UCSF UC San Francisco Previously Published Works

Title

Predicting the Risk of Readmission in Pneumonia. A Systematic Review of Model Performance.

Permalink https://escholarship.org/uc/item/5g0588kb

Journal Annals of the American Thoracic Society, 13(9)

ISSN 2329-6933

Authors

Weinreich, Mark Nguyen, Oanh K Wang, David <u>et al.</u>

Publication Date

2016-09-01

DOI

10.1513/annalsats.201602-135sr

Peer reviewed

Predicting the Risk of Readmission in Pneumonia A Systematic Review of Model Performance

Mark Weinreich¹, Oanh K. Nguyen^{1,2}, David Wang¹, Helen Mayo³, Eric M. Mortensen^{1,2,4}, Ethan A. Halm^{1,2}, and Anil N. Makam^{1,2}

¹Department of Internal Medicine, ²Department of Clinical Sciences, and ³Health Sciences Digital Library and Learning Center, University of Texas Southwestern Medical Center, Dallas, Texas; and ⁴Veterans Affairs North Texas Health Care System, Dallas, Texas

ORCID ID: 0000-0001-7072-9946 (A.N.M.).

Abstract

Rationale: Predicting which patients are at highest risk for readmission after hospitalization for pneumonia could enable hospitals to proactively reallocate scarce resources to reduce 30-day readmissions.

Objectives: To synthesize the available literature on readmission risk prediction models for adults who are hospitalized because of pneumonia and describe their performance.

Methods: We systematically searched Ovid MEDLINE, Embase, The Cochrane Library, and Cumulative Index to Nursing and Allied Health Literature databases from inception through July 2015. We included studies of adults discharged with pneumonia that developed or validated a model that predicted hospital readmission. Two independent reviewers abstracted data and assessed the risk of bias.

Measurements and Main Results: Of 992 citations reviewed, 7 studies met inclusion criteria, which included 11 unique risk prediction models. All-cause 30-day readmission rates ranged from 11.8 to 20.8% (median, 17.3%). Model discrimination (C statistic)

ranged from 0.59 to 0.77 (median, 0.63) with the highest-quality, best-validated model, the Centers for Medicare and Medicaid Services Pneumonia Administrative Model performing modestly (C Statistic of 0.63 in 4 separate multicenter cohorts). The best performing model (C statistic of 0.77) was a single-site study that lacked internal validation. The models had adequate calibration, with patients predicted as high risk for readmission having a higher average observed readmission rate than those predicted to be low risk. None of the studies included pneumonia illness severity scores, and only one included measures of in-hospital clinical trajectory and stability on discharge, robust predictors of readmission.

Conclusions: We found a limited number of validated pneumoniaspecific readmission models, and their predictive ability was modest. To improve predictive accuracy, future models should include measures of pneumonia illness severity, hospital complications, and stability on discharge.

Keywords: patient readmission; pneumonia; model; risk; prediction

(Received in original form February 21, 2016; accepted in final form June 13, 2016)

Supported by UT Southwestern KL2 Scholars Program National Center for Advancing Translational Sciences/National Institutes of Health grant KL2TR001103 and UT Southwestern Center for Patient-Centered Outcomes Research Agency for Healthcare Research and Quality grant R24HS022418.

The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health or Department of Veterans Affairs. This material is the result of work supported with resources and the use of facilities at the VA North Texas Health Care System. The funding agencies had no role in conducting the study or in the preparation, review, or approval of the manuscript.

Author Contributions: M.W., O.K.N., H.M., E.A.H., and A.N.M. contributed to the study design; M.W., H.M., and A.N.M. contributed to the literature search; M.W., D.W., and A.N.M. contributed to the review of the abstracts for eligibility, the identification of the eligible full-text studies, data extraction, and quality assessment; A.N.M. contributed to the final consensus decisions; M.W., O.K.N., D.W., E.M.M., E.A.H., and A.N.M. contributed to the data analysis; M.W. and A.N.M. contributed to the drafting of the manuscript; and all authors contributed to the critical revision of the manuscript and approved the final manuscript. A.N.M. had full access to all the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis.

Correspondence and requests for reprints should be addressed to Anil N. Makam, M.D., M.A.S., Division of General Internal Medicine, 5323 Harry Hines Boulevard, Dallas, TX 75390-9169. E-mail: anil.makam@utsouthwestern.edu

This article has an online supplement, which is accessible from this issue's table of contents at www.atsjournals.org

Ann Am Thorac Soc Vol 13, No 9, pp 1607–1614, Sep 2016 Copyright © 2016 by the American Thoracic Society DOI: 10.1513/AnnalsATS.201602-135SR Internet address: www.atsjournals.org Hospital readmissions among patients with pneumonia are frequent, costly, and potentially avoidable (1–5). Despite efforts to optimize inpatient care delivery, 30-day readmissions are estimated to occur in 17 to 25% of patients hospitalized for pneumonia, at a cost of \$10 billion (2–5). Since the Centers for Medicare and Medicaid Services (CMS) implemented the Hospital Readmission Reduction Program in 2012, there has been an increased focus on pneumonia readmissions, because hospitals with higher-than-expected riskadjusted 30-day readmission rates face major financial penalties (6).

