

Risk Prediction Models for Hospital Readmission

A Systematic Review

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AN INCREASING BODY OF LITERATURE attempts to describe and validate hospital readmission risk prediction tools. Interest in such models has grown for 2 reasons. First, transitional care interventions may reduce readmissions among chronically ill adults.¹⁻³ Readmission risk assessment could be used to help target the delivery of these resource-intensive interventions to the patients at greatest risk. Ideally, models designed for this purpose would provide clinically relevant stratification of readmission risk and give information early enough during the hospitalization to trigger a transitional care intervention, many of which involve discharge planning and begin well before hospital discharge. Second, there is interest in using readmission rates as a quality metric. The Centers for Medicare & Medicaid Services (CMS) recently began using readmission rates as a publicly reported metric and has plans to lower reimbursement to hospitals

Context Predicting hospital readmission risk is of great interest to identify which patients would benefit most from care transition interventions, as well as to risk-adjust readmission rates for the purposes of hospital comparison.

Objective To summarize validated readmission risk prediction models, describe their performance, and assess suitability for clinical or administrative use.

Data Sources and Study Selection The databases of MEDLINE, CINAHL, and the Cochrane Library were searched from inception through March 2011, the EMBASE database was searched through August 2011, and hand searches were performed of the retrieved reference lists. Dual review was conducted to identify studies published in the English language of prediction models tested with medical patients in both derivation and validation cohorts.

Data Extraction Data were extracted on the population, setting, sample size, follow-up interval, readmission rate, model discrimination and calibration, type of data used, and timing of data collection.

Data Synthesis Of 7843 citations reviewed, 30 studies of 26 unique models met the inclusion criteria. The most common outcome used was 30-day readmission; only 1 model specifically addressed preventable readmissions. Fourteen models that relied on retrospective administrative data could be potentially used to risk-adjust readmission rates for hospital comparison; of these, 9 were tested in large US populations and had poor discriminative ability (*c* statistic range: 0.55-0.65). Seven models could potentially be used to identify high-risk patients for intervention early during a hospitalization (*c* statistic range: 0.56-0.72), and 5 could be used at hospital discharge (*c* statistic range: 0.68-0.83). Six studies compared different models in the same population and 2 of these found that functional and social variables improved model discrimination. Although most models incorporated variables for medical comorbidity and use of prior medical services, few examined variables associated with overall health and function, illness severity, or social determinants of health.

Conclusions Most current readmission risk prediction models that were designed for either comparative or clinical purposes perform poorly. Although in certain settings such models may prove useful, efforts to improve their performance are needed as use becomes more widespread.

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and questions on p 1716.

with excess risk-standardized readmission rates.⁴ Valid risk adjustment methods are required for calculation of risk-standardized readmission rates, which could be used for hospital comparison, public reporting, and reimbursement determinations. Models designed for these purposes should have good predictive ability; be deployable in large populations; use reliable data that can be easily obtained; and use variables that are clinically related to and validated in the populations in which use is intended.⁵

This systematic review was performed to synthesize the available literature on validated readmission risk prediction models, describe their performance, and assess their suitability for clinical or administrative use.

METHODS

Data Sources and Searches

We searched Ovid MEDLINE, CINAHL, and the Cochrane Library (Central Trial Registry, Systematic Reviews, and Abstracts of Reviews of Effectiveness) from database inception through March 2011, and EMBASE through August 2011, for studies published in the English language of readmission risk prediction models in medical populations. All citations were imported into an electronic database (EndNote X2, Thomson Reuters, New York, NY). The search strategies are provided in detail in eAppendix 1 at <http://www.jama.com>.

Study Selection

All of the authors reviewed the citations and abstracts identified from electronic literature searches using the eligibility criteria shown in eAppendix 2. Full-text articles of potentially relevant references were retrieved and each was independently assessed for eligibility by 2 of the authors. Eligible articles were published in English and evaluated the ability of statistical models to predict hospital readmission risk. Because a set of predictive factors derived in only 1 population may lack validity and applicability,⁶ we included only studies of models that were tested in both a derivation and a validation cohort, even if these results

were presented in separate reports. We neither prespecified the method of validation, nor excluded studies in which the derivation and validation cohorts were drawn from the same population (ie, split-half validation). We did not limit studies by diagnosis within medical populations. We excluded studies that focused on psychiatric, surgical, and pediatric populations because factors contributing to readmission risk might be considerably different in these patient groups. Finally, we excluded studies from developing nations because these were unlikely to provide directly applicable results.

Data Extraction and Quality Assessment

From each study, we abstracted the following: population characteristics, setting, number of patients in the derivation and validation cohorts, timeframe of readmission outcome, readmission rate, range of readmission rates according to predicted risk, and model discrimination. To facilitate a high-level comparison of predictor variables, we grouped final model variables into 1 of 6 categories (medical comorbidity, mental health comorbidity, illness severity, prior use of medical services, overall health and function, and sociodemographic and social determinants of health).⁷

To characterize the practical utility of each model, 2 of the authors independently abstracted the type of data used and the timing of data collection from each study. Disagreements between reviewers about these classifications were resolved through group discussion. Data type consisted of administrative, primary (eg, survey, chart review), or both. Regarding timing, we classified a model as using real-time data if the variables would be available on or shortly after index hospital admission, and as using retrospective data if the variables would not be available early during a hospitalization. For example, a model using prior health care use and data from patient surveys conducted early during a hospitalization would be classified as using real-time data, while a model using length of

stay or discharge diagnostic codes for the index hospitalization would be classified as using retrospective data. Because of coding delays, models relying on administrative codes from index hospital admissions were considered retrospective.

The *c* statistic with 95% confidence intervals (when available) were used to describe model discrimination. The *c* statistic, which is equivalent to the area under the receiver operating characteristic curve, is defined as the proportion of times the model correctly discriminates a pair of high- and low-risk individuals.⁸ A *c* statistic of 0.50 indicates that the model performs no better than chance; a *c* statistic of 0.70 to 0.80 indicates modest or acceptable discriminative ability; and a *c* statistic of greater than 0.80 indicates good discriminative ability.^{9,10} If the *c* statistic was not reported, we abstracted other operational statistics such as sensitivity, specificity, and predictive values for representative risk score cutoffs when available. Model calibration is the degree to which predicted rates are similar to those observed in the population. To describe model calibration, we report the range of observed readmission rates from the predicted lowest to highest risk groupings.

To guide our methodological assessment of included studies, we adapted elements (including cohort definition, follow-up, adequacy of prognostic and outcome variable measurement, and the validation method) from a prognosis study quality tool and clinical decision rule assessment tool (eTable at <http://www.jama.com>).^{6,11}

Data Synthesis

The included studies were too heterogeneous to permit meta-analysis. Therefore, we qualitatively synthesized results, focusing on model discrimination, the populations in which the model has been tested, practical aspects of model implementation, and the types of variables included in each model.

RESULTS

From 7843 titles and abstracts, 286 articles were selected for full-text re-

view (FIGURE). Of these, 30 studies of 26 unique models across a broad variety of settings and patient populations met our inclusion criteria (TABLE 1, TABLE 2, and TABLE 3). Most studies (n=23) were based on US health care data. The remainder were from Australia (2 studies), England (n=2), Ireland (n=1), Switzerland (n=1), or Canada (n=1). Fourteen studies included only patients aged 65 years or older. Of these, 7 relied solely on Medicare administrative data. Four studies used Veterans Affairs' data.

