Automatically Explaining Machine Learning Predictions on Severe Chronic Obstructive Pulmonary Disease Exacerbations: Retrospective Cohort Study

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Abstract

Background: Chronic obstructive pulmonary disease (COPD) is a major cause of death and places a heavy burden on healthcare. To optimize the allocation of precious preventive care management resources and improve the outcomes for high-risk patients with COPD, we recently built the most accurate model to date to predict severe COPD exacerbations, which need inpatient stays or emergency department visits, in the following 12 months. Our model is a machine learning model. As is the case with most machine learning models, our model does not explain its predictions, forming a barrier for clinical use. Previously, we designed a method to automatically give rule-type explanations for machine learning predictions and suggest tailored interventions with no loss of model performance. This method has been tested on asthma outcome prediction, but not on COPD outcome prediction before.

Objective: To assess the generalizability of our automatic explanation method for predicting severe COPD exacerbations.

Methods: The patient cohort included all patients with COPD who ever visited the University of Washington Medicine facilities during 2011-2019. In a secondary analysis on 43,576 data instances, we used our formerly developed automatic explanation method to automatically explain our model’s predictions and suggest tailored interventions.

Results: Our method explained the predictions for 97.1% (100/103) of the patients with COPD whom our model correctly predicted to have severe COPD exacerbations in the following 12 months, and the predictions on 73.6% (134/182) of the patients with COPD who had ≥1 severe COPD exacerbation in the following 12 months.

Conclusions: Our automatic explanation method worked well for predicting severe COPD exacerbations. After further improving our method, we hope we can use it to facilitate future clinical use of our model.

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Keywords: Chronic obstructive pulmonary disease; forecasting; machine learning; patient care management

Introduction

Background

Chronic obstructive pulmonary disease (COPD) is a leading cause of death [1] and affects 6.5% of American adults [2]. In the United States, COPD leads to 0.7 million inpatient stays and 1.5 million emergency department (ED) visits every year [2]. Severe COPD exacerbations are exacerbations needing inpatient stays or ED visits [3]. These exacerbations often result in irreversible deterioration in health status and lung function [4-9] and account for 90.3% of America’s US $32.1 billion total annual medical cost associated with COPD [2,10]. Many of these exacerbations, which include 47% of inpatient stays and a lot of ED visits due to COPD, are regarded preventable with suitable outpatient care [3,11]. To reduce severe COPD exacerbations, many healthcare systems and health plans use predictive models to identify high-risk patients [12] for preventive care management [13]. Once a patient is enrolled in the care management program, care managers will regularly follow up with the patient on the phone to assess health status and help schedule health and related services. For patients with COPD, successful care management can cut up to 40% of their inpatient stays [14] and 27% of their ED visits [15].

As a care management program can take ≤3% of patients due to resource limits [16], the effectiveness of the program depends critically on the performance of the predictive model that is used. To optimize the allocation of precious care management resources and improve the outcomes for high-risk patients with COPD, we recently built the most accurate model to date to predict severe COPD exacerbations in the following 12 months [17]. Our model gained an area under the receiver operating characteristic curve of 0.866, a sensitivity of 56.6% (103/182), and a specificity of 91.17% (6,698/7,347). In comparison, to the best of our knowledge, each published prior model for this prediction target [18-51] had an area under the receiver operating characteristic curve of ≤0.809 and a sensitivity of <50% when the specificity was set at around 91%. Our model was based on the machine learning algorithm of extreme gradient boosting (XGBoost) [52]. As is the case with most machine learning models, our model does not explain its predictions, forming a barrier for clinical use [53]. Offering explanations is essential for care managers to make sense of and trust the model’s predictions in order to make care management enrollment decisions and identify suitable interventions. Currently, there is no consensus on what explanation means for machine learning predictions. In this paper, by explaining a prediction that a machine learning model makes on a patient, we mean finding one or more rules whose left hand sides are fulfilled by the patient and whose right hand sides are consistent with the prediction. Previously, we developed a method to automatically give rule-type explanations for any machine learning model’s predictions on tabular data and suggest tailored interventions with no loss of model performance [54-58]. This method has been tested on asthma outcome prediction, but not on COPD outcome prediction before.
Objectives

The goal of this particular study is to assess the generalizability of our automatic explanation method for predicting severe COPD exacerbations. After further improving our method in the future, our eventual goal is that care managers can use our method to make COPD care management enrollment and intervention decisions more quickly and more reliably.

Methods

Ethics approval and study design

The institutional review board of the University of Washington Medicine (UWM) approved this retrospective cohort study using administrative and clinical data.

Patient population

In Washington State, the UWM is the largest academic healthcare system. The enterprise data warehouse of the UWM contains administrative and clinical data from 12 clinics and 3 hospitals. This study used the same patient cohort from our previous predictive model paper [17]. The patient cohort included all patients with COPD who ever visited the UWM facilities during 2011-2019. As adapted from the literature [59-62], a patient was deemed to have COPD if the patient was at least 40 years old and met at least one of the following criteria:

1) The patient had “an outpatient visit diagnosis code of COPD (International Classification of Diseases, Ninth Revision (ICD-9): 491.22, 491.21, 491.9, 491.8, 493.2x, 492.8, 496; International Classification of Diseases, Tenth Revision (ICD-10): J42, J41.8, J44.*, J43.*) followed by ≥1 prescription of long-acting muscarinic antagonist (aclidinium, glycopyrrolate, tiotropium, and umclidinium) within 6 months.”
2) The patient had “≥1 ED or ≥2 outpatient visit diagnosis codes of COPD (ICD-9: 491.22, 491.21, 491.9, 491.8, 493.2x, 492.8, 496; ICD-10: J42, J41.8, J44.*, J43.*)”
3) The patient had “≥1 inpatient stay discharge having a principal diagnosis code of COPD (ICD-9: 491.22, 491.21, 491.9, 491.8, 493.2x, 492.8, 496; ICD-10: J42, J41.8, J44.*, J43.*)”
4) The patient had “≥1 inpatient stay discharge having a principal diagnosis code of respiratory failure (ICD-9: 518.82, 518.81, 799.1, 518.84; ICD-10: J96.0*, J80, J96.9*, J96.2*, R09.2) and a secondary diagnosis code of acute COPD exacerbation (ICD-9: 491.22, 491.21, 493.22, 493.21; ICD-10: J44.1, J44.0)” [17].

We used one exclusion criterion. When calculating the data instances in a given year, the patients who died or had no encounter at the UWM during that year were excluded.

