

Title: Prediction of Pneumonia 30-Day Readmissions: A Single-Center Attempt to Increase Model Performance.

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Location of Study: Hartford Hospital

Funding Support: None

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Conflicts of Interest: None for any of the authors listed.

Abstract

Background: Existing models developed to predict 30 days readmissions for pneumonia lack discriminative ability. This study is an attempt to increase model performance with the addition of variables found of benefit in other studies.

Methods: From 133,368 admissions to a tertiary-care hospital from Jan 2009 to March 2012, the study cohort consisted of 956 index admissions for pneumonia using the CMS definition. We collected variables previously reported to be associated with 30-day all-cause readmission, including vital signs, comorbidities, laboratory values, demographics, socio-economic indicators, and indicators of hospital utilization. Separate logistic regression models were developed to identify the predictors of all-cause hospital readmission 30 days after discharge from the index pneumonia admission for pneumonia-related readmissions, and for pneumonia-unrelated readmissions.

Result: Of the 965 index admissions for pneumonia, 148 (15.5%) patients were readmitted within 30 days. Variables in the multivariate-model significantly associated with 30-day all cause readmission include male gender (odds ratio (OR)=1.59, 95% confidence interval(CI) = 1.03-2.45), 3 or more previous admissions (OR=1.84, 95% CI = 1.22-2.78), chronic lung disease (OR=1.63, 95% CI = 1.07-2.48), cancer (OR=2.18, 95% CI = 1.24-3.84), median income \leq \$43,000 (OR=1.82, 95% CI = 1.18-2.81), history of anxiety or depression (OR=1.62, 95% CI = 1.04-2.52) and hematocrit $<$ 30% (OR=1.86, 95% CI = 1.07-3.22). The model performance as measured by the c-statistic was 0.71 (0.66-0.75), with minimal optimism according to bootstrap re-sampling (optimism corrected c-statistic = 0.67).

Conclusions: The addition of variables to measure socio-economic status (SES), health-care utilization significantly improved model performance when compared to the model using CMS variables alone.

Introduction

Reduction in pneumonia related readmission has been identified as a marker for quality care. CMS Readmission Reduction Program¹ has challenged hospital and health care delivery model in US to uncover novel ways to reduce readmission rates and maximize reimbursement by the CMS. Over 2,000 hospitals have been levied penalties varying from 0.01% to 1% of their Medicare revenue in fiscal year 2013 for subpar readmission rates for heart failure, pneumonia, and heart attack, totaling approximately \$280 million in penalties paid back to Medicare. With a substantial increase in the level of penalties in the next two years to 2 percent in fiscal year 2014 and to 3% in fiscal year 2015, it becomes readily apparent why there is added incentive to develop predictive algorithms to define which patients are at highest risk for readmission.

Despite this need to identify patients at risk for readmission, the applicability of available models is circumspect. A recent systematic review² of 26 models uncovered the following: most models perform poorly, including the 3 CMS models (pneumonia, heart failure and myocardial infarction); only one clinical model successfully met the goals set forth for clinical application and had what is considered acceptable discriminative ability when detecting readmission for heart failure³; the successful addition of social or functional variables offer opportunities for improvement in model performance^{4,5}.

There are few readmission models centered on Pneumonia 30 day readmissions⁶⁻¹² and only a few reported on discriminative ability^{6,11,12}. In this single-center, retrospective analysis, our intention is to leverage variables shown to be significant in previously reported predictive models and supplement the CMS medical record model⁶ with additional variables shown to be of benefit in other models in an effort to produce a model that could be potentially used to identify patients at high-risk for readmission pre-discharge.

Materials and Methods:

Setting and Design

This retrospective, observational study was carried out at Hartford Hospital, an 800-bed teaching hospital in Hartford Connecticut. The Hartford Hospital Institutional Review Board for (Assurance #FWA000000601) approved the study and certified that it met the criteria for a waiver of the requirement to obtain informed consent.

Study Sample

The patient population used in this analysis was derived from an electronic database collected at Hartford Hospital.

The CMS definition^{6, 12} for inclusion in the study cohort for index admissions for Pneumonia: Briefly, Medicare patients (enrolled in fee-for-service Medicare Parts A and B) who were admitted to Hartford Hospital from January 2009 to March 2012 with principal diagnosis of pneumonia (International Classification of Diseases, 9th Revision, Clinical Modification codes 480.XX, 481, 482.XX, 483.X, 485, 486, 487.0) as potential index pneumonia admissions. Patients less than 65 year of age, who died in the hospital, were transferred to another acute care facility, or where data was incomplete, were excluded. In addition, if a patient was admitted more than once over a 30 day period, only the first admission was counted as an index admission.

Outcomes

The primary outcome was 30-day all-cause readmission¹². Hospital administrative data sources were used to assess readmissions. A pneumonia-related readmission was defined using the CMS^{13, 14} definitions as follows: 1. pneumonia (480.XX, 481, 482.XX, 483.X, 485, 486, 487.0) as a primary diagnosis regardless of secondary diagnosis, or 2. septicemia (038.0-038.99) or

respiratory failure (518.81 or 518.84) as a primary diagnosis with a secondary diagnosis of pneumonia.

