)
Adherence≥85, ≤100, n (%)	26 (60.5)

414 *Adherence was defined as the operation time of the application per the total expected monitoring
 415 time.

416 **Table 3.** Comparison of patient characteristics according to adherence to continuous cough
 417 monitoring

Characteristic	Adherence ≥85% (n=26)	Adherence <85% (n=17)	P-value
Age, years [†]	36.5 [29.0 to 53.0]	62.0 [47.0 to 65.0]	0.001
Female sex, n (%)	18 (69.2)	15 (88.2)	0.283
BMI, kg/m ^{2†}	24.0 [21.5 to 26.5]	23.6 [23.0 to 24.5]	0.737
Cough duration, months [†]	12.0 [2.0 to 120.0]	48.0 [10.0 to 72.0]	0.344
Previous diagnosis			
Asthma, n (%)	4 (15.4)	8 (47.1)	0.055
AR or CRS, n (%)	9 (34.6)	6 (35.3)	1.000
GERD, n (%)	6 (23.1)	2 (11.8)	0.595
Hypertension, n (%)	5 (19.2)	4 (23.5)	1.000
Never smoker, n (%)	19 (73.1)	14 (82.4)	0.060
FEV1/FVC, % [†]	84.5 [81.0 to 87.5]	79.0 [74.0 to 83.0]	0.009
FEV1% of predicted [†]	91.5 [82.0 to 98.5]	89.0 [84.0 to 94.0]	0.653
FVC% of predicted [†]	87.5 [78.0 to 100.5]	89.0 [82.0 to 95.0]	0.731
FeNO, ppb [†]	19.0 [16.0 to 31.0]	14.0 [9.0 to 25.0]	0.128
Abnormal chest X-ray, n (%)	3 (14.3)	4 (28.6)	0.546
Cough monitoring duration (days) ^{†, ††}	14.0 [10.5 to 17.0]	13.0 [7.0 to 14.0]	0.214
CHQ at V1 [†]	11.0 [8.0 to 13.0]	10.0 [6.0 to 12.0]	0.501
Cough severity NRS at V1 [†]	6.5 [4.0 to 7.0]	7.0 [5.0 to 8.0]	0.389
Cough severity NRS at V2 [†]	3.0 [2.0 to 4.0]	3.0 [1.2 to 4.0]	0.627
LCQ at V1 [†]	9.5 [7.5 to 13.0]	10.2 [9.1 to 12.5]	0.517
LCQ at V2 [†]	12.4 [9.1 to 14.9]	15.3 [12.2 to 18.5]	0.071

Hourly cough rate at V1, coughs/hour [†]	11.4 [3.4 to 27.2]	9.8 [4.4 to 12.0]	0.514
Hourly cough rate at V2, coughs/hour [†]	2.9 [0.6 to 9.4]	2.8 [0.7 to 6.0]	0.645

418 [†]Median (IQR)

419 ^{††}Cough monitoring duration (in days) was calculated based on the time between the initiation and
420 termination of app usage.

421 AR, allergic rhinitis; BMI, body mass index; CHQ, Cough Hypersensitivity Questionnaire; CRS, chronic
422 rhinosinusitis; FEV1, forced expiratory volume in the first second; FeNO, fractional exhaled nitric oxide;
423 FVC, forced vital capacity; GERD, gastroesophageal reflux disease; LCQ, Leicester Cough Questionnaire.

424

425 **Table 4.** Time-series correlations for agreement between daily cough severity scores and hourly cough
 426 rates and adherence in each subject

Subject	Spearman correlation between daily cough severity scores and hourly cough rates	Adherence for cough frequency monitoring
Case 001*	NA	1
Case 002	0.668	0.99
Case 003	0.561	1
Case 004	0.600	0.99
Case 005	-0.182	1
Case 006	0.498	1
Case 007	0.000	0.95
Case 008	-0.106	1
Case 009	0.204	1
Case 010	0.664	0.94
Case 011	-0.612	1
Case 012	0.934	0.95
Case 013	0.248	1
Case 014	0.116	1
Case 015	0.652	0.93
Case 016	-0.318	0.86
Case 017*	NA	0.89

Case 018	0.863	0.88
Case 019	0.431	0.99
Case 020	0.692	1
Case 021	-0.158	0.91
Case 022	0.783	0.96
Case 023**	NA	0.95
Case 024	0.000	0.85
Case 025	0.094	0.98
Case 026	0.630	1

427 *Standard deviations were zero.