Data set

This study used the same structured data set from our previous predictive model paper [17]. The data set contained the administrative and clinical data of the patient cohort’s encounters at the 12 UWM clinics and 3 UWM hospitals during 2011-2020.

Prediction target (the dependent or outcome variable)

This study used the same prediction target from our previous predictive model paper [17]. For a patient with COPD and ≥1 encounter at the UWM in a particular year (the index year), we employed the patient’s data up to the end of the year to predict the outcome – whether the patient would have ≥1 severe COPD exacerbation in the following 12 months. A severe COPD exacerbation is defined as an inpatient stay or an ED visit with a principal diagnosis of COPD (ICD-9: 491.22, 491.21, 491.9, 491.8, 493.2x, 492.8, 496; ICD-10: J42, J41.8, J44.*, J43.*).

Data pre-processing, predictive model, and features (independent variables)

We applied the same methods in our previous predictive model paper [17] to perform data pre-processing. Using the upper and lower bounds provided by a clinical expert in our team as well as the upper and lower bounds from the Guinness World Records, we pinpointed the biologically implausible values, marked them missing, and normalized each numerical feature. Our model used 229 features and the XGBoost classification algorithm [52] to make predictions. As listed in Table 2 in the online multimedia appendix of our previous paper [17], these features were calculated on the attributes in our structured data set and covered various aspects such as vital signs, diagnoses, visits, procedures, medications, laboratory tests, and patient demographics. One example feature is the number of days since the patient had the last diagnosis of acute COPD exacerbation. Each input data instance to the predictive model contained these 229 features, corresponding to a distinct (patient, index year) pair, and was used to predict the outcome of the patient in the following 12 months. As in our previous predictive model paper [17], the cutoff threshold for the binary classification was set at the top 10% of patients with the largest predicted risk. A care management program can take ≤3% of patients due to resource limits [16]. After using our model to identify the top 10% of patients with the largest predicted risk and using our automatic explanation method to explain the predictions, care managers could review patient charts, consider factors like social dimensions, and choose ≤3% of patients for care management
enrollment. The value of 10% was chosen to strike a balance between covering a large percentage of patients who would have ≥1 severe COPD exacerbation in the following 12 months and keeping the care managers’ workload manageable.

Review of our automatic explanation method

Previously, we developed a method to automatically give rule-type explanations for any machine learning model’s predictions on tabular data and suggest tailored interventions with no loss of model performance [54-58]. When creating the automatic explanation function before the prediction time, our method requires one or more experts in the function’s design team to manually provide some information, such as marking the feature-value pairs that could have a positive correlation with the bad outcome value and compiling interventions for these feature-value pair items. This can typically be done in a few man-hours. Once this information is obtained and stored in the function’s knowledge base, our method can automatically explain the machine learning model’s predictions and suggest tailored interventions at the prediction time.

Main idea

Our automatic explanation method [54-58] uses two models at the same time to separate making predictions and giving explanations. Each model plays a different role. The first model is used to predict the outcome. This model can be any model taking continuous and categorical features as its inputs and is typically chosen to be the model that performs the best at making predictions. The second model is composed of class-based association rules [63,64] mined from the training set. We use the second model to explain the first model’s predictions rather than to make predictions. After we convert each continuous feature to one or more categorical features via automatic discretization [63,65], the association rules are mined using Apriori, while other standard methods such as FP-growth could also be used [64]. Every rule shows that a feature pattern links to a value of the outcome variable in the form of

\[ p_1 \text{ AND } p_2 \text{ AND } \ldots \text{ AND } p_k \rightarrow z. \]

Here, each item \( p_i \ (1 \leq i \leq k) \) is a feature-value pair \((x, c)\) indicating that feature \( x \) has value \( c \) if \( c \) is a value or a value within \( c \) if \( c \) is a range. The values of \( k \) and \( z \) can vary by rules. For the binary classification of good versus bad outcomes, \( z \) is usually the bad outcome value. The rule indicates that a patient’s outcome tends to take value \( z \) if the patient satisfies all of \( p_1, p_2, \ldots, \) and \( p_k \). Below is an example of a rule:

- The patient’s last diagnosis of acute COPD exacerbation was from the past 81.4 days
- AND the patient’s COPD reliever prescriptions in the past year included >10 distinct medications
- \( \rightarrow \) The patient will probably have at least one severe COPD exacerbation in the following 12 months.

Mining and pruning rules

Each rule has two quality measures: commonality and confidence. For a rule

\[ p_1 \text{ AND } p_2 \text{ AND } \ldots \text{ AND } p_k \rightarrow z, \]

its commonality is defined as the percentage of data instances satisfying \( p_1, p_k, \ldots, \) and \( p_k \) among all of the data instances linked to \( z \). Its confidence is defined as the percentage of data instances linked to \( z \) among all of the data instances satisfying \( p_1, p_2, \ldots, \) and \( p_k \). The commonality measures the coverage of the rule within the context of \( z \). The confidence measures the precision of the rule.

The process of mining and pruning rules is controlled by five parameters: the number of top features that are used to form rules, the upper limit of the number of items on the left hand side of a rule, the lower limit of confidence, the lower limit of commonality, and the upper limit of the confidence difference. Our method uses rules that each contains at most the upper limit number of items on its left hand side, has a commonality that is ≥ the lower limit of commonality, and has a confidence that is ≥ the lower limit of confidence.

Our automatic explanation method is intended to be used for real-time clinical decision support. Once the first model provides its predicted outcome of a patient, we need to use the second model to give automatic explanations for the prediction quickly, ideally within a sub-second. For this purpose, we need to control the number of association rules in the second model to help reduce the overhead of retrieving and ranking the relevant rules at the prediction time. We use the following three techniques to cut the number of rules:

1. Some machine learning algorithms like XGBoost [52] automatically calculate the importance value of each feature. When the data set includes many features, we use only the top few features in the first model with the highest importance values to form rules. Usually, we set the number of top features to be used to be the maximum possible number without making the association rule mining process run out of memory.