Variable Selection

The selection of candidate variables was based on the CMS-developed Hierarchical Condition Category (HCC) clinical classification system selection algorithm as described⁶ and used the 35 variables in the final CMS medical record model. Twenty six of the CMS variables are listed in Table 2 (see column CMS). The nine remaining variables were defined as missing (yes/No) for the following: sodium, glucose, hematocrit, Creatinine, WBC, BUN, heart rate, systolic blood pressure, and respiratory rate. Briefly, using the HCC algorithm, the >15,000 ICD-9 diagnosis codes are mapped to one of 189 clinically coherent condition categories (CCs). Of the 189, 35 were selected as potentially related to readmission outcome based on: 1) review of a list of variables used for validating the National Quality Forum approved pneumonia mortality measure; 2) reviewing a list of variables from the National Pneumonia Project set; and 3), variables chosen based on a systematic review of the literature. For each patient, the presence of the condition was assessed from the secondary diagnosis at the index admission.

The laboratory and vital signs were extracted from the hospital electronic health record, where the first value after admission was used. Age, gender, diagnosis, readmission from a skilled nursing facility (SNF), marital status, prior admission, and length of stay (LOS) were extracted from administrative registries.

Additional variables used, not present in the CMS model, included: marital status, LOS, anxiety/depression (as coded by the CCs as described previously), the number of hospitalizations prior to the index admission was used as a measure of health care utilization, and defined as: a cutoff of 3 or more hospitalizations, 3 years prior to the index admission for

pneumonia, Year 2000 Census data¹⁵ was used to obtain data on median household income for Connecticut zip codes and used as a measure of socio-economic status.

Statistical Analysis

Descriptive statistics included frequency tables, mean, SDs, and median. The chi-square test was used to compare categorical variables and the Student t test or nonparametric Wilcoxon test were used for continuous variables in univariate analysis. When converting continuous data to binary variables (Number of visits prior to the index visit, Median Income), we used a receiver operating curve (ROC) to estimate the optimum combination of sensitivity and specificity to arrive at an endpoint¹⁶. Differences between AUC's were detected as described¹⁷

We used multivariate logistic regression analyses to identify baseline patient characteristics that were independently associated with all-cause 30-day readmission. All predictors that were statistically significant at $P < 0.15$ in univariate analysis were entered logistic regression model. We repeated the logistic regression procedure as described in separate models using: 1. only significant CMS medical record model⁶ variables with an endpoint of all-cause 30-day readmission, 2. All significant univariate predictors with pneumonia-related 30-day readmissions as the outcome variable, and 3. All significant univariate predictors with pneumonia-unrelated 30-day readmissions as the outcome variable.

The predictive accuracy of the multivariate models was determined by calculating the area under the receiver operating curve (ROC or c-statistic)¹⁷, and calculated observed readmission rates in the lowest and highest deciles on the basis of predicted readmission probabilities. The method as described by Hanley and McNeil¹⁷ was used to test for significant differences between ROC's. Overall model performance was measured using Nagelkerke's R^2 , a measure of explained variance¹⁸ and the Hosmer–Lemeshow¹⁹ test.

In order to ensure that the model's predictions are generalizable, it is important to evaluate the performance of the model more realistically than simply by calculating its accuracy on the training sample.

To do this, we used bootstrapping as an internal validation technique.²⁰ Briefly, this method involves drawing repeated samples from the original sample with some randomly excluded, others included more than once, resulting in a bootstrap sample. This procedure was repeated 200 times, resulting in an average c-statistic for the bootstrap sample. This is then subtracted from the c-statistic developed from the original sample. The result is termed the optimism of the apparent performance of the model on the training data set. The observed performance is moderated by subtracting the degree of optimism from the apparent performance. One of the benefits of bootstrapping is that it allows all of the available patient data to be included in the data set. It has been shown to estimate model performance more accurately than other approaches such as those that involve setting aside data for a separate validation sample. All effects were considered significant at $p \leq 0.05$. All statistical analyses were performed using SPSS (SPSS Inc. Released 2007. SPSS for Windows, Version 16.0. Chicago, SPSS Inc.) with the exception of bootstrapping, where STATA was used (StataCorp. 2009. *Stata Statistical Software: Release 11*. College Station, TX: StataCorp LP).

Results

A total of 1,249 inpatients met the CMS inclusion criteria¹² for a pneumonia index admission. Of the 1,249 cases, CMS exclusion criteria eliminated the following: 14.1% < 65 years of age, 5.7% inpatient deaths, 0.2% were transferred to another acute care facility, 1.3% had >1 admission in the 30-day readmission period, and 2.1% were eliminated due to missing data. This resulted in a final population of 956 (Figure 1), of which 148 were readmitted within 30 days, for an unadjusted readmission rate of 15.5% (Figure 2). As shown, the readmission rate was uniformly distributed over the 30-day period. Pneumonia-related hospital readmissions

accounted for 16.9 % of total 30 day readmissions (Table 1). Five (20%) of the patients readmitted for pneumonia related causes died in the hospital and 13 (52%) were transferred to a skilled nursing facility. The most frequent diagnosis for pneumonia-unrelated readmissions included food/vomit pneumonitis, congestive heart failure, and cardio-respiratory failure and shock.

Variables Statistically Associated with All-Cause 30-Day Readmission

Table 2 provides the univariate analysis of all study subjects with comparisons between readmitted and non-readmitted patients. As shown, there were significant differences in LOS, discharge to a skilled nursing facility, 3 or more previous admissions, median income \leq \$43,000, chronic lung disease, renal disease, cancer, creatinine greater or equal to 2.5 mg/dL, hematocrit less than 30% and history of anxiety or depression.

When defining readmissions as pneumonia-related (Table 3.), 3 or more previous admissions, cancer, hematocrit less than 30% and WBC 6-12 showed statistically significant differences. When the outcome is defined as Pneumonia-unrelated, in accord with all readmissions, there were significant differences in LOS, 3 or more previous admissions, median income \leq \$43,000, chronic lung disease, renal disease, creatinine greater or equal to 2.5 mg/dL and hematocrit less than 30%.

