

Differentiation of Clinical Patterns Associated With Rhinologic Disease

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Abstract

Background: Common rhinologic diagnoses have similar presentations with a varying degree of overlap. Patterns may exist within clinical data that can be useful for early diagnosis and predicting outcomes.

Objective: To explore the feasibility of artificial intelligence to differentiate patterns in patient data in order to develop clinically-meaningful diagnostic groups.

Methods: A cross-sectional study of prospectively-acquired patient data at a tertiary rhinology clinic was performed. Data extracted included objective findings on nasal endoscopy, patient reported quality of life (PRQOL) instrument ratings, peripheral eosinophil fraction, and past medical history. Unsupervised non-hierarchical cluster analysis was performed to discover patterns in the data using 22 input variables.

Results: A total of 545 patients were analyzed after application of inclusion and exclusion criteria yielding 7 unique patient clusters, highly dependent on PRQOL scores and demographics. The clusters were clinically-relevant with distinct characteristics. Chronic rhinosinusitis without nasal polyposis (CRSsNP) was associated with two clusters having low frequencies of asthma and low eosinophil fractions. Chronic rhinosinusitis with nasal polyposis (CRSwNP) was associated with high frequency of asthma, mean (standard deviation [SD]) NOSE scores of 66 (19) and SNOT-22 scores of 41 (15), and high eosinophil fractions. AR was present in multiple clusters. RARS was associated with the youngest population with mean (SD) NOSE score of 54 (23) and SNOT-22 score of 41 (19).

Conclusion: Broader consideration of initially available clinical data may improve diagnostic efficiency for rhinologic conditions without ancillary studies, using computer-driven algorithms. PRQOL scores and demographic information appeared to be useful adjuncts, with associations to diagnoses in this pilot study.

Keywords

sinusitis, allergic rhinitis, gastroesophageal reflux, cluster analysis, machine learning, artificial intelligence

Introduction

Common rhinologic disorders often share similar signs and symptoms leading to ambiguity in diagnosis and may lead to deleterious health and financial consequences. The patient reported symptoms commonly include nasal congestion, postnasal drip, facial pressure or pain, and headache. Although one or more of these symptoms are present in chronic rhinosinusitis (CRS), such symptoms can overlap with a larger differential of conditions including allergic rhinitis (AR), gastroesophageal reflux disease (GERD) or laryngopharyngeal reflux, and neurologic headache disorders.¹ The combination of vague symptoms and limited objective information (e.g., lack

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of radiographic imaging or laboratory studies) increases the diagnostic challenge of an initial clinical evaluation. In practice, empiric therapy is often employed while diagnostic results are pending. If the initial diagnosis is incorrect, this can result in direct and indirect costs that fail to address the patient's underlying condition.² The ability to predict the diagnosis early in a patient's presentation may mitigate these costs and improve overall healthcare delivery.

The use of artificial intelligence (AI) may be one method to help elucidate patterns in patient signs and symptoms at the time of the initial encounter. In recent decades there has been increasing use of AI in the field of otolaryngology as well as other medical specialties though the clinical role of such technologies is incompletely defined.³ Despite this, early investigations using artificial neural networks and unsupervised learning algorithms have shown promise in medical diagnostic applications.⁴ Clinical input variables have been used to successfully predict the diagnosis of obstructive sleep apnea (OSA) as well as coronary artery disease using artificial neural networks.^{5,6} Other authors have utilized unsupervised cluster analysis to categorize patients based on clinical variables and predict outcomes. In rhinology, patient characteristics and patient reported quality of life (PRQOL) instruments have been used to predict response to endoscopic sinus surgery for CRS and to better characterize disease endotypes and phenotypes.⁷⁻¹⁰ This method has also been used to define patterns distinguishing patients with CRS versus those with primary headache disorder.¹¹

As computing power increases, machine learning and computer-driven algorithms for diagnosis are of interest as a means to decrease healthcare costs and improve healthcare delivery. Given the nonspecific nature of rhinologic symptomatology, AI-driven diagnoses may aid in the initial evaluation of patients and help delineate ambiguous diagnoses. The aim of this exploratory cross-sectional study was to investigate the ability of unsupervised cluster analysis to define clinically meaningful diagnostic groups using initially available clinical information, including PRQOL scores and basic laboratory data, in a group of patients newly presenting to a tertiary rhinology practice. We hypothesized that given a constellation of variables, patients could be categorized to assist in prediction of the underlying rhinologic diagnosis.