Total sample size ranged from 173 patients to more than 2.7 million patients. The outcome of 30-day readmission was reported most commonly, although some models chose other follow-up intervals ranging from 14 days to 4 years. Among 21 studies reporting *c* statistics (Table 1, Table 2, and Table 3), values ranged from 0.55 to 0.83, but only 6 studies re-

ported a *c* statistic above 0.70, indicating modest discriminative ability. Performance was similar between studies using split-sample validation methods (n=21; *c* statistic range: 0.59-0.75), and those that used external validation methods (n=9; *c* statistic range: 0.53-0.83). Among models that analyzed the relationship between risk categories and actual readmission rates, a substantial gradient in readmission rate was present between patients at the lowest and at the highest risk level. For example, among 6 models using 30-day readmission as an outcome, the lowest and highest risk groups differed by 20.4 to 34.5 percentage points in their actual readmission rates.

Models Relying on Retrospective Administrative Data

Fourteen models were based on retrospective administrative data and could

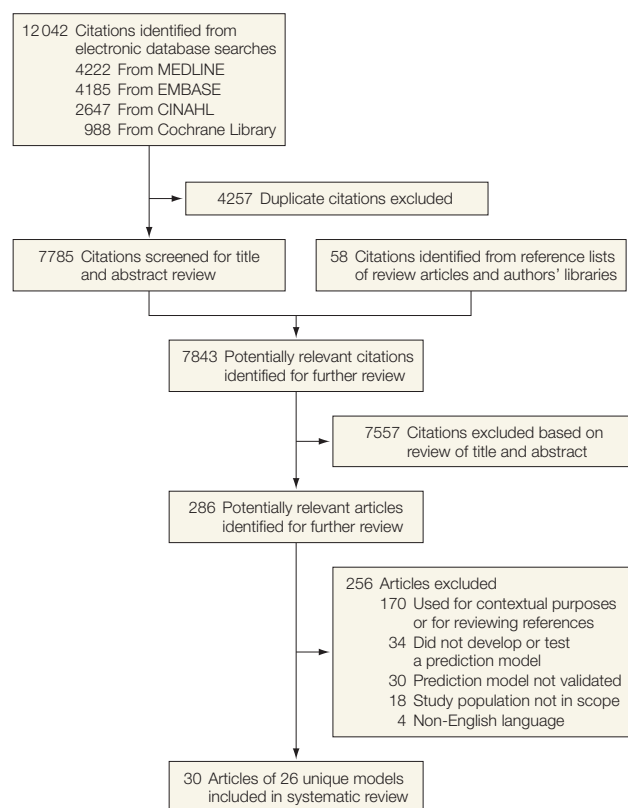
potentially be used for hospital comparison purposes (Table 1). Most of these included variables for medical comorbidity and use of prior medical services, but a few considered mental health, functional status, and social determinant variables (TABLE 4). The 3 models with *c* statistics of 0.70 or higher were developed and tested in large European or Australian cohorts. One examined the risk of 2 or more unplanned readmissions for all hospitalized patients in England, including pediatric and obstetric patients, for 1 calendar year.¹³ A Swiss study¹⁷ examined potentially preventable readmissions. An Australian model incorporating more than 100 medical comorbidities and administrative social determinant variables performed at a modest level in asthma patients, but poorly in patients with myocardial infarction.²⁰

The 9 large population-based or multicenter US studies generally had poor discriminative ability (*c* statistic range: 0.55-0.65). The CMS used a methodologically rigorous process to create 3 models for congestive heart failure, acute myocardial infarction, and pneumonia admissions based on hierarchical condition categories, which are groups of related comorbidities.¹⁴⁻¹⁶ All 3 models showed relatively poor ability to predict 30-day all-cause readmissions (*c* statistics: 0.61 for congestive heart failure, 0.63 for acute myocardial infarction, and 0.63 for pneumonia). A recent study evaluating the CMS heart failure model and an older heart failure model fared similarly (*c* statistics: 0.59 and 0.61, respectively).^{18,23} The other 4 US models have limited generalizability; for example, one model captured readmissions to 1 medical center only,²⁴ and the other models were developed more than 2 decades ago.^{12,22,25}

Models Using Real-Time Administrative Data

Three administrative data-based models were designed to identify high-risk patients in real-time to potentially facilitate targeted interventions (Table 2).

Figure. Literature Flow of Risk Prediction Models for Hospital Readmission



eAppendix 2 at <http://www.jama.com> lists the inclusion and exclusion criteria for title and abstract review. Specific exclusion codes were not recorded at the abstract level.

Table 1. Characteristics of Models Using Retrospective Administrative Data

| Source | Population and Setting | No. of Patients by Cohort | | Outcome ^b | Readmission | | Model Discrimination ^c |
|--|---|---------------------------------|-----------------------------|------------------------------|---------------------------|---|--|
| | | DC | VC ^a | | Actual Rate, % | Range of Rates (VC) | |
| Anderson and Steinberg, ¹² 1985 | Medicare patients in general US population (excluded those with ESRD) from 1974-1977 | 21 043 | 10 522 | 60 d | NR in both cohorts | 4-40 ^d (lowest to highest decile) | NR |
| Bottle et al, ¹³ 2006 | Inpatients from general population in England from 2000-2001 | ~ 1.4 million ^e | ~ 1.4 million ^e | 12 mo | 9.80 overall | NR | All patients: 0.72 (0.70 when 12-mo deaths excluded); sensitive conditions ^f : 0.75 |
| CMS model | | | | | | | |
| Krumholz et al, ¹⁴ 2008 | Medicare patients aged ≥65 y with AMI in general US population from 2005-2006 | 100 465 | 100 285 | 30 d | DC: 18.9 VC: 19.2 | 8.0-33.0 (lowest to highest decile) | 0.63 |
| Krumholz et al, ¹⁵ 2008 | Medicare patients aged ≥65 y with CHF in general US population from 2003-2004 | 283 919 | 283 528 | 30 d | DC: 23.6 VC: 23.7 | 15.0-37.0 (lowest to highest decile) | 0.60 |
| Krumholz et al, ¹⁶ 2008 | Medicare patients aged ≥65 y with pneumonia in general US population from 2005-2006 | 226 545 | 226 706 | 30 d | DC: 17.4 VC: 17.5 | 9.0-31.0 (lowest to highest decile) | 0.63 |
| Halfon et al, ¹⁷ 2006 | All hospitalizations in general population in Switzerland in 2000 | 65 740 | 66 069 | 30 d (potentially avoidable) | DC: 5.1 VC: 5.2 | NR | Nonclinical: 0.67; Charleson-based: 0.69; SQLape: 0.72 |
| Hammill et al, ¹⁸ 2011 | Patients aged ≥65 y from CHF registry in general US population from 2004-2006 | 24 163 ^g | NA | 30 d | 21.9 overall | Claims-only model: 14.4-32.7 (lowest to highest decile); clinical claims model: 13.5-33.9 | Claims-only model: 0.59; clinical claims model: 0.60 |
| Holloway et al, ¹⁹ 1990 | US medical, neurological, surgical, and geriatric inpatients at single VA hospital from 1981-1982 | 2970 | Unclear | 30 d | 22.0 overall | NR | NR |
| Holman et al, ²⁰ 2005 | Medical, surgical, and psychiatric inpatients from Western Australia's general population from 1989-1997 | 326 456 | 5289 (asthma) 5265 (AMI) | 30 d | NR | NR | Asthma: 0.71; AMI: 0.64 |
| Howell et al, ²¹ 2009 | General medical inpatients with ambulatory care sensitive condition ^f in Queensland, Australia's general population from 2005-2006 | 13 207 | 4492 | 12 mo | DC: 45.5 VC: 45.1 | Risk scores (positive LR): 50 (2.04), 70 (3.11), 80 (7.02); (overall range: 0-100) | 0.65 |
| Naessens et al, ²² 1992 | Inpatients aged ≥65 y from general US population and living in a single county in 1980, 1985, and 1987 | 5854 | 10% of DC | 60 d (and mortality) | 20.8 overall | 15.6-36.0 (lowest to highest quartile) | HCFA model: 0.59 HCFA model plus COMPLEX measure: 0.61 (SE, 0.01) |
| Philbin and DiSalvo, ²³ 1999 | Inpatients with CHF treated at multiple centers in a single US state in 1995 | 21 227 | 21 504 | Within calendar year for CHF | 21.3 overall | 9.8-45.4 (lowest to highest ninth) | Simple scoring system: 0.60; weighted scoring system: 0.61 |
| Silverstein et al, ²⁴ 2008 | Inpatients aged ≥65 y treated at multiple centers in a single US city from 2002-2004 | 19 528 | 9764 | 30 d | 11.7 overall | NR | 0.65 (same for both Elixhauser and HRDES methods) |
| Thomas, ²⁵ 1996 | Medicare inpatients aged ≥65 y treated at multiple centers in a single US state from 1989-1991 | Range: 1163-14 590 ^h | NA | 15, 30, 60, and 90 d | 3-40 overall ^h | NR | Range among 8 conditions and 4 periods: 0.55-0.61 |

Abbreviations: AMI, acute myocardial infarction; CHF, congestive heart failure; CMS, Centers for Medicare & Medicaid Services; COMPLEX, a measurement of comorbidity and disease severity²²; DC, derivation cohort; ESRD, end-stage renal disease; HCFA, Health Care Financing Administration; HRDES, High-risk Diagnoses for the Elderly Scale; LR, likelihood ratio; NA, not applicable; NR, not reported; SE, standard error; SQLape, Striving for Quality Level and Analyzing of Patient Expenditures; VA, Veterans Affairs; VC, validation cohort.

^aThe most recent cohort is listed if a study had multiple VCs.

^bUnplanned, all-cause readmissions unless otherwise indicated.

^cValues are from the c statistic unless otherwise indicated.

^dApproximate values of data that were presented in a bar graph.

^eThe total number of patients was divided equally between the DC and the VC, but the exact numbers of patients were not specified.

^fIncludes patients with ambulatory care reference conditions such as CHF, chronic obstructive pulmonary disease, diabetes, and asthma, for which timely and effective case management has the potential to reduce the risk of readmission.

^gThe bootstrap method was used for internal validation. There was not a separate VC.

^hStudy had 12 different cohorts based on diagnosis and reported 15-, 30-, 60-, and 90-day readmission rates for 12 conditions.

A model with modest discriminative ability (*c* statistic: 0.72; 95% CI, 0.70-0.75) examined 30-day heart failure readmissions in a single urban US health

system with a large socioeconomically disadvantaged population.²⁶ It incorporated variables from an automated electronic medical record system, in-

cluding numerous social factors such as number of address changes, census tract socioeconomic status, history of cocaine use, and marital status. The

Table 2. Characteristics of Models Using Real-Time Administrative Data and Retrospective Primary Data Collection

| Source | Population and Setting | No. of Patients by Cohort | | Outcome ^b | Readmission | | Model Discrimination ^c |
|--|---|-----------------------------------|---|--|----------------------|---|--|
| | | DC | VC ^a | | Actual Rate, % | Range of Rates (VC) | |
| Models Using Administrative Data in Real Time | | | | | | | |
| Amarasingham et al, ²⁶ 2010 | Patients with CHF treated at a single US center from 2007-2008 | 1029 | 343 | 30 d | 24.1 overall | 12.2-45.7 (lowest to highest quintile) | 0.72 (95% CI, 0.70-0.75) |
| Billings and Mijanovich, ²⁷ 2007 | Patients eligible for mandatory Medicaid managed care enrollment in general US population in a single city from 2000-2004 | ~ 35 000 ^d | ~ 35 000 ^d | 12 mo | NR in both cohorts | NR (overall range: 0-100) ^e | Risk score range: 0-100; using risk scores >50: sensitivity: 58%; specificity: 74%; PPV: 69.5%; positive LR: 2.23 |
| Billings et al, ²⁸ 2006 ^f | Inpatients with an ambulatory care sensitive reference condition ^g in general population of England from 2002-2003 | 10% sample of hospital episodes | Another 10% sample of hospital episodes | 12 mo | NR in both cohorts | NR | 0.69 |
| Models Using Retrospective Primary Data Collection | | | | | | | |
| Coleman et al, ²⁹ 2004 | Medicare inpatients aged ≥65 y in general US population from 1997-1998 | 700 | 704 | 30 d ^g | DC: 21.9 VC: 25.0 | NR | Administrative data model: 0.77; administrative data model plus self-report data model: 0.83 |
| Krumholz et al, ³⁰ 2000 | Medicare patients aged ≥65 y with CHF and treated at multiple centers in a single US state from 1994-1995 | 1129 | 1047 | 180 d | DC: 50.0 VC: 47.0 | All-cause: 26.0-59.0; CHF: 9.0-31.0 (lowest to highest tertile) | No. of risk factors associated with readmission risk (<i>P</i> <.001); 0 risk factors: 26%; 3-4 risk factors: 59% |
| Morrissey et al, ³¹ 2003 | Medical inpatients aged ≥65 y treated at a single rural hospital in Ireland from 1997-1998 | 487 | 732 | 12 mo | DC: 40.7 VC: 29.0 | NR | 0.70 |
| Smith et al, ³² 1985 | Medical inpatients treated at a single US county hospital from 1979-1980 | 1007 | 499 | 90 d | DC: 16.9 VC: NA | 7.3-38.0 (lowest to highest octile) | Sensitivity: 59.0%; specificity: 69.3%; PPV: 29.9%; positive LR: 1.92 |
| Smith et al, 1988 ³³ | Medical inpatients treated at a single US county hospital in 1985 | 502 (control); 499 (intervention) | 0 | By month/patient; mean: 180 d of follow-up | DC: NA VC: 10.0 | 0.07-0.18 (lowest to highest tertile) | NR |
| Smith et al, ³⁴ 1996 | US medical inpatients aged ≥45 y treated at a single VA hospital from 1988-1990 | 0 | 662 | 90 d | DC: NA VC: 20.1 | NR | 0.66 |
| van Walraven et al, ³⁵ 2010 | Medical and surgical inpatients treated at multiple centers in Canada | 4812 (split DC and internal VC) | 1 million from external VC | 30 d | DC: 7.3 VC: 7.3 | 0-42.9 ^h | 0.68 (95% CI, 0.65-0.71) |

Abbreviations: CHF, congestive heart failure; DC, derivation cohort; LR, likelihood ratio; NA, not applicable; NR, not reported; PPV, positive predictive value; VA, Veterans Affairs; VC, validation cohort.

^aThe most recent cohort is listed if a study had multiple VCs.

^bUnplanned, all-cause readmissions unless otherwise indicated.

^cValues are from the *c* statistic unless otherwise indicated.

^dThe total number of patients was divided equally between the DC and the VC, but the exact numbers of patients were not specified.

^eInpatient costs ranged from \$23 687 to \$44 385 for risk scores of 50 to 90.

^fThe patients at risk for rehospitalization algorithm was used for this study. Ambulatory care sensitive reference conditions include CHF, chronic obstructive pulmonary disease, diabetes, and asthma, for which timely and effective case management has the potential to reduce the risk of readmission.

^gIncludes patients who were transferred at least once from a lower- to a higher-intensity care environment (ie, complicated care transitions).

^hScores that ranged from 0 to 17 correspond to an expected probability range of 2.0% to 34.6% for readmission or death.

only study that focused specifically on Medicaid enrollees used a risk score range of 0 to 100 for 12-month readmissions and found that patient cost profiles varied widely with risk score.²⁷ Finally, a British model used data on use of prior medical services and comorbidity, and also controlled for observed and expected hospital readmission rates, but predictive ability remained modest (*c* statistic: 0.69).²⁸

Models Incorporating Primary Data Collection

Nine models incorporated survey or chart review data and could potentially be used for clinical intervention purposes, although 5 used data unlikely to be available early during a hospitalization (Table 2). The best performing of these models used administrative data on comorbidity

and prior use of medical services (*c* statistic: 0.77) along with functional status data (*c* statistic: 0.83) from the Medicare Beneficiaries Survey to predict a composite outcome of hospital readmissions and nursing home transfers.²⁹ The survey was not routinely administered during index hospitalization and it is unclear to what extent the use of retrospective survey data affects the predictive ability of the model. Similarly, a medical record study in Ireland retrospectively applied a 9-item questionnaire, including items such as discharge polypharmacy, and performed modestly well (*c* statistic: 0.70).³¹ A simple Canadian model used medical comorbidities up through index hospital discharge along with index hospital length of stay and prior use of medical services (*c* statistic: 0.68; 95% CI,

0.65-0.71).³⁵ Increasing scores on another 4-item model of medical comorbidities, prior use of medical services, and levels of creatinine at discharge were associated with increasing readmission rates in patients with heart failure.³⁰

Four models incorporated primary data collected in real time (Table 3). Only 2 of these models have been tested in contemporary populations; the others were conducted more than 2 decades ago. One survey-based model developed at 6 academic hospitals included social determinant, comorbidity, prior use of medical services, and self-rated health variables, but had poor predictive ability (*c* statistic: 0.61).³⁸ The Probability of Repeated Admission is a simple 8-item survey tool developed in older Medicare beneficiaries; however, it also had poor predictive ability

Table 3. Characteristics of Models Using Primary Data Collected in Real Time

| Source | Population and Setting | No. of Patients by Cohort | | Outcome ^b | Readmission | | Model Discrimination ^c |
|--|--|---------------------------|-----------------|--------------------------------|----------------------|--|--|
| | | DC | VC ^a | | Actual Rate, % | Range of Rates (VC) | |
| Burns and Nichols, ³⁶ 1991 | US medical inpatients aged ≥65 y treated at a single VA hospital in 1987 | 134 | 34 | 60 d | 30.6 overall | NR | NR |
| Evans et al, ³⁷ 1988 | US medical, neurological, and surgical inpatients treated over a 6-wk period at a single VA hospital | 532 | 177 | Composite of 60 d ^d | 21.0 overall | Patients with high use of care: 34.7%-91.7% (lowest to highest eighth) | Risk score range: 0-8 using risk scores ≥3: sensitivity: 0.60; specificity: 0.76; positive LR: 2.5; using risk scores ≥4: sensitivity: 0.42; specificity: 0.93; positive LR: 6 |
| Hasan et al, ³⁸ 2010 | Medical inpatients treated at multiple US centers from 2001-2003 | 7287 | 3659 | 30 d | DC: 17.5 VC: 17.4 | 5.9-28.9 (lowest to highest quartile) | 0.61 |
| PRA | | | | | | | |
| Boult et al, ³⁹ 1993 | US noninstitutionalized Medicare patients aged ≥70 y in 1984 | 2942 | 2934 | 4 y | DC: 28.4 VC: NA | 26.1 (score range: 0-3) to 41.8 (score range: >4) | 0.61 (SE, 0.01) |
| Allaudeen et al, ⁴⁰ 2011 | Medical inpatients aged ≥65 y treated at a single US academic center during 5-wk period in 2008 | NA | 159 | 30 d | DC: NA VC: 32.7 | NR | PRA: 0.56 (95% CI, 0.44-0.67) ^e |
| Novotny and Anderson, ⁴¹ 2008 | Medical inpatients treated at a single US academic center from 2005-2007 | 1077 | NR | 41 d | DC: NA VC: 14.0 | NR | PRA score: 0.53; positive LR: 1.67 |

Abbreviations: DC, derivation cohort; LR, likelihood ratio; NA, not applicable; NR, not reported; PRA, Probability of Repeated Admission; SE, standard error; VA, Veterans Affairs; VC, validation cohort.

^aThe most recent validation cohort is listed if a study had multiple VCs.

^bUnplanned, all-cause readmissions unless otherwise indicated.

^cValues are from the *c* statistic unless otherwise indicated.

^dIncludes readmission, nursing home placement, or length of stay longer than expected per mean length of stay of diagnosis-related group.

^eThe prediction range by a physician is 0.58 to 0.59 (SE range, 0.46-0.70) and by a nonphysician is 0.50 to 0.55 (SE range, 0.38-0.67).

across several studies (*c* statistic range: 0.56-0.61; 95% CI, 0.44-0.67).³⁹⁻⁴¹

Use of Variables

A comparison of the types of variables considered for and included in the final models can provide some information about the contribution of different types of variables to readmission risk

prediction (Table 4). Nearly all studies included medical comorbidity data and many included variables for prior use of medical services, usually prior hospitalizations. Basic sociodemographic variables such as age and sex were considered by most studies but, in many instances, these variables did not contribute enough to be included

in the final model. Table 4 also highlights important gaps in model development in that few studies considered variables associated with illness severity, overall health and function, and social determinants of health.

Six studies compared the performance of different models within the same population and offer further insights about the incremental value of different types of variables (TABLE 5). Amarasingham et al²⁶ found a model based on automated electronic medical records that incorporated sociodemographic factors such as drug use and housing discontinuities was more predictive than comorbidity-based models. Coleman et al²⁹ found that the inclusion of variables such as functional status from survey data improved model performance slightly compared with the use of medical services and comorbidity-based administrative data alone (*c* statistics: 0.83 vs 0.77, respectively). A large Swiss study of potentially preventable readmission risk compared a simple nonclinical model, a Charlson comorbidity-based model, and a more complex hierarchical diagnosis and procedures-based model called SQLape (Striving for Quality Level and Analyzing of Patient Expenditures), and found small differences among them (*c* statistics: 0.67, 0.69, and 0.72, respectively).¹⁷

Other comparative studies found little difference among models. Clinical data such as laboratory and physiological variables from medical records or registries did not enhance performance of claims-only CMS models.^{14-16,31} A US study of older patients found that an intricate *International Classification of Diseases, Ninth Revision* code-based disease complexity system added little discriminative ability to a poorly performing Health Care Financing Administration model.²² Finally, Allaudeen et al⁴⁰ found internal medicine interns using a gestalt approach predicted readmissions with a similarly poor level of ability as an older, established survey-based model (ie, Probability of Repeated Admission) in a small, single-center cohort.

Table 4. Variables Considered by Studies in Evaluating the Risk of Hospital Readmission

| | No. of Studies | | |
|---|--|--------------------------------------|---|
| | Included in Final Model | Evaluated, but Not Included | Not Considered ^a |
| Specific medical diagnoses or comorbidity index | 24 ^{13-25,27-31,34-39} | 0 | 3 ^{12,26,32} |
| Mental health comorbidities | | | |
| Mental illness | 9 ^{15-18,20,21,26,27,37} | 4 ^{14,24,28,36} | 11 ^{12,19,22,23,30-32,34,35,38,39} |
| Alcohol or substance use | 11 ^{15-21,23,26-28} | 5 ^{14,24,31,34,37} | 8 ^{12,22,30,32,35,36,38,39} |
| Illness severity | | | |
| Severity index | 1 ²⁶ | 1 ³⁶ | 19 ^{13-19,21,22,24,28,30-32,34,35,37-39} |
| Laboratory findings | 4 ^{18,30,32,34} | 1 ³¹ | 15 ^{13-17,19,21,22,24,28,35-39} |
| Other ^b | 4 ^{2,3,24} | 4 ^{18,30,34,37} | 11 ^{14-16,21,24,28,31,32,35,38,39} |
| Prior use of medical services | | | |
| Hospitalizations | 14 ^{12,13,17,21,26-31,36-39} | 1 ³⁵ | 10 ^{14-16,18,19,22-24,32,34} |
| Emergency department visits | 4 ^{27,32,34,35} | 1 ²⁶ | 17 ^{12,14-16,18,19,21-24,28,30,31,36-39} |
| Clinic visits or missed clinic visits | 3 ^{26,27,39} | 0 | 19 ^{12,14-16,18,19,21-24,28,30-32,34-38} |
| Index hospital length of stay | 4 ^{23,25,35,38} | 3 ^{19,30,36} | 15 ^{12,14-16,18,21,22,24,26,28,31,32,34,37,39} |
| Overall health and function | | | |
| Functional status, ADL dependence, and mobility | 2 ^{29,34} | 6 ^{30,35-39} | 14 ^{12,14-16,18,19,21-24,26,28,31,32} |
| Self-rated health, quality of life | 3 ^{29,38,39} | 2 ^{31,34} | 17 ^{12,14-16,18,19,21-24,26,28,30,32,35-37} |
| Cognitive impairment | 7 ^{14-16,18,31,34,37} | 5 ^{21,24,36,38,39} | 9 ^{12,19,22,23,26,28,30,32,35} |
| Visual or hearing impairment | 1 ²⁹ | 1 ³⁹ | 21 ^{12,14-16,18,19,21-24,26,28,30-32,34-39} |
| Sociodemographic factors | | | |
| Age | 19 ^{12-22,24,25,27-29,34,37,39} | 7 ^{23,26,30,32,35,36,38} | 1 ³¹ |
| Sex | 15 ^{12-18,20,22,24-28,39} | 8 ^{19,21,23,30,32,35,36,38} | 1 ³¹ |
| Race/ethnicity | 7 ^{12,13,20,23,24,27,28} | 8 ^{21,26,30,32,34,36,38,39} | 8 ^{14-16,18,19,22,31,35} |
| Social determinants of health | | | |
| SES, income, and employment status | 5 ^{13,20,21,26,27} | 7 ^{24,28,34,36-39} | 10 ^{12,14-16,18,19,22,23,31,35} |
| Insurance status ^c | 6 ^{19,23,24,26,29,38} | 1 ³⁴ | 5 ^{30,32,36,37,39} |
| Education | 0 | 4 ^{31,36,38,39} | 17 ^{12,14-16,18,19,21-24,26,28,30,32,34,35,37} |
| Marital status and No. of people in home | 4 ^{26,31,37,38} | 6 ^{19,21,34-36,39} | 11 ^{12,14-16,18,22-24,28,30,32} |
| Caregiver availability, other social support | 2 ^{34,39} | 1 ³⁸ | 19 ^{12,14-16,18,19,21-24,26,28,30-32,34-37} |
| Access to care or limited access (eg, rural area) | 5 ^{12,19,21,23,38} | 2 ^{24,35} | 14 ^{14-16,18,22,26,28,30-32,34,36,37,39} |
| Discharge location (home, nursing home) | 2 ^{23,24} | 1 ¹⁹ | 18 ^{12,14-16,18,21,22,26,28,30-32,34-39} |

Abbreviations: ADL, activities of daily living; SES, socioeconomic status.

^aSix studies did not report candidate variables and only reported the final model.^{13,17,20,25,27,29}

^bExamples include use of telemetry, shock, planned vs emergent index hospitalization, heart rate, and left ventricular ejection fraction.

^cThis category is not relevant to studies of Medicare patients^{14-16,18,22} and non-US studies.^{13,17,21,31,35}

Potentially Preventable Readmissions

Only 1 model attempted to explicitly define and identify potentially preventable readmissions.⁴⁶ Investigators conducted a systematic medical record review to define potentially preventable readmissions and develop an administrative data–based algorithm. A subsequent Swiss study compared the performance of 3 models in predicting readmissions according to their algorithm.¹⁷

COMMENT

In this systematic review, we found 26 readmission risk prediction models of

medical patients tested in a variety of settings and populations. Several are being applied currently in clinical, research, and policy arenas. Half of the models were largely designed to facilitate calculation of risk-standardized readmission rates for hospital comparison purposes. The other half were clinical models that could be used to identify high-risk patients for whom a transitional care intervention might be appropriate. Most models in both categories have poor predictive ability.

Readmission risk prediction remains a poorly understood and complex endeavor. Indeed, models of patient-level factors such as medical

comorbidities, basic demographic data, and clinical variables are much better able to predict mortality than readmission risk.^{18,26,35} Broader social, environmental, and medical factors such as access to care, social support, substance abuse, and functional status contribute to readmission risk in some models, but the utility of such factors has not been widely studied.

It is likely that hospital and health system–level factors, which are not present in current readmission risk models, contribute to risk.⁴⁷ For instance, the timeliness of postdischarge follow-up, coordination of care with the primary care physician, and quality of

Table 5. Studies That Compared Models Within a Population

| Model Description | | C Statistic ^a |
|--|---|--------------------------|
| Halfon et al, ¹⁷ 2006 | | |
| Nonclinical model | Age, sex, prior medical services use | 0.67 |
| Modified Charlson score–based model | Charlson score ⁴² plus prior medical services use | 0.69 |
| Modified SQLape model ⁴³ | Complex administrative model combining comorbidity, age, and medical services use data into 49 risk categories | 0.72 |
| Hammill et al, ¹⁸ 2011 | | |
| Claims-only model | CMS administrative heart failure model ¹⁵ | 0.59 |
| Clinical claims model | CMS administrative heart failure model plus levels of serum creatinine, serum sodium, and hemoglobin, and systolic blood pressure | 0.60 |
| Allaudeen et al, ⁴⁰ 2011 | | |
| Probability of repeated admission ^{32b} | Age, sex, self-rated health, availability of informal caregiver, coronary disease, diabetes, hospital admission within past year, prior medical services use | 0.56 (0.44-0.67) |
| Prediction by physician | Interns, residents, and attending physicians predicted risk of readmission based on overall evaluation of patient | 0.58-0.59 (0.46-0.70) |
| Prediction by nonphysician | Nurses and case managers predicted risk of readmission based on overall evaluation of patient | 0.50-0.55 (0.38-0.67) |
| Amarasingham et al, ²⁶ 2010 | | |
| ADHERE mortality model | Levels of blood urea nitrogen and creatinine, and systolic blood pressure | 0.56 (0.54-0.59) |
| Tabak mortality model ⁴⁴ | Age, 17 laboratory and vital sign variables within 24 h of hospital presentation | 0.61 (0.59-0.64) |
| CMS heart failure model ¹⁵ | Complex administrative comorbidity model consisting of age, sex, and 35 hierarchical condition categories | 0.66 (0.63-0.68) |
| Electronic readmission model | Includes Tabak mortality score, history of depression or anxiety, single status, sex, residential stability, Medicare status, residential census tract in lowest socioeconomic quintile, history of confirmed cocaine use, history of missed clinic visit, use of a health system pharmacy, number of prior admissions, presented to emergency department between 6 AM and 6 PM for index admission | 0.72 (0.70-0.75) |
| Coleman et al, ²⁹ 2004 | | |
| Administrative model | Age, sex, prior medical services use, Medicaid status, Charlson score, ⁴² heart disease, cancer, or diabetes | 0.77 |
| Administrative model plus self-report model | Self-rated health, activities of daily living assistance need, visual impairment, functional status | 0.83 |
| Naessens et al, ²² 1992 | | |
| Modified HCFA mortality model ⁴⁵ | Age, sex, disease diagnosis from 1 of 16 diagnosis-related groups, and 8 comorbidities | 0.59 (0.01) |
| HCFA model plus COMPLEX measure | Complicated administrative model incorporating diagnosis-related group–based disease staging and number of body systems affected plus HCFA model | 0.61 (0.01) |

Abbreviations: ADHERE, Acute Decompensated Heart Failure registry; CMS, Centers for Medicare & Medicaid Services; COMPLEX, a measurement of comorbidity and disease severity²²; HCFA, Health Care Financing Administration; SQLape, Striving for Quality Level and Analyzing of Patient Expenditures.

^aIf reported, values in parentheses are expressed as 95% CI or standard error.

^bVariables were obtained from chart abstraction, whereas original probability of repeated admission instrument is based on patient surveys.

medication reconciliation may be associated with readmission risk.^{48,49} The supply of hospital beds may independently contribute to higher readmission rates.⁵⁰ Finally, the quality of inpatient care could also contribute to risk,⁵¹ although the evidence is mixed.⁵² Although the inclusion of such hospital-level factors would conceivably improve the predictive ability of models, it would be inappropriate to include them in models that are used for risk-standardization purposes. Doing so would adjust hospital readmission rates for the very deficits in quality and efficiency that hospital comparison efforts seek to reveal, and which could be targets for quality improvement interventions.

Public reporting and financial penalties for hospitals with high 30-day readmission rates are spurring organizations to innovate and implement quality improvement programs.^{53,54} Nevertheless, the poor discriminative ability of most of the administrative models we examined raises concerns about the ability to standardize risk across hospitals to fairly compare hospital performance. Until risk prediction and risk adjustment become more accurate, it seems inappropriate to compare hospitals in this way and reimburse (or penalize) them on the basis of risk-standardized readmission rates. Others have reached similar conclusions,⁵⁵ and also have expressed concern that such financial penalties could exacerbate health disparities by penalizing hospitals with fewer resources.⁵⁶ Still others have argued that readmission rate is an incomplete accountability measure that fails to consider “the real outcomes of interest—health, quality of life, and value.”⁵⁷

Use of readmission rates as a quality metric assumes that readmissions are related to poor quality care and are potentially preventable. However, the preventability of readmissions remains unclear and understudied. We found only 1 validated prediction model that explicitly examined potentially preventable readmissions as an outcome, and it found that only about one-quarter of readmissions were clearly prevent-

able.¹⁷ A recent systematic review of 34 studies found wide variation in the percentage of readmissions considered preventable and estimates ranged from 5% to 79% (median, 27%).⁵⁸ More work is needed to develop readmission risk prediction models with an outcome of preventable readmissions. This could not only improve risk-standardization efforts, but also allow hospitals to better focus limited clinical resources in readmission avoidance programs.

As with models that are used for risk-standardization, readmission risk models that are intended for clinical use also have certain requirements and limitations. Clinical models would ideally provide data prior to discharge, discriminate high- from low-risk patients, and would be adapted to the settings and populations in which they are to be used. Few models met all these criteria, and only 1 of these (a single-center study) had acceptable discriminative ability.²⁶ As with the risk-adjustment models, most of the models developed for clinical purposes had poor predictive ability, although notable exceptions suggest the addition of social or functional variables may improve overall performance.^{26,29}

The best choice of model may depend on setting and the population being studied. The success of some models in certain populations and the lack of success of others suggest that the patient-level factors associated with readmission risk may differ according to the population studied. For example, while medical comorbidities may account for a large proportion of risk in some populations, social determinants may disproportionately influence risk in socioeconomically disadvantaged populations. Our review found that few models have incorporated such variables.

Even though the overall predictive ability of the clinical models was poor, we did find that high- and low-risk scores were associated with a clinically meaningful gradient of readmission rates. This is important given resource constraints and the need to selectively apply potentially costly care

transition interventions. Even limited ability to identify a proportion of patients at risk for future high-cost medical services use can increase the cost-effectiveness of such programs.^{28,59}

Of note, few models incorporated clinically actionable data that could be used to triage patients to different types of interventions. For example, marginally housed patients or those struggling with substance abuse might require unique discharge services. Relatively simple, practical models that use real-time clinically actionable data, such as the Project BOOST model, have been created, but their performance has not yet been rigorously validated.⁶⁰

Our review concurs with and adds to the findings of several other reviews that found deficiencies in risk prediction models. One recent review limited to US studies examined general risk factors for preventable readmissions, but did not search explicitly for validated models, and many of the included studies had poor study designs.⁶¹ The study's authors suggested that measures of poor health such as comorbidity burden, prior medical services use, and increasing age were associated with readmissions. Three other reviews focused on specific diagnoses and found few readmission risk models for heart failure,⁵⁵ chronic obstructive pulmonary disease,⁶² and myocardial infarction.⁶³

Our review has certain limitations. We included studies outside of the United States, given that portions of US health care may resemble other countries' health systems, but applicability of models from other countries to the United States may still be limited. Our classifications of data types, data collection timing, and the intended use of each model are subject to interpretation, but we attempted to mitigate subjectivity by using a dual-review and consensus process. Finally, few studies directly compared models within the same population, and summary statistics such as the *c* statistic should not be used to directly compare models across different populations.