Pneumonia-related readmissions included a higher percent with a history of cancer (36.0% and 12.2%, $p < .01$), and a lower percent with heart failure (20.0% and 48.0%, $p = .01$) and white blood cell count 6-12 b/ μ L (28.0% and 54.9%, $p = .01$), when compared to pneumonia-unrelated 30-day readmissions.

Multivariate analysis

As shown in Table 4, variables significantly associated with a risk for 30-day all-cause readmission include male gender, 3 or more previous admissions, chronic lung disease,

cancer, median income \leq \$43,000, history of anxiety or depression and hematocrit $<$ 30%. In the logistic regression model using pneumonia-related readmissions as the dependent variable, factors associated with a higher risk of readmission include 3 or more previous admissions, cancer, and history of anxiety or depression. The model using pneumonia unrelated readmissions included median income \leq \$43,000, 3 or more previous admissions, Chronic Lung Disease, and Heart rate \geq 125 as significant risk factors.

Model Performance

As shown in table 5, the logistic regression model showed reasonable discrimination (c-statistic 0.71 (0.66 – 0.75)). Validation, by means of 300 bootstrap samples resulted in an optimism-corrected c-statistic of 0.67. The predicted readmission rates ranged from 7.5% in the lowest to 43.0% in the highest predicted decile and the model was well calibrated as the Hosmer-Lemeshow goodness of fit statistic was $X_2 = 5.92$, $p = 0.656$. The model predicting pneumonia-unrelated readmission gave a Hosmer-Lemeshow goodness of fit statistic of $X_2 = 2.47$, $p = 0.963$ and demonstrated fair discrimination (c-statistic .68 (0.64 – 0.73)), however, the models predictive ability was less as the observed readmission rate ranged from 3.3% in the lowest predicted decile to only 36.6% in the highest. When predicting pneumonia-related readmission, the model, likewise, was well calibrated with Hosmer-Lemeshow goodness of fit statistic was $X_2 = 3.44$, $p = 0.904$. The model demonstrated poor to fair discrimination (c-statistic 0.65 (0.60 – 0.70)), and the models predictive ability was also poor, with the observed readmission rate ranging from only 9.1% in the lowest predicted decile to only 34.0% in the highest.

Looking at the relative contribution of each risk factor's predictive ability in the multivariable model for all cause 30-day readmissions (Figure 3) we calculate low income and high hospital utilization account for nearly 40% of the variance in the model.

We compared our model to a model that used only factors used in the CMS medical record sample (excludes LOS, Marital Status, Health Care Utilization and Socio-economic status, and a measure of anxiety/depression) and found a significant improvement in the c-statistic (Figure 4.), 0.71 vs. 0.67, $z=2.14$, $p=0.03$.

Discussion:

We present an in-patient 30-day risk-adjusted all-cause readmission model for pneumonia patients that can be used in performance measurement and quality improvement at a similar tertiary care hospital. We included 956 patients hospitalized for pneumonia who showed a 30-day readmission rate of 15.5%. Our model identified seven variables as significant risk factors for pneumonia 30-day all cause readmissions. Some these factors offer confirmation of previous findings, and other are newly reported. In addition, three significant risk factors associated were revealed in the pneumonia-related 30-day readmission model and four risk factors were associated with pneumonia-unrelated readmissions. The measure of hospital utilization was significant regardless of the model outcome.

We chose to select baseline variables for univariate analysis from the CMS Medical Record risk adjusted model for pneumonia readmissions⁶ as we were using a similar patient population with identical inclusion/exclusion criteria, were measuring the same outcome, and because of the robustness of the CMS Medical Record risk dataset (47,429 patients). Despite the size of the population and the number of variables initially screened for use, the CMS models perform poorly², demonstrating that there is substantial variance not accounted for by the CMS models. The reason for the lack of discrimination becomes clear if you consider the multitude of factors influencing the likelihood of readmission after hospital discharge.^{9, 10, 22-24} that are not included in the CMS model. With the inclusion of some of these variables in our model, we were able to increase the discriminatory ability of the model significantly over the CMS model.

Our finding of prior health care utilization as a significant risk factor is in agreement with others²⁵⁻³⁰ and it remained significant across all three models (all readmissions, PN related, or PH-unrelated). Risk factors of prior health care utilization (e.g., prior hospitalizations and emergency room visits) are likely surrogates of patients with unstable or more severe disease states. Our inclusion of history of anxiety or depression was based on evidence provided by others, where the mental component score of the SF-36 was determined as a significant multivariate predictor of non-elective readmissions²⁸.

Our finding of lower income is in agreement with others who have shown socio-economic status (SES) indicators as predictors of higher readmission rates. Billings⁴ studied the effect of household income on hospital readmission for the non-Medicare population in New York City and discovered admission rates to be higher for the low-income population than for the high-income population. Amarasingham³ found median income as a significant univariate predictor of heart failure readmission, with borderline significance and Philbin et al³¹ showed that income is significantly associated with increased readmission in heart failure.

On the contrary, Arbaje et al¹⁰ failed to include lower income as a significant multivariate predictor of 60-day non-elective readmissions; however, the study lacked power to detect differences in readmission in the designated levels of income. They acknowledged that if the readmission rate had been higher, then low income may have had significant associations with early readmission.