Predicting which patients hospitalized for pneumonia are at highest risk for readmission could enable hospitals to proactively identify patients and deploy interventions in real time to reduce 30-day readmissions. A systematic review by Kansagara and colleagues has shown that most readmission risk prediction models have modest performance (7). However, this review did not identify a single pneumonia-specific readmission model in the peer-reviewed literature and focused primarily on multi-condition and cardiovascular disease models.

Therefore, the objective of this study was to conduct a high-quality synthesis of the available literature on readmission risk prediction models for patients hospitalized with pneumonia to assess model performance and methodologic quality.

Methods

Data Sources and Searches

We searched Ovid MEDLINE and Ovid MEDLINE InProcess, the Cumulative Index to Nursing and Allied Health Literature (CINAHL), the Cochrane Library (Cochrane Central Register of Controlled Trials, Cochrane Database of Systematic Reviews, and the Database of Abstracts of Reviews of Effect), and Embase from database inception through July 2015 for studies of readmission risk prediction models in adults hospitalized with pneumonia.

All citations were imported into an electronic database (EndNote X7; Thomson-Reuters Corp, New York, NY). We used subject headings and text words to identify articles that contained the following three concepts: (1) readmission (readmi^{*}, re-admi^{*}, rehosp^{*}, re-hosp^{*}, patient readmission/, readmission/), (2) risk (model*, predict*, risk*, util*, use*, usage, risk/, risk assessment/ risk factors/), and (3) pneumonia (pneumonia, pneumonia/). The search strategies are provided in detail in the online supplement.

Study Selection

Two authors (M.W. and D.W.) reviewed the abstracts and full-text articles of potentially relevant references identified from the literature search for eligibility. References of included articles were also searched to identify additional eligible studies. Criteria for inclusion were: (1) full text in English; (2) study population included adult patients 18 years or older discharged from the hospital with pneumonia; (3) article is a primary study that derives and/or validates a risk prediction model for hospital readmission after an index admission for pneumonia; (4) the model predicts the risk for the first 30-day hospital readmission, not a series or sequence of hospital readmissions; and (5) at least one measure of model performance (discrimination or calibration) was reported in the article or made available by contacting the corresponding author.

Data Extraction and Methodological Quality Assessment

Using a standardized form, two reviewers (M.W. and D.W.) extracted data on the population characteristics, setting, number of patients and hospitals in the derivation and validation cohorts, definition of pneumonia, method and time interval of readmission outcome ascertainment, method of derivation and validation, domains of predictors tested, predictors included in the final model, accuracy of risk prediction, and quality assessment.

To facilitate a comparison of the models, we classified predictors into one of nine categories on the basis of prior conceptual frameworks of readmission risk (demographics, socioeconomic status, comorbidities, utilization, laboratory results, vital signs, imaging, procedures, and medications) (4, 7). Disagreements between reviewers were resolved through discussion. If consensus could not be achieved, a third author (A.N.M) resolved discrepancies. Corresponding authors were contacted if data were missing.

The accuracy of risk prediction was assessed by evaluating the model's discrimination and calibration. We assessed discrimination on the basis of the C statistic, which is the probability that, given two individuals hospitalized with pneumonia (one who was readmitted and the other who was not), the model will predict a higher risk for the readmitted patient than for the non-readmitted patient (8). A C statistic of 0.5 indicates a model performs no better than chance, 0.6 to 0.7 is considered modest discrimination, 0.71 to 0.8 indicates very good discrimination, and greater than 0.8 is considered strong (9). Model calibration is the degree to which predicted rates are similar to those observed in the population (7). To examine calibration, we reported the observed risk for readmission for the predicted lowestand highest-risk groups.

We assessed the quality of included studies using elements from the standards of evidence for evaluating clinical prediction rules and the study quality assessment criteria used by Kansagara and colleagues (7, 10). Studies were considered to be high quality if they included an adequate description and generalizability of the population, had nonbiased selection of patients, ascertained readmissions within 30 days beyond the index hospital, and broadly validated the model in external cohorts (vs. narrow validation in a single cohort or no validation altogether).

Data Synthesis

A metaanalysis was not able to be performed due to the heterogeneity of the included studies. Results were qualitatively synthesized with a focus on the predictors included in each model, model performance, and methodological quality.

Results

Of 992 titles identified by our search algorithm, 91 qualified for abstract review, 12 for full-text review, and 7 met our inclusion criteria (Figure 1) (11–17). Of the seven included studies, 11 unique riskprediction models were tested. The CMS Pneumonia Administrative Model was the most commonly studied—validated in five separate cohorts (12, 14, 15). The objective of eight of the models was to identify patients hospitalized for pneumonia at high risk for readmission for potential intervention (11, 13, 16, 17), whereas for three of the models the objective was to estimate hospital-level risk-adjusted 30-day



Figure 1. Systematic review study selection flowchart.

readmission rates for the purpose of hospital profiling (12, 14, 15).

