Predicting Mortality Among Patients Hospitalized for Heart Failure

Derivation and Validation of a Clinical Model

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Context A predictive model of mortality in heart failure may be useful for clinicians to improve communication with and care of hospitalized patients.

Objectives To identify predictors of mortality and to develop and to validate a model using information available at hospital presentation.

Design, Setting, and Participants Retrospective study of 4031 community-based patients presenting with heart failure at multiple hospitals in Ontario, Canada (2624 patients in the derivation cohort from 1999-2001 and 1407 patients in the validation cohort from 1997-1999), who had been identitifed as part of the Enhanced Feedback for Effective Cardiac Treatment (EFFECT) study.

Main Outcome Measures All-cause 30-day and 1-year mortality.

Results The mortality rates for the derivation cohort and validation cohort, respectively, were 8.9% and 8.2% in hospital, 10.7% and 10.4% at 30 days, and 32.9% and 30.5% at 1 year. Multivariable predictors of mortality at both 30 days and 1 year included older age, lower systolic blood pressure, higher respiratory rate, higher urea nitrogen level (all $P<.001$), and hyponatremia ($P<.01$). Comorbid conditions associated with mortality included cerebrovascular disease (30-day mortality odds ratio [OR], 1.43; 95% confidence interval [CI], 1.03-1.98; $P=.03$), chronic obstructive pulmonary disease (OR, 1.66; 95% CI, 1.22-2.27; $P=.002$), hepatic cirrhosis (OR, 3.22; 95% CI, 1.08-9.65; $P=.04$), dementia (OR, 2.54; 95% CI, 1.77-3.65; $P<.001$), and cancer (OR, 1.86; 95% CI, 1.28-2.70; $P=.001$). A risk index stratified the risk of death and identified low- and high-risk individuals. Patients with very low-risk scores (≤60) had a mortality rate of 0.4% at 30 days and 7.8% at 1 year. Patients with very high-risk scores (>150) had a mortality rate of 59.0% at 30 days and 78.8% at 1 year. Patients with higher 1-year risk scores had reduced survival at all times up to 1 year (log-rank, $P<.001$). For the derivation cohort, the area under the receiver operating characteristic curve for the model was 0.80 for 30-day mortality and 0.77 for 1-year mortality. Predicted mortality rates in the validation cohort closely matched observed rates across the entire spectrum of risk.

Conclusions Among community-based heart failure patients, factors identifiable within hours of hospital presentation predicted mortality risk at 30 days and 1 year. The externally validated predictive index may assist clinicians in estimating heart failure mortality risk and in providing quantitative guidance for decision making in heart failure care.

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HEART FAILURE IS A CONDITION with an adverse prognosis; 1-year mortality rates in population-based studies have been reported to be 35% to 40%.[1-5] Important prognostic factors have been identified among clinical trial enrollees. However, factors that predict mortality in the community setting may differ.[6] Although heart failure is a common, serