Derivation and Validation of an In-Hospital Mortality Prediction Model Suitable for Profiling Hospital Performance in Heart Failure

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Background—Comparing heart failure (HF) outcomes across hospitals requires adequate risk adjustment. We aimed to develop and validate a model that can be used to compare quality of HF care across hospitals.

Methods and Results—We included patients with HF aged ≥18 years admitted to one of 433 hospitals that participated in the Premier Inc Data Warehouse. This model (Premier) contained patient demographics, comorbidities, and acute conditions present on admission, derived from administrative and billing records. In a separate data set derived from electronic health records, we validated the Premier model by comparing hospital risk-standardized mortality rates calculated with the Premier model to those calculated with a validated clinical model containing laboratory data (LAPS [Laboratory-Based Acute Physiology Score]). Among the 200 832 admissions in the Premier Inc Data Warehouse, inpatient mortality was 4.0%. The model showed acceptable discrimination in the warehouse data (C statistic 0.75; 95% confidence interval, 0.74–0.76). In the validation data set, both the Premier model and the LAPS models showed acceptable discrimination (C statistic: Premier: 0.76 [95% confidence interval, 0.74–0.77]; LAPS: 0.78 [95% confidence interval, 0.76–0.80]). Risk-standardized mortality rates for both models ranged from 2% to 7%. A linear regression equation describing the association between Premier- and LAPS-specific mortality rates revealed a regression line with a slope of 0.71 (SE: 0.07). The correlation coefficient of the standardized mortality rates from the 2 models was 0.82.

Conclusions—Compared with a validated model derived from clinical data, an HF mortality model derived from administrative data showed highly correlated risk-standardized mortality rate estimates, suggesting it could be used to identify high- and low-performing hospitals for HF care. (J Am Heart Assoc. 2018;7:e005256. DOI: 10.1161/JAHA.116.005256.)

Key Words: heart failure • mortality • quality of care

Heart failure (HF) accounts for ≈1 million hospital admissions and $39 billion spent per year.¹ ² This large volume and high cost has led inpatient HF care to become a major focus of hospital quality measurement and improvement efforts, including public reporting of hospital-level mortality and readmission rates on websites such as Hospital Compare.³

To ensure that observed differences in outcomes between hospitals are not largely the result of differences in patient characteristics, care must be taken to adjust for case mix when describing differences in quality across hospitals. When estimating risk-standardized outcomes, analyses should also take into account hospital size and the clustered nature of the data (patients within hospitals) and should include only variables that are not related to the quality of care delivered.⁴ Finally, the risk-adjustment model should be validated in different populations of patients and across hospitals. Although electronic health record (EHR) data are likely to become the data used for these purposes in the future, EHR data are not routinely available, meaning that there is still a need for risk-adjustment methods that do not use clinical data. The aim of this study was to develop and validate a model that can be used to compare quality of HF care across hospitals in situations in which clinical data are not available.

A recent innovation that will facilitate severity adjustment in claims data is the development of multihospital databases (eg, Premier, University HealthSystem Consortium) that
We included patients who were aged ≥18 years and had a principal International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) diagnosis of HF or a principal diagnosis of respiratory failure with secondary diagnosis of HF when both HF and respiratory failure were coded “present on admission” (POA; ICD-9-CM codes for HF: 402.01, 402.11, 402.91, 404.01, 404.03, 404.11, 404.13, 404.91, 404.93, 428.xx10,11; for respiratory failure: 518.81, 518.82, 518.84). Given the broad set of inclusion codes, we ensured that patients were treated for acute decompensated HF during the hospitalization by restricting the cohort to patients in whom at least 1 HF therapy (including diuretics, metolazone, inotropes, vasodilators, or intra-aortic balloon pump) was initiated within the first 2 days of hospitalization. In administrative data sets, the duration of the first hospital day includes partial days that can vary in length, so we chose the first 2 days of hospitalization (rather than just the first day) for initiation of an HF therapy. We excluded patients with a pediatric or psychiatric attending physician, those with elective admissions, and those who were transferred from or to another acute care facility (because we could not accurately determine the onset or subsequent course of their illness). For patients with repeat visits at a single hospital, 1 visit was randomly selected for inclusion. Patients were randomly assigned to a derivation cohort (80%) and an internal validation cohort (20%). The institutional review board at Baystate Medical Center granted permission to conduct the study and granted a waiver of informed consent because of the deidentified nature of the data.

External Validation Cohort

We validated the model in a population of patients with HF seen at hospitals that contributed to the HealthFacts database (Cerner Corp.) between January 2010 and December 2012. HealthFacts is a multihospital data set derived from the comprehensive EHRs of 116 geographically and structurally diverse hospitals throughout the United States. HealthFacts contains time-stamped pharmacy, laboratory, and billing information and contains records, including clinical data such as laboratory data, of >84 million acute admissions, emergency room visits, and ambulatory visits. We limited the sample to hospitals that contributed to the pharmacy, laboratory, and diagnosis segments of the database and had at least 20 eligible HF patients during the study period (to obtain stable hospital rates) after applying the same patient-level inclusion criteria.

Outcome

The primary outcome for both cohorts was hospital-specific risk-standardized all-cause in-hospital mortality.
Model Derivation

Patient predictors of mortality

Using the derivation cohort, we identified candidate variables that were used in prior risk adjustment models, including patient age, sex, marital status, insurance status, and race/ethnicity. We used software provided by the Healthcare Costs and Utilization Project of the Agency for Healthcare Research and Quality to identify the presence of comorbid conditions. In addition, we used POA codes to identify other acute conditions that are of concern in the setting of HF but that are not recognized in the Elixhauser comorbidity index. These conditions included atrial fibrillation, acute myocardial infarction, pneumonia, and acute kidney injury. Because we lacked echocardiogram results, we used ICD-9-CM codes to identify HF subtypes: systolic only, diastolic only, or both.

Premier model development

In the PDW population, we used a generalized estimating equation logistic regression model, clustering on hospital, to predict each patient’s in-hospital mortality. We initially included all clinically relevant variables in the model, including variables with a well-established association with mortality (eg, age), all conditions included in the Elixhauser comorbidity index, and selected comorbid acute illnesses (eg, acute myocardial infarction that was present on admission). Using backward selection, we retained variables in the final model (hereafter called the “Premier” model) with P<0.05. We calculated the area under the receiver operating characteristic curve (C statistic) and examined the model’s calibration. We then applied the model coefficients to the validation cohort and examined model fit. Of note, we previously externally validated, at the patient level, the Premier model by comparing its performance to the performance of other published clinical HF models in a separate clinical data set.

Laboratory-Based Acute Physiology Score model development

The Laboratory-Based Acute Physiology Score (LAPS) is a validated score that uses laboratory data derived from an EHR to predict in-hospital mortality across conditions, including HF. LAPS uses a 2-stage algorithm. First, selected variables are used to stratify patients into low and high mortality risk groups. Then 14 laboratory values (anion gap; albumin; arterial oxygen, pH, and carbon dioxide; bicarbonate; bilirubin; blood urea nitrogen; creatinine; glucose; hematocrit; sodium; troponin I; white blood cell count) are added to the algorithm to calculate a score. Because LAPS is designed to be used as a variable in a model that includes other patients characteristics when predicting mortality, we developed a generalized estimating equation logistic mortality prediction model using the LAPS score along with age, sex, race, and comorbidities. Using backward selection, we retained variables in the final model with P<0.05. We also previously externally validated (at the patient level, in a population with HF) the LAPS model by comparing its performance to the performance of other published clinical HF models.

Calculation of RSMRs

For the external hospital-level validation of the Premier model in the HealthFacts data set, we compared RSMRs derived using the Premier model to those derived using the LAPS model. To calculate RSMRs for each hospital, we fit hierarchical generalized linear models using variables selected in the model-development step. We used generalized linear mixed models with a logit link to predict mortality and included covariates and a random effect for hospital. We assumed that random hospital effects are normally distributed and independent of hospital-level covariates. This method adjusts for within-hospital correlation of the observed outcomes. It also models the assumption that there are underlying differences between hospitals by allowing a random hospital intercept. For each model, we estimated RSMRs as the ratio of predicted mortality in each hospital given its patient mix and hospital-specific effect, divided by expected mortality given the patient mix and average hospital effect (ie, the mortality if the patients were treated at the “average” hospital). Next, we used bootstrap methods to develop a 95% confidence interval (CI) estimate of risk-standardized mortality for each hospital. To do this, we repeatedly sampled 55 hospitals with replacement (500 samples) from the 55 hospitals in the data set; we repeated the hierarchical generalized linear modeling with each sample and derived the risk-standardized mortality for each hospital, ultimately giving us ~500 RSMR estimates for each hospital. We then used the 2.5 and 97.5 percentiles of the distribution for each hospital as the 95% CI estimate of RSMR. To compare RSMRs derived from the Premier and LAPS models, we first examined the distribution of RSMRs using histograms. We then used linear regression to model the association between the 2 rates, weighting each hospital by number of observations. An intercept close to 0 and slope close to 1 would indicate similar RSMRs by the 2 models. We also calculated correlation coefficient between the RSMRs for Premier and LAPS, and the median difference between model estimates.

Description of cohort definition and sensitivity analyses

To better understand the HealthFacts validation cohort (which included both patients with a principal diagnosis of...
HF and patients with a principal diagnosis of respiratory failure and secondary diagnosis of HF, we compared characteristics of patients with each principal diagnosis using χ² or Wilcoxon tests. We then conducted a sensitivity analysis limiting our cohort to patients with a principal diagnosis of HF and compared model fit to the results from the full cohort. All analyses were carried out using SAS version 9.4 (SAS Institute) and STATA version 13 (StataCorp).

Results

Derivation and Internal Validation Cohort

The PDW included 433 hospitals that contributed a total of 200,832 HF patients during the study period, with between 1 and 2125 patients per hospital (Table 1). Mean patient age was 73 years; approximately half were women (53%), and the majority (65%) were white. The principal diagnosis was HF in 90% of patients and respiratory failure in 10% of patients. Approximately 71% of patients had hypertension, 41% of patients had chronic obstructive pulmonary disease, 46% had diabetes mellitus, and 40% had chronic renal insufficiency. Patients commonly had additional POA acute diagnoses, including acute myocardial infarction (4%), acute kidney injury (17%), and atrial fibrillation (39%). Within the first 2 days of hospitalization, 19% of the patients were admitted to the intensive care unit, 5% received invasive mechanical ventilation, 6% received noninvasive ventilation, 5% received inotropes, and 7% received intravenous vasodilators. Overall, 8110 patients (4%) died in the hospital. The 80% derivation sample and the 20% internal validation sample were statistically similar to each other and to the larger cohort.

Validation Cohort

For external validation, we included 19,050 patients from 55 hospitals that contributed pharmacy, diagnosis, and laboratory data to the HealthFacts database. Compared with the PDW, the HealthFacts cohort had a higher percentage of black patients (28%), a slightly younger mean age (72), fewer Medicare patients (56% versus 77% in PDW), and a similar prevalence of comorbidities (Table 1). The rates of early mechanical ventilation (5%), noninvasive ventilation (7%), inotropes (6%), vasodilators (7%), and in-hospital death (4%) were also similar.

The majority (17,391 of 19,050, or 91.3%) of the included patients had a principal diagnosis of HF, whereas the remaining 1659 had a principal diagnosis of respiratory failure with a secondary diagnosis of HF (Table 2). Nearly all (18,737 or 19,050, or 98.3%) patients included in the HealthFacts cohort received diuretics during their first 2 days of hospitalization. Among patients with a principal diagnosis of HF, 98.8% received diuretics within the first 2 days of hospitalization, and the remainder received ≥1 of the other HF therapies. Among patients with a principal diagnosis of respiratory failure, 93% received diuretics within the first 48 hours, and the remaining 7% received ≥1 of the other therapies (inotropes, vasodilators, or intra-aortic balloon pump).

There were further differences between patients with a principal diagnosis of HF and a principal diagnosis of respiratory failure. Patients with a principal diagnosis of respiratory failure and secondary diagnosis of HF were slightly younger than patients with a principal diagnosis of HF and were more likely to be white (versus other races), to have comorbid illnesses, or to have acute conditions (Table 2). The respiratory failure group also had a much higher mortality rate (13% versus 3%) than the group with a principal diagnosis of HF.

Model Performance

The Premier model showed acceptable calibration across deciles of predicted mortality ranging from 0.9% to 14.9% with C statistics of 0.75 (95% CI, 0.74–0.76) in the PDW cohort and 0.76 in the validation cohort (95% CI, 0.74–0.77). For further details, please see the prior publication16; for the model coefficients, see Table 3.

LAPS also showed good calibration in the validation cohort across deciles of predicted mortality ranging from 0.7% to 16.0% with a C statistic of 0.78 (95% CI, 0.76–0.80; for the model coefficients, see Table 4).

Premier Versus LAPS: Profiling Hospitals

RSMRs in the HealthFacts data had distributions that varied slightly by model. For both Premier and LAPS, distributions of hospital-level RSMRs ranged from 2% to 7% (Figure 1). The slope of the weighted regression line of the Premier versus LAPS-specific mortality rates was 0.71 (SE: 0.07). The Pearson correlation coefficient of the standardized mortality rates from the 2 models was 0.82 (P<0.001; Figure 2). The median difference between RSMRs estimated from the models was 0.0001.

Sensitivity Analyses

We conducted a sensitivity analysis in which we applied the model developed in the Premier data set to a HealthFacts cohort limited to patients with a principal diagnosis of HF to determine if our inclusion of patients with a principal diagnosis of respiratory failure and secondary diagnosis
# Table 1. Patient and Hospital Characteristics in Premier and HealthFacts

|                          | Premier Data | HealthFacts Data | P Value |
|--------------------------|--------------|------------------|---------|
| **Total patients, N**    | 200,832      | 19,050           |         |
| **Number of hospitals**  | 433          | 55               |         |
| **Demographics**         |              |                  |         |
| Age, mean (median, Q1–Q3)| 73.4 (76, 65–85) | 72.0 (75, 62–84) | <0.0001 |
| Female                   | 105,413 (52.5) | 98,922 (51.9)    | 0.1380  |
| **Race/ethnicity**       |              |                  |         |
| White                    | 130,634 (65.0) | 12,585 (66.1)    | <0.0001 |
| Black                    | 34,165 (17.0)  | 5,304 (27.8)     |         |
| Hispanic                 | 9,442 (4.7)   | 341 (1.8)        |         |
| Other                    | 26,591 (13.2) | 820 (4.3)        |         |
| **Insurance**            |              |                  |         |
| Medicare                 | 154,219 (76.8) | 10,606 (55.7)   |         |
| Medicaid                 | 13,133 (6.5)  | 1,063 (5.6)      |         |
| Private                  | 22,343 (11.1) | 1,906 (10.0)     |         |
| Uninsured                | 7,257 (3.6)   | 629 (3.3)        |         |
| Other/unknown            | 3,880 (1.9)   | 4,846 (25.4)     |         |
| **Clinical characteristics** |          |                  |         |
| **Comorbidities**        |              |                  |         |
| Valvular disease         | 4,069 (2.0)  | 562 (3.0)        | <0.0001 |
| Pulmonary circulation disease | 5,423 (2.7)  | 559 (2.9)        | 0.0577  |
| Peripheral vascular disease | 26,472 (13.2) | 1,849 (9.7)     | <0.0001 |
| Hypertension             | 142,658 (71.0) | 11,468 (60.2) | <0.0001 |
| Paralysis                | 4,010 (2.0)  | 322 (1.7)        | 0.0036  |
| Other neurological disorders | 16,712 (8.3) | 1,253 (6.6)     | <0.0001 |
| Chronic pulmonary disease | 82,606 (41.1) | 6,588 (34.6)   | <0.0001 |
| Diabetes mellitus        | 91,594 (45.6) | 7,823 (41.1)    | <0.0001 |
| Hypothyroidism           | 36,652 (18.3) | 2,701 (14.2)    | <0.0001 |
| Renal failure            | 80,713 (40.2) | 6,976 (36.6)    | <0.0001 |
| Liver disease            | 5,047 (2.5)  | 432 (2.3)        | 0.0379  |
| Peptic ulcer disease, excluding bleeding | 74 (0.0) | 2 (0.0) | 0.0615 |
| AIDS                     | 351 (0.2)    | 27 (0.1)         | 0.2928  |
| Lymphoma                 | 2,012 (1.0)  | 161 (0.8)        | 0.0367  |
| Metastatic cancer        | 2,459 (1.2)  | 181 (1.0)        | 0.0009  |
| Solid tumor without metastasis | 3,822 (1.9) | 329 (1.7)   | 0.0879  |
| Rheumatoid arthritis/collagen vascular disease | 6,193 (3.1) | 511 (2.7) | 0.0021 |
| Coagulopathy             | 12,225 (6.1) | 1,061 (5.6)     | 0.0042  |
| Obesity                  | 38,337 (19.1) | 3,423 (18.0)    | 0.0002  |
| Weight loss              | 10,218 (5.1) | 750 (3.9)       | <0.0001 |
| Fluid and electrolyte disorders | 6,083 (33.4) | 5,547 (29.1)   | <0.0001 |
| Chronic blood loss anemia | 2,331 (1.2)  | 134 (0.7)       | <0.0001 |
| Deficiency anemias       | 67,130 (33.4) | 5,194 (27.3)    | <0.0001 |
| Alcohol abuse            | 5,997 (3.0)  | 491 (2.6)        | 0.0014  |
| Drug abuse               | 3,916 (1.9)  | 444 (2.3)        | 0.0003  |
| Psychoses                | 6,182 (3.1)  | 450 (2.4)        | <0.0001 |
| Depression               | 21,684 (10.8) | 1,461 (7.7)   | <0.0001 |

Continued
of HF affected our results. We found that the Premier model in a cohort of patients with a principal diagnosis of HF had a C statistic of 0.76 (95% CI, 0.75–0.76) and a similar calibration curve to the full cohort. The C statistic for the LAPS model was also very similar to the main cohort (0.76; 95% CI, 0.74–0.78) and had a similar

| Table 1. Continued |
|---------------------|
|                     | Premier Data | HealthFacts Data | P Value |
| Comorbidity score (median, IQR) | 4.8 (5, 3–6) | 4.7 (4, 3–6) | <0.0001 |
| ≤2                  | 30 966 (15.4) | 4093 (21.5) | <0.0001 |
| 3–4                 | 63 576 (31.7) | 6157 (32.3) | <0.0001 |
| 5–6                 | 61 185 (30.5) | 5451 (28.6) | <0.0001 |
| ≥7                  | 45 105 (22.5) | 3349 (17.6) | <0.0001 |
| Acute and chronic conditions present on admission | | | |
| Acute myocardial infarction | 8518 (4.2) | 829 (4.4) | 0.4706 |
| Acute kidney injury | 34 041 (17.0) | 4105 (21.5) | <0.0001 |
| Atrial fibrillation | 78 434 (39.1) | 6735 (35.4) | <0.0001 |
| Coronary artery disease | 108 125 (53.8) | 9333 (49.0) | <0.0001 |
| Pneumonia | 30 097 (15.0) | 2370 (12.4) | <0.0001 |
| Malnutrition | 6328 (3.2) | 510 (2.7) | 0.0003 |
| Ischemic heart disease | 107 818 (53.7) | 9224 (48.4) | <0.0001 |
| Heart failure type | | | |
| Systolic | 78 012 (38.8) | 8668 (45.5) | <0.0001 |
| Diastolic | 67 027 (33.4) | 7438 (39.0) | <0.0001 |
| Treatments | | | |
| Diuretics | 198 244 (98.7) | 18 737 (98.4) | <0.0001 |
| Noninvasive ventilation | 11 611 (5.8) | 1324 (7.0) | <0.0001 |
| Invasive mechanical ventilation | 9069 (5.0) | 939 (4.9) | 0.8330 |
| Vasopressors | 3145 (1.6) | 375 (2.0) | <0.0001 |
| Inotropes | 9586 (4.8) | 1125 (5.9) | <0.0001 |
| Vasodilators | 15 024 (7.5) | 1308 (6.9) | 0.0020 |
| Intra-aortic balloon pump | 138 (0.1) | 29 (0.2) | <0.0001 |
| Prior year HF admissions | | | |
| 0 | 169 496 (84.4) | 15 628 (82.0) | <0.0001 |
| 1 | 22 634 (11.3) | 2382 (12.5) | <0.0001 |
| ≥2 | 8702 (4.3) | 1040 (5.5) | <0.0001 |
| Outcomes | | | |
| Mortality | 8110 (4.0) | 800 (4.2) | 0.2806 |
| Hospital characteristics | | | |
| Urban (vs rural) | 178 393 (88.8) | 19 028 (99.9) | <0.0001 |
| Teaching | 75 626 (37.7) | 15 299 (80.3) | <0.0001 |
| Geographical location | | <0.0001 |
| Midwest | 39 329 (19.6) | 2593 (13.6) | <0.0001 |
| Northeast | 40 522 (20.2) | 7384 (38.8) | <0.0001 |
| South | 87 607 (43.6) | 7326 (38.5) | <0.0001 |
| West | 33 374 (16.6) | 1747 (9.2) | <0.0001 |
| Number of beds | | | |
| <199 | 32 998 (16.4) | 2143 (11.2) | <0.0001 |
| 200–499 | 111 854 (55.7) | 11 421 (60.0) | <0.0001 |
| ≥500 | 55 980 (27.9) | 5486 (28.8) | <0.0001 |