A systemic review of risk prediction models for readmission concludes that the vast majority, including the three CMS models (Heart Failure, AMI, and pneumonia) performed poorly in predicting which patients were at high or low risk for readmission². Indeed, only a handful reported a c-statistic above 0.7. Their finding showed that most models were limited to medical comorbidity, prior healthcare utilization, and basic sociodemographic data. Only a few considered variables such as functional status, overall health, social determinants of health (income, employment, SES, access to care, social support) or illness severity in their models.

Two of the studies^{3,5} that did include these variables in their models demonstrated increased predictive ability.

An important limitation to this study was that it was conducted in a single, inner-city tertiary care hospital, as such, its external validity may suffer in that it is limited to the geographic area and practice type. However, many of the variables shown as significant risk-factors in other studies with varied environments were replicated as significant variables in this study. A further limitation is the census file used for median income was from the year 2000, thus, there is the recognition that regional changes in income may have occurred in the last decade. Finally, the power of the multivariate analysis is limited when segmenting the outcome as pneumonia related/unrelated, though we did not observe large parameter estimates or standard errors which can be diagnostic of too few events relative to variables.

Conclusion

We successfully produced a model that could by potentially be used to identify patients at high-risk for readmission pre-discharge. We sought to build on previously published predictive models for pneumonia readmission, many of which displayed relatively weak performance with an attempt to enhance the predictive ability with the addition of variables related to marital status, prior hospitalizations, median income, diagnosis of anxiety or depression, and index hospital length of stay. Of these additions, prior hospitalization, median income, and depression/anxiety were all significant predictors in the all-cause readmission model and made substantial contributions to model performance.

Despite the significant improvement over previously published models of pneumonia 30 day readmission⁶, there is much need for improvement as the maximum predictive ability remains inadequate. It is apparent that much of the influence on the risk of readmission lies outside of the hospital. Factors such as, confirmed and timely post discharge visit to the patients primary care provider, medication and diet compliance, social support, health literacy,

communication between providers may all be significant contributors to a predictive algorithm for readmission. Further research is needed to develop a more comprehensive model that incorporates potential influential variables such as these.

Acknowledgements

Author contributions: Mr. Mather, Mr. Davis, Ms. Ash contributed to the conception and design of the study. Mr. Fortunato and Mr. Mather contributed to the data retrieval, cleaning, and validation. Mr. Mather contributed to the analysis. Mr. Mather and Dr. Kumar contributed to the interpretation of the data. Mr. Mather and Dr. Kumar contributed to writing the article. Mr. Davis, Ms. Ash, Mr. Fortunato and Dr. Kumar contributed to proofing and revising the article. All authors approved the final version of the article.

Financial/nonfinancial Disclosures: The authors report no conflicts of interest.

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FIGURE 1. Pneumonia admissions included in measure calculation.

FIGURE 2. Kaplan-Meier curve of 30-day hospital readmission.

FIGURE 3. Relative contribution of risk-factors for Pneumonia 30-day readmission prediction model. SNF indicates readmission from a skilled nursing facility; HCT, hematocrit; LOS, Length of stay; CR, creatinine.

FIGURE 4. Area under the ROC curve. The area under the receiver operating characteristic curve (ROC) demonstrates significantly better discrimination using the all significant univariate predictors (HH model) when compared to using the CMS Medical Record model⁶ variables alone. The diagonal line represents an AUC = 0.5, or no discrimination.

Table 1. Pneumonia 30 Day Readmission Diagnosis

	Count	Percent
Pneumonia related		
Pneumonia - primary	19	76.0%
Septicemia - pneumonia	5	20.0%
Respiratory Failure - pneumonia	1	4.0%
Total	25	16.9%
Pneumonia unrelated*		
Aspiration and Specified Bacterial Pneumonias (Food/vomit pneumonitis)	13	10.6%
Congestive Heart Failure	12	9.8%
Cardio-Respiratory Failure and Shock	11	8.9%
Chronic Obstructive Pulmonary Disease	8	6.5%
Renal Failure	7	5.7%
Other Infectious Diseases	6	4.9%
Septicemia/Shock	6	4.9%
Lung, Upper Digestive Tract, and Other Severe Cancers	4	3.3%
Urinary Tract Infection	4	3.3%
Hip Fracture/Dislocation	3	2.4%
Other Gastrointestinal Disorders	3	2.4%
Central Nervous System Infection	2	1.6%
Disorders of Fluid/Electrolyte/Acid-Base Balance	2	1.6%
Major Complications of Medical Care and Trauma	2	1.6%
Other Heart Rhythm and Conduction Disorders	2	1.6%
Vascular Disease	2	1.6%
Acute Myocardial Infarction	1	0.8%
Breast, Prostate, Colorectal and Other Cancers and Tumors	1	0.8%
Chronic Ulcer of Skin, Except Decubitus	1	0.8%
Dementia/Cerebral Degeneration	1	0.8%
Diabetes with Acute Complications	1	0.8%
Diabetes with Neurologic or Other Specified Manifestation	1	0.8%
Dialysis Status	1	0.8%
Disorders of Immunity	1	0.8%
Fibrosis of Lung and Other Chronic Lung Disorders	1	0.8%
Intestinal Obstruction/Perforation	1	0.8%
Lymphatic, Head and Neck, Brain, and Other Major Cancers	1	0.8%
Other Circulatory Disease	1	0.8%
Other Psychiatric Disorders	1	0.8%
Other Significant Endocrine and Metabolic Disorders	1	0.8%
Pleural Effusion/Pneumothorax	1	0.8%
Seizure Disorders and Convulsions	1	0.8%
Vascular Disease with Complications	1	0.8%
Other	19	15.4%
Total	123	83.1%

*Primary ICD-9 diagnosis on 30 day readmission.