Study characteristics are shown in Table 1. All studies were based in the United States except for Capelastegui and colleagues (11), which was conducted at a single academic medical center in Spain. All studies defined pneumonia as the primary discharge diagnosis using International Classification of Diseases, Ninth Revision codes for any type, except for one prospective study that defined communityacquired pneumonia using a clinical diagnosis of symptoms and imaging (11). The study populations ranged from single academic medical centers to national data (Medicare and Veterans Affairs). Five studies predicted all-cause 30-day readmissions, and two studies developed separate models to predict 30-day pneumonia-related and pneumoniaunrelated readmissions (11, 13). Across all the studies, the all-cause 30-day readmission rates ranged from 11.8 to 20.8% (median, 17.3%). Only two studies reported the rates of pneumonia-related readmissions, which were much lower (2.6 and 7.2%).

Predictors of Readmission

The predictors included in each model varied (Table 2). The number of predictors included per model ranged from 2 to 45. All

models included medical comorbidities. Demographics were included in 9 models, socioeconomic status in 10, prior healthcare use in 6, laboratory values in 9, vital signs in 4, medications in 6, imaging in 4, and procedures in 2. No studies included pneumonia severity-of-illness scores, such as the Pneumonia Severity Index or CURB-65 (confusion of new onset, blood urea nitrogen, respiratory rate, blood pressure, age 65 yr or older), and only one study included predictors on the in-hospital evolution of clinical severity (treatment failure, decompensation of comorbidities, and number of instability factors on discharge) (11). The remaining studies included predictors available within the first day of admission. The complete list of included predictors and their associated effect sizes are shown in Table E1 in the online supplement.

Model Performance

For predicting all-cause readmission, model discrimination (C statistic) ranged from 0.59 to 0.77 (median, 0.63). The CMS Pneumonia Administrative Model, which was the most commonly tested risk prediction model, consistently had a C statistic of 0.63 in four separate cohorts (Table 3) (12, 15). However, for unclear reasons, when validated using state-level Medicare data from Missouri, the C statistic

for the CMS Model was 0.72 (E. Nagasako, M.D., Ph.D.; e-mail communication, September 2, 2015) (14). Notably, the addition of census tract-level socioeconomic data to the CMS Pneumonia Administrative Model did not improve model discrimination (C statistic of 0.72 for both) (14). Risk prediction models derived using more clinically granular data (i.e., laboratory results and vital signs) than administrative claims data did not necessarily have better discrimination, with C statistics ranging from 0.59 to 0.67 for all-cause readmission (13, 16, 17).

The two studies that derived models separately predicting pneumonia-related and pneumonia-unrelated readmissions were conducted in single academic medical centers. One study was not internally validated (*see* quality assessment below) (11), thus limiting the interpretability of the study's findings, and the other study derived and internally validated models with extremely poor discrimination (C statistic, 0.39 to 0.56) (13).

Calibration for included models is shown in Table 3. The models were able to adequately risk stratify patients, with observed readmission rates ranging from approximately a 3- to 10-fold difference between the lowest and highest predicted risk groups.

Table 1. Deta	ails of pneumo	nia readmission	prediction mod	lel studies
---------------	----------------	-----------------	----------------	-------------

Study	Model	Purpose of Model	Setting	Population Age; Study Dates	Type of Pneumonia; Definition	Derivation Cohort, N	Validation Cohort, N (Method of Validation)	Observed 30-Day Readmit Rates, N (%)*
Capelastegui <i>et al.</i> , 2009 (11) Hebert <i>et al.</i> , 2014 (17)	Pneumonia related Pneumonia unrelated EMR model	Identify high-risk patients Identify high-risk patients	1 AMC in Spain 1 AMC in Ohio	 > 18 yr; July 2003 to June 2007 > 18 yr; August 2009 to July 2011 	CAP; prospective All types; ICD-9 codes	1,117 1,117 1,171	None None Cohort 1: 258 (split sample) Cohort 2: 552 (historical)	81 (7.2) 51 (4.5) 48 (18.6) 98 (17.8)
Lindenauer et al., 2011 (12)	CMS Pneumonia Administrative Model	Risk adjustment to profile hospitals	National Medicare data	≥ 65 yr; 2005–2006	All types; ICD-9 codes	226,545	Cohort 1: 226,706 (split-sample) Cohort 2: 536,015 (historical) Cohort 3: 47,429 (separate cohort)	39,673 (17.5) [†] 92,730 (17.3) [†] 8,063 (17.0)
	CMS Pneumonia Medical Becord Model					47,429	None	8,063 (17.0)
Mather <i>et al.</i> , 2014 (13)	All cause Pneumonia related Pneumonia unrelated Modified CMS Pneumonia Medical Becord Model [‡]	Identify high-risk patients	1 AMC in Connecticut	≥ 65 yr; January 2009 to March 2012	All types; ICD-9 codes	956 956 956 956	956 (bootstrapping) 956 (bootstrapping) 956 (bootstrapping) 956 (bootstrapping)	148 (15.5) 25 (2.6) 123 (12.8) 148 (15.5)
Nagasako <i>et al.,</i> 2014 (14)	SES-enriched CMS Pneumonia Administrative Model	Risk adjustment to profile bospitals	Medicare data from Missouri	≥ 65 yr; June 2009 to May 2012	All types; ICD-9 codes	25,729	29,855 (bootstrapping) †	3,877 (15.0) [†]
	CMS Pneumonia Administrative Model	neopitale				N/A	29,855 (bootstrapping) †	3,877 (15.0) [†]
O'Brien <i>et al.</i> , 2015 (15)	CMS Pneumonia Administrative Model	Risk adjustment to profile hospitals	National VA data	≥ 65 yr; October 2005 to September 2010	All types; ICD-9 codes	N/A	Cohort 1: 31,068 (VA data only) Cohort 2: 30,758 (VA & Medicare)	5,499 (17.7) 6,398 (20.8)
Tang <i>et al.</i> , 2014 (16)	VA predictor model	Identify high-risk patients	National VA data	≥ 65 yr; October 2001 to September 2007	All types; ICD-9 codes	22,567	22,567 (split sample)	3,024 (13.4)†