Data are shown as n (%), unless otherwise noted. HF indicates heart failure; IQR, interquartile range.
**Table 2.** Comparison of Patients With Principal Diagnosis of HF to Those With Principal Diagnosis of Respiratory Failure With Secondary Diagnosis of HF

|                                | Principal Diagnosis HF | Principal Diagnosis Respiratory Failure | P Value |
|--------------------------------|------------------------|----------------------------------------|---------|
| **Total patients**             | 17 391 (91.3)          | 1659 (8.7)                             |         |
| **Demographics**               |                        |                                        |         |
| Age, mean (median, Q1–Q3)      | 72.2 (75, 62–85)       | 70.4 (71, 61–81)                       | <0.0001 |
| Female                         | 8922 (51.3)            | 970 (58.5)                             | <0.0001 |
| Race/ethnicity                 |                        |                                        | <0.0001 |
| White                          | 11 360 (65.3)          | 1225 (73.8)                            |         |
| Black                          | 4952 (28.5)            | 352 (21.2)                             |         |
| Hispanic                       | 310 (1.8)              | 31 (1.9)                               |         |
| Other                          | 769 (4.4)              | 51 (3.1)                               |         |
| Insurance                      |                        |                                        | <0.0001 |
| Medicare                       | 9561 (55.0)            | 1045 (63.0)                            |         |
| Medicaid                       | 953 (5.5)              | 110 (6.6)                              |         |
| Private                        | 1750 (10.1)            | 156 (9.4)                              |         |
| Uninsured                      | 574 (3.3)              | 55 (3.3)                               |         |
| Other/unknown                  | 4553 (26.2)            | 293 (17.7)                             |         |
| **Clinical characteristics**   |                        |                                        |         |
| Comorbidities                  |                        |                                        |         |
| Valvular disease               | 259 (1.5)              | 303 (18.3)                             | <0.0001 |
| Pulmonary circulation disease  | 164 (0.9)              | 395 (23.8)                             | <0.0001 |
| Peripheral vascular disease    | 1701 (9.8)             | 148 (8.9)                              | 0.2583  |
| Hypertension                   | 10 356 (59.5)          | 1112 (67.0)                            | <0.0001 |
| Paralysis                      | 273 (1.6)              | 49 (3.0)                               | <0.0001 |
| Other neurological disorders   | 1049 (6.0)             | 204 (12.3)                             | <0.0001 |
| Chronic pulmonary disease      | 5466 (31.4)            | 1122 (67.6)                            | <0.0001 |
| Diabetes mellitus              | 7056 (40.6)            | 767 (46.2)                             | <0.0001 |
| Hypothyroidism                 | 2419 (13.9)            | 282 (17.0)                             | <0.0001 |
| Renal failure                  | 6483 (37.3)            | 493 (29.7)                             | <0.0001 |
| Liver disease                  | 403 (2.3)              | 29 (1.7)                               | 0.1367  |
| Peptic ulcer disease x bleeding| 2 (0.0)                | 0 (0.0)                                | 0.6622  |
| AIDS                           | 26 (0.1)               | 1 (0.1)                                | 0.3560  |
| Lymphoma                       | 145 (0.8)              | 16 (1.0)                               | 0.5785  |
| Metastatic cancer              | 147 (0.8)              | 34 (2.0)                               | <0.0001 |
| Solid tumor without metastasis | 279 (1.6)              | 50 (3.0)                               | <0.0001 |
| Rheumatoid arthritis/collagen vascular disease | 457 (2.6) | 54 (3.3) | 0.1309 |
| Coagulopathy                   | 910 (5.2)              | 151 (9.1)                              | <0.0001 |
| Obesity                        | 2944 (16.9)            | 479 (28.9)                             | <0.0001 |
| Weight loss                    | 611 (3.5)              | 139 (8.4)                              | <0.0001 |
| Fluid and electrolyte disorders| 4721 (27.1)            | 826 (49.8)                             | <0.0001 |
| Chronic blood loss anemia      | 125 (0.7)              | 9 (0.5)                                | 0.4118  |
| Deficiency anemias             | 4697 (27.0)            | 497 (30.0)                             | 0.0100  |
| Alcohol abuse                  | 433 (2.5)              | 58 (3.5)                               | 0.0135  |
| Drug abuse                     | 400 (2.3)              | 44 (2.7)                               | 0.3637  |
| Psychoses                      | 369 (2.1)              | 81 (4.9)                               | <0.0001 |
| Depression                     | 1278 (7.3)             | 183 (11.0)                             | <0.0001 |

Continued
Because limiting the cohort to a principal diagnosis of HF excluded a large proportion of the deaths, with more deaths excluded from some hospitals than others (due to variation in coding of respiratory failure across hospitals), we opted not to calculate RSMRs in this limited cohort.