Additional research is needed to assess the true preventability of read-

missions in US health systems. Given the broad variety of factors that may contribute to preventable readmission risk, models that include factors obtained through medical record review or patient report may be valuable. Innovations to collect broader variable types for inclusion in administrative data sets should be considered. Future studies should assess the relative contributions of different types of patient data (eg, psychosocial factors) to readmission risk prediction by comparing the performance of models with and without these variables in a given population. These models should ideally be based on population-specific conceptual frameworks of risk. Implementation of risk stratification models and their effect on work flow and resource prioritization should be assessed in a broad variety of hospital settings. Also, given that many models have limited predictive ability and may require some investment of time and cost to implement, future studies should further evaluate the relative value of clinician gestalt compared with predictive models in assessing readmission risk.

In summary, readmission risk prediction is a complex endeavor with many inherent limitations. Most models created to date, whether for hospital comparison or clinical purposes, have poor predictive ability. Although in certain settings such models may prove useful, better approaches are needed to assess hospital performance in discharging patients, as well as to identify patients at greater risk of avoidable readmission.

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Online-Only Material: eAppendix 1, eAppendix 2, and the eTable are available at <http://www.jama.com>.

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REFERENCES

- Jack BW, Chetty VK, Anthony D, et al. A reengineered hospital discharge program to decrease rehospitalization: a randomized trial. *Ann Intern Med*. 2009; 150(3):178-187.
- Coleman EA, Parry C, Chalmers S, Min SJ. The care transitions intervention: results of a randomized controlled trial. *Arch Intern Med*. 2006;166(17):1822-1828.
- Naylor MD, Broton D, Campbell R, et al. Comprehensive discharge planning and home follow-up of hospitalized elders: a randomized clinical trial. *JAMA*. 1999;281(7):613-620.
- QualityNet. Readmission measures overview: publicly reporting risk-standardized, 30-day readmission measures for AMI, HF and PN. <http://www.qualitynet.org/dcs/ContentServer?cid=1219069855273&pagename=QnetPublic%2FPage%2FQnetTier2&c=Page>. Accessed May 28, 2011.
- Krumholz HM, Brindis RG, Brush JE, et al; American Heart Association; Quality of Care and Outcomes Research Interdisciplinary Writing Group; Council on Epidemiology and Prevention; Stroke Council; American College of Cardiology Foundation; Endorsed by the American College of Cardiology Foundation. Standards for statistical models used for public reporting of health outcomes: an American Heart Association Scientific Statement from the Quality of Care and Outcomes Research Interdisciplinary Writing Group: cosponsored by the Council on Epidemiology and Prevention and the Stroke Council. *Circulation*. 2006;113(3):456-462.
- McGinn TG, Guyatt GH, Wyer PC, Naylor CD, Stiell IG, Richardson WS; Evidence-Based Medicine Working Group. Users' guides to the medical literature, XXII: how to use articles about clinical decision rules. *JAMA*. 2000;284(1):79-84.
- National Center for HIV/AIDS, Viral Hepatitis, STD, and TB Prevention; US Centers for Disease Control and Prevention. Establishing a holistic framework to reduce inequities in HIV, viral hepatitis, STDs, and tuberculosis in the United States, October 2010. <http://www.cdc.gov/socialdeterminants/docs/SDH-White-Paper-2010.pdf>. Accessed August 10, 2011.
- Iezzoni LI, ed. *Risk Adjustment for Measuring Health Care Outcomes*. 3rd ed. Chicago, IL: Health Administration Press; 2003.
- Schneeweiss S, Seeger JD, Maclure M, Wang PS, Avorn J, Glynn RJ. Performance of comorbidity scores to control for confounding in epidemiologic studies using claims data. *Am J Epidemiol*. 2001;154(9):854-864.
- Ohman EM, Granger CB, Harrington RA, Lee KL. Risk stratification and therapeutic decision making in acute coronary syndromes. *JAMA*. 2000;284(7):876-878.
- Hayden JA, Côté P, Bombardier C. Evaluation of the quality of prognosis studies in systematic reviews. *Ann Intern Med*. 2006;144(6):427-437.
- Anderson GF, Steinberg EP. Predicting hospital readmissions in the Medicare population. *Inquiry*. 1985; 22(3):251-258.
- Bottle A, Aylin P, Majeed A. Identifying patients at high risk of emergency hospital admissions: a logistic regression analysis. *J R Soc Med*. 2006;99(8):406-414.
- Krumholz HM, Normand S-LT, Keenan PS, et al. Hospital 30-day acute myocardial infarction readmission measure: methodology, June 9, 2008. <http://www.qualitynet.org/dcs/ContentServer?c=Page&pagename=QnetPublic%2FPage%2FQnetTier3&cid=1219069855841>. Accessibility verified September 22, 2011.
- Krumholz H, Normand S-L, Keenan P, et al. Hospital 30-day heart failure readmission measure: methodology, April 23, 2008. <http://www.qualitynet.org/dcs/ContentServer?c=Page&pagename=QnetPublic%2FPage%2FQnetTier3&cid=1219069855841>. Accessibility verified September 22, 2011.
- Krumholz HM, Normand S-LT, Keenan PS, et al. Hospital 30-day pneumonia readmission measure: methodology, June 9, 2008. <http://www.qualitynet.org/dcs/ContentServer?c=Page&pagename=QnetPublic%2FPage%2FQnetTier3&cid=1219069855841>. Accessibility verified September 22, 2011.
- Halfon P, Eggl Y, Prêtre-Rohrbach I, Meylan D, Marazzi A, Burnand B. Validation of the potentially avoidable hospital readmission rate as a routine indicator of the quality of hospital care. *Med Care*. 2006; 44(11):972-981.
- Hammill BG, Curtis LH, Fonarow GC, et al. Incremental value of clinical data beyond claims data in predicting 30-day outcomes after heart failure hospitalization. *Circ Cardiovasc Qual Outcomes*. 2011; 4(1):60-67.
- Holloway JJ, Medendorp SV, Bromberg J. Risk factors for early readmission among veterans. *Health Serv Res*. 1990;25(1 pt 2):213-237.
- Holman CDAJ, Preen DB, Baynham NJ, Finn JC, Semmens JB. A multipurpose comorbidity scoring system performed better than the Charlson index. *J Clin Epidemiol*. 2005;58(10):1006-1014.
- Howell S, Coory M, Martin J, Duckett S. Using routine inpatient data to identify patients at risk of hospital readmission. *BMC Health Serv Res*. 2009; 9:96.
- Naessens JM, Leibson CL, Krishan I, Ballard DJ. Contribution of a measure of disease complexity (COMPLEX) to prediction of outcome and charges among hospitalized patients. *Mayo Clin Proc*. 1992; 67(12):1140-1149.