Definition of abbreviations: AMC = academic medical center; CAP = community-acquired pneumonia; CMS = Centers for Medicare and Medicaid Services; EMR = electronic medical record; ICD-9 = International Classification of Diseases, Ninth Revision; N/A = not applicable; SES = socioeconomic status; VA = Veterans Affairs.

*Reported for the respective validation cohort. If no validation cohort was used, then observed readmission rates were reported among the derivation cohort. All models predicted all-cause 30-day readmission, unless otherwise specified.

[†]Data obtained from contacting study author.

[‡]Included variables (n = 11) in the CMS Medical Record Model that were available to the study authors.

Aside from the study by Nagasako and colleagues, the CMS Pneumonia Administrative Model had a somewhat narrower spread of predicted risk than models derived from electronic health record (EHR) data (14).

Quality Assessment of Study Methods

Model quality was variable across studies (Table 4). All studies included an adequate description of the population and had nonbiased selection of patients; however, three studies developed models from a single academic medical center without external validation, which greatly limits external generalizability. Furthermore, these three studies only partially ascertained readmissions, because they only captured readmission outcomes at the

Table 2. Domains of predictors evaluated and included in pneumonia readmission risk prediction models

Study	Model	Domains of Predictors Evaluated	Domains of Predictors Included in Final Model
Capelastegui <i>et al.</i> , 2009 (11)	Pneumonia related Pneumonia unrelated	D, SES, C, U, L, V, I, P, M D, SES, C, U, L, V, I, P, M	L, V, I, P D. C
Hebert <i>et al.</i> , 2014 (17)	EMR model	D. SES. C. U. L. V. I. P. M	C. U. L. P. M
Lindenauer et al., 2011 (12)	CMS Pneumonia Administrative Model	D, C	D, C
	CMS Pneumonia Medical Record Model	D, C, U, L, V, I, M	D, C, L, V, I, M
Mather et al., 2014 (13)	All cause	D, SES, C, U, L, V, I, M	D, SES, C, U, L, M
	Pneumonia related	D, SES, C, U, L, V, I, M	D, SES, C, U, L, M
	Pneumonia unrelated	D, SES, C, U, L, V, I, M	D, SES, C, U, L, V, I
	Modified CMS Pneumonia Medical Record Model	D, SES, C, L, V, I, M	D, C, L, M
Nagasako et al., 2014 (14)	SES-enriched CMS Pneumonia Administrative Model	D, SES, C, U	D, SES, C, U
	CMS Pneumonia Administrative Model	D, C	D, C
O'Brien et al., 2015 (15)	CMS Pneumonia Administrative Model	D, C	D, C
Tang et al., 2014 (16)	VA predictor model	D, SES, C, U, P, M	D, SES, C, U, M

Definition of abbreviations: C = comorbidities; CMS = Centers for Medicare and Medicaid Services; D = demographics; EMR = electronic medical record; I = imaging; L = laboratory results; M = medications; P = procedures; SES = socioeconomic status; U = utilization; V = vital signs; VA = Veterans Affairs.

Study	Model*	Discrimination, C Statistic [†]	Pseudo R ²	Calibration: Observed Readmission Rate [‡]		
				Lowest Predicted Risk Group (%)	Highest Predicted Risk Group (%)	
Capelastegui et al., 2009 (11) Hebert et al., 2014 (17)	Pneumonia related Pneumonia unrelated EMR model	0.65 (derivation cohort) 0.77 (derivation cohort) Cohort 1: 0.73 Cohort 2: 0.66	Not reported Not reported 0.09 [§] 0.02 [§]	1.2 (tertile) [§] 0.6 (sextile) [§] 6.0	6.3 (tertile) [§] 16.2 (sextile) [§] 36.0	
Lindenauer et al., 2011 (12)	CMS Pneumonia Administrative Model	Cohort 1: 0.63 Cohort 2: 0.63 Cohort 3: 0.63	0.05 0.05 0.05	9 8 8	31 31 30	
	CMS Pneumonia Medical Record Model	0.59 (derivation cohort)	0.02	10	26	
Mather <i>et al.</i> , 2014 (13)	All cause Pneumonia related Pneumonia unrelated Modified CMS Pneumonia Medical Record Model	0.67 0.56 [§] 0.39 [§] 0.48 [§]	0.13 0.16 0.11 0.08	7.5 3.3 9.1 4.2	43.0 36.6 34.0 35.1	
Nagasako <i>et al.,</i> 2014 (14)	SES-enriched CMS Pneumonia Administrative Model CMS Pneumonia Administrative Model	0.72 [§] 0.72 [§]	0.14 [§] 0.14 [§]	3.6 [§] 3.6 [§]	38.7 [§] 38.6 [§]	
O'Brien <i>et al.</i> , 2015 (15) Tang <i>et al.</i> , 2014 (16)	CMS Pneumonia Administrative Model VA predictor model	Cohort 1: 0.63 Cohort 2: 0.63 0.61	Not reported Not reported 0.03 [§]	10.0 12.0 7.5 (quintile) [§]	31.8 36.7 21.1 (quintile) [§]	

