# Using machine learning for personalized prediction of revision paranasal sinus surgery

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**Abstract**

**Background:** Uncontrolled chronic rhinosinusitis (CRS) needing consideration of surgery is a growing health problem yet its risk factors at individual level are not known. Our aim was to examine risk factors of revision endoscopic sinus surgery (ESS) at the individual level by using artificial intelligence. **Methods:** Demographic and visit variables were collected from electronic health records (EHR) of 790 operated CRS patients. The effect of variables on the prediction accuracy of revision ESS was examined at the individual level via machine learning models. **Results:** Revision ESS was performed to 114 (14.7%) CRS patients. The logistic regression, gradient boosting and random forest classifiers had similar performance (AUC values .746, .745 and .747, respectively) for predicting revision ESS. The best performance was yielded by using logistic regression and long predictor data retrieval time (AUC .809, precision 36%, sensitivity 70%) as compared with data collection time from baseline visit until 0, 3 and 6 months after the baseline ESS (AUC values .668, .717 and .746, respectively). The number of visits, number of days from the baseline visit to the baseline ESS, age, CRS with nasal polyps (CRSwNP), asthma, NERD and immunodeficiency or its suspicion were associated with revision ESS. Age and the number of visits before baseline ESS had non-linear effects for the predictions. **Conclusions:** Intelligent data analysis found important predictors of revision ESS at the individual level, such as visit frequency, age, Type 2 high diseases and immunodeficiency or its suspicion.

**Running title:**

Machine learning for prediction of revision paranasal sinus surgery

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**Keywords:** chronic rhinosinusitis, endoscopic sinus surgery, machine learning, personalized prediction, revision surgery

*Abbreviations used*

| | |
|---|---|
| AUC | Area Under Curve |
| CRS | Chronic rhinosinusitis |
| CRSwNP | Chronic rhinosinusitis with nasal polyps |
| ERH | Electronic health records |
| ESS | Endoscopic sinus surgery |
| PDP | Partially dependence plots |
| ROC | Receiver operator characteristic |
| SFS | Sequential forward selection |
| SHAP | Shapley values |

## Introduction

Chronic rhinosinusitis (CRS) is a symptomatic inflammatory disease of the nasal and paranasal mucosalasting more than 12 weeks[1]. It has a prevalence of about 11% and a remarkable impact on health and costs[1]. The main phenotypes are CRS with nasal polyps (CRSwNP) and without (CRSsNP)[1-3]. The majority of western CRS cases are characterized by type 2 -high inflammation with elevated levels of eosinophils, interleukin-4 (IL-4), IL-5 and IL-13[1]. Endoscopic sinus surgery (ESS) has shown to be cost-effective treatment[4], if conservative therapy (such as intranasal corticosteroids and nasal saline irrigation) is insufficient[1]. About a sixth of patients respond unsatisfactory to initial ESS and require revision ESS[1].

Early identification of the risk of CRS recurrence after ESS is cost-effective[5,6]. It helps target treatment correctly[39] and prevent permanent tissue changes[1]. A substantial number of studies have identified risk factors of revision ESS[7–15]. The studies vary according to sample sizes (n=66[15] or n=61000[9]), variable collection (large retrospective data base[9] or prospective questionnaires[8]) or geographic locations (such as US[9], Australia[16] or Finland[7]). The commonly recognized risk factors include nasal polyps, asthma, allergy, non-steroidal anti-inflammatory drug (NSAID), exacerbated respiratory disease (NERD) and previous ESS. In a meta-analysis[13], the strongest predictors of revision ESS were allergic fungal rhinosinusitis, NERD, asthma, prior polypectomy. However, no prior research has analysed the prediction accuracy of revision ESS at the individual level or for variables having a non-linear association.

The aim of this study was to examine accuracy of personalized prediction of revision ESS, and to identify most important predictor variables via modern machine learning algorithms.

## Methods

### Patients

This study was carried out of the rhinitis or rhinosinusitis patients visiting Departments of Otorhinolaryngology at the Hospital District of Helsinki and Uusimaa (HUS), Finland. The study (nro 31/13/03/00/2015) was approved by the ethical committee of the Hospital District. Ethics committee provided an approval that there was no need for written informed consent for this retrospective follow-up study.