2. A rule \( r_1 \) is dropped if there exists another rule \( r_2 \) satisfying three conditions: (a) \( r_1 \) and \( r_2 \) have the same value on their right hand sides; (b) the items on the left hand side of \( r_2 \) are a proper subset of the items on the left hand side of \( r_1 \), i.e., \( r_2 \) is more general than \( r_1 \); and (c) the confidence of \( r_2 \) is ≥ the confidence of \( r_1 \) – the upper limit of the confidence difference.
Explaining the predictions

For each patient predicted by the first model to have a bad outcome, we explain the prediction by presenting the association rules in the second model whose left hand sides the patient fulfills and whose right hand sides have the bad outcome value. The rules are sorted using the method given in our paper [57]. This method incorporates five factors into a rule scoring function striking a balance among them. These factors include confidence, commonality, the number of items on the left hand side of the rule, whether the rule is actionable, and the degree of information redundancy with the higher-ranked rules. The rules are ranked based on the computed scores in an iterative fashion. Every rule offers an explanation for why the patient is predicted to have the bad outcome. For each actionable rule that is presented, the associated interventions are shown next to it. This helps the user of the automatic explanation function pinpoint suitable interventions for the patient. Typically, the rules in the second model give common reasons for a patient to have a bad outcome. While some patients could have bad outcomes because of rare reasons not covered by these rules, the second model usually explains the majority, although not all, of the bad outcomes correctly predicted by the first model.

Parameter setting

Our model [17] used 229 features to predict a patient’s outcome. In this study, we used the top 80 features that our model ranked with the highest importance values to form association rules. Regardless of whether all 229 features or only the top 80 features were used, our model had the same area under the receiver operating characteristic curve of 0.866.

As in our prior study on automatically explaining predictions of asthma outcomes on the UWM data [55], we set the upper limit of the number of items on the left hand side of a rule to five, the lower limit of commonality to 1%, and the lower limit of confidence to 50%. The last two values are commonly used to mine association rules [63], whereas commonality is essentially support computed on all of the data instances linked to the bad outcome [54]. The first value struck a balance between the explanation power of our automatic explanation method and not making the rules too complex to understand. To set the upper limit value of the confidence difference, we plotted the number of association rules remaining from the rule pruning process versus the upper limit of the confidence difference. Our prior automatic explanation papers [54-56,58] showed that the number of remaining rules first decreased rapidly as the upper limit of the confidence difference increased, and then slowly decreased after the upper limit of the confidence difference became large enough. The upper limit value of the confidence difference was set at a point where further increase in the confidence difference has a minor impact on reducing the number of remaining rules.

Data analysis

Split of the training and test sets

We adopted the method from our previous predictive model paper [17] to split the whole data set into the training and test sets. Since the outcomes were from the following year, the data set contained 9 years of effective data (2011-2019) over the 10-year period of 2011-2020. To reflect how our predictive model and our automatic explanation method will be used in clinical practice in the future, we used the 2011-2018 data as the training set to train our model and compute the association rules used by our automatic explanation method, and the 2019 data as the test set to assess the performance of our model and our automatic explanation method.

Providing examples of automatic explanations

To give the reader a concrete feeling of the results produced by our automatic explanation method, we randomly selected three example patients from the patients who were correctly predicted by our model to have ≥1 severe COPD exacerbation in the following 12 months and for whom our automatic explanation method could offer one or more explanations. For each example patient, we list the top three explanations given by our automatic explanation method.
Performance metrics
We examined the performance of our automatic explanation method using the following performance metrics from our prior automatic explanation papers [54-56,58]. Regarding the explanation power of our automatic explanation method, a performance metric is the percentage of patients for whom our method could provide explanations among the patients with COPD who were correctly predicted by our model to have $\geq 1$ severe COPD exacerbation in the following 12 months. We assessed both the average number and the median number of (actionable) rules matching such a patient. A rule matches a patient if the patient satisfies all items on its left hand side.

As shown by our prior automatic explanation papers [54-56,58], often many rules matching a patient differ from each other by only one item on their left hand sides. In this case, the number of rules greatly exceeds the amount of non-repeated information contained in these rules. To give a comprehensive overview of the amount of information provided by the automatic explanations, we examined the distributions of 1) the number of (actionable) rules and 2) the number of unique actionable items in the rules matching a patient who was correctly predicted by our model to have $\geq 1$ severe COPD exacerbation in the following 12 months.

Results
Characteristics of our patient cohort
Each data instance corresponds to a distinct (patient, index year) pair. Tables 1 and 2 summarize the patient demographic and clinical characteristics of the data instances in the training set and in the test set, respectively. These two sets of characteristics are relatively similar to each other. In the training set, 5.66% (2,040/36,047) of data instances were related to severe COPD exacerbations in the following 12 months. In the test set, 2.42% (182/7,529) of data instances were related to severe COPD exacerbations in the following 12 months. A detailed comparison of these two sets of characteristics was given in our previous predictive model paper [17].

| Table 1. The patient demographic and clinical characteristics of the data instances in the training set. |
|---------------------------------------------------------------|
| Patient characteristic | Data instances related to no severe COPD exacerbation in the following 12 months \( (N=34,007) \), \( n \) (%) | Data instances related to severe COPD exacerbations in the following 12 months \( (N=2,040) \), \( n \) (%) | Data instances \( (N=36,047) \), \( n \) (%) |
| Sex | | | |
| Female | 14,665 (43.12) | 749 (36.72) | 15,414 (42.76) |
| Male | 19,342 (56.88) | 1,291 (63.28) | 20,633 (57.24) |
| Age | | | |
| 40 to 65 | 17,574 (51.68) | 1,219 (59.75) | 18,793 (52.13) |
| 65+ | 16,433 (48.32) | 821 (40.25) | 17,254 (47.87) |
| Race | | | |
| White | 26,117 (76.80) | 1,330 (65.20) | 27,447 (76.14) |
| Black or African American | 4,271 (12.56) | 524 (25.69) | 4,795 (13.30) |
| Asian | 1,948 (5.73) | 144 (7.06) | 2,092 (5.80) |
| American Indian or Alaska Native | 687 (2.02) | 26 (1.27) | 713 (1.98) |
| Native Hawaiian or other Pacific Islander | 176 (0.52) | 8 (0.39) | 184 (0.51) |
| Other, unknown, or not reported | 808 (2.37) | 8 (0.39) | 816 (2.27) |
| Ethnicity | | | |
| Hispanic | 804 (2.36) | 53 (2.60) | 857 (2.38) |
| Non-Hispanic | 30,644 (90.11) | 1,941 (95.15) | 32,585 (90.39) |
| Unknown or not reported | 2,559 (7.53) | 46 (2.25) | 2,605 (7.23) |
| Insurance | | | |
| Public | 27,831 (81.84) | 1,767 (86.62) | 29,598 (82.11) |
| Private | 16,679 (49.05) | 834 (40.88) | 17,513 (48.58) |
| Self-paid or charity | 1,765 (5.19) | 229 (11.23) | 1,994 (5.53) |
| Number of years since the first encounter related to COPD in the data set | | | |
| $\leq 3$ | 28,749 (84.54) | 1,566 (76.76) | 30,315 (84.10) |
| $>3$ | 5,258 (15.46) | 474 (23.24) | 5,732 (15.90) |
| Smoking status | | | |


| Current smoker                          | 15,863 (46.65) | 1,089 (53.38) | 16,952 (47.03) |
|----------------------------------------|----------------|---------------|----------------|
| Former smoker                          | 7,022 (20.65)  | 345 (16.91)   | 7,367 (20.44)  |
| Never smoker or unknown                 | 11,122 (32.70)| 606 (29.71)   | 11,728 (32.53)|