Table 3. Performance of pneumonia-specific risk prediction models for 30-day readmission

Definition of abbreviations: EMR = electronic medical record; CMS = Centers for Medicare and Medicaid Services; SES = socioeconomic; VA = Veterans Affairs. *All models predicted all-cause 30-day readmission, unless otherwise specified.

[†]Discrimination reported is for predicting 30-day readmission in the validation cohort, unless otherwise specified.

[‡]Range of mean observed risk for 30-day readmission is reported by lowest-risk to highest-risk decile, unless otherwise specified.

[§]Data obtained from contacting study author.

index hospital. The level of evidence for model validation also varied across studies. The models derived in the study by Capelastegui and colleagues (11) were neither internally nor externally validated. The CMS Pneumonia Administrative Model had the highest level of evidence for model validation, as it was broadly validated in five distinct cohorts spanning different populations and time periods.

Discussion

In this systematic review, we identified 11 unique pneumonia readmission risk prediction models. The median all-cause 30-day readmission rate was 17.3%, meaning that one in six patients hospitalized for pneumonia was readmitted within 30 days of discharge. The majority of models were developed in U.S. populations of patients 65 years of age or older. Three models were developed from administrative claims data with the intent of estimating riskstandardized readmission rates for hospital profiling and benchmarking purposes,

including the CMS Pneumonia Administrative Model. Eight models were derived from EHR data or Veterans Affairs administrative data (which included more clinical detail than traditional claims data). with the goal of identifying patients at high risk for 30-day readmission for whom realtime identification and enrollment in a transitional care intervention may improve outcomes (18). Most models had poor to modest predictive ability (median C statistic of 0.63). The one model with very good discrimination was a single hospital site study of low methodological rigor (not internally or externally validated).

We found that models derived from more clinically granular data, which incorporated laboratory results and vital sign values, did not necessarily have better predictive ability than models derived from administrative claims data. Unlike for other disease-specific readmissions risk prediction models (e.g., congestive heart failure), the inclusion of more domains of predictors and increased granularity of data did not necessarily improve model performance for predicting 30-day readmissions among patients hospitalized with pneumonia (7, 19).

One potential explanation for this phenomenon is that models derived from more clinically enriched data did not adequately incorporate measures of pneumonia illness severity. None of the studies included in this review incorporated the Pneumonia Severity Index or the CURB-65 score, which are strong predictors of mortality and have also been shown to be associated with hospital readmissions (11, 20-24). Furthermore, the only study that included measures of in-hospital clinical trajectory and stability on discharge, robust predictors of postdischarge adverse outcomes, had very good discrimination (C statistic of 0.77); however, because of the study's low quality due to limited generalizability, incomplete ascertainment of readmissions, and lack of validation, it is unclear whether inclusion of these measures improved readmission risk prediction (11, 23, 25-27). Nonetheless, this approach is promising and warrants further investigation.

Table 4. Assessment of study quality

Study	Model	Generalizability of Population	Nonbiased Selection	Readmission Adequately Ascertained	Level of Evidence for Model Validation
Capelastegui <i>et al.</i> , 2009 (11)	Pneumonia related	No (single center)	Yes	Partly, only index hospital	No validation performed
	Pneumonia unrelated	No (single center)	Yes	Partly, only index hospital	No validation performed
Hebert <i>et al.</i> , 2014 (17)	EMR model	No (single center)	Yes	Partly, only index hospital	Narrow validation (split cohort, historical cohort)
Lindenauer <i>et al.</i> , 2011 (12)	CMS Pneumonia Administrative Model	Yes (national Medicare data)	Yes	Yes	Broad validation (split cohort, historical cohort, and separate cohort)
	CMS Pneumonia Medical Record Model	Yes (national Medicare data)	Yes	Yes	No validation performed
Mather <i>et al.</i> , 2014 (13)	All cause	No (single center)	Yes	Partly, only index hospital	Narrow validation (bootstrapping)
	Pneumonia related	No (single center)	Yes	Partly, only index hospital	Narrow validation (bootstrapping)
	Pneumonia unrelated	No (single center)	Yes	Partly, only index hospital	Narrow validation (bootstrapping)
	Modified CMS Pneumonia Medical Record Model	No	Yes	Partly, only index hospital	Narrow validation (bootstrapping)
Nagasako <i>et al.</i> , 2014 (14)	SES-enriched CMS Pneumonia Administrative Model	Partial (Medicare data in Missouri)	Yes	Yes	Narrow validation (bootstrapping using same cohort)
	CMS Pneumonia Administrative Model	Partial (Medicare data in Missouri)	Yes	Yes	Narrow validation (bootstrapping)
O'Brien <i>et al.</i> , 2015 (15)	CMS Pneumonia Administrative Model	Yes (national VA data)	Yes	Yes	Broad validation (separate cohort)
Tang <i>et al.</i> , 2014 (16)	VA predictor model	Yes (national VA data)	Yes	Yes	Narrow validation (split sample)