Methods

Study Population and Clinical Diagnosis

A cross-sectional study was performed using prospectively-acquired clinical data from consecutive patients presenting for initial consultation at a tertiary rhinology practice between November 2015 and October

2016. Subjects were included if they presented with at least 1 cardinal symptom of CRS defined as either anterior or posterior rhinorrhea, nasal blockage or congestion, facial pressure or pain, or hyposmia.¹ Patients presenting without one of these complaints, including those with other rhinologic complaints such as epistaxis or a nasal mass, were excluded. All subjects were at least 18 years of age and had no prior sinonasal diagnosis by a rhinologist. This study was approved by the Ochsner Health System Institutional Review Board. The Strengthening the Reporting of Observational Studies in Epidemiology reporting recommendations for cross-sectional studies were used to ensure adequate reporting of findings.¹²

All subjects completed the 22-item Sinonasal Outcome Test (SNOT-22) and the Nasal Obstruction Symptom Evaluation (NOSE) surveys. Nasal endoscopy was performed on all patients and the presence of polyps were recorded. Medical history and comorbidities were also recorded using the 10th revision of the International Classification of Disease (ICD-10) codes including history of asthma, diabetes mellitus (DM), cystic fibrosis (CF), aspirin sensitivity or aspirin exacerbated respiratory disorder, tobacco use, GERD, chronic obstructive pulmonary disease (COPD), and OSA.

After review of the participants' symptoms and clinical examination findings, a diagnosis of either AR, CRS, GERD, or recurrent acute rhinosinusitis (RARS) was attributed to each patient based on accepted diagnostic standards. The diagnosis of AR was ascribed if a patient presented with symptoms of nasal congestion, rhinorrhea, nasal pruritis, or sneezing with elevation of specific IgE antibody titers to an allergen. A diagnosis of CRS was made according to criteria established by the Clinical Practice Guidelines of the American Academy of Otolaryngology–Head and Neck Surgery.¹ CRS was further categorized as CRS with nasal polyposis (CRSwNP) and CRS without nasal polyposis (CRSSNP). The diagnosis of GERD was ascribed using the guidelines suggested by the American College of Gastroenterology.¹³

Cluster Variables

The dataset consisted of 22 variables. This included two demographic variables (age and gender), seven PRQOL variables (global SNOT-22 score, SNOT-22 Rhinologic domain score, SNOT-22 Extranasal domain score, SNOT-22 Ear and Face domain score, SNOT-22 Psychologic domain score, SNOT-22 Sleep domain score, and global NOSE score), 9 comorbidity/exposure variables (history of asthma, aspirin sensitivity, OSA, CF DM, COPD, tobacco use; presence of nasal polyps; and peripheral blood eosinophil fraction), and 4 final diagnosis variables (AR, CRS, GERD, and RARS). All variables were required for inclusion in the

cluster analysis. Participants with missing data were excluded.

Statistical Analysis

All analyses were performed using RStudio Version 1.2.1335 (RStudio, Inc., Boston, MA). Due to the use of continuous and categorical variables, unsupervised non-hierarchical cluster analysis was performed using the partitioning around medoids (PAM) method. The Gower distance was used to calculate distance between objects and medoids for mixed continuous and categorical variables. Patients were clustered based on dissimilarity between the combinations of variables during the analysis. The silhouette width was calculated to determine the optimal number of clusters based on the data. Tests were performed with significance level of $\alpha = 0.05$ and any values were considered statistically significant if $P < \alpha$. Descriptive statistics were calculated for frequencies, mean and median values, standard deviation (SD), and normality test. For categorical variables, chi-square and Fisher's exact tests were used to determine P -values. Student's T-test was used for normally distributed data and Wilcoxon test and Kruskal-Wallis test for skewed data. Correlation statistics were used to test correlation between continuous and categorical variables. Once clusters were generated, differences between clusters for all predictors were tested using analysis of variance. A backward stepwise functional discriminant analysis was then performed on all predictors to identify the main cluster-defining variables.

Results

Study Population and Demographics

A total of 595 consecutive patients met inclusion criteria for the study. Of these, 50 patients were excluded due to lack of complete data, yielding 545 patients for analysis. Patient age ranged from 19 to 92 years with a mean (SD) age of 54.1 (16.3) years. The total cohort showed a slight predilection for female gender, with 312 females (57.2%), compared to 233 males (42.8%). Among included patients, 67 (12.3%) had nasal polyposis, 71 (13.0%) had asthma, 12 (2.2%) had a history of aspirin sensitivity, 119 (21.8%) had OSA, 8 (1.5%) had CF, 83 (15.2%) had DM, 25 (4.6%) had COPD, and 80 (14.7%) were current smokers. The demographics and clinical characteristics for the final cohort are given in Table 1.

Cluster Predictions

The Gower distance was used to calculate silhouette widths, with the highest width corresponding to 7 clusters. Using an input of 7 clusters, non-hierarchical cluster analysis was performed on the 22 input variables,

yielding the cluster diagram represented in Figure 1. The differences across clusters are described according to demographics, medical comorbidity, PRQOL total and individual domain scores, and final rhinologic diagnoses in Table 1. Several variables including history of aspirin sensitivity, COPD, DM, and tobacco use did not significantly differ across clusters. Discriminant analysis was performed on all 22 variables to determine which variables significantly affected cluster formation. The specific rhinologic diagnoses of AR, CRS, and RARS as well as presence of nasal polyps, SNOT-22 total score and Psychologic domain score, and patient age were the most selective variables. History of COPD and asthma were least selective.

The specific rhinologic diagnoses were associated with multiple clusters and a summary of these cluster-defining variables and associated diagnoses can be found in Tables 1 and 2. CRSsNP was present in Clusters 1, 2, and 3 and was associated with variable SNOT-22 and NOSE scores depending on demographics. Notably, men were more likely to have lower SNOT-22 and NOSE scores compared with females and females were more likely to have concomitant AR (Cluster 3) with higher PRQOL scores.

AR was present in Clusters 3, 5, and 6 and differed predominantly based on SNOT-22 scores, NOSE scores, and presence of comorbid asthma. The groups were predominantly female and the patients with concomitant asthma were more likely to have higher NOSE and SNOT-22 scores. In addition to an association with AR, Cluster 6 was highly associated with RARS and differed from Clusters 3 and 5 primarily in age, being the youngest cluster. CRSwNP was associated with Cluster 7. This cluster was predominantly male with intermediate SNOT-22 and NOSE scores and had the highest frequency of asthma compared to all clusters. Additionally, this cluster was associated with AR and patients had the highest fraction of peripheral eosinophils.

In contrast to the prior clusters, Cluster 4 was not strongly associated with rhinologic diagnoses though had the highest frequency of GERD (27.4% of patients). There was a smaller subset of patients with CRS (10.8% of patients) though there was a poor correlation between the diagnosis of CRS and GERD ($\rho = -0.36$). This group was comprised mostly of males with lower SNOT-22 scores but high NOSE scores. Additionally this group had higher rates of OSA and DM. Table 2 provides a summary of the cluster characteristics and the predicted rhinologic diagnoses for each cluster.

Discussion

In this cross-sectional exploratory study, we report the feasibility of clustering characteristics of patients based

Table 1. Baseline Characteristics and Clustering Variables.

Variable	Total	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	P
N	545	101	100	61	83	109	48	43	
Age, y (SD)	54.1 (16.3)	57.0 (18.0)	56.7 (15.3)	54.0 (14.7)	56.5 (14.4)	54.2 (16.4)	42.7 (13.8)	49.2 (16.4)	<.001
Gender									<.001
Male, N (%)	233 (42.8%)	71 (70.3%)	20 (20.0%)	10 (16.4%)	62 (74.7%)	22 (20.2%)	10 (20.8%)	38 (88.4%)	
Female, N (%)	312 (57.2%)	30 (29.7%)	80 (80.0%)	51 (83.6%)	30 (36.1%)	87 (79.8%)	38 (79.2%)	5 (11.6%)	
SNOT-22 Scores, N (SD)									
Total		19 (10)	57 (14)	62 (14)	38 (14)	32 (13)	41 (19)	41 (15)	
Rhinologic		7 (5)	16 (5)	18 (5)	10 (5)	10 (6)	11 (6)	17 (6)	
Extranasal		3 (3)	9 (4)	10 (3)	5 (4)	5 (4)	6 (3)	7 (3)	
Ear/face		3 (3)	11 (5)	12 (5)	5 (4)	5 (4)	10 (5)	7 (4)	
Psychologic		5 (4)	17 (8)	19 (7)	13 (7)	9 (7)	11 (8)	9 (6)	
Sleep		5 (4)	16 (6)	17 (5)	14 (5)	10 (6)	12 (7)	10 (5)	
NOSE Score, N (SD)		30 (19)	70 (23)	74 (19)	59 (21)	45 (23)	54 (23)	66 (19)	
Comorbidities									
Asthma, N (%)	71 (13.0%)	7 (6.9%)	8 (8.0%)	16 (26.2%)	9 (10.8%)	12 (11.0%)	4 (8.3%)	15 (34.9%)	<.001
Aspirin sensitivity, N (%)	12 (2.2%)	1 (1.0%)	3 (3.0%)	2 (3.3%)	0 (0.0%)	3 (2.8%)	0 (0.0%)	3 (6.7%)	.175
Cystic fibrosis, N (%)	8 (1.5%)	5 (5.0%)	0 (0.0%)	2 (3.3%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	1 (2.3%)	.028
COPD, N (%)	25 (4.6%)	4 (4.0%)	4 (4.0%)	5 (8.2%)	6 (7.2%)	4 (3.7%)	1 (2.1%)	1 (2.3%)	.582
Diabetes mellitus, N (%)	83 (15.2%)	15 (14.9%)	20 (20.0%)	6 (9.8%)	17 (20.4%)	20 (18.3%)	2 (4.2%)	3 (6.7%)	.051
Nasal polyps, N (%)	67 (12.3%)	10 (10.0%)	7 (7.0%)	7 (11.5%)	2 (2.4%)	1 (1.0%)	1 (2.1%)	38 (88.3%)	<.001
OSA, N (%)	119 (21.8%)	8 (7.9%)	14 (14.0%)	12 (19.7%)	63 (75.9%)	14 (12.8%)	2 (4.2%)	6 (14.0%)	<.001
Peripheral eosinophil fraction, % (SD)	3.1 (2.6)	3.1 (2.6)	2.7 (2.7)	2.5 (1.9)	3.0 (2.3)	2.9 (2.4)	2.6 (1.7)	5.6 (4.0)	<.001
Tobacco use, N (%)	80 (14.7%)	11 (10.9%)	18 (18.0%)	8 (13.1%)	14 (16.7%)	11 (10.1%)	11 (22.9%)	7 (16.3%)	.321
Diagnoses, N (%)									
CRS	259 (47.5%)	76 (75.2%)	76 (76.0%)	49 (80.3%)	9 (10.8%)	9 (8.3%)	2 (4.2%)	37 (86.0%)	<.001
AR	239 (43.9%)	10 (10.0%)	0 (0.0%)	61 (100.0%)	14 (16.9%)	83 (76.1%)	39 (81.3%)	32 (74.4%)	<.001
RARS	64 (11.7%)	5 (5.0%)	7 (7.0%)	2 (3.3%)	1 (1.2%)	0 (0.0%)	48 (100.0%)	1 (2.3%)	<.001
GERD	76 (13.9%)	9 (8.9%)	12 (12.0%)	6 (9.8%)	23 (27.7%)	21 (19.2%)	4 (8.3%)	1 (2.3%)	<.001

AR: allergic rhinitis; COPD: chronic obstructive pulmonary disease; CRS: chronic rhinosinusitis; GERD: gastroesophageal reflux disease; NOSE: Nasal Obstruction Symptom Evaluation; OSA: obstructive sleep apnea; RARS: recurrent acute rhinosinusitis; SD: standard deviation; SNOT-22: 22-item Sinonasal Outcome Test.

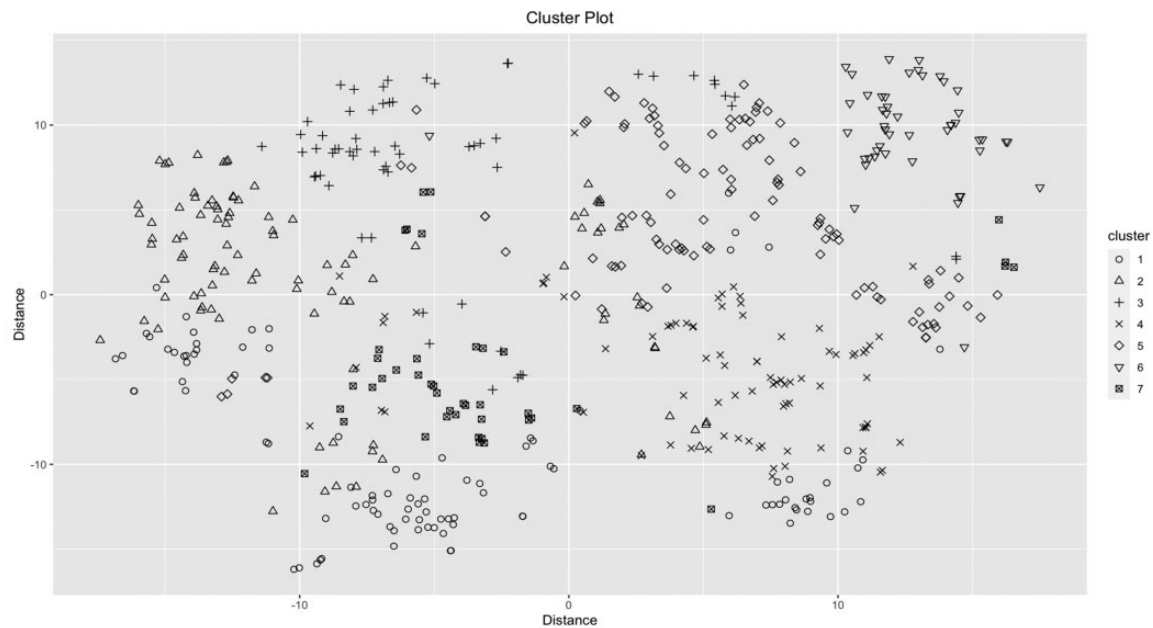


Figure 1. Cluster diagram produced by unsupervised nonhierarchical cluster analysis. The figure demonstrates the emergence of seven clusters using the Gower distance. The horizontal and vertical axes represent the distance between point in arbitrary distance units.

on readily available clinical variables at initial presentation, including demographics, medical comorbidities, SNOT-22 and NOSE scores, and endoscopic exam findings. Though the objective of this study was to assess the ability of a computer-driven model to group patients based on clinical variables, these clusters were associated with specific rhinologic diagnoses that may aid in prediction of a final diagnosis during the initial encounter. The 545 patients included in the analysis formed 7 distinct clusters using unsupervised non-hierarchical cluster analysis with patient demographics and SNOT-22 total and individual domains scores being most selective.

This study is the first to analyze undifferentiated patient populations based on minimal clinical information to discover patterns in patient characteristics associated with specific rhinologic diagnoses. Our results suggest that patients in a tertiary rhinologic practice may have key similarities and differences that separate them into several groups based on self-reported symptoms and preexisting comorbidities, which may aid in predicting diagnoses. In our study population, the identified clusters appear to delineate patients diagnosed with AR, CRS, and RARS. One cluster (Cluster 4) had a large proportion of patients with GERD; however, this was not the main cluster-defining variable making this association less clinically useful. Despite a potential link between GERD and CRS, there was not a significant proportion of patients in this group with CRS and only 1 patient had both CRS and GERD. This is an interesting finding as GERD has been associated with

increased rates of CRS recurrence.¹⁴ The clinical significance of this lack of association is unclear.

