Using an electronic diary and wristband accelerometer to detect exacerbations and activity levels in COPD: a feasibility study

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Shareable abstract (@ERSpublications)
Digital symptom and activity monitoring is feasible in COPD patients and age was not a barrier to using digital technology. Activity monitoring can be motivating for some patients. https://bit.ly/3S8aoYg

Abstract

Background Early and accurate identification of acute exacerbations of COPD may lead to earlier treatment and prevent hospital admission. Electronic diaries have been developed for symptom monitoring and accelerometers to monitor activity. However, it is unclear whether this technology is usable in the COPD population. This study aimed to assess the feasibility of an electronic diary (eDiary) for symptom reporting using the MoreCare app and activity monitoring with the Garmin Vivofit 2 in COPD.

Methods Participants were recruited from the London COPD Cohort. Participants were provided a Garmin Vivofit 2 activity monitor and an android tablet with the MoreCare app for a period of 3 months.

Results 25 COPD patients were recruited (mean±SD age 70.8±7.1 years, forced expiratory volume in 1 s (FEV_1) 49.8±14.8% predicted). Age, gender, disease severity and exacerbation frequency had no impact on eDiary compliance. There was a moderate positive correlation between median daily very active minutes and FEV_1 % pred (ρ=0.62, p=0.005). Daily step counts decreased during the initial 7 days of exacerbation and recovery compared to a pre-exacerbation baseline. A decision-tree model identified change in sputum colour, change in step count, severity of cold, exacerbation history and use of rescue medication as the most important predictors of acute exacerbations of COPD in this cohort.

Conclusions Symptom and activity monitoring using digital technology is feasible in COPD. Further large-scale digital health studies are needed to assess whether eDiaries can be used to identify patients at risk of exacerbation and guide early intervention.

Background

Acute exacerbations of COPD (AECOPD) are important outcomes as they are associated with accelerated lung function decline, impaired quality of life and increased risk of hospitalisation [1, 2]. Early treatment of AECOPD is associated with a shorter symptomatic duration and reduced risk of hospital admission [3]. Accurate and early detection of AECOPD would therefore be useful for patients and their physicians and for clinical trials. As a result, there is increasing interest in the use of machine learning to develop predictive models to identify COPD exacerbations and risk of hospital admission in COPD [4].

Advancements in digital technology have made it easy for individuals to self-monitor activity levels through wristband accelerometers such as Garmins; similarly, availability of mobile phones/tablets have supported development of electronic diaries (eDiary) to record symptoms and connect to wearable

monitoring devices. It is possible that these tools could be used to monitor for early changes in symptoms and activity for early detection of AECOPD. However, a key consideration is whether an elderly patient population, who may not be as experienced with digital tools, could successfully adopt these data capturing tools, as previous studies have shown variable compliance with activity monitoring in COPD [5, 6].

The aims of this exploratory study in COPD patients were to compare paper diary cards (pDiary) with an eDiary to assess whether it was possible to monitor patient respiratory symptoms; secondly, to evaluate whether it was feasible for a wristband accelerometer device to be used to monitor physical activity; and thirdly, to investigate whether such information could be used to develop a model to predict exacerbation onset. We report experiences and learnings from this small feasibility study to assist others in designing digital health studies.

Methods

COPD patients were recruited from the London COPD Exacerbation Cohort. The London COPD Exacerbation Cohort is a rolling cohort of 200 COPD patients who are trained to record and report respiratory symptoms to allow early detection of exacerbations, as described previously [7, 8]. All participants gave written informed consent (London-Hampstead Ethics Committee: reference 09/H0720/8). To investigate whether participants were able to use an eDiary to record exacerbation symptoms, participants were instructed to complete over 3 months an eDiary that recorded daily symptom data (graded on a 0–5 scale), medication use, hours spent outdoors and morning peak expiratory flow rate (PEFR). In addition, patients maintained their current practice of completing pDiary cards on which daily symptom data were recorded on a single A4 sheet (supplementary table E1), as described previously [1, 2]. Questions in the eDiary were derived from the pDiary, which has been used extensively in previous work investigating the impact of COPD exacerbations, but used a grading system for symptom severity (supplementary table E2) [3–5].