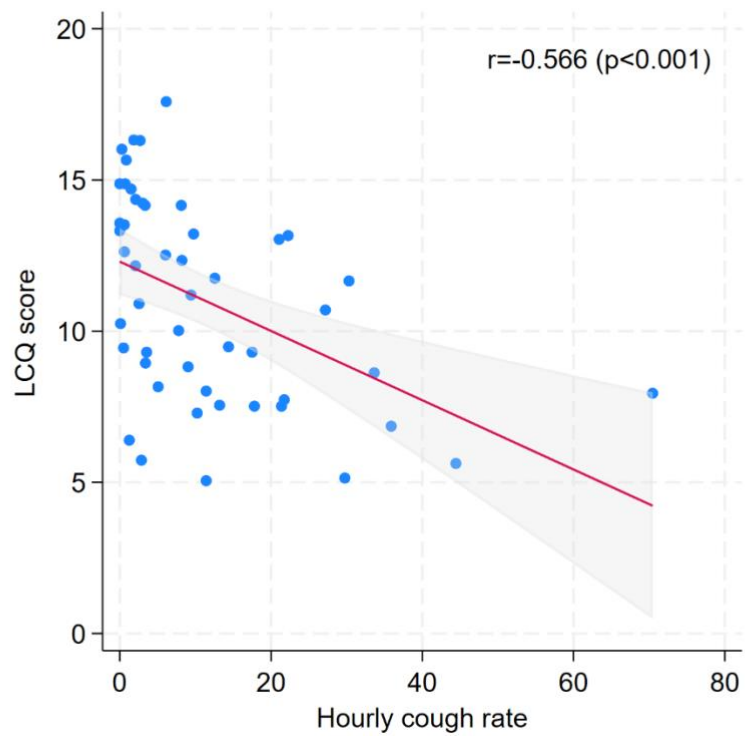
428 **Diary score was not recorded.

429 **Table 5.** User experience

Survey responses, %	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1. Monitoring cough frequency is important for cough treatment.	10	0	2	32	56
2. Monitoring cough frequency is helpful in cough treatment.	12	2	2	34	50
3. Overall, this cough monitoring tool was helpful.	16	10	4	32	38
4. This cough monitoring tool helped me identify when and how much I was coughing.	18	8	6	22	46
5. It helped me to see if my cough improved after treatment.	20	4	4	32	40
6. Overall, this cough monitoring tool was acceptable.	8	2	4	36	50
7. It was easy to learn how to use this cough monitoring tool.	6	4	0	28	62
8. This cough monitoring tool was easy to use.	6	8	2	18	66
9. It was comfortable to wear.	22	14	2	28	34
10. I wore it most of the time during the study period.	14	8	2	34	42
11. I am willing to use this cough monitoring tool in the future.	18	6	2	32	40

431 **Figure legends**

432 **Figure 1.** Spearman correlations between subjective cough scores and hourly cough rates in subjects with
433 adherence $\geq 85\%$ (n=26): Hourly cough rate compared with (A) Leicester Cough Questionnaire (LCQ) score, and
434 (B) cough severity numerical rating scale (NRS).