Definition of abbreviations: EMR = electronic medical record; CMS = Centers for Medicare and Medicaid Services; SES = socioeconomic; VA = Veterans Affairs.

As opposed to mortality, which is easier to predict based on illness severity and comorbidity burden (19), hospital readmissions are a more complex phenomenon stemming from the interplay among patient-, hospital-, community-, and environmental-level factors. Despite the fact that current readmission risk prediction models have not taken full advantage of incorporating measures of pneumonia illness severity, clinical trajectory, and stability on discharge that are currently available in the EHR, readmissions after pneumonia hospitalization may have less to do with traditional medical factors than once believed (28, 29).

Although several studies in this review included marital status, mental illness diagnoses, and census-tract income levels as predictors, these metrics may not fully capture an individual's social support, self-sufficiency, health literacy, and socioeconomic disadvantage. Thus, further improvement in pneumonia readmission models may require accounting for psychosocial and behavioral factors not routinely captured in health information systems.

Another reason it may be difficult to predict readmissions among this population is because readmissions specifically related to the pneumonia itself are uncommon, ranging from 2.6 to 7.2%. Thus, most readmissions are not due to a recurrence or inadequate treatment of the pneumonia itself but rather from the impact of the acute illness on their other comorbidities and general health. To identify patients at high risk for readmission, it is essential to not only include predictors of pneumonia illness severity and compliance with guidelineconcordant therapies but also include predictors of frailty and medical complexity that may put patients at greater risk for posthospital syndrome or decompensation of their other chronic conditions (30).

Although predictive accuracy at the individual level is modest, risk scores estimated from pneumonia-specific readmissions models corresponded to a clinically meaningful gradient of observed readmission risk, such that the group of patients predicted as being at high risk for readmission had an approximately twofold higher observed readmission rate than the median readmission rate and a 3- to 10-fold higher readmission rate than the group of patients identified by the risk prediction models as being at low risk. Therefore, hospitals and health systems can currently use available pneumonia risk prediction models to help identify a subset of patients at highest risk and enroll these patients in resource-intensive transitional care interventions to potentially prevent readmissions (18). This is essential to the sustainability and durability of interventions aimed at lowering readmission rates, because most hospitals do not have the resources to enroll every patient hospitalized for pneumonia for a transitional care intervention, nor would such an approach be cost effective.

An important caveat to this approach is that there is insufficient evidence that transitional care interventions specifically targeted to patients hospitalized for

pneumonia decrease readmissions. However, given that the national pneumonia readmission rate decreased by 6% from 2009 to 2013 after the implementation of hospital financial penalties (31), a proportion of these readmissions are likely preventable. Further research is needed to assess the type and intensity of transitional care intervention best suited to this population. Because only a small proportion of readmissions are directly related to pneumonia itself, transitional care interventions for patients with pneumonia will need to be multifaceted and address factors unique to pneumonia, including appropriate antibiotic selection and readiness for discharge using Halm's criteria for clinical stability, as well as the most common factors associated with potentially avoidable readmissions in general, including improved communication between inpatient and outpatient providers, patient education, and timely access to care after discharge (32).

An alternative strategy to identify patients with pneumonia at highest risk for readmission is to use existing multicondition risk prediction models, such as the LACE index (length of stay, acuity of admission, comorbidities, and emergency department visits), HOSPITAL score (hemoglobin level at discharge, discharge from oncology service, sodium level at discharge, procedure during hospital stay, index admission type as urgent or emergent, number of admissions in previous year, and length of stay), or EHR-based models (33–35). Implementing readmission risk prediction models for every condition may

be time-consuming and costly. Although we hypothesize that the inclusion of predictors specific to pneumonia would result in superior risk prediction, future research is needed to perform head-to-head comparisons between these two strategies to test whether using a pneumonia-specific risk prediction model is worth the added effort and complexity. Furthermore, because pneumonia-specific readmissions risk prediction models would be most clinically useful if implemented earlier in the hospitalization when in-hospital components of transitional care interventions can be more effectively implemented (36), further research is needed to assess whether models that include predictors available on admission perform as well as models that include predictors available on the day of discharge.

Limitations

Our review has certain limitations. First, despite a comprehensive literature search strategy, we may have overlooked studies published in non-English languages or nonindexed studies in the gray literature. Second, few studies directly compared models within the same population, so caution should be used when directly comparing model performance across different populations.