While some diagnoses were associated with a single cluster, others were associated with multiple clusters, which may represent differences in endotypes or host factors that differentiate the clusters. Clusters 1 and 2 were both associated with CRSsNP; however, the primary difference was demographics and severity of SNOT-22 and NOSE scores. This finding suggests that within a specific clinical entity there can be variation in presentation and severity of symptoms. This trend was also noted with AR as three clusters were associated with the diagnosis, encompassing a broad clinical presentation.

Additionally, the differences between clusters may be useful in determination or prediction of a specific diagnosis. For example, Clusters 2 and 3 were largely the same other than their associated rhinologic diagnosis as Cluster 2 was associated with CRSsNP and Cluster 3 was associated with AR. The largest difference between these groups was the presence of asthma, which was more prevalent in Cluster 3 suggesting that patients with high total SNOT-22 scores (between 57 and 62) are more likely to have AR when they have a concomitant diagnosis of asthma.

In the case of CRSwNP, Cluster 7 was associated with higher SNOT-22 Rhinologic domain scores and the highest eosinophil fraction on peripheral blood count. Aside from presence of nasal polyps, peripheral eosinophil fraction was the main differentiating factor between this group and the CRSsNP groups (Clusters 1, 2, and

Table 2. Cluster Analysis Description and Predictions.

Cluster	Description	Rhinologic Diagnosis
1	Male patients with low SNOT-22 and intermediate NOSE scores with low frequency of medical comorbidities. Intermediate Psychologic domain score.	CRSsNP
2	Mostly females (80.0%) with moderate to high SNOT-22 and NOSE scores. High Rhinologic, Psychologic, and Sleep domain scores. There were low frequencies of medical comorbidities.	CRSsNP
3	Mostly females (83.6%) with high total SNOT-22 and NOSE scores. Highest Ear/Face and Psychologic domain scores and high Sleep domain scores. Higher frequency of asthma and OSA. Lowest peripheral eosinophil fraction.	AR, CRSsNP
4	Oldest population of mostly males (74.7%) with intermediate SNOT-22 and NOSE scores. They have low Ear/Face domain scores and the highest Sleep domain scores. High Psychologic domain scores. Highest frequency of OSA and other comorbidities. This cluster had weak association with a diagnosis. GERD was not correlated with concomitant rhinologic disease.	GERD ^a
5	Mostly females (79.8%) with low SNOT-22 scores and intermediate NOSE scores. They have low Ear/Face domain scores and intermediate Psychologic domain scores.	AR
6	Youngest group of mostly females (79.2%) with no medical comorbidities. Intermediate SNOT-22 and NOSE scores. Intermediate SNOT-22 Rhinologic, Ear/Face, and Psychologic domain scores. There are higher rates of concomitant AR.	RARS, AR
7	Younger group of mostly males (88.4%) with intermediate total SNOT-22 and NOSE scores. High Rhinologic and Extranasal domain scores with the lowest Psychologic domain scores. High rates of concomitant asthma and highest peripheral eosinophil fraction.	AR, CRSwNP

AR: allergic rhinitis; CRSsNP: chronic rhinosinusitis without nasal polyposis; CRSwNP: chronic rhinosinusitis with nasal polyposis; DM: diabetes mellitus; GERD: gastroesophageal reflux disease; OSA: obstructive sleep apnea; RARS: recurrent acute rhinosinusitis.

^aThere was a limited association with GERD. Only present in 27.7% of patients.