The inclusion criterion of the initial patient population (n = 5080) was the ICD-10 diagnosis of J30., J31., J32., J33. or J01 registered in outpatient visits for the years 2005, 2007, 2009, 2011 or 2013. Longitudinal data of random patient samples were collected from electronic health records (EHR), so that the sample size was the same for each sampling year and each month of the sampling year. The last data collection day of the follow-up data was 31.9.2019. CRS was defined as having the diagnosis codes of J33. and/or J32. ESS was defined by the operation codes (Table S2). The baseline visit was defined as the first visit, and baseline ESS was the first ESS, found in the EHR at the given sampling time. Revision ESS was defined as ESS that was performed after the baseline ESS during the follow-up.

A total of 114/790 (14.7%) CRS patients underwent revision ESS in (mean±stdev) 30.3±31.0 months after the baseline ESS (Figure S3A, Table S4). Of the revised patients 91 had one revision ESS and 23 patients had two or more revisions (Figure S3B).

### Variables

The patient variables (Table 1) were processed both from the structured and coded EHR data (visits, procedure codes and diagnoses of the patients) and free clinical texts (diagnoses and comorbidities, Figure S2, Table S1). Comorbidity-related variables were obtained from ICD-10 codes (Table S3) and by using validated keyword-based information extraction from free clinical texts (Please see further methods in this article's supporting information). For asthma we used ICD-10 codes J45., which is doctor-diagnosed lung-function test -confirmed asthma. NERD diagnosis was obtained from EHR text and was based on typical history of airway symptoms after ingestion of NSAID ± challenge test confirmation of NERD.

### Machine learning algorithms

Univariate logistic regression models were used to study the prediction accuracy of individual variables. Predictive performance was compared between three classifiers: random forest, logistic regression and extreme gradient boosting. The effect of variable collection time on predictive performance was studied by using logistic regression classifier. Shapley values (SHAP)[17] were used to rank the important variables for the trained classifier. Partially dependence plots (PDP)[18] were used to explore how the predictions of the trained classifier partially depend on the values of variables (Please see further methods in this article's supporting information).

**Results**

The CRS patient population who underwent baseline ESS (n=790) consisted of 460 (58%) females, and the age ranged from 6 to 90 years. The following comorbidities were significantly associated with the group who underwent revision ESS in the follow-up: doctor-diagnosed lung-function test -confirmed asthma, CRSwNP, allergy, chronic respiratory disease, and EHR text -based NERD and immunodeficiency or its suspicion (Table 1). The following continuous variables were significantly associated with revision ESS: higher age, shorter time from the baseline visit to the baseline ESS, higher visit frequency between the baseline visit to the baseline ESS and higher number of visits from the baseline ESS to 3 months postoperatively, 6 months postoperatively and 12 months postoperatively (Table 1).

**Univariate analyses**

The variables were entered in univariate logistic regression classifier to predict revision ESS after baseline ESS. Of the continuous variables, the highest AUC values were for the number of visits 12, 6, and 3 months after the baseline visit (AUC = .76, .69, .65, respectively, Table 2). The next highest AUC values were for the time between baseline visit and baseline ESS (AUC = .59) and, visit frequency from baseline visit to baseline ESS (AUC = .59). Of the categorical variables, the highest AUC values were for CRSwNP (AUC = .65), asthma (AUC = .65), immunodeficiency or its suspicion (AUC = .61), allergy (AUC = .61) and NERD (AUC = .60). The coefficients of the continuous variables were positive with one exception, which indicated that a higher visit number/frequency and, a shorter time between baseline visit and baseline ESS, increased revision ESS probability (Table 2)

**Machine learning classifier comparison**

We next applied sequential forward selection (SFS) method to select variables collected from the baseline visit until 6 months after the baseline ESS for the three classifiers: random forest, logistic regression and gradient boosting. The AUC values and F1-score values of the trained classifiers were averages from 10 reformations of training and test folds (Figure S1A). Performance values first increased fast and then reached the plateau as a function of the number of variables (Figure 1, Tables S5, S6). For the logistic regression classifier the highest average AUC (.746) and the highest F1-score (.404) were achieved with six and eleven variables, respectively. For the gradient boosting classifier the highest AUC (.745) was with twelve variables and F1-score (.407) was with three variables. For the random forest classifier the highest AUC (.747) was with fifteen and F1-score (.409) was with twelve variables.