Table 2. Univariate Predictors of 30-Day Readmission for Pneumonia

Study Sample = 956					
	Not Readmitted n=808	Readmitted n=148	p value	Population %*	CMS†
Patient Demographics					
Age (years > 65)	15.7 ± 8.5	14.5 ± 8.4	0.12	15.5 ± 8.5	15.2 ± 7.9
Length of Stay (LOS)	5.3 ± 4.0	6.2 ± 4.9	0.03	5.4 ± 4.2	
Sex (Male)	42.1%	49.3%	0.10	43.2%	46.2%
Nursing Home Resident	41.3%	52.0%	0.02	43.0%	17.7%
Marital Status			0.13		
Divorced	10.5%	9.5%		10.4%	
Married	36.0%	33.8%		35.0%	
Single	11.5%	14.9%		12.0%	
Widowed	41.6%	39.9%		41.3%	
Separated	0.4%	2.0%		60.0%	
Health Care Utilization					
>= 3 Previous Admissions	47.0%	68.2%	<0.01	50.3%	
Socio-economic status					
Median Income <=\$43,000	18.9%	30.8%	<0.01	20.7%	
Comorbidities					
Diabetes mellitus	33.4%	39.2%	0.17	34.3%	20.9%
History of heart Failure	35.5%	43.2%	0.07	36.7%	29.0%
Coronary Artery Disease	44.1%	50.0%	0.18	45.0%	39.6%
Chronic Lung Disease	44.9%	57.4%	0.01	46.9%	42.2%
Liver Disease	.0%	.0%		.0%	1.0%
Renal Disease	15.2%	27.7%	0.00	17.2%	8.5%
Splenectomy	.2%	.0%	0.54	.2%	.4%
Dementia/Alzheimer's Disease	25.5%	21.6%	0.32	24.9%	16.4%
Cancer	10.0%	16.2%	0.03	9.4%	6.8%
Alcohol/Drug Abuse	6.8%	10.1%	0.15	7.3%	3.4%
Immunosuppressive Therapy	22.3%	29.7%	0.05	23.4%	15.0%
Major psychiatric disorders	4.5%	8.1%	0.06	5.0%	18.0%
Pleural Effusion/Pneumothorax	6.8%	10.1%	0.15	7.3%	21.2%
Anxiety/Depression	19.6%	27.0%	0.04	20.7%	
Vital Signs					
SBP<90 mmHg	1.0%	.7%	0.72	.9%	2.9%
HR>=125/min	2.4%	4.1%	0.23	2.6%	7.7%
RR>=30/min	3.8%	3.4%	0.79	3.8%	16.4%
Labs					
NA<130 mol/L	7.0%	6.8%	0.94	7.0%	4.8%
BUN>=30 mg/dL	24.7%	27.2%	0.52	25.1%	23.3%
CR>=2.5 mg/dL	5.5%	10.9%	0.01	6.3%	4.7%
HCT<30%	8.6%	17.0%	<0.01	9.9%	7.8%
GLU>=250 mg/dL	5.7%	6.1%	0.85	5.8%	5.2%
WBC6-12 b/μL	50.1%	50.3%	0.52	50.2%	38.0%
WBC>12 b/μL	40.5%	36.7%	0.96	39.9%	41.4%

Values are shown as percent or mean ± standard deviation

Abbreviations: SBP, Systolic Blood Pressure; HR, Heart Rate; RR, Respiratory Rate; NA, Sodium; BUN, Blood Urea Nitrogen; CR, Creatinine; HCT, Hematocrit; Glu, Glucose

* entire population

† CMS⁶ values for comparison. Not shown are values for missing (yes/No) for the following: sodium, glucose, hematocrit, Creatinine, WBC, BUN, heart rate, systolic blood pressure, and respiratory rate, as the maximum missing for any of these 9 variables was 8 and all were insignificant.

Comorbidities used in the model were represented by CC groupings as follows: Diabetes Mellitus (CC 15-20, 119-120); History of Heart Failure (CC 80); Coronary Artery Disease (CC 83-86, 104-106); Chronic Lung Disease (CC 108-09, 115); Liver Disease (CC 25-30); History of Renal Disease (CC 129-131); Dementia/Alzheimer's disease (CC 49-50); Cancer/Neoplastic disease (CC 7-14); Alcohol/Drug Abuse (CC 51-53); Major psychiatric disorders (CC 54-56); pleural effusion (CC 114); Anxiety/Depression (CC 58-59). Splenectomy was defined using an ICD-9 procedure coding of 41.5. Immunosuppressive therapy was defined as medication usage using Healthcare Common Procedure Coding System (HCPCS) codes for the following: Azathioprine, Cyclophosphamide, Cyclosporine, Daclizumab, Methotrexate, Methylprednisolone, Mycophenolate mofetil, Sirolimus, or Tacrolimus.

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and proofread, and as a result, may differ substantially when published in final version in the online and print editions of RESPIRATORY CARE.