Data shown as n (%), unless otherwise noted. HF indicates heart failure; IQR, interquartile range.

| Table 2. Continued |
|---------------------|
| **Comorbidity score mean (median, IQR)** | Principal Diagnosis HF | Principal Diagnosis Respiratory Failure | P Value |
| ≤2 | 3951 (22.7) | 142 (8.6) | <0.0001 |
| 3–4 | 5538 (31.8) | 619 (37.3) | |
| 5–6 | 4937 (28.4) | 514 (31.0) | |
| ≥7 | 2965 (17.0) | 384 (23.1) | |

| Acute and chronic conditions present on admission |
|-----------------------------------------------|
| **Acute myocardial infarction** | 663 (3.8) | 166 (10.0) | <0.0001 |
| **Acute kidney injury** | 3600 (20.7) | 505 (30.4) | <0.0001 |
| **Atrial fibrillation** | 6174 (35.5) | 561 (33.8) | 0.1700 |
| **Coronary artery disease** | 8575 (49.3) | 758 (45.7) | 0.0049 |
| **Pneumonia** | 581 (35.0) | <0.0001 |
| **Malnutrition** | 406 (2.3) | 406 (2.3) | 0.0001 |
| **Ischemic heart disease** | 8486 (48.8) | 738 (44.5) | 0.0008 |

| **Heart failure type** |
|------------------------|
| **Systolic** | 8218 (47.3) | 450 (27.1) | <0.0001 |
| **Diastolic** | 6867 (39.5) | 571 (34.4) | <0.0001 |

| **Treatments** |
|----------------|
| **Diuretics** | 17 191 (98.8) | 1546 (93.2) | <0.0001 |
| **Noninvasive ventilation** | 921 (5.3) | 403 (24.3) | <0.0001 |
| **Invasive mechanical ventilation** | 235 (1.4) | 704 (42.4) | <0.0001 |
| **Vasopressors** | 200 (1.2) | 175 (10.5) | <0.0001 |
| **Inotropes** | 907 (5.2) | 218 (13.1) | <0.0001 |
| **Vasodilators** | 1112 (6.4) | 196 (11.8) | <0.0001 |
| **Intra-aortic balloon pump** | 29 (0.2) | 0 (0.0) | 0.0960 |
| **Prior year HF admissions** | 0.7585 |
| **0** | 14 261 (82) | 1367 (82.4) |
| **1** | 2174 (12.5) | 208 (12.5) |
| **≥2** | 956 (5.5) | 84 (5.1) |

| **Outcomes** |
|--------------|
| **Mortality** | 577 (3.3) | 223 (13.4) | <0.0001 |

| **Hospital characteristics** |
|----------------------------|
| **Urban (vs rural)** | 17 369 (99.9) | 1659 (100) | 0.1472 |
| **Teaching** | 13 961 (80.3) | 1338 (80.7) | 0.7145 |
| **Geographical location** | 0.0001 |
| **Midwest** | 2369 (13.6) | 224 (13.5) |
| **Northeast** | 6828 (39.3) | 556 (33.5) |
| **South** | 6591 (37.9) | 735 (44.3) |
| **West** | 1603 (9.2) | 144 (8.7) |
| **Number of beds** | 0.0001 |
| **<199** | 1970 (11.3) | 173 (10.4) |
| **200–499** | 10 348 (59.5) | 1073 (64.7) |
| **≥500** | 5073 (29.2) | 413 (24.9) |
Using a mortality prediction model that showed good performance in a multihospital billing data set composed of inpatients with HF, we calculated hospital RSMRs in a multihospital data set containing information from >50 hospitals’ EHRs. When we compared the Premier model’s RSMRs with RSMR estimates derived from a clinical model that uses laboratory data, we found that the 2 models produced estimates of hospitals’ risk-standardized mortality that were similar, with a correlation coefficient of 0.82. This suggests that the Premier model could be a useful tool for describing the quality of HF care provided by hospitals in situations in which clinical data are not available.

Our model builds on an existing hospital-profiling model used for hospitalized HF patients. Krumholz et al developed and validated an administrative claims–based risk-adjustment model for HF with the purpose of characterizing hospital quality. This model, which is used by the Centers for Medicare and Medicaid Services (CMS) to compare mortality rates across hospitals for public reporting purposes, produces results that are very similar to medical records–based models.10,11,19,20 There are several key differences between our model and the CMS model. First, the CMS model was developed to predict 30-day mortality rates, whereas ours predicts in-hospital mortality. Second, unlike our model, the CMS model contains all claims in the year before hospitalization. These claims are not available in data sets that contain only information on hospitalizations, such as PDW. Consequently, our model may be more broadly applicable to