The best variable selected by SFS (e.g. with highest AUC) of each run was given 15 points, the next best variable 14 points, and so on. A rank score (varying between 0-150 points) was formed from the sum of the points for each variable (see Eq. S1, in this article's supporting information) after 10 reformations of training and test folds. When using any of the three classifiers, the following variables had the highest rank scores and were thus the most important predictors: the number of visits 6 months after the baseline ESS, CRSwNP, NERD and asthma (Table 3). When using the logistic regression classifier, the visit frequency from baseline visit to baseline ESS and, the time between baseline visit and baseline ESS were also important (Table 3).

**Effect of the data collection time**

We examined the effect of the length of data collection time on the model's ability to predict revision ESS risk by using only Logistic Regression model (Figure 2), because the three classifiers performed with a similar pattern and with a fair discrimination ability (the highest AUC values between 0.7-0.8, see Figure 1). We

found that the highest AUC value was obtained when the variable data were collected from the baseline visit until 12 months after the baseline ESS (.81, Figure 2, Table S7), as compared with data collection time from baseline visit until 0, 3 and 6 months after the baseline ESS.

**Interpretability analysis**

Logistic regression classifier is linear and thus not able to model possible non-monotonic relations between predictors and outcome. Random forest and gradient boosting classifiers are able model complex, non-monotonous relations, but they are so called black box models which means non-interpretable classifiers. Relations between inputs and output are difficult to understand directly from the parameters or structure of trained model. Hence, SHAP values and PDP plots were used to conduct post-hoc interpretability analysis for the random forest classifier. SHAP values enable to calculate exactly for the tree classifiers (such as random forest) by using the mature treeSHAP method[17].

We performed data flow (Figure S1B) to train the random forest classifier and calculated SHAP values of the variables collected from the baseline visit until 6 months after the baseline ESS. Figure 3 shows variables sorted by the highest sum of absolute SHAP values over all patients. The distributions of the data points on the plots show the impacts of each variable for the classifier output. We detected that high number of visits after baseline ESS and short time between baseline visit and baseline ESS both increased the revision ESS risk. In addition, CRSwNP, asthma and NERD increased revision ESS risk. SHAP values show that the age of patients and the visit frequency from baseline visit to baseline ESS affected revision ESS risk in a non-monotonic way. That is, the red values (the higher than the average values) of these variables are dispersed on both sides of the scale (Figure 3).

We formed PDP plots of the ten variables with the highest SHAP values. The plots of the following variables showed a large risk score scale for a revision ESS: the number of visits 6 (or 3) months after the baseline ESS, the time between baseline visit and baseline ESS, age, the number of visits between baseline visit and baseline ESS, CRSwNP and asthma. The average predicted risk score varied more than .02 units between the low and high value of these predictors, whereas for the other predictors the PDP risk score varied less than .02 units (Figure S4). The PDP plot of the number of visits 6 months after the baseline ESS, showed a large scale of the risk score ranging from value of .1 for patients with less than two visits after baseline ESS, up to a value of about .35 for patients with more than seven visits (Figure S4A). Similarly, if patient had two or more postoperative visits within the 3 months, the risk score for revision ESS increased (Figure S4D). The plot of the time between baseline visit and baseline ESS showed a sharp drop of the risk score after about 100 days (Figure S4F). When the time between baseline visit and ESS was less than 100 days, the risk score was about .15. When the time increases to $>$ 500 days, the risk score decreases to $<$ .13. The PDP curve for age was non-monotonic and the risk scores varied from .1 for patients with age from 10-30 years, to about .17 for patients with age from 60-70 years (Figure S4E). The risk scores were .13- .15 for patients with age from 30-60 or over 70 years. The number of visits between baseline visit and baseline ESS was non-monotonic. The patients with 10-20 visits between the baseline visit and baseline ESS had smaller risk for revision ESS than the patients with less than 10 or more than 20 visits (Figure S4I).

**Discussion**

This study was carried out to evaluate the personalized risk factors of revision ESS for CRS patients. By using machine learning algorithms we discovered novel, previously unpublished, important variables predicting revision ESS, such as high number of visits before and after the baseline ESS and, short time between the baseline visit and baseline ESS. Our data also demonstrated that demographic variables of age, Type 2 high diseases (CRSwNP, asthma, NERD) and immunodeficiency or its suspicion, were important predictors of revision ESS at the individual level, which is in line to previous observations at the population level[19].