Table 3. Univariate Predictors of 30-Day Readmission for Pneumonia Related and Pneumonia Unrelated Readmissions

	Pneumonia Related			Pneumonia Unrelated		
	Not Readmitted n=931	Readmitted n=25	p value	Not Readmitted n=833	Readmitted n=123	p value
Patient Demographics						
Age (yrs > 65)	15.6(8.5)	13.9(9.8)	0.34	15.6(8.5)	14.6(8.4)	0.22
Length of Stay (LOS)	5.4(4.1)	6.6(5.4)	0.17	5.3(4.1)	6.1(4.8)	0.04
Sex (Male)	43.1%	48.0%	0.62	42.3%	49.6%	0.13
Nursing Home Resident	42.5%	60.0%	0.08	41.9%	50.4%	0.08
Marital Status			0.28			0.30
Divorced	12.1%	8.0%		11.4%	7.8%	
Married	35.7%	36.0%		36.0%	16.3%	
Single	10.3%	12.0%		10.6%	33.3%	
Widowed	41.4%	40.0%		41.5%	8.9%	
Separated	.5%	4.0%		.5%	39.8%	
>= 3 Previous Admissions	49.6%	76.0%	0.01	47.9%	66.7%	0.00
Median Income <=\$43,000	20.3%	36.0%	0.06	19.4%	29.8%	0.01
Comorbidities						
Diabete mellitus	34.4%	32.0%	0.81	33.4%	40.7%	0.11
History of heart Failure	37.2%	20.0%	0.79	35.1%	48.0%	0.06
Coronary Artery Disease	44.7%	56.0%	0.26	44.4%	48.8%	0.36
Chronic Lung Disease	47.0%	40.0%	0.49	44.8%	61.0%	0.00
Liver Disease	.0%	.0%		.0%	.0%	
Renal Disease	17.1%	20.0%	0.70	15.4%	29.3%	0.00
Splenectomy	.2%	.0%	0.82	.2%	.0%	0.59
Dementia/Alzheimer's Disease	25.1%	16.0%	0.30	25.2%	22.8%	0.56
Cancer	10.3%	36.0%	0.00	10.8%	12.2%	0.65
Alcohol/Drug Abuse	7.4%	4.0%	0.52	6.7%	11.4%	0.06
Immunosuppressive Therapy	23.1%	36.0%	0.13	22.7%	28.5%	0.16
Major psychiatric disorders	5.0%	4.0%	0.81	4.4%	8.9%	0.03
Pleural Effusion/Pneumothorax	7.3%	8.0%	0.89	6.8%	10.6%	0.14
Anxiety/Depression	20.3%	36.0%	0.06	20.0%	25.2%	0.19
Vital Signs						
SBP<90 mmHg	1.0%	.0%	0.62	1.0%	.8%	0.87
HR>=125/min	2.7%	.0%	0.41	2.3%	4.9%	0.09
RR>=30/min	3.9%	.0%	0.31	3.7%	4.1%	0.85
Labs						
NA<130 mol/L	7.0%	4.0%	0.56	6.8%	7.3%	0.85
BUN>=30 mg/dL	25.0%	28.0%	0.73	24.8%	27.0%	0.59
CR>=2.5 mg/dL	6.3%	8.0%	0.73	5.6%	11.5%	0.01
HCT<30%	9.5%	24.0%	0.02	9.1%	15.6%	0.03
GLU>=250 mg/dL	5.9%	.0%	0.21	5.6%	7.4%	0.42
WBC6-12 b/ μ L	50.8%	28.0%	0.03	49.5%	54.9%	0.26
WBC>12 b/ μ L	39.6%	52.0%	0.22	40.9%	33.6%	0.13

Values are shown as percent or mean(standard deviation)

Abbreviations:SBP, Systolic Blood Pressure; HR, Heart Rate; RR, Respiratory Rate; NA, Sodium; BUN, Blood Urea Nitrogen; CR, Creatinine; HCT, Hematocrit; Glu, Glucose

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and proofread, and as a result, may differ substantially when published in final version in the online and print editions of RESPIRATORY CARE.

Table 4. Pneumonia 30-day Readmission Logistic Regression Results

Variable	Percent	Coefficient	Standard Error	Odds Ratio	95% CI		p
					LCL	UCL	
Age (yrs > 65)	15.7(8.5)	-.008	.013	.992	.968	1.017	.539
Length of Stay (LOS)	5.3(4.0)	.008	.023	1.008	.964	1.054	.715
Sex (Male)	42.1%	.463	.221	1.589	1.031	2.448	.036
Nursing Home Resident	41.3%	.300	.208	1.349	.898	2.026	.149
History of heart Failure	35.5%	.106	.213	1.112	.733	1.686	.618
Chronic Lung Disease	44.9%	.489	.214	1.631	1.072	2.481	.022
Renal Disease	15.2%	.311	.252	1.364	.832	2.236	.218
Cancer	10.0%	.780	.288	2.182	1.241	3.837	.007
Immunosuppressive Therapy	22.3%	.174	.233	1.190	.754	1.878	.455
CR>=2.5 mg/dL	5.5%	.111	.385	1.117	.525	2.375	.774
HCT<30%	8.6%	.620	.281	1.859	1.071	3.225	.027
Major psychiatric disorders	8.1%	.622	.385	1.863	.876	3.966	.106
Median Income <=\$43,000		.599	.221	1.821	1.180	2.809	.007
>= 3 Previous Admissions	25.2%	.608	.210	1.838	1.218	2.772	.004
Marital Status							
Single(reference)							.217
Married	9.5%	-.329	.320	.719	.384	1.347	.303
Divorced	33.8%	-.706	.415	.494	.219	1.114	.089
Widowed	14.9%	-.152	.322	.859	.457	1.616	.638
Separated	39.9%	1.123	.950	3.074	.477	19.788	.237
Anxiety/Depression	2.0%	.481	.225	1.618	1.040	2.516	.033
Constant		-2.976	.426	.051			.000

Values are shown as percent or mean(standard deviation)

Abbreviations: CR, Creatinine; HCT, Hematocrit; CI, Confidence Interval; LLC, Lower Confidence limit; UCL, Upper Confidence Limit