**COPD medication prescription**

| Short-acting beta-2 agonist (SABA)     | 20,865 (61.36) | 1,684 (82.55) | 22,549 (62.55) |
|----------------------------------------|----------------|---------------|----------------|
| Short-acting muscarinic antagonist (SAMA)| 8,566 (25.19) | 1,042 (51.08) | 9,608 (26.65)  |
| SABA and SAMA combination              | 6,364 (18.71)  | 810 (39.71)   | 7,174 (19.90)  |
| Long-acting beta-2 agonist (LABA)      | 8,062 (23.71)  | 842 (41.27)   | 8,904 (24.70)  |
| Long-acting muscarinic antagonist (LAMA)| 9,242 (27.18)  | 1,001 (49.07) | 10,243 (28.42) |
| LABA and LAMA combination              | 386 (1.14)     | 40 (1.96)     | 426 (1.18)     |
| Inhaled corticosteroid (ICS)           | 12,208 (35.90) | 1,119 (54.85) | 13,327 (36.97) |
| ICS and LABA combination               | 7,544 (22.18)  | 782 (38.33)   | 8,326 (23.10)  |
| ICS, LABA, and LAMA combination        | 7,174 (19.90)  | 0 (0.00)      | 7,174 (19.90)  |
| Phosphodiesterase-4 inhibitor          | 84 (0.25)      | 10 (0.49)     | 94 (0.26)      |

**Comorbidity**

| Anxiety or depression                  | 10,061 (29.59) | 725 (35.54) | 10,786 (29.92) |
|----------------------------------------|----------------|------------|---------------|
| Allergic rhinitis                      | 2,271 (6.68)   | 174 (8.53) | 2,445 (6.78)  |
| Asthma                                 | 4,377 (12.87)  | 417 (20.44) | 4,794 (13.30) |
| Diabetes                               | 7,177 (21.10)  | 446 (21.86) | 7,623 (21.15) |
| Congestive heart failure               | 5,568 (16.37)  | 495 (24.26) | 6,063 (16.82) |
| Eczema                                 | 1,460 (4.29)   | 98 (4.80)   | 1,558 (4.32)  |
| Hypertension                           | 17,211 (50.61) | 1,150 (56.37)| 18,361 (50.94)|
| Gastroesophageal reflux                | 6,655 (19.57)  | 507 (24.85) | 7,162 (19.87) |
| Ischemic heart disease                 | 6,934 (20.39)  | 486 (23.82) | 7,420 (20.58) |
| Obesity                                | 3,232 (9.50)   | 255 (12.50) | 3,487 (9.67)  |
| Lung cancer                            | 742 (2.18)     | 52 (2.55)   | 794 (2.20)    |
| Sleep apnea                            | 2,926 (8.60)   | 253 (12.40) | 3,179 (8.82)  |
| Sinusitis                              | 1,299 (3.82)   | 83 (4.07)   | 1,382 (3.83)  |

**Table 2. The patient demographic and clinical characteristics of the data instances in the test set.**

| Patient characteristic | Data instances related to no severe COPD exacerbation in the following 12 months (N=7,347), n (%) | Data instances related to severe COPD exacerbations in the following 12 months (N=182), n (%) | Data instances (N=7,529), n (%) |
|------------------------|-------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------|----------------------------------|
| **Sex**                |                                                                                                |                                                                                                |                                  |
| Female                 | 3,242 (44.13)                                                                                    | 47 (25.8)                                                                                        | 3,289 (43.68)                    |
| Male                   | 4,105 (55.87)                                                                                    | 135 (74.2)                                                                                      | 4,240 (56.32)                    |
| **Age**                |                                                                                                |                                                                                                |                                  |
| 40 to 65               | 3,324 (45.24)                                                                                    | 118 (64.8)                                                                                      | 3,442 (45.72)                    |
| 65+                    | 4,023 (54.76)                                                                                    | 64 (35.2)                                                                                      | 4,087 (54.28)                    |
| **Race**               |                                                                                                |                                                                                                |                                  |
| White                  | 5,682 (77.34)                                                                                    | 111 (61.0)                                                                                      | 5,793 (76.94)                    |
| Black or African American| 839 (11.42)                                                                                   | 57 (31.3)                                                                                        | 896 (11.90)                      |
| Asian                  | 432 (5.88)                                                                                      | 7 (3.9)                                                                                         | 439 (5.83)                       |
| American Indian or Alaska Native | 151 (2.06)                                                                                       | 5 (2.7)                                                                                         | 156 (2.07)                       |
| Native Hawaiian or other Pacific Islander | 51 (0.69)                                                                                       | 2 (1.1)                                                                                         | 53 (0.71)                        |
| Other, unknown, or not reported | 192 (2.61)                                                                                   | 0 (0.0)                                                                                         | 192 (2.55)                       |
| **Ethnicity**          |                                                                                                |                                                                                                |                                  |
| Hispanic               | 185 (2.52)                                                                                      | 3 (1.6)                                                                                         | 188 (2.50)                       |
| Non-Hispanic           | 6,909 (94.04)                                                                                    | 179 (98.4)                                                                                      | 7,088 (94.14)                    |
| Unknown or not reported| 253 (3.44)                                                                                      | 0 (0.0)                                                                                         | 253 (3.36)                       |
| **Insurance**          |                                                                                                |                                                                                                |                                  |
| Public                 | 6,722 (91.49)                                                                                    | 179 (98.4)                                                                                      | 6,901 (91.66)                    |
| Private | 4,532 (61.69) | 110 (60.4) | 4,642 (61.65) |
| Self-paid or charity | 499 (6.79) | 41 (22.5) | 540 (7.17) |

**Number of years since the first encounter related to COPD in the data set**

| ≤3 | 5,073 (69.05) | 81 (44.5) | 5,154 (68.46) |
| >3 | 2,274 (30.95) | 101 (55.5) | 2,375 (31.54) |