None of the previous studies have presented models designed to predict revision ESS at the individual level and for non-linear predictors. Success rate for initial ESS range from 76% to 98%[20,21]. Revision ESS risk has previously been studied at the population level by using such as Cox's proportional hazard[7,9,10] or logistic regression[8,9,12,14] models, which usually assume that associations are linear and that an alpha error $<$ 5%

indicates importance of a predictor.

Increased number of visits, increased visit frequency, and short time between the baseline visit and the baseline ESS, were associated with revision ESS. Our findings suggest that increased visits before ESS might signal to a more severe disease that seems not only to affect to the physician's and patient's decision of ESS at baseline but also that of revision ESS in the follow-up. The results reflect that patients who achieved disease control after the baseline ESS did not need any more follow-up visits at Tertiary care and were unsubscribed from the hospital, whereas those with continuous problems visit more frequently and have higher probability to end up with revision ESS. There is little literature evidence of the predictive potential of visit variables at the individual level. A retrospective cohort study from US (n = 6985) showed that the number of post-operative outpatient visits was associated with revision surgery of anterior cruciate ligament reconstructions[22]. The findings are thus similar findings to ours, in other surgery and in population level. Our findings that patients who have a high visit frequency at baseline are in a higher risk to be only partially controlled by surgery, might be helpful in patient counseling.

The current study showed that CRSwNP, asthma, and NERD are important predictors of revision ESS also at the individual level. In accordance to this, previous studies have demonstrated on hospital population level that several factors are associated with the CRS recurrence and/or revision ESS, such as CRSwNP, asthma, AR, NERD, eosinophilia and smoking[1,7,23,24]. CRSwNP patients with co-morbid asthma and/or NERD have an increased risk for recurrence and revision ESS, although these patients seem benefit from initial ESS[13,19,25–27]. This may reflect a more severe disease, with usually co-morbid NERD, anosmia, Type 2 high eosinophilic inflammation, and a greater tendency of polyp re-growth[23,28–37]. When performing SFS, Immunodeficiency or its suspicion showed also to one of the top ten predictors by all three classifiers. This is in line to previous study that has shown on hospital population level that immunodeficiency and granulomatosis with polyangiitis increase the revision ESS risk[38].

We showed that the length of EHR data collection time increased the predictive accuracy of the models. Data collection time from the baseline visit until 12 months after the baseline ESS had the highest predictive accuracy in our models. Time span of data collection for the model is an optimization task between required time slot after baseline ESS and model accuracy.

We validated the predictive accuracy by using three classifiers. We chose in this study to use logistic regression, gradient boosting and random forest -classifiers as they have different properties as and have been generally used in prediction of such as surgery outcomes[39, 40] or persistent asthma[41]. Logistic regression classifier is linear and thus not able to model possible nonmonotonic and non-linear relations between predictors and outcome[42]. Random forest and gradient boosting classifiers can model complex relations, but they are so called black box models which means non-interpretable classifiers, which means relations between their inputs and output are difficult to understand directly from the parameters or structure of trained model[42]. As the predictive accuracy of the variables was similar by the three classifiers in our study, logistic regression was mainly used in validation of variable collection time. Altogether, our findings point out the importance of validating outcome prediction by using different classifiers and evaluating the effect of data collection time, as has also been suggested in previous literature[43,44].

The study groups of ours and others have previously demonstrated that younger age is associated with revision ESS on hospital populations of CRSwNP[32] or CRS[7] patients. In the present study we found that age actually affects revision ESS risk in a non-monotonic way. Hence, logistic regression models seems not solely ideal to study the effect of the individual patient's age on revision ESS risk. By performing partial dependency plots analysis we showed that the revision ESS risk was the highest for patients with age from 60-70 years, and medium high from 30-60 years or over 70 years, whereas the risk was the lowest from 10-30 years of age. Younger patients have less CRSwNP, or their CRSwNP often comprises antrochoanal polyps, which have shown to bear a smaller revision surgery risk[1]. An increased risk of revision ESS between 60-70 years may be related to worsening of CRS and/or comorbidities, such as asthma. Studies have shown that CRS is more frequent in severe asthma phenotype in the oldest subjects[45]. In addition, the number of visits before baseline ESS had non-linear effects for the predictions in our study. Patients with 10-20 visits between

the baseline visit and baseline ESS had smaller risk for revision ESS than the patients with less than 10 or more than 20 visits. Those patients visiting 10-20 times before baseline ESS, would possibly have CRSsNP with acute recurrent exacerbations, yet this subgroup warrants confirmation in further studies as the number of subjects in this study was small. Previous studies have shown that CRSsNP patients with recurrent acute rhinosinusitis episodes, benefits from initial ESS[1]. Previous studies exist of other conditions and of other predictors showing U-shaped association between predictor variable and outcome, such as intraoperative net fluid balance and early atrial tachyarrhythmia recurrence[46], and body mass index and asthma in Japanese children[47]. These findings point out the importance of evaluating the linearity of the association to improve personalized prediction.