23. Philbin EF, DiSalvo TG. Prediction of hospital readmission for heart failure: development of a simple risk score based on administrative data. *J Am Coll Cardiol*. 1999;33(6):1560-1566.
24. Silverstein MD, Qin H, Mercer SQ, Fong J, Haydar Z. Risk factors for 30-day hospital readmission in patients ≥ 65 years of age. *Proc (Bayl Univ Med Cent)*. 2008;21(4):363-372.
25. Thomas JW. Does risk-adjusted readmission rate provide valid information on hospital quality? *Inquiry*. 1996;33(3):258-270.
26. Amarasingham R, Moore BJ, Tabak YP, et al. 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(11):981-988.
27. Billings J, Mijanovich T. Improving the management of care for high-cost Medicaid patients. *Health Aff (Millwood)*. 2007;26(6):1643-1654.
28. Billings J, Dixon J, Mijanovich T, Wennberg D. Case finding for patients at risk of readmission to hospital: development of algorithm to identify high risk patients. *BMJ*. 2006;333(7563):327.
29. Coleman EA, Min SJ, Chomiak A, Kramer AM. Post-hospital care transitions: patterns, complications, and risk identification. *Health Serv Res*. 2004;39(5):1449-1465.
30. Krumholz HM, Chen YT, Wang Y, Vaccarino V, Radford MJ, Horwitz RJ. Predictors of readmission among elderly survivors of admission with heart failure. *Am Heart J*. 2000;139(1 pt 1):72-77.
31. Morrissey EFR, McElnay JC, Scott M, McConnell BJ. Influence of drugs, demographics and medical history on hospital readmission of elderly patients: a predictive model. *Clin Drug Invest*. 2003;23(2):119-128.
32. Smith DM, Norton JA, McDonald CJ. Nonelective readmissions of medical patients. *J Chronic Dis*. 1985;38(3):213-224.
33. Smith DM, Weinberger M, Katz BP, Moore PS. Postdischarge care and readmissions. *Med Care*. 1988;26(7):699-708.
34. Smith DM, Katz BP, Huster GA, Fitzgerald JF, Martin DK, Freedman JA. Risk factors for nonelective hospital readmissions. *J Gen Intern Med*. 1996;11(12):762-764.
35. van Walraven C, Dhalla IA, Bell C, et al. Derivation and validation of an index to predict early death or unplanned readmission after discharge from hospital to the community. *CMAJ*. 2010;182(6):551-557.
36. Burns R, Nichols LO. Factors predicting readmission of older general medicine patients. *J Gen Intern Med*. 1991;6(5):389-393.
37. Evans RL, Hendricks RD, Lawrence KV, Bishop DS. Identifying factors associated with health care use: a hospital-based risk screening index. *Soc Sci Med*. 1988;27(9):947-954.
38. Hasan O, Meltzer DO, Shaykevich SA, et al. Hospital readmission in general medicine patients: a prediction model. *J Gen Intern Med*. 2010;25(3):211-219.
39. Boulton C, Dowd B, McCaffrey D, Boulton L, Hernandez R, Krulwich H. Screening elders for risk of hospital admission. *J Am Geriatr Soc*. 1993;41(8):811-817.
40. Allaudeen N, Schnipper JL, Orav EJ, Wachter RM, Vidyarthi AR. Inability of providers to predict unplanned readmissions. *J Gen Intern Med*. 2011;26(7):771-776.
41. Novotny NL, Anderson MA. Prediction of early readmission in medical inpatients using the Probability of Repeated Admission instrument. *Nurs Res*. 2008;57(6):406-415.
42. Charlson ME, Pompei P, Ales KL, MacKenzie CR. A new method of classifying prognostic comorbidity in longitudinal studies: development and validation. *J Chronic Dis*. 1987;40(5):373-383.
43. Egli Y. *Pre'vision Des Cou'ts Hospitaliers Fonde's sur le Profil des Patients [in Swiss]*. Chardonne, Switzerland: SQLape sa'rl; 2005.
44. Tabak YP, Johannes RS, Silber JH. Using automated clinical data for risk adjustment: development and validation of six disease-specific mortality predictive models for pay-for-performance. *Med Care*. 2007;45(8):789-805.
45. Bowen OR, Roper WL. *Medicare Hospital Mortality Information, 1987, Region IX: American Samoa, Arizona, Guam, Hawaii, Nevada*. Washington, DC: US Government Printing Office; 1988. HCFA publication 00651.
46. Halfon P, Egli Y, van Melle G, Chevalier J, Wasserfallen JB, Burnand B. Measuring potentially avoidable hospital readmissions. *J Clin Epidemiol*. 2002;55(6):573-587.
47. Oddone EZ, Weinberger M, Horner M, et al; Veterans Affairs Cooperative Studies in Health Services Group on Primary Care and Hospital Readmissions. Classifying general medicine readmissions: are they preventable? *J Gen Intern Med*. 1996;11(10):597-607.
48. Hernandez AF, Greiner MA, Fonarow GC, et al. Relationship between early physician follow-up and 30-day readmission among Medicare beneficiaries hospitalized for heart failure. *JAMA*. 2010;303(17):1716-1722.
49. Kripalani S, Jackson AT, Schnipper JL, Coleman EA. Promoting effective transitions of care at hospital discharge: a review of key issues for hospitalists. *J Hosp Med*. 2007;2(5):314-323.
50. Fisher E, Goodman D, Skinner J, Bronner K. *Health Care Spending, Quality, and Outcomes—More Isn't Always Better*. Hanover, NH: Dartmouth Institute for Health Policy and Clinical Practice; 2009.
51. Ashton CM, Wray NP. A conceptual framework for the study of early readmission as an indicator of quality of care. *Soc Sci Med*. 1996;43(11):1533-1541.
52. Weissman JS, Ayanian JZ, Chasan-Taber S, Sherwood MJ, Roth C, Epstein AM. Hospital readmissions and quality of care. *Med Care*. 1999;37(5):490-501.
53. Fung CH, Lim YW, Mattke S, Damberg C, Shekelle PG. Systematic review: the evidence that publishing patient care performance data improves quality of care. *Ann Intern Med*. 2008;148(2):111-123.
54. Colorado Foundation for Medical Care. National Coordinating Center for the Integrating Care for Populations and Communities. <http://www.cfmc.org/caretransitions>. Accessibility verified September 22, 2011.
55. Ross JS, Mulvey GK, Stauffer B, et al. Statistical models and patient predictors of readmission for heart failure: a systematic review. *Arch Intern Med*. 2008;168(13):1371-1386.
56. Joynt KE, Jha AK. Who has higher readmission rates for heart failure, and why? implications for efforts to improve care using financial incentives. *Circ Cardiovasc Qual Outcomes*. 2011;4(1):53-59.
57. Axon RN, Williams MV. Hospital readmission as an accountability measure. *JAMA*. 2011;305(5):504-505.
58. van Walraven C, Bennett C, Jennings A, Austin PC, Forster AJ. Proportion of hospital readmissions deemed avoidable: a systematic review. *CMAJ*. 2011;183(7):E391-E402.
59. Mukamel DB, Chou CC, Zimmer JG, Rothenberg BM. The effect of accurate patient screening on the cost-effectiveness of case management programs. *Gerontologist*. 1997;37(6):777-784.
60. Society of Hospital Medicine Project BOOST. Tool for addressing risk: a geriatric evaluation for transitions. http://www.hospitalmedicine.org/ResourceRoomRedesign/RR_CareTransitions/PDFs/TARGET_screen_v22.pdf. Accessed May 28, 2011.
61. Vest JR, Gamm LD, Oxford BA, Gonzalez MI, Slawson KM. Determinants of preventable readmissions in the United States: a systematic review. *Implementation Sci*. 2010;5:88.
62. Bahadori K, FitzGerald JM. Risk factors of hospitalization and readmission of patients with COPD exacerbation—systematic review. *Int J Chron Obstruct Pulmon Dis*. 2007;2(3):241-251.
63. Desai MM, Stauffer BD, Feringa HHH, Schreiner GC. Statistical models and patient predictors of readmission for acute myocardial infarction: a systematic review. *Circ Cardiovasc Qual Outcomes*. 2009;2(5):500-507.