**Smoking status**

| Current smoker | 3,781 (51.46) | 112 (61.5) | 3,893 (51.71) |
| Former smoker | 1,242 (16.91) | 25 (13.7) | 1,267 (16.83) |
| Never smoker or unknown | 2,324 (31.63) | 45 (24.7) | 2,369 (31.47) |

**COPD medication prescription**

| Short-acting beta-2 agonist (SABA) | 4,083 (55.57) | 158 (86.8) | 4,241 (56.33) |
| Short-acting muscarinic antagonist (SAMA) | 1,134 (15.43) | 68 (37.4) | 1,202 (15.96) |
| SABA and SAMA combination | 1,694 (23.06) | 115 (63.2) | 1,809 (24.03) |
| Long-acting beta-2 agonist (LABA) | 1,683 (22.91) | 77 (42.3) | 1,760 (23.38) |
| Long-acting muscarinic antagonist (LAMA) | 1,951 (26.56) | 110 (60.4) | 2,061 (27.37) |
| LABA and LAMA combination | 388 (5.28) | 12 (6.6) | 400 (5.31) |
| Inhaled corticosteroid (ICS) | 2,537 (34.53) | 98 (53.8) | 2,635 (35.00) |
| ICS and LABA combination | 1,729 (23.53) | 75 (41.2) | 1,804 (23.96) |
| ICS, LABA, and LAMA combination | 68 (0.93) | 1 (0.5) | 69 (0.92) |
| Systemic corticosteroid | 2,282 (31.06) | 103 (56.6) | 2,385 (31.68) |
| Phosphodiesterase-4 inhibitor | 24 (0.33) | 2 (1.1) | 26 (0.35) |

**Comorbidity**

| Anxiety or depression | 2,090 (28.45) | 63 (34.6) | 2,153 (28.60) |
| Allergic rhinitis | 396 (5.39) | 14 (7.7) | 410 (5.45) |
| Asthma | 1,053 (14.33) | 43 (23.6) | 1,096 (14.56) |
| Diabetes | 1,649 (22.44) | 40 (22.0) | 1,689 (22.43) |
| Congestive heart failure | 1,369 (18.63) | 43 (23.6) | 1,412 (18.75) |
| Eczema | 247 (3.36) | 11 (6.0) | 258 (3.43) |
| Hypertension | 3,686 (50.17) | 105 (57.7) | 3,791 (50.35) |
| Gastroesophageal reflux | 1,396 (19.00) | 47 (25.8) | 1,443 (19.17) |
| Ischemic heart disease | 1,604 (21.83) | 54 (29.7) | 1,658 (22.02) |
| Obesity | 648 (8.82) | 21 (11.5) | 669 (8.89) |
| Lung cancer | 200 (2.72) | 3 (1.6) | 203 (2.70) |
| Sleep apnea | 887 (12.07) | 28 (15.4) | 915 (12.15) |
| Sinusitis | 272 (3.70) | 7 (3.8) | 279 (3.71) |

The number of association rules

![Figure 1](image-url)  
**Figure 1.** The number of remaining association rules versus the upper limit of the confidence difference.
Using the top 80 features ranked with the highest importance values in our predictive model, 7,729,134 association rules were mined from the training set. Figure 1 shows the number of remaining rules versus the upper limit of the confidence difference. The number of remaining rules first rapidly decreases as the upper limit of the confidence difference increases, and then slowly decreases after the upper limit of the confidence difference becomes ≥0.15. We set the upper limit of the confidence difference to the value of 0.15, obtaining 492,803 remaining rules. The top 80 features totally had 219 distinct feature-value pairs, 141 of which were actionable. A clinical expert on COPD (MA) in our team reviewed all distinct feature-value pairs of the top 80 features and labeled those that could have a positive correlation with severe COPD exacerbations in the following 12 months. After dropping the rules containing any other feature-value pair items, 460,592 rules were left. These rules were all actionable.

Examples of the produced automatic explanations

To give the reader a concrete feeling of the results produced by our automatic explanation method, we randomly selected three example patients from the patients who were correctly predicted by our model to have ≥1 severe COPD exacerbation in the following 12 months and for whom our automatic explanation method could offer one or more explanations. Table 3-5 show the top three explanations that our automatic explanation method gave for every example patient.

Table 3. The top 3 association rules generated for the first example patient.

| Rank | Rule | Item on the rule’s left hand side | Interpretation of the item | Interventions linked to the item |
|------|------|----------------------------------|---------------------------|---------------------------------|
| 1    | • The patient’s last diagnosis of acute COPD exacerbation was from the past 81.4 days<br>• AND the patient’s COPD reliever prescriptions in the past year included >10 distinct medications<br>→ The patient will probably have at least one severe COPD exacerbation in the following 12 months. | The patient’s last diagnosis of acute COPD exacerbation was from the past 81.4 days<br>The patient’s COPD reliever prescriptions in the past year included >10 distinct medications | Having a recent acute COPD exacerbation shows a need for better control of the disease.<br>Using many rescue medications for COPD indicates ineffective regimen, poor treatment adherence, or a poor control of the disease. | • Provide education on managing COPD and more frequent follow-ups<br>• Ensure use of appropriate COPD medications<br>• Consider flu shot, pneumonia vaccination, or smoking cessation<br>• Assess the need for pulmonary rehabilitation or home care<br>• Ensure that the patient has a primary care provider or is referred to a specialist<br>• Simplify COPD medications to once-a-day formulations or combination medications<br>• Address concerns for adverse interactions between medications<br>• Provide education on correct use of COPD medications or inhalers<br>• Consider strategies to improve medication adherence such as providing reminders for taking medications in time<br>• Medication reconciliation review by a medical doctor or a pharmacist |
| 2    | • The patient had between 8 and 19 diagnoses of acute COPD exacerbation in the past year<br>• AND the patient’s last COPD diagnosis was from the past 25.6 days<br>• AND the patient’s nebulizer medication prescriptions in the past year included >11 medications | The patient had between 8 and 19 diagnoses of acute COPD exacerbation in the past year<br>The patient’s last COPD diagnosis was from the past 25.6 days<br>The patient’s nebulizer medication | Frequently having acute COPD exacerbations shows a need for better control of the disease.<br>Having a recent COPD diagnosis associated with an ED visit or an inpatient stay indicates a poor control of the disease. | • Provide education on managing COPD and more frequent follow-ups<br>• Ensure use of appropriate COPD medications<br>• Consider flu shot, pneumonia vaccination, or smoking cessation<br>• Assess the need for pulmonary rehabilitation or home care<br>• Simplify COPD medications to once-a-day formulations or combination medications |
The patient will probably have at least one severe COPD exacerbation in the following 12 months.