There is a high need to detect risk factors of severity and to organize personalized patient care. Artificial intelligence has shown to be effective in EHR-based research of allergy, asthma, and immunology research[48], such as to predict eosinophilic esophagitis[49], and early childhood asthma persistence[41]. As far as we know, machine learning models have been used only in few previous CRS studies, to classify osteomeatal complex inflammation on computed tomography[50] and olfactory recovery after ESS[51]. In surgery research, machine learning models have been used to predict surgical site infections[52], postoperative outcome of degenerative cervical myelopathy[39], revision surgery after knee replacement[53], prolonged opioid prescription after surgery for lumbar disc herniation[54], and blood transfusion after adult spinal deformity surgery[55].

The strengths of this study include random sample of hospital patients, long follow-up time and discovery of non-linear associations between certain variables and outcome. In addition, a novelty is that the models were validated by several classifiers and were tested at the individual level.

Limitations include the small number of patients, yet this was compensated by the cross-validation methods. In addition, patients from only one unit, i.e., generalization of results, should be ensured in a further study with an expanded data set. We acknowledge that we lacked the data of some important factors such as validated symptoms, endoscopic nasal polyp score, medication, Lund Mackay score of sinus computed tomography scans, eosinophils, and extent of baseline ESS. The inclusion of these variables would most probably have improved the estimates. Our analysis of revision surgery may have been influenced by several factors unrelated to recurrence of CRS, including wait-times, operative technique, and surgeons/patients' personal preferences. Public medical care covers over 90% of our operations[56] thus minimizing possibility of bias due to loss of follow up, yet we acknowledge that some individual patients with recurrence may have sought treatment elsewhere. Despite these limitations, we found that intelligent data analysis is feasible to obtain individual probability of revision ESS, and thus could help in informing discussions and decision making of advanced therapy, such as biologicals[57].

## Conclusions

Our results suggest that Type 2-high conditions (CRSwNP, asthma, NERD), high visit frequency, short time between baseline visit and ESS, and immunodeficiency or its suspicion increase likelihood of revision ESS at individual level. Moreover, age and the number of preoperative visits predict non-linearly the revision ESS risk. These data could be usable in clinical decision making and patient counseling.

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Table 1. Characteristics of patients without/with status of revision ESS. P values by Fisher's exact test.

| | No revision ESS | Revision ESS | P va |
|---|---|---|---|
| Female sex, n (%) | 394 (58.28%) | 66 (57.89%) | 1 |
| Asthma, n (%) | 241 (35.65%) | 68 (59.65%) | <0.0 |
| Allergy, n (%) | 238 (35.21%) | 58 (50.88%) | 0.00 |
| Chronic respiratory diseases, n (%) | 192 (28.4%) | 43 (37.72%) | 0.04 |
| Mental disorders, n (%) | 85 (12.57%) | 17 (14.91%) | 0.54 |
| Memory disorders, n (%) | 13 (1.92%) | 3 (2.63%) | 0.71 |
| Cancer, n (%) | 67 (9.91%) | 17 (14.91%) | 0.13 |
| Cardiovascular disease, n (%) | 221 (32.69%) | 48 (42.11%) | 0.05 |
| Obesity, n (%) | 61 (9.02%) | 8 (7.02%) | 0.59 |
| Diabetes, n (%) | 67 (9.91%) | 14 (12.28%) | 0.40 |
| Musculoskeletal diseases, n (%) | 258 (38.17%) | 51 (44.74%) | 0.21 |
| NERD, n (%) | 56 (8.28%) | 22 (19.3%) | <0.0 |
| Immunodeficiency, n (%) | 3 (0.44%) | 2 (1.75%) | 0.15 |