Third, the included studies did not report positive predictive value and likelihood ratios for the highest risk group of patients for readmission. However, we assessed the ability of risk prediction models to identify patients hospitalized with pneumonia at highest risk for readmission using calibration, which is an appropriate method for stratifying individuals into different risk categories for prognosis of a future event (37, 38). Fourth, because all studies except for one defined pneumonia using discharge International Classification of Diseases, Ninth Revision codes, it is unclear whether defining pneumonia prospectively on admission meaningfully influences risk prediction.

Conclusions

There are currently a limited number of validated pneumonia-specific readmission risk prediction models. The predictive accuracy (discrimination) of published models is modest at best. However, model calibration of existing pneumonia readmissions models is adequate to enable a risk-stratified approach to identifying and enrolling high-risk patients for resourceintensive transitional care interventions. Future research in this area should include measures of pneumonia illness severity, hospital complications, and stability on discharge available in the EHR from the entire hospital course and not just from the first day of admission. At present, many factors influencing readmissions in this population likely remain unmeasured and/or unaccounted for.

Author disclosures are available with the text of this article at www.atsjournals.org.

Acknowledgment: The authors thank Eric Bass, M.D., M.P.H., and Karen Robinson, Ph.D., from the Johns Hopkins Evidence-Based Practice Center, for their assistance in adopting and implementing our search strategy for the Embase database.

References

- Jencks SF, Williams MV, Coleman EA. Rehospitalizations among patients in the Medicare fee-for-service program. N Engl J Med 2009; 360:1418–1428.
- 2 Epstein AM, Jha AK, Orav EJ. The relationship between hospital admission rates and rehospitalizations. *N Engl J Med* 2011;365:2287–2295.
- 3 De Alba I, Amin A. Pneumonia readmissions: risk factors and implications. *Ochsner J* 2014;14:649–654.
- 4 Calvillo-King L, Arnold D, Eubank KJ, Lo M, Yunyongying P, Stieglitz H, Halm EA. Impact of social factors on risk of readmission or mortality in pneumonia and heart failure: systematic review. *J Gen Intern Med* 2013;28:269–282.
- 5 Joynt KE, Orav EJ, Jha AK. Thirty-day readmission rates for Medicare beneficiaries by race and site of care. *JAMA* 2011;305:675–681.
- 6 Lu N, Huang KC, Johnson JA. Reducing excess readmissions: promising effect of hospital readmissions reduction program in US hospitals. *Int J Qual Health Care* 2016;28:53–58.
- 7 Kansagara D, Englander H, Salanitro A, Kagen D, Theobald C, Freeman M, Kripalani S. Risk prediction models for

hospital readmission: a systematic review. *JAMA* 2011;306: 1688–1698.

- 8 Pencina MJ, D'Agostino RB Sr. Evaluating discrimination of risk prediction models: the C statistic. JAMA 2015;314:1063–1064.
- 9 Hosmer DW, Lemeshow S. Applied logistic regression, 2nd ed. New York, NY: John Wiley & Sons; 2000.
- 10 Reilly BM, Evans AT. Translating clinical research into clinical practice: impact of using prediction rules to make decisions. *Ann Intern Med* 2006;144:201–209.
- 11 Capelastegui A, España Yandiola PP, Quintana JM, Bilbao A, Diez R, Pascual S, Pulido E, Egurrola M. Predictors of short-term rehospitalization following discharge of patients hospitalized with community-acquired pneumonia. *Chest* 2009;136:1079–1085.
- 12 Lindenauer PK, Normand SL, Drye EE, Lin Z, Goodrich K, Desai MM, Bratzler DW, O'Donnell WJ, Metersky ML, Krumholz HM. Development, validation, and results of a measure of 30-day readmission following hospitalization for pneumonia. J Hosp Med 2011;6:142–150.
- 13 Mather JF, Fortunato GJ, Ash JL, Davis MJ, Kumar A. Prediction of pneumonia 30-day readmissions: a single-center attempt to increase model performance. *Respir Care* 2014;59:199–208.