Table 3. Premier Model Coefficients From Development Sample (Premier Database), Derived Using Generalized Estimating Equation Modeling

| Covariate                              | Estimate | SE    | P Value |
|----------------------------------------|----------|-------|---------|
| Intercept                              | -4.1603  | 0.0949| <0.0001 |
| Demographics                           |          |       |         |
| Age, y                                 |          |       |         |
| <50 Ref                                |          |       |         |
| 50–59 Ref                              | 0.1305   | 0.0924| 0.1579  |
| 60–69 Ref                              | 0.2940   | 0.0885| 0.0009  |
| 70–74 Ref                              | 0.3784   | 0.0948| <0.0001 |
| 75–79 Ref                              | 0.6849   | 0.0920| <0.0001 |
| 80–84 Ref                              | 0.7570   | 0.0912| <0.0001 |
| ≥89 Ref                                | 0.9584   | 0.0920| <0.0001 |
| Race/ethnicity                         |          |       |         |
| White Ref                              |          |       |         |
| Black                                  | -0.2282  | 0.0463| <0.0001 |
| Hispanic                               | -0.1202  | 0.0740| 0.1042  |
| Other                                  | 0.0521   | 0.0433| 0.2297  |
| Sex                                    |          |       |         |
| Male Ref                               |          |       |         |
| Female                                 | -0.1209  | 0.0272| <0.0001 |
| Insurance                              |          |       |         |
| Medicare Ref                           |          |       |         |
| Private                                | -0.1016  | 0.0527| 0.0540  |
| Uninsured                              | -0.2119  | 0.1084| 0.0507  |
| Other/unknown                          | 0.3766   | 0.0936| <0.0001 |
| Medicaid                               | 0.0245   | 0.0705| 0.7284  |
| Clinical characteristics               |          |       |         |
| Comorbidities                          |          |       |         |
| Valvular disease                       | 0.8410   | 0.0579| <0.0001 |
| Pulmonary circulation disease          | 1.0029   | 0.0544| <0.0001 |
| Peripheral vascular disease            | 0.1364   | 0.0361| 0.0002  |
| Hypertension                           | -0.2556  | 0.0281| <0.0001 |
| Paralysis                              | 0.5022   | 0.0727| <0.0001 |
| Other neurological disorders           | 0.3745   | 0.0395| <0.0001 |
| Chronic pulmonary disease              | 0.1245   | 0.0269| <0.0001 |
| Renal failure                          | 0.1817   | 0.0286| <0.0001 |
| Liver disease                          | 0.4563   | 0.0708| <0.0001 |
| Rheumatoid arthritis                   | 0.1936   | 0.0693| 0.0052  |
| Coagulopathy                           | 0.6321   | 0.0405| <0.0001 |
| Drug abuse                             | -0.2767  | 0.1344| 0.0396  |
| Lymphoma                               | 0.3998   | 0.1051| 0.0001  |
| Solid tumor without metastasis         | 0.4095   | 0.0758| <0.0001 |

Continued

Table 3. Continued

| Covariate                              | Estimate | SE    | P Value |
|----------------------------------------|----------|-------|---------|
| Metastatic cancer                      | 0.8896   | 0.0794| <0.0001 |
| Acute myocardial infarction            | 1.2192   | 0.0413| <0.0001 |
| Acute kidney injury                    | 0.7337   | 0.0305| <0.0001 |
| Atrial fibrillation                    | 0.2415   | 0.0269| <0.0001 |
| Coronary artery disease                | 0.5637   | 0.1781| 0.0015  |
| Ischemic heart disease                 | -0.7037  | 0.1782| <0.0001 |
| Pneumonia                              | 0.6165   | 0.0301| <0.0001 |
| Malnutrition                           | 0.6160   | 0.0526| <0.0001 |
| Systolic heart failure                 | -0.2137  | 0.0289| <0.0001 |
| Diastolic heart failure                | -0.3350  | 0.0298| <0.0001 |
| Prior heart failure hospitalization    |          |       |         |
| 0 Ref                                  |          |       |         |
| 1                                       | 0.1394   | 0.0398| 0.0005  |
| >1                                      | 0.1794   | 0.0625| 0.0041  |

Ref indicates referent.
Table 4. LAPS Model Coefficients From the HealthFacts Cohort, Derived Using Generalized Estimating Equation Modeling

| Covariate                        | Estimate | SE    | P Value |
|----------------------------------|----------|-------|---------|
| Intercept                        | -4.6381  | 0.2280| <0.0001 |
| Demographics                     |          |       |         |
| Age, y                           |          |       |         |
| <50                              |          |       |         |
| 50–59                            | 0.1185   | 0.2278| 0.6030  |
| 60–69                            | 0.1010   | 0.2154| 0.6393  |
| 70–74                            | 0.0480   | 0.2296| 0.8343  |
| 75–79                            | 0.2655   | 0.2199| 0.2272  |
| 80–84                            | 0.3230   | 0.2181| 0.1387  |
| 85–88                            | 0.6662   | 0.2168| 0.0021  |
| ≥89                              | 0.6472   | 0.2149| 0.0026  |
| Race/ethnicity                   |          |       |         |
| White                            |          |       |         |
| Black                            | -0.4706  | 0.1200| <0.0001 |
| Hispanic                         | -0.4442  | 0.3352| 0.1850  |
| Other                            | -0.3141  | 0.2036| 0.1229  |
| Comorbidities                    |          |       |         |
| Pulmonary circulation disease    | 0.5229   | 0.1521| 0.0006  |
| Hypertension                     | -0.3618  | 0.0806| <0.0001 |
| Paralysis                        | 0.6055   | 0.2171| 0.0053  |
| Other neurological disorders     | 0.5606   | 0.1162| <0.0001 |
| Renal failure                    | 0.1591   | 0.0787| 0.0433  |
| Coagulopathy                     | 0.3795   | 0.1112| <0.0001 |
| Solid tumor without metastasis   | 0.5547   | 0.2121| 0.0089  |
| Metastatic cancer                | 1.2072   | 0.2275| <0.0001 |
| LAPS                             | 0.0324   | 0.0017| <0.0001 |