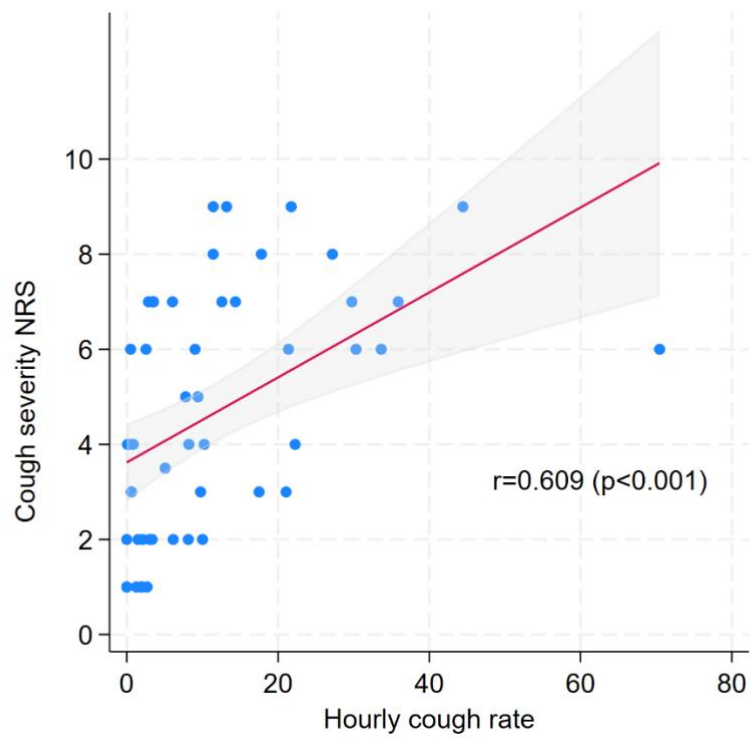
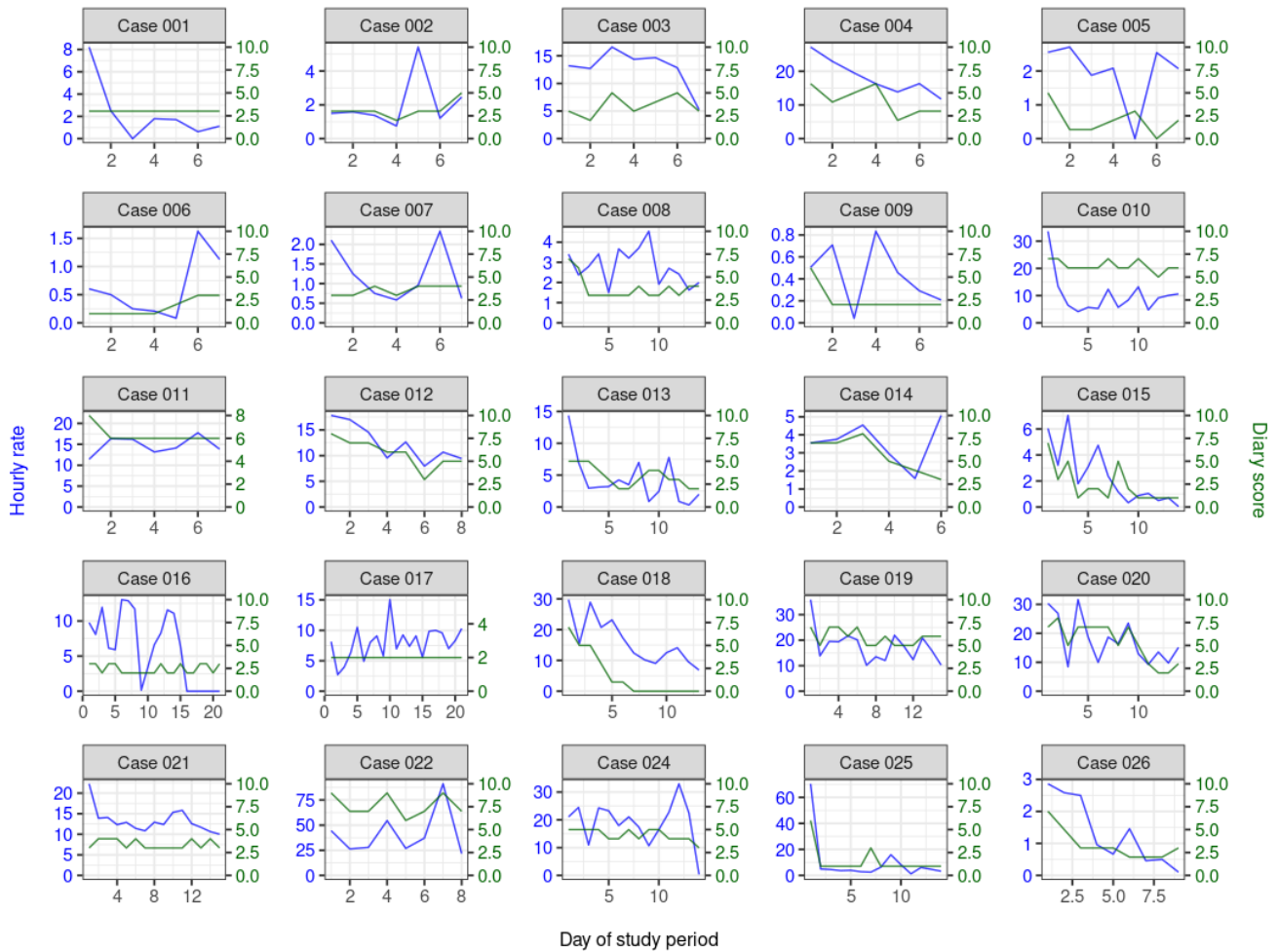
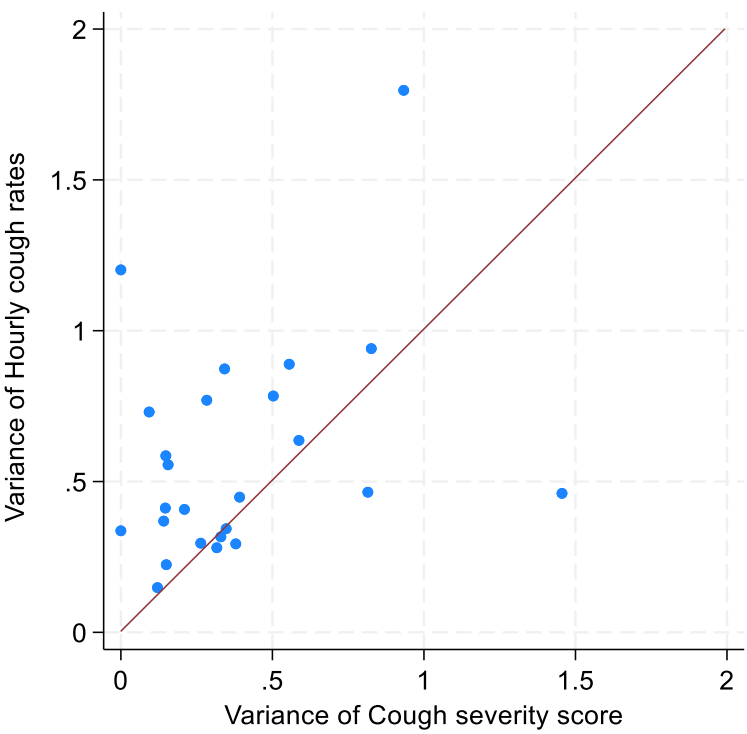


Figure 2. Longitudinal changes in hourly cough rate and daily cough severity diary score in individuals with adherence $\geq 85\%$ ($n=25$). The x-axis represents the number of days since visit 1. The left y-axis denotes the hourly cough rate for each day, while the right y-axis indicates the daily cough severity diary score.



444 **Figure 3.** Scatter plot comparing variance indices of the daily cough severity diary score and hourly cough rate
 445 in individuals with adherence $\geq 85\%$ ($n=25$). Each dot represents a subject, and the diagonal line is the reference
 446 for an equal variance (1:1) between the cough severity score and hourly cough rate.



447

448