To assess whether a wristband accelerometer device was acceptable to COPD patients monitor physical activity, participants wore a Garmin Vivofit2 to monitor activity throughout the study and were educated on how to upload data every few days to Garmin servers *via* a cellular network-connected tablet over Bluetooth. Participants were provided with written instructions on how to use the eDiary and upload data from the Garmin. Data were extracted from Garmin *via* a Validic API and stored in the clinical study database. An exit survey was administered to participants on study completion to evaluate participants' views on the usability of the eDiary and their opinions on whether they felt the activity monitor provided useful feedback.

To characterise patients, post-bronchodilator spirometry and 6-min walk tests were performed at baseline clinic visits according to American Thoracic Society criteria. History of exacerbations over the preceding year was established according to previously defined criteria based on pDiary recorded symptoms [1, 3].

All analyses were performed in R version 3.5.3 [9]. A mixed-effects model comparing step count at baseline and exacerbation onset was fitted in lme4 with period and weekday as fixed effects and a random intercept by subject identifier [10]. A decision-tree model was trained on 401 days from six subjects with 10 exacerbations and validated on 121 days from two subjects with four exacerbations. The predictive model was built with the caret package from classification trees in rpart *via* 10 repeats of 10-fold cross-validation with synthetic minority over-sampling [11–13]. The input variables for the predictive model included three participant-level variables (gender, age and number of exacerbations in the preceding year), daily step count (from Garmin Vivofit 2), a selection of 10 daily pDiary questions and 12 daily eDiary questions. Two features were created from daily step count to capture changes within individuals. "Step count z-score" is a scaled z-score value of a given day using all preceding days of available steps per participant and "step count change" was calculated as the ratio of a given day's step count to the previous day's step count. eDiary-recorded symptoms, medication use, hours spent outdoors and morning PEFR were included as features for a given day in addition to calculating the change from the previous day. In total there were 39 input features chosen based on clinical knowledge and derived from participant-level baseline data (three features), eDiary (24 features), pDiary (10 features) and accelerometer (two features). Performance was assessed by area under the receiver operating characteristic curve (AUROC). Figures were created in ggplot2 [14].