LAPS indicates Laboratory-Based Acute Physiology Score; Ref, referent.

databases that contain information about hospitalizations but lack outpatient data. The CMS model does not include patients with a principal diagnosis of respiratory failure, and that limits its use to patients with HF as a principal diagnosis. The CMS model was also developed before widespread use of POA codes, so it did not originally include POA acute diagnoses, and POA acute diagnoses have not been added to the CMS model in recent years. In contrast, our model attempts to adjust for presenting severity by including some acute diagnoses that were present at the time of admission (eg, pneumonia or acute myocardial infarction). Finally, our model includes all patients aged ≥18 years, whereas the CMS model includes only Medicare patients, the vast majority of whom are aged ≥65 years. Despite these differences, our C statistics compare favorably to the CMS model, which had a C statistic of 0.70.11

The validation of a model that can be used to profile hospital quality of HF care has some important implications. Because it can be used with almost any multihospital data set, this model can be used by groups of hospitals that come together to improve quality (“quality improvement collaboratives”) and will allow such collaboratives to identify hospitals that need the most focused efforts. Perhaps more important, our model can be used to identify high-performing hospitals (eg, Figure 2). It is possible that hospitals with lower mortality rates use quality-improvement and care-coordination strategies to standardize the care of patients with HF that may lead to better patient outcomes. Although we cannot use this current data set to identify the strategies that are most likely to improve care, future studies should consider using qualitative methods, such as those described by Bradley and Krumholz,21 to do so. These interviews might include questions about hospital units that specialize in the care of HF patients (including nurses, physicians, and managers with expertise in HF care), use of protocols for early identification of volume status, coordinated efforts to identify patients who would most benefit from intensive care and procedures, appropriate use of palliative care and hospice for patients with end-stage disease, and interventions to integrate team members.

This study has several strengths. First, we validated the model for use at the hospital level in a separate population with different demographic characteristics. Second, we previously demonstrated the patient-level performance of the Premier model compared with published clinical HF mortality prediction models.16 Third, our model is one of only 2 clinical prediction models in the HF literature aimed specifically at benchmarking hospitals and is potentially more broadly applicable than the CMS model for the reasons stated. Among published HF models that predict mortality in hospitalized HF patients,22–26 most contain clinical variables, such as systolic blood pressure and serum creatinine level.22,23,25 In contrast, our model does not require clinical data but performed similarly to a model that does.

Despite these strengths, this study also has several limitations. First, our model predicts in-hospital mortality rather than 30- or 90-day mortality because our data sets do not contain information about postdischarge deaths. Although inpatient mortality is widely used in outcomes research,26–28 there are concerns that hospitals with shorter length of stay or patterns of discharging end-of-life patients to palliative care or hospice might have lower in-hospital mortality but similar 30-day mortality.29 This is also an issue because CMS quality metrics use 30-day rather than inpatient mortality. Second, the lack of clinical data also introduced an additional limitation: We could not determine HF etiology or ejection...
fraction, except by using diagnosis codes. Finally, our
definition of HF was based on a combination of diagnosis
and billing codes and does not include clinical data. We used a
broad set of diagnosis codes to identify patients (with both HF
and respiratory failure as principal diagnoses), but also
required the presence of at least 1 HF-specific treatment
early in the hospitalization as a proxy for clinical findings of
HF. Although many prior studies and CMS quality metrics use
diagnosis codes alone to identify patients hospitalized with
HF,10,30–32 we believe that using criteria that combine the
principal diagnosis code with early therapies is a more
specific method for identifying hospitalizations for which the
primary issue is HF.16 Furthermore, the high percentage of
patients treated with diuretics provides additional evidence
that these were hospitalizations for which the primary issue
was HF. Slightly fewer patients with a principal diagnosis of
respiratory failure received diuretics, but we feel that this is to
be expected, given that these patients are the sickest and are
most likely to suffer from low blood pressure, acute kidney
injury, and other factors that would limit the use of diuretics
but would increase the likelihood that they would receive
other HF therapies (eg, inotropes). Finally, we used this broad
set of diagnosis codes because prior work suggests that there
is variation in coding across hospitals in the use of the code
for acute respiratory failure, with some hospitals using this
code more often than others.33 If we failed to include patients
with a principal diagnosis of respiratory failure for a hospital-
level validation, the hospitals that use this code more
frequently for their sicker patients with HF might appear to
have a healthier cohort of patients with HF.

In conclusion, a mortality model designed to support
hospital profiling of inpatient mortality for patients with HF
appeared to produce similar results to a clinical model. These
data suggest that this model could be useful for comparing
quality of HF care across hospitals, especially if using data
sets that contain only information from hospitalizations (i.e., those that lack prior outpatient data) or if clinical data are not available. This model also allows for identification of hospitals with low mortality rates, creating an opportunity to conduct future studies that examine strategies of high-performing hospitals for HF care.

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None.

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