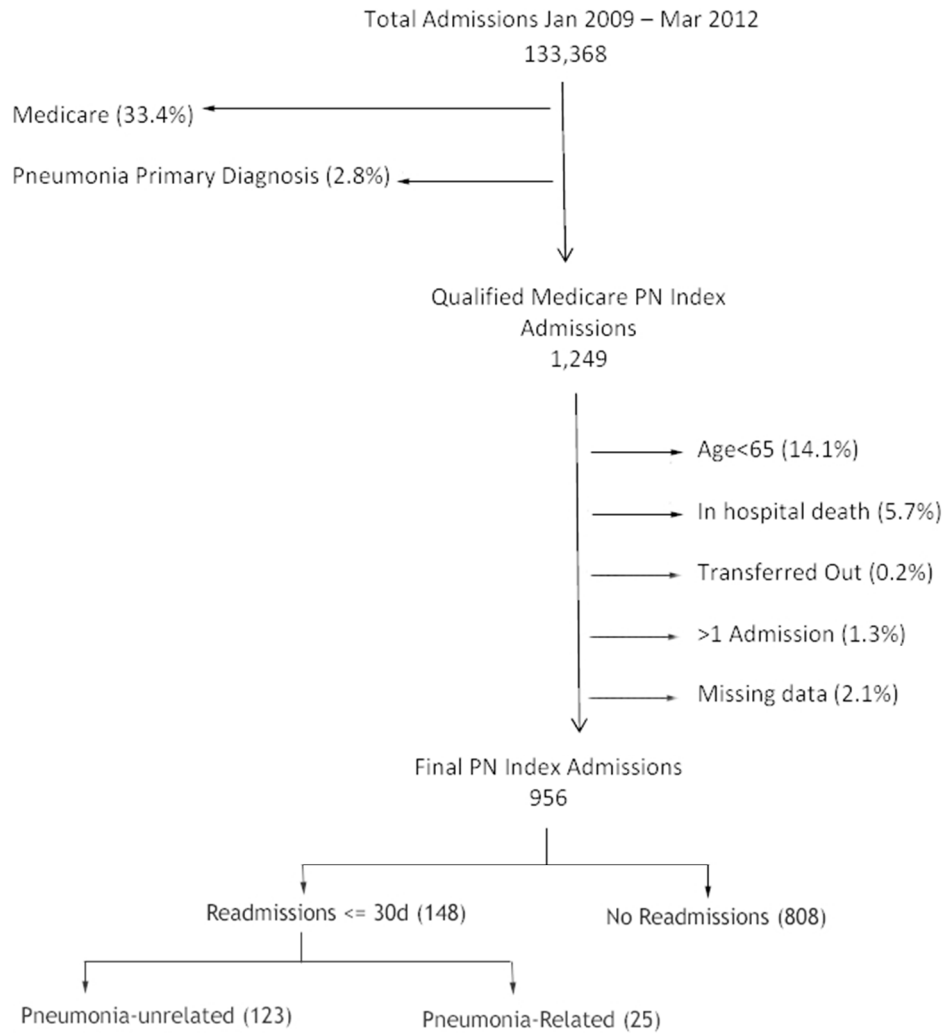
Table 5. Model Performance

Model		Discrimination			
<u>Predictors</u>	<u>Readmission Type</u>	<u>n</u>	<u>Predictive Ability (Lowest Decile - Highest Decile)</u>	<u>AUC †</u>	<u>R²*</u>
All significant	All Cause	956	7.5% - 43.0%	0.71(0.66 - 0.75)	0.13
All significant	PN-unrelated	956	3.3% - 36.6%	0.68(0.64 - 0.73)	0.11
All significant	PN-related	956	9.1% - 34.0%	0.65(0.59 - 0.70)	0.16
CMS Medical Record Model Variables only‡	All Cause	956	4.2% - 35.1%	0.67(0.62 - 0.72)	0.08