Results

25 COPD patients were recruited: 16 males, mean±SD age 71±7.3 years. Baseline mean forced expiratory volume in 1 s (FEV$_1$) was 49.8±14.8% predicted. Participants reported a median of two (interquartile range
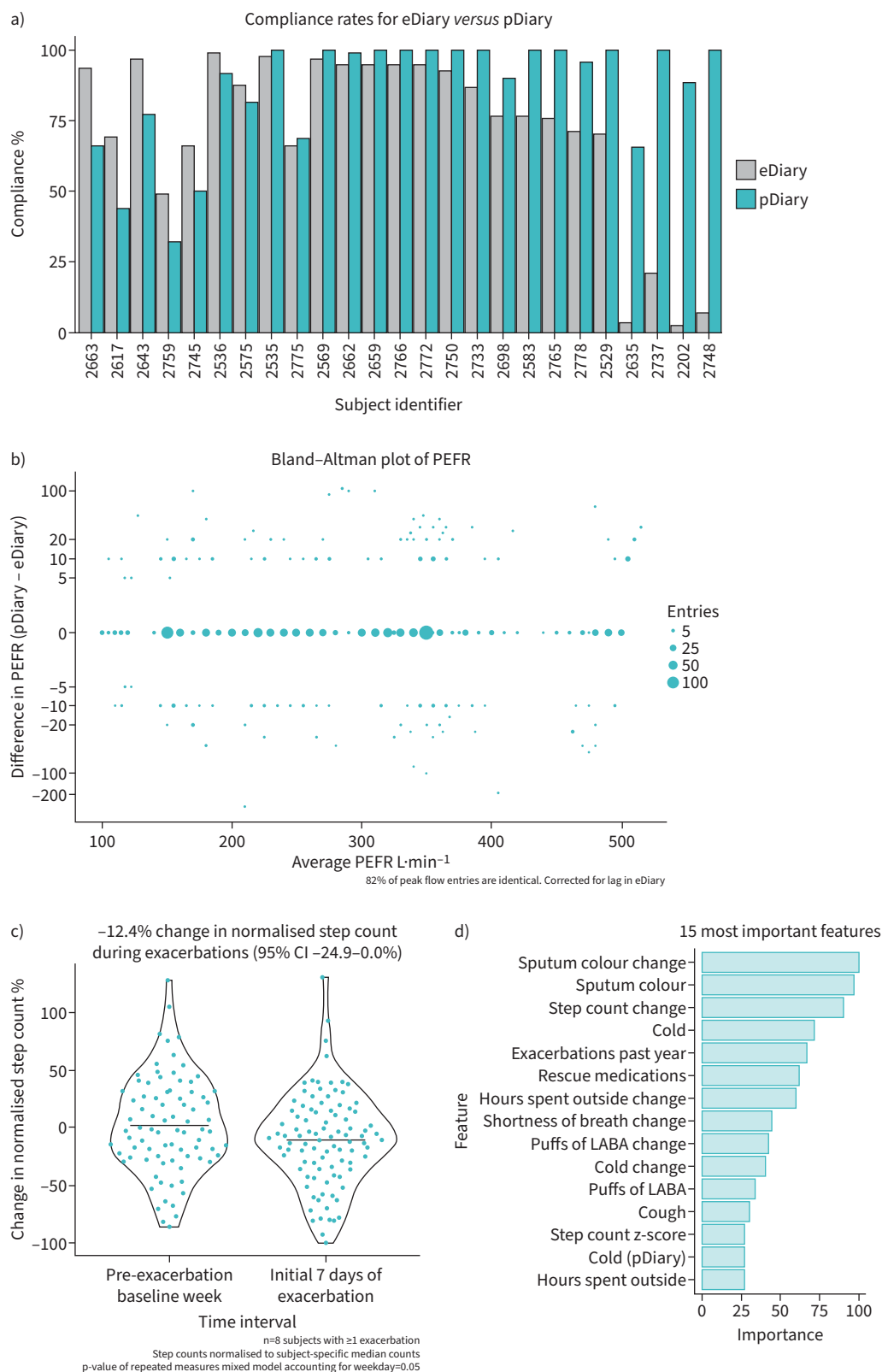
FIGURE 1 Compliance, concordance and changes before/after acute exacerbation of COPD. a) A bar plot of compliance rates for electronic diary (eDiary) and paper diary (pDiary) for each subject over the 90-day study. b) Bland–Altman plot showing peak expiratory flow rate (PEFR) recorded by pDiary *versus* eDiary. c) Dotplot with violin plot overlaid showing the change in normalised step count during an exacerbation for each subject-day during the specified interval. Bars indicate mean. d) Relative importance of the top 15 features in a predictive model of COPD exacerbation onset. Change indicates the change from the previous day. All symptoms were from the eDiary except when noted as "pDiary". LABA: long-acting β_2-agonist.

(IQR) two to three) exacerbations over the past year, and five (25%) were current smokers. The most common comorbidities were cardiovascular disease (64%), gastro-oesophageal reflux disease (32%), type II diabetes (16%), bronchiectasis (12%) and depression (12%). Participants used the eDiary for a median 91 (IQR 84–103) days. Inhaled triple therapy with long-acting β_2-agonist (LABA)/long-acting muscarinic antagonist (LAMA)/inhaled corticosteroid (ICS) was prescribed for 64% of participants, with another 12% using LABA/LAMA, 12% using ICS/LABA and 12% using LAMA monotherapy. Activity data were only available for 19 patients due to problems participants had uploading and syncing data. We observed 19 exacerbations in 15 participants during the study. Eight participants had daily activity data collected during 14 exacerbations.

Over 2250 patient days of monitoring, participants completed 1855 (82%) pDiary entries and 1593 (71%) eDiary entries. There was no significant difference in completion in favour of either pDiary or eDiary usage (p=0.09; figure 1a). When patient preference was defined by the difference in compliance between pDiary and eDiary for each subject, there was no significant effect of age, gender, FEV_1 % pred or exacerbation frequency by simple linear regression. Patients were asked to record time spent outdoors during the previous 24 h and morning PEFR on the same eDiary screen. Concordance between PEFR entries in both diaries was 82% (figure 1b).