Table 4. The top 3 association rules generated for the second example patient.

| Rank | Rule | Item on the rule’s left hand side | Interpretation of the item | Interventions linked to the item |
|------|------|-----------------------------------|-----------------------------|---------------------------------|
| 1    | The patient’s last diagnosis of acute COPD exacerbation | Having a recent acute COPD exacerbation shows a need for better control of the disease. | Provide education on managing COPD and more frequent follow-ups |
| 3    | The patient’s average length of an inpatient stay in the past year was between 0.61 and 7.66 days AND the patient’s last outpatient visit on COPD occurred in the past 82.4 days AND the patient’s nebulizer medication prescriptions in the past year included >11 medications AND the patient’s maximum percentage of neutrophils in the past year was >76.5% | Having a long inpatient stay can indicate that the patient has a more severe disease or comorbidities. | Provide education on managing COPD and resources for care Assess the need for home care or pulmonary rehabilitation |

References:
- Address concerns for adverse interactions between medications
- Provide education on correct use of COPD medications or inhalers
- Consider strategies to improve medication adherence such as providing reminders for taking medications in time
- Medication reconciliation review by a medical doctor or a pharmacist
- Ensure that the patient has a primary care provider
- Assess the need for home care or referral to a skilled nursing facility
- Provide education on managing COPD and resources for care
- Ensure use of appropriate COPD medications
- Provide education on managing COPD and resources for care
- Ensure use of appropriate COPD medications
- Assess the need for home care or pulmonary rehabilitation
- Simplify COPD medications to once-a-day formulations or combination medications
- Address concerns for adverse interactions between medications
- Provide education on correct use of COPD medications or inhalers
- Consider strategies to improve medication adherence such as providing reminders for taking medications in time
- Medication reconciliation review by a medical doctor or a pharmacist
- Evaluate the respiratory system, e.g., using radiographic imaging
- Consider doing diagnostic tests such as viral panel, sputum culture, or procalcitonin
- Evaluate other potential morbidities like cardiovascular disease with an electrocardiogram, an echocardiography, or laboratory tests such as brain natriuretic peptide or D-dimer
|  |  |
|---|---|
| was from the past 81.4 days | The patient had >2 ED visits in the past 6 months AND the patient’s nebulizer medication prescriptions in the past year included >11 medications → The patient will probably have at least one severe COPD exacerbation in the following 12 months. | The patient had >2 ED visits in the past 6 months Using the ED indicates a poor control of conditions or a lack of access to primary, specialty, or home care. The patient’s nebulizer medication prescriptions in the past year included >11 medications Using many medications for COPD with a nebulizer indicates ineffective regimen, poor treatment adherence, or a poor control of the disease. Using nebulizer medications could be a sign of having a mild exacerbation or more severe COPD. | Ensure use of appropriate COPD medications Consider flu shot, pneumonia vaccination, or smoking cessation Assess the need for pulmonary rehabilitation or home care Ensure that the patient has a primary care provider or is referred to a specialist |
| 2 | The patient’s maximum body mass index in the past year was <22.81 AND the patient’s last ED visit related to COPD occurred no less than 27.2 days ago and no more than 94.3 days ago AND the patient’s average length of stay of an ED visit in the past year was between 0.03 and 0.29 day AND the patient had between 2 and 4 encounters related to acute COPD exacerbation or respiratory failure in the past year → The patient will probably have at least one severe COPD exacerbation in the following 12 months. | The patient’s maximum body mass index in the past year was <22.81 Having an unintentional weight loss can indicate comorbidities or other complications, such as malnutrition or metabolic syndrome. The patient’s last ED visit related to COPD occurred no less than 27.2 days ago and no more than 94.3 days ago Having a recent ED visit related to COPD shows a need for better control of the disease. The patient’s average length of stay of an ED visit in the past year was between 0.03 and 0.29 day Using the ED indicates a poor control of conditions or a lack of access to primary, specialty, or home care. The patient had between 2 and 4 encounters related to acute COPD exacerbation or respiratory failure in the past year Frequently having acute COPD exacerbations or respiratory failures shows a need for better control of the disease. | Optimize nutritional status to address low body mass index Provide dietary education and advise appropriate exercise Provide education on managing COPD and more frequent follow-ups Ensure use of appropriate COPD medications Consider flu shot, pneumonia vaccination, or smoking cessation Assess the need for pulmonary rehabilitation or home care Ensure that the patient has a primary care provider or is referred to a specialist |
| 3 | The patient had between 3 and 5 ED visits in the past year AND the patient’s minimum peripheral capillary oxygen | The patient had between 3 and 5 ED visits in the past year Using the ED indicates a poor control of conditions or a lack of access to primary, specialty, or home care. | Provide education on managing COPD and more frequent follow-ups Ensure use of appropriate COPD medications Consider flu shot, pneumonia vaccination, or smoking cessation |
saturation (SpO2) in the past year was between 17.0% and 89.5%
- AND the patient’s maximum percentage of neutrophils in the past year was >76.5%
- AND the patient smoked >0.48 pack of cigarettes per day in the past year
→ The patient will probably have at least one severe COPD exacerbation in the following 12 months.

The patient’s minimum SpO2 in the past year was between 17.0% and 89.5%
- Having a low SpO2 indicates worsening of symptoms or other complications such as hypoxemia.

The patient’s maximum percentage of neutrophils in the past year was >76.5%
- Having a large percentage of neutrophils can indicate infections or distress.

The patient smoked >0.48 pack of cigarettes per day in the past year
- Smoking is a key risk factor for COPD complications.