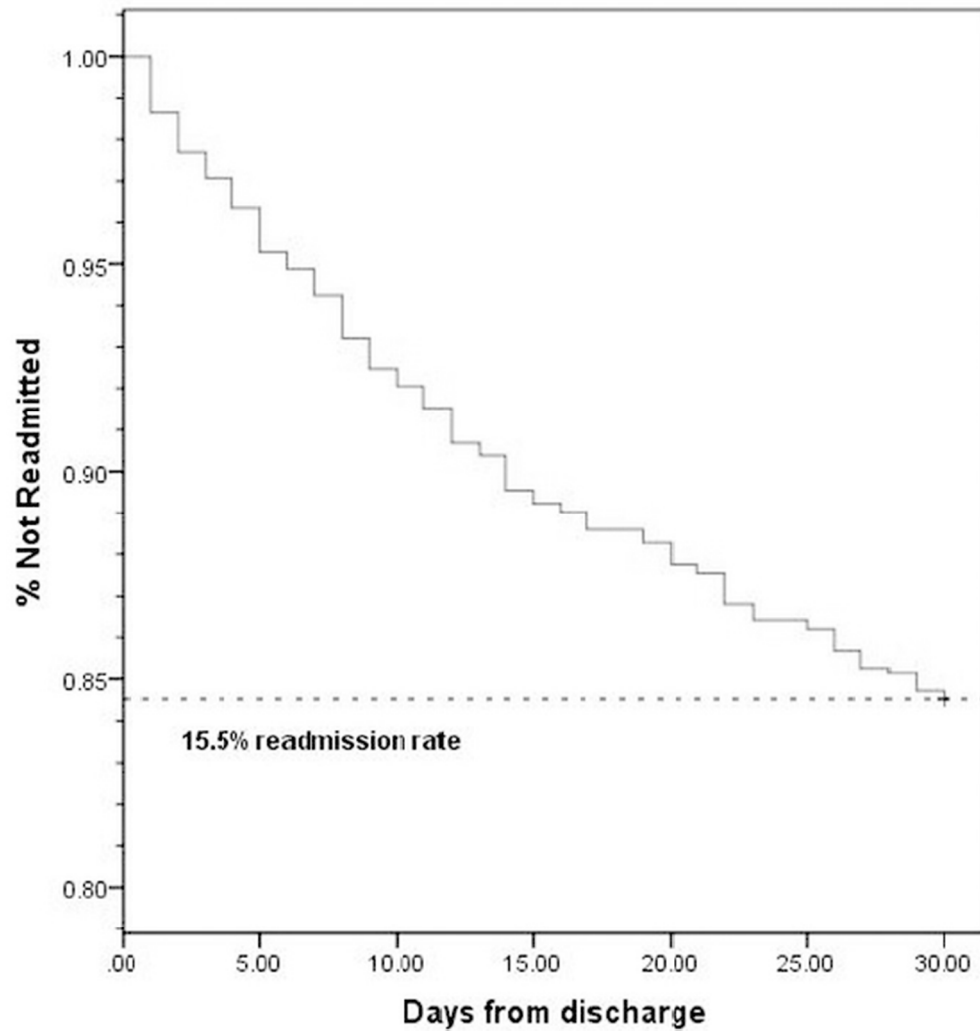
*Nagelkerke R Square¹⁸

† AUC (Area under the curve) shown with 95% confidence interval.

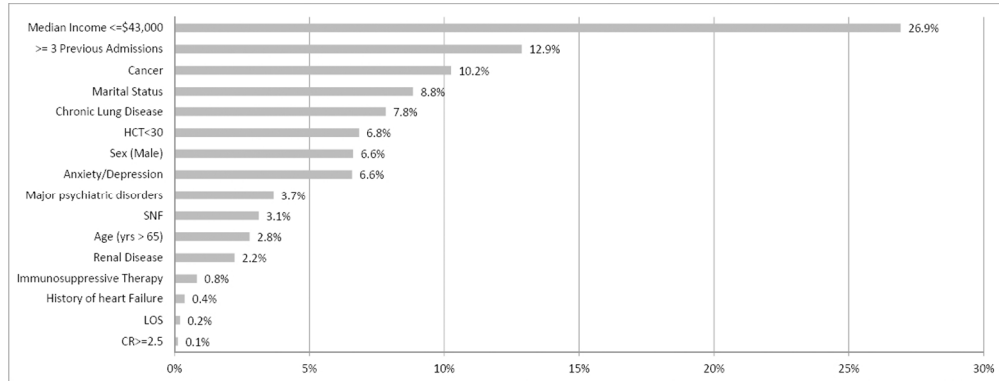
‡ Lindenauer et al⁶



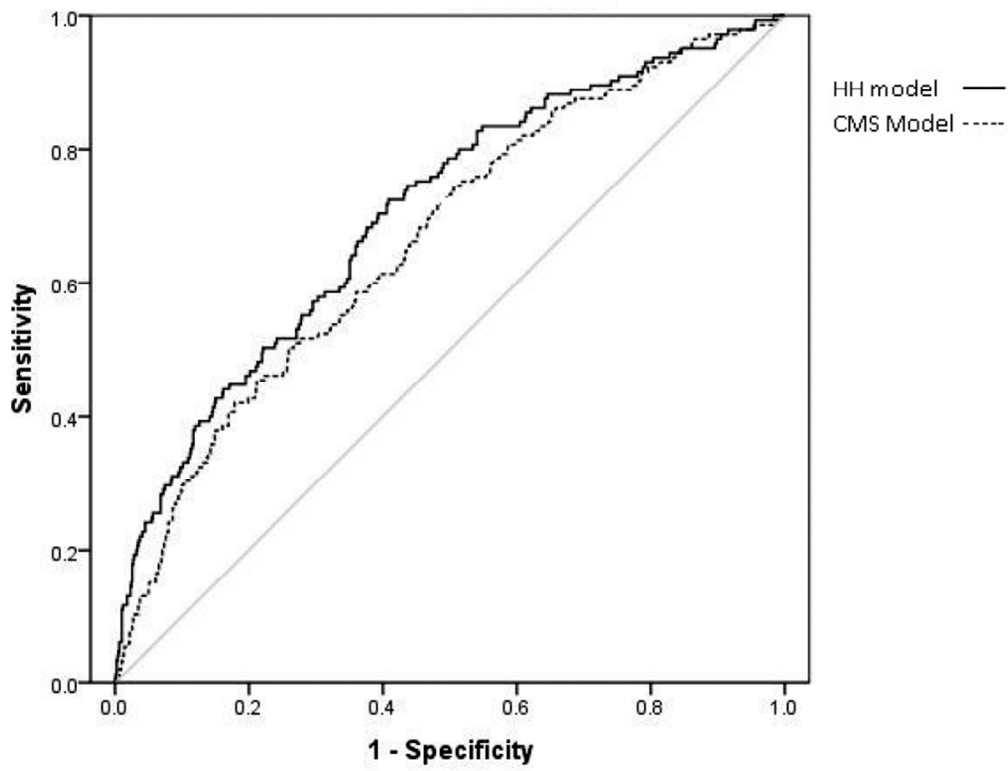
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