3). Additionally, these patients were prone to allergies with many of them also having a diagnosis of AR. While this finding is not novel, prior research has established a link between CRSwNP, atopy, and eosinophilic inflammation, supporting the validity of our results.^{15–17} The most similar group to Cluster 7 based on PRQOL scores and demographics was Cluster 6 with the largest difference being the presence of AR and asthma. Cluster 6 was also associated with a diagnosis of RARS, suggesting that in these two groups, the lack of asthma may predict a diagnosis of RARS over CRSwNP. While the association of AR and asthma is well documented in the literature, our results also suggest an association between AR and RARS. This finding may have a biologic basis as patients with AR and RARS have been shown to exhibit increased expression of toll-like receptor 9, increasing the likelihood of recurrent infections.¹⁸

Determining patterns associated with a clinical pathology may aid in management strategies and has the potential to predict overall outcome of therapy. Prior investigation has demonstrated the utility of AI in the diagnosis of other disease states such as Alzheimer disease, lymphoma, and solid tumors, though this has not been applied to diagnosis of rhinologic conditions.^{19–21} In the setting of rhinologic complaints, even subtle differences may be valuable given the nonspecific symptoms between clinical entities and the

observation that phenotypic information does not uniformly reflect patients responses to treatment.^{22,23} While phenotypic expression is classifiable based on clinical observation, endotypes may play a larger role in treatment response and are difficult to identify early.²⁴ Management may also be complicated by host factors that may alter the response to treatment. These factors may be hidden within clinical characteristics and patient-reported symptom severity, which have been used to predict outcomes, suggesting their clinical utility in disease management.^{10,25} For instance, Rudmik et al. demonstrated through cluster analysis that patients with SNOT-22 scores greater than 30 would likely benefit from surgery leading to improved quality of life, while those with scores less than 20 had little quality of life improvement postoperatively.¹⁰ By stratifying patients based on PRQOL scores and other clinical information, improvements in treatment and outcomes may be possible.

While the clinical descriptions presented in this study are interesting, caution is advised when making interpretations from the data. The primary objective was to determine the feasibility of an AI algorithm to group patients using minimal clinical data for eventual use as a predictive model. This is demonstrated in our data; however, there are some caveats on the generalizability of the results. Namely, the current algorithm separated

patients based on 22 variables yielding 7 clusters of patients; however, there are some similarities between clusters that may necessitate further modifications before predictive modeling is possible. Furthermore, the modeling capabilities are limited to the input data and the model fidelity was not tested against another population and thus, the cluster descriptions are limited to our study population. Formal conclusions about the model predictions are not appropriate at this time; however, the clinical patterns that arise could be used to quickly narrow a differential diagnosis or direct further testing. For example, using the clinical descriptions in Table 2, a male patient with a history of OSA and a SNOT-22 score of 38 ± 14 has a low likelihood of having a rhinologic diagnosis (patient from Cluster 4) and an allergy workup and/or advanced imaging will likely not yield useful clinical information. Conversely, a young female patient with low SNOT-22 and NOSE scores and no other medical history may benefit from allergy workup or imaging study to rule out AR or RARS (patient from Cluster 5).

Though our observations corroborate many findings in the literature suggesting that the results may be valid in another independent population, this study is not without limitations. Misclassification bias is possible due to the use of past medical history for comorbidities coded in the EMR, which may have erroneously been ascribed and assigned to the patients' charts leading to altered cluster relationships. Selection bias may be present as patients were not randomly enrolled and included consecutively. Furthermore, undiagnosed comorbidities or those not provided as part of the history would not have been included. The use of SNOT-22 and NOSE surveys also poses risk for recall bias as both instruments require patients to reflect on their symptoms over the past 14 days.

In conclusion, the present study demonstrates that multifactorial clinical assessments may have a role in generating diagnostic groups among patients with rhinologic signs and symptoms. These patterns may be beneficial in determining a diagnosis based on minimal clinical information, including demographics, past medical history, and PRQOL responses. While the aim of this exploratory study was descriptive in nature, these results suggest patterns may exist that can aid in clinical decision making, expediting and improving the quality and efficiency of care. However, in order to form definitive conclusions, future investigation assessing the predictive capabilities of the model or similar methods are necessary.

Declaration of Conflicting Interests

The author(s) declared the following potential conflicts of interest with respect to the research, authorship, and/or

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