Activity monitoring using the Garmin Vivofit 2 showed that there was large variation in daily activity of patients. Median daily active minutes for each patient ranged from 2 to 158 min per day and very active minutes from 3 to 95 min per day. Median daily step count ranged from 1617 to 16 321. There was a moderate positive correlation between median daily very active minutes and FEV_1 % pred (ρ=0.62, p=0.005). During the 14 exacerbations where activity monitoring data were available, patients experienced significant decreases in daily step counts during the initial 7 days of exacerbation and recovery compared to a pre-exacerbation baseline week commencing 2 weeks before exacerbation onset (12.4% mean decrease from baseline; p=0.05) (figure 1c). In the exit survey, 17 (71%) out of 24 patients reported finding on a five-point scale that the activity monitor was "easy" or "very easy" to use and 14 (58%) out of 24 patients found the data on activity and sleep "informative" or "very informative". The number of very active minutes was significantly greater among patients who found the activity monitor informative/very informative compared to those who did not find it informative (median difference +18 min; p=0.05).

A decision-tree model was trained to predict onset of exacerbation in the next 2 days with a balanced accuracy of 74% (AUROC=0.84) on the training data, but the performance was close to random when resampling (cross-validated AUROC=0.45) or testing on the validation data (AUROC=0.60). While the model did not generalise well, it revealed the most important predictors of AECOPD in this cohort: change in sputum colour, change in step count, severity of cold (based on the five-point scale), exacerbation history and use of rescue medication (figure 1d).

Discussion

Few studies have reported on the feasibility of using an eDiary and wrist-worn accelerometer in patients with COPD. There was good compliance in most participants with the eDiary with participants completing the diary 71% of the time, and there were no meaningful differences noted across ages or by disease status. Activity levels were greater among patients who reported activity monitoring to be informative or very informative. Daily step count measured by accelerometer decreased during AECOPD by 12% on average. In a predictive model, change in daily step count was an important predictor of onset of AECOPD along with change in sputum colour and the presence of cold symptoms. This demonstrates that not only did step count decrease during exacerbations, but that a change in step count preceded exacerbation. This is consistent with previous studies suggesting that activity monitoring may be important for prediction of exacerbation [5]. The limitations of this study were a relatively small sample size, short follow-up time and limited number of exacerbations. These limitations may restrict the generalisability of the results. Participants were required to complete both pDiaries and eDiaries which may have had an impact on adherence and also increased the number of variables incorporated into the decision-tree model. While we aimed to recruit participants across a range of socioeconomic backgrounds, this was not a primary aim of the study. Participants were provided with a tablet and Garmin rather than limiting the study to participants who already owned smartphones, which may have mitigated the impact of digital poverty. However, further work is needed to evaluate the impact of socioeconomic status on digital health in COPD.

There were some important learning points. Difficulties were encountered after a database update disrupted the tablet-to-database connection rendering the eDiary unresponsive. It is therefore recommended that in future studies remote access to devices is enabled to allow off-site repair. Some data were lost as participants struggled to upload data. These two factors may partially explain the reduced compliance to eDiary compared to the pDiary in some individuals. We would recommend that syncing with devices

should be automatic instead of requiring user action. In addition, participants in this study were familiar with pDiary card use, which may have resulted in some participants preferentially using pDiaries. Consideration should be given to the eDiary user experience as we observed that presenting two questions on the same screen referring to different recall periods led to confusion. The Vivofit 2 used proprietary algorithms for classifying levels of activity which limited access to the raw accelerometer data which otherwise might have been used to engineer additional physical activity features when predicting AECOPD. In addition, it appeared that some patients gave up using the eDiary after a week or so. This could be improved by a run-in period with an eDiary to improve selection of individuals compliant to the eDiary, or a routine follow up at 1 week to check motivation and compliance.

Conclusions

Generally, COPD patients recorded symptoms on tablets as well as on paper, and utilised the activity monitor well. Age was not an impediment to using digital technology. Activity monitoring was motivating in some cases. These findings suggest that digital symptom and activity monitoring is feasible in COPD patients. Change in sputum colour, cold symptoms and decrease in step count were important predictors of an exacerbation in this study. Further large-scale digital health studies are needed to validate these findings and assess whether these factors can be used to identify patients at risk of exacerbation and guide early intervention.

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