| | No revision ESS | Revision ESS | P va |
|---|---|---|---|
| Immunodeficiency or its suspicion, n (%) | 18 (2.66%) | 13 (11.4%) | <0.0 |
| Obstructive sleep apnea, n (%) | 56 (8.28%) | 14 (12.28%) | 0.21 |
| Mouth breathing, n (%) | 36 (5.33%) | 11 (9.65%) | 0.08 |
| Gastroesophageal reflux, n (%) | 43 (6.36%) | 11 (9.65%) | 0.22 |
| CRSwNP, n (%) | 206 (30.47%) | 60 (52.63%) | <0.0 |
| Age, baseline ESS, mean±SD | 44.57 (16.71) | 47.48 (15.12) | 0.03 |
| ASA value, mean±SD | 1.68 ± 0.64 | 1.78 (0.65) | 0.05 |
| Time from the base line visit to the baseline ESS (days), mean±SD | 567.51 ± 827.06 | 474.5 ± 758.66 | <0.0 |
| Number of visits from the baseline to the baseline ESS, mean±SD | 4.27 ± 4.82 | 4.91 ± 7.61 | 0.25 |
| Visit frequency between the baseline visit to the baseline ESS, mean±SD | 8.7 ± 23.29 | 13.64 ± 38.14 | <0.0 |
| Number of visits before the baseline ESS (0-12months), mean±SD | 2.82 ± 2.49 | 3.05 ± 3.28 | 0.41 |
| Number of visits before the baseline ESS (0-6months), mean±SD | 2.05 ± 1.95 | 2.43 ± 2.42 | 0.14 |
| Number of visits from the baseline ESS to 3 months postoperatively, mean±SD | 1.44 ± 1.24 | 2.31 ± 1.96 | <0.0 |
| Number of visits from the baseline ESS to 6 months postoperatively, mean±SD | 1.88 ± 1.79 | 3.87 ± 3.65 | <0.0 |
| Number of visits from the baseline ESS to 12 months postoperatively, mean±SD | 2.36 ± 2.52 | 6.18 ± 5.53 | <0.0 |

ASA= physical status classification system, CRSwNP=chronic rhinosinusitis with nasal polyps, ESS=endoscopic sinus surgery, NERD=non-steroidal anti-inflammatory drug exacerbated respiratory disease, SD= standard deviation.

Table 2. Variable coefficients and performance values for univariate logistic regression models

| Variable | Coef (95% CI) | AUC (95% CI) | Precision (Mean) |
|---|---|---|---|
| Number of visits from the baseline ESS to 12 months postop. | 4.69 (4.63 - 4.75) | 0.76 (0.75 - 0.77) | 0.33 |
| Number of visits from the baseline ESS to 6 months postop. | 3.68 (3.61 - 3.75) | 0.69 (0.68 - 0.7) | 0.25 |
| CRSwNP | 0.92 (0.89 - 0.94) | 0.65 (0.64 - 0.66) | 0.22 |
| Number of visits from the baseline ESS to 3 months postop. | 2.37 (2.31 - 2.44) | 0.65 (0.64 - 0.66) | 0.21 |
| Asthma | 0.87 (0.83 - 0.9) | 0.65 (0.64 - 0.66) | 0.22 |
| Immunodeficiency or its suspicion | 1.22 (1.18 - 1.27) | 0.61 (0.6 - 0.62) | 0.19 |
| Allergy | 0.57 (0.55 - 0.6) | 0.61 (0.6 - 0.62) | 0.19 |
| NERD | 0.8 (0.77 - 0.84) | 0.6 (0.6 - 0.61) | 0.18 |
| Mouth breathing | 0.48 (0.43 - 0.53) | 0.59 (0.58 - 0.6) | 0.19 |
| Chronic respiratory diseases | 0.31 (0.28 - 0.33) | 0.59 (0.58 - 0.6) | 0.19 |
| Visit frequency between the baseline visit to the baseline ESS | 0.78 (0.69 - 0.87) | 0.59 (0.58 - 0.6) | 0.18 |
| Obstructive sleep apnea | 0.29 (0.25 - 0.33) | 0.59 (0.58 - 0.59) | 0.18 |
| Time from the baseline visit to the baseline ESS (days) | -0.91 (-0.98 - -0.85) | 0.59 (0.58 - 0.6) | 0.19 |
| Age | 0.74 (0.68 - 0.8) | 0.58 (0.58 - 0.59) | 0.18 |
| Number of visits before the baseline ESS (0-6 months) | 0.55 (0.47 - 0.64) | 0.58 (0.57 - 0.59) | 0.18 |
| Number of visits from the baseline to the baseline ESS | 0.04 (-0.04 - 0.12) | 0.58 (0.57 - 0.59) | 0.18 |
| Cancer | 0.18 (0.14 - 0.21) | 0.58 (0.57 - 0.59) | 0.18 |
| Cardiovascular disease | 0.26 (0.23 - 0.29) | 0.58 (0.57 - 0.59) | 0.17 |
| Gastroesophageal reflux | 0.27 (0.23 - 0.32) | 0.58 (0.57 - 0.59) | 0.18 |
| Immunodeficiency | 0.42 (0.34 - 0.5) | 0.58 (0.57 - 0.59) | 0.18 |
| Musculoskeletal diseases | 0.13 (0.1 - 0.15) | 0.58 (0.57 - 0.59) | 0.17 |
| Obesity | -0.39 (-0.44 - -0.34) | 0.58 (0.58 - 0.59) | 0.18 |
| Memory disorders | 0.11 (0.04 - 0.18) | 0.58 (0.57 - 0.59) | 0.18 |
| Gender female | -0.06 (-0.09 - -0.03) | 0.57 (0.56 - 0.58) | 0.18 |
| ASA value | 0.38 (0.32 - 0.45) | 0.57 (0.57 - 0.58) | 0.18 |
| Number of visits before the baseline ESS (0-12 months) | 0.03 (-0.07 - 0.12) | 0.57 (0.57 - 0.58) | 0.18 |