- 14 Nagasako EM, Reidhead M, Waterman B, Dunagan WC. Adding socioeconomic data to hospital readmissions calculations may produce more useful results. *Health Aff (Millwood)* 2014;33:786–791.
- 15 O'Brien WJ, Chen Q, Mull HJ, Shwartz M, Borzecki AM, Hanchate A, Rosen AK. What is the value of adding Medicare data in estimating VA hospital readmission rates? *Health Serv Res* 2015;50:40–57.
- 16 Tang VL, Halm EA, Fine MJ, Johnson CS, Anzueto A, Mortensen EM. Predictors of rehospitalization after admission for pneumonia in the Veterans Affairs healthcare system. J Hosp Med 2014;9:379–383.
- 17 Hebert C, Shivade C, Foraker R, Wasserman J, Roth C, Mekhjian H, Lemeshow S, Embi P. Diagnosis-specific readmission risk prediction using electronic health data: a retrospective cohort study. *BMC Med Inform Decis Mak* 2014;14:65.
- 18 Amarasingham R, Patel PC, Toto K, Nelson LL, Swanson TS, Moore BJ, Xie B, Zhang S, Alvarez KS, Ma Y, *et al.* Allocating scarce resources in real-time to reduce heart failure readmissions: a prospective, controlled study. *BMJ Qual Saf* 2013;22:998–1005.
- 19 Amarasingham R, Moore BJ, Tabak YP, Drazner MH, Clark CA, Zhang S, Reed WG, Swanson TS, Ma Y, Halm EA. An automated model to identify heart failure patients at risk for 30-day readmission or death using electronic medical record data. *Med Care* 2010;48:981–988.
- 20 Loke YK, Kwok CS, Niruban A, Myint PK. Value of severity scales in predicting mortality from community-acquired pneumonia: systematic review and meta-analysis. *Thorax* 2010;65:884–890.
- 21 Kwok CS, Loke YK, Woo K, Myint PK. Risk prediction models for mortality in community-acquired pneumonia: a systematic review. *Biomed Res Int.* 2013;2013:504136.
- 22 Chalmers JD, Singanayagam A, Akram AR, Mandal P, Short PM, Choudhury G, Wood V, Hill AT. Severity assessment tools for predicting mortality in hospitalised patients with community-acquired pneumonia. Systematic review and meta-analysis. *Thorax* 2010;65:878–883.
- 23 Hougham GW, Ham SA, Ruhnke GW, Schulwolf E, Auerbach AD, Schnipper JL, Kaboli PJ, Wetterneck TB, Gonzalez D, Arora VM, et al. Sequence patterns in the resolution of clinical instabilities in community-acquired pneumonia and association with outcomes. J Gen Intern Med 2014;29:563–571.
- 24 Micek ST, Lang A, Fuller BM, Hampton NB, Kollef MH. Clinical implications for patients treated inappropriately for community-acquired pneumonia in the emergency department. *BMC Infect Dis* 2014;14:61.
- 25 Aliberti S, Peyrani P, Filardo G, Mirsaeidi M, Amir A, Blasi F, Ramirez JA. Association between time to clinical stability and outcomes after discharge in hospitalized patients with community-acquired pneumonia. *Chest* 2011;140:482–488.

- 26 Capelastegui A, España PP, Bilbao A, Martinez-Vazquez M, Gorordo I, Oribe M, Urrutia I, Quintana JM. Pneumonia: criteria for patient instability on hospital discharge. *Chest* 2008;134:595–600.
- 27 Halm EA, Fine MJ, Kapoor WN, Singer DE, Marrie TJ, Siu AL. Instability on hospital discharge and the risk of adverse outcomes in patients with pneumonia. *Arch Intern Med* 2002;162:1278–1284.
- 28 Sheingold SH, Zuckerman R, Shartzer A. Understanding Medicare hospital readmission rates and differing penalties between safety-net and other hospitals. *Health Aff (Millwood)* 2016;35:124–131.
- 29 Barnett ML, Hsu J, McWilliams JM. Patient characteristics and differences in hospital readmission rates. JAMA Intern Med 2015; 175:1803–1812.
- 30 Krumholz HM. Post-hospital syndrome: an acquired, transient condition of generalized risk. *N Engl J Med* 2013;368:100–102.
- 31 Fingar K, Washington R. Trends in hospital readmissions for four high-volume conditions, 2009–2013: statistical brief #196. Healthcare Cost and Utilization Project (HCUP) statistical briefs. Rockville, MD: Agency for Healthcare Research and Quality; 2006.
- 32 Auerbach AD, Kripalani S, Vasilevskis EE, Sehgal N, Lindenauer PK, Metlay JP, Fletcher G, Ruhnke GW, Flanders SA, Kim C, et al. Preventability and causes of readmissions in a national cohort of general medicine patients. JAMA Intern Med 2016;176:484–493.
- 33 Gruneir A, Dhalla IA, van Walraven C, Fischer HD, Camacho X, Rochon PA, Anderson GM. Unplanned readmissions after hospital discharge among patients identified as being at high risk for readmission using a validated predictive algorithm. *Open Med* 2011;5:e104–e111.
- 34 Donzé JD, Williams MV, Robinson EJ, Zimlichman E, Aujesky D, Vasilevskis EE, Kripalani S, Metlay JP, Wallington T, Fletcher GS, et al. International validity of the HOSPITAL score to predict 30-day potentially avoidable hospital readmissions. JAMA Intern Med 2016;176:496–502.
- 35 Nguyen OK, Makam AN, Clark C, Zhang S, Xie B, Velasco F, Amarasingham R, Halm EA. Predicting all-cause readmissions using electronic health record data from the entire hospitalization: model development and comparison. *J Hosp Med* [online ahead of print] 29 Feb 2016; DOI: 10.1002/jhm.2568.
- 36 Rennke S, Nguyen OK, Shoeb MH, Magan Y, Wachter RM, Ranji SR. Hospital-initiated transitional care interventions as a patient safety strategy: a systematic review. Ann Intern Med 2013;158:433–440.
- 37 Cook NR. Use and misuse of the receiver operating characteristic curve in risk prediction. *Circulation* 2007;115:928–935.
- 38 Cook NR. Statistical evaluation of prognostic versus diagnostic models: beyond the ROC curve. *Clin Chem* 2008;54:17–23.