Table 5. The top 3 association rules generated for the third example patient.

| Rank | Rule | Item on the rule’s left hand side | Interpretation of the item | Interventions linked to the item |
|------|------|----------------------------------|-----------------------------|----------------------------------|
| 1    | • The patient had between 24 and 49 COPD diagnoses in the past year  
• AND the patient had >11 nebulizer medication prescriptions in the past year  
• AND the patient is a Black or an African American  
• → The patient will probably have at least one severe COPD exacerbation in the following 12 months. | The patient had between 24 and 49 COPD diagnoses in the past year | Frequently receiving COPD diagnoses indicates a poor control of the disease. | • Provide education on managing COPD and more frequent follow-ups  
• Ensure use of appropriate COPD medications  
• Consider flu shot, pneumonia vaccination, or smoking cessation  
• Assess the need for pulmonary rehabilitation or home care |
|      |      | The patient had >11 nebulizer medication prescriptions in the past year | Using many medications for COPD with a nebulizer indicates ineffective regimen, poor treatment adherence, or a poor control of the disease. Using nebulizer medications could be a sign of having a mild exacerbation or more severe COPD. | • Simplify COPD medications to once-a-day formulations or combination medications  
• Address concerns for adverse interactions between medications  
• Provide education on correct use of COPD medications or inhalers  
• Consider strategies to improve medication adherence such as providing reminders for taking medications in time  
• Medication reconciliation review by a medical doctor or a pharmacist |
|      |      | The patient is a Black or an African American | Poor respiratory outcomes and low quality of life are more prevalent in Black and African American patients. | • Ensure that the patient has needed resources and access to care  
• Assess the need for social work or home care |
| 2 | **The patient’s last ED visit related to COPD occurred no less than 27.2 days ago and no more than 94.3 days ago**  
AND the patient’s COPD medication prescriptions in the past year included between 13 and 16 distinct medications  
AND the patient’s last outpatient visit on COPD occurred no less than 82.4 days ago and no more than 327.6 days ago  
AND the patient’s maximum percentage of neutrophils in the past year was >76.5%  
→ The patient will probably have at least one severe COPD exacerbation in the following 12 months. | **The patient’s last ED visit related to COPD occurred no less than 27.2 days ago and no more than 94.3 days ago**  
**The patient’s COPD medication prescriptions in the past year included between 13 and 16 distinct medications**  
**The patient’s last outpatient visit on COPD occurred no less than 82.4 days ago and no more than 327.6 days ago**  
**The patient’s maximum percentage of neutrophils in the past year was >76.5%**  
**→ The patient will probably have at least one severe COPD exacerbation in the following 12 months.** | **Having a recent ED visit related to COPD shows a need for better control of the disease.**  
**Using many COPD medications can indicate ineffective regimen, poor treatment adherence, or a poor control of the disease.**  
**If the patient’s last outpatient visit on COPD was for acute problems with COPD, it could indicate a poor control of the disease and a need for additional support to control COPD.**  
**Having a large percentage of neutrophils can indicate infections or distress.**  
**Frequently having acute COPD exacerbations shows a need for better control of the disease.** | **Provide education on managing COPD and more frequent follow-ups**  
**Ensure use of appropriate COPD medications**  
**Consider flu shot, pneumonia vaccination, or smoking cessation**  
**Assess the need for pulmonary rehabilitation or home care**  
**Ensure that the patient has a primary care provider or is referred to a specialist**  
**Provide education on managing COPD and more frequent follow-ups**  
**Ensure use of appropriate COPD medications**  
**Consider flu shot, pneumonia vaccination, or smoking cessation**  
**Assess the need for pulmonary rehabilitation or home care**  
**Ensure that the patient has a primary care provider or is referred to a specialist**  
**Provide education on managing COPD and more frequent follow-ups**  
**Ensure use of appropriate COPD medications**  
**Consider flu shot, pneumonia vaccination, or smoking cessation**  
**Assess the need for pulmonary rehabilitation or home care**  
**Ensure that the patient has a primary care provider or is referred to a specialist**  
**Provide education on managing COPD and more frequent follow-ups**  
**Ensure use of appropriate COPD medications**  
**Consider flu shot, pneumonia vaccination, or smoking cessation**  
**Assess the need for pulmonary rehabilitation or home care**  
**Ensure that the patient has a primary care provider or is referred to a specialist** | | | | |
| 3 | **The patient had between 8 and 19 diagnoses of acute COPD exacerbation in the past year**  
**AND the relative decline of the patient’s body mass index in the past year was >0.44%**  
**AND the patient’s total length of inpatient stays in the** | **The patient had between 8 and 19 diagnoses of acute COPD exacerbation in the past year**  
**The relative decline of the patient’s body mass index in the** | **Frequently having acute COPD exacerbations shows a need for better control of the disease.**  
**Having an unintentional weight loss can indicate comorbidities or other complications, such as**  
**Optimize nutritional status to address low body mass index**  
**Provide dietary education and advise appropriate exercise** | **Provide education on managing COPD and more frequent follow-ups**  
**Ensure use of appropriate COPD medications**  
**Consider flu shot, pneumonia vaccination, or smoking cessation**  
**Assess the need for pulmonary rehabilitation or home care**  
**Ensure that the patient has a primary care provider or is referred to a specialist**  
**Provide education on managing COPD and more frequent follow-ups**  
**Ensure use of appropriate COPD medications**  
**Consider flu shot, pneumonia vaccination, or smoking cessation**  
**Assess the need for pulmonary rehabilitation or home care**  
**Ensure that the patient has a primary care provider or is referred to a specialist**  
**Provide education on managing COPD and more frequent follow-ups**  
**Ensure use of appropriate COPD medications**  
**Consider flu shot, pneumonia vaccination, or smoking cessation**  
**Assess the need for pulmonary rehabilitation or home care**  
**Ensure that the patient has a primary care provider or is referred to a specialist**  
**Provide education on managing COPD and more frequent follow-ups**  
**Ensure use of appropriate COPD medications**  
**Consider flu shot, pneumonia vaccination, or smoking cessation**  
**Assess the need for pulmonary rehabilitation or home care**  
**Ensure that the patient has a primary care provider or is referred to a specialist** | | | | |
past year was >0.6 day
• The patient will probably have at least one severe COPD exacerbation in the following 12 months.

The patient’s total length of inpatient stays in the past year was >0.6 day
Having a long inpatient stay can indicate that the patient has a more severe disease or comorbidities. Having frequent inpatient stays shows a need for better control of the disease.

Performance of the automatic explanation method
Our automatic explanation method was evaluated on the test set. Our method explained the predictions for 97.1% (100/103) of the patients with COPD who were correctly predicted by our model to have severe COPD exacerbations in the following 12 months. For each such patient, our method gave an average of 13,880.19 (SD 18700.60) explanations covering 39.80 (SD 11.98) distinct actionable items, a median of 4474 explanations, and a median of 41 distinct actionable items covered by the explanations. Each explanation corresponds to one association rule.

Figure 2. The distribution of the number of actionable rules matching a patient who was correctly predicted by our model to have ≥1 severe COPD exacerbation in the following 12 months.
For the patients with COPD who were correctly predicted by our model to have severe COPD exacerbations in the following 12 months, Figure 2 shows the distribution of the number of actionable rules matching a patient. This distribution is highly skewed toward the left with a long tail. As the number of actionable rules matching a patient increases, the frequency of cases in the corresponding equi-width bucket tends to rapidly decrease in a non-monotonic way. The largest number of actionable rules matching a patient is rather large (111,062). Nevertheless, only one patient matches so many rules.