| Variable | Coef (95% CI) | AUC (95% CI) | Precision (Mean) |
|---|---|---|---|
| Diabetes | 0.01 (-0.04 - 0.06) | 0.57 (0.56 - 0.58) | 0.18 |
| Mental disorders | -0.05 (-0.09 - -0.01) | 0.57 (0.56 - 0.58) | 0.18 |

ASA= physical status classification system, CRSwNP=chronic rhinosinusitis with nasal polyps, ESS=endoscopic sinus surgery, NERD=non-steroidal anti-inflammatory drug exacerbated respiratory disease, postop.=postoperatively.

Table 3. Top-10 features selected for different classifiers by the SFS

| Classifier | Variables | Score |
|---|---|---|
| Random forest | Number of visits from the baseline ESS to 6 months postoperatively | 133 |
| | Asthma | 94 |
| | CRSwNP | 93 |
| | NERD | 85 |
| | Immunodeficiency | 84 |
| | Age, baseline ESS | 60 |
| | Musculoskeletal diseases | 56 |
| | Immunodeficiency or its suspicion | 54 |
| | Obstr sleep apnea | 52 |
| | Cancer | 51 |
| Logistic regression | Number of visits from the baseline ESS to 6 months postoperatively | 150 |
| | CRSwNP | 134 |
| | Immunodeficiency or its suspicion | 103 |
| | NERD | 90 |
| | Time from the baseline visit to the baseline ESS (days) | 76 |
| | Asthma | 74 |
| | Visit frequency between the baseline visit to the baseline ESS | 72 |
| | Allergy | 45 |
| | ASA value | 42 |
| | Number of visits before the baseline ESS (0-12 months) | 42 |
| Gradient boosting | Number of visits from the baseline ESS to 6 months postoperatively | 149 |
| | CRSwNP | 110 |
| | Asthma | 103 |
| | Memory disorders | 77 |
| | Obesity | 71 |
| | Immunodeficiency | 61 |
| | NERD | 57 |
| | Immunodeficiency or its suspicion | 54 |
| | Cancer | 51 |
| | Mental disorders | 48 |

ASA= physical status classification system, CRSwNP=chronic rhinosinusitis with nasal polyps, ESS=endoscopic sinus surgery, NERD=non-steroidal anti-inflammatory drug exacerbated respiratory disease.

**Figure 1.** AUC (a) and F1-score (b) as a number of variables for different classifiers. AUC = Area under the Receiver operating characteristic (ROC) -curve

**Figure 2.** ROC curves for logistic regression classifiers when data were collected from the baseline visit

until 0, 3, 6 and 12 months after the baseline ESS. AUC = Area under the Receiver operating characteristic (ROC) -curve

**Figure 3.** SHAP values for the ten most important (sum of the absolute SHAP values) variables for random forest classifier. The red points indicate higher and the blue points lower values than the average value of the variable. SHAP = Shapley value.