For the patients with COPD who were correctly predicted by our model to have severe COPD exacerbations in the following 12 months, Figure 3 shows the distribution of the number of unique actionable items in the rules matching a patient. The largest number of unique actionable items in the rules matching a patient is 57, much smaller than the largest number of actionable rules matching a patient. As shown in Tables 3-5, the same intervention could link to more than one distinct actionable item in the rules matching a patient.

![Figure 3](https://via.placeholder.com/150)

**Figure 3.** The distribution of the number of unique actionable items in the rules matching a patient who was correctly predicted by our model to have \( \geq 1 \) severe COPD exacerbation in the following 12 months.

Our automatic explanation method explained the predictions on 73.6% (134/182) of the patients with COPD who had \( \geq 1 \) severe COPD exacerbation in the following 12 months.

**Discussion**

**Key findings**

Our automatic explanation method generalizes well to predicting severe COPD exacerbations. Our method explained the predictions for 97.1% (100/103) of the patients with COPD who were correctly predicted by our model to have severe COPD exacerbations in the following 12 months. This percentage is comparable with the corresponding percentages of 87.6%-97.6% that we formerly obtained for explaining the predictions of asthma outcomes [54-56]. This percentage is sufficiently large for applying our automatic explanation method to routine clinical use for COPD management. After further improving the performance of our model for predicting severe COPD exacerbations and our automatic explanation method, we hope our model can be used in conjunction with our automatic explanation method to provide decision support for allocating COPD care management resources and improve outcomes.

Our automatic explanation method explained the predictions on 73.6% (134/182) of the patients with COPD who had \( \geq 1 \) severe COPD exacerbation in the following 12 months. This percentage is smaller than 97.1% (100/103), the success rate at which our method explained the predictions on the patients with COPD whom our model correctly predicted to have severe COPD exacerbations in the following 12 months. This seems likely to be due to the correlation between the prediction results of our model and the association rules. Among the patients whom our model correctly predicted to have severe COPD exacerbations in the following 12 months, many seem to be easy cases for using association rules to explain the outcomes. Among the patients who had severe COPD exacerbations but were incorrectly predicted by our model to have no severe COPD exacerbation in the following 12 months, many seem to be difficult cases for any model to correctly predict or explain the outcomes.

**Related work**

Several years ago, we designed our automatic explanation method to handle relatively balanced data and demonstrated our method on the case of predicting diagnoses of type 2 diabetes [58]. Later, other researchers demonstrated our method on several other clinical predictive modeling tasks, such as predicting lung transplantation or mortality in patients with cystic fibrosis [66] and predicting cardiac mortality in patients with cancer [67]. Recently, we extended our automatic explanation method so it
can also handle imbalanced data, where one value of the outcome variable appears much less often than another. We demonstrated our extended method on predicting hospital encounters for asthma in patients with asthma in three healthcare systems separately [54-56]. Imbalanced data also appear in the case of predicting severe COPD exacerbations, the use case of this paper.

As discussed in the reviews [68,69], other researchers have developed a variety of methods to automatically explain the predictions made by machine learning models. Many of these methods lower model performance or work for only a specific machine learning algorithm. Most of these methods provide explanations that are not of rule type. More importantly, none of these methods can automatically suggest tailored interventions, which is desired in many clinical applications. In comparison, our automatic explanation method has four properties that make it particularly suitable for providing clinical decision support: 1) it provides rule-type explanations, which are easier to understand than other kinds of explanations; 2) it works for any machine learning model on tabular data; 3) it does not lower model performance; and 4) it is the only automatic explanation method that can automatically suggest tailored interventions.

Rudin et al. [70], Ribeiro et al. [71], Rasouli et al. [72], Pastor and Baralis [73], Guidotti et al. [74], and Panigutti et al. [75] employed rules to automatically explain machine learning predictions. These rules are not known before the prediction time, making it impossible to use them to automatically suggest tailored interventions at the prediction time. Except for the case in Pastor and Baralis [73], these rules are not association rules. In comparison, our automatic explanation method mines association rules before the prediction time and uses them to automatically suggest tailored interventions at the prediction time.

Limitations

This study has five limitations that are worth to be addressed in future work.

First, this study used data from a single healthcare system. It is worth assessing our automatic explanation method’s performance for explaining the predictions on severe COPD exacerbations in other healthcare systems.

Second, this study focuses on the prediction of one outcome – whether a patient with COPD will have ≥1 severe COPD exacerbation in the following 12 months. It is worth assessing our automatic explanation method’s performance for explaining the predictions of other outcomes.

Third, our automatic explanation method currently works for explaining the predictions that traditional, non-deep learning machine learning algorithms make on tabular data. It is worth investigating extending our method to handle the predictions that deep learning models make on longitudinal data [76,77].

Fourth, we currently know no optimal way to present the automatic explanations and the automatically suggested interventions. It is worth investigating an optimal way to present this information based on user-centered design.

Fifth, researchers have assessed automatic explanations’ impact on decision making for several other applications [78-82], but not for care management before. For the automatic explanation function on predicting severe COPD exacerbations presented in this paper, it is worth assessing the impact of showing automatic explanations and automatically suggested interventions on care management enrollment and intervention decisions.

Conclusions

Our automatic explanation method generalizes well to predicting severe COPD exacerbations. After further improving the performance of our model for predicting severe COPD exacerbations and our automatic explanation method, we hope our model can be used in conjunction with our automatic explanation method to provide decision support for allocating COPD care management resources and improve outcomes.

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Authors' contributions

GL and SZ were mainly responsible for the paper. SZ conducted a literature review, did most of the data analysis, and wrote the first draft of the paper. GL conceptualized and designed the study, participated in doing data analysis, and rewrote the whole paper. MA provided clinical expertise, contributed to conceptualizing the presentation, and revised the paper.

Conflicts of interest

None declared.
Abbreviations:
COPD: chronic obstructive pulmonary disease
ED: emergency department
ICD-9: International Classification of Diseases, Ninth Revision
ICD-10: International Classification of Diseases, Tenth Revision
ICS: inhaled corticosteroid
LABA: long-acting beta-2 agonist
LAMA: long-acting muscarinic antagonist
SABA: short-acting beta-2 agonist
SAMA: short-acting muscarinic antagonist
SpO2: peripheral capillary oxygen saturation
UWM: University of Washington Medicine
XGBoost: extreme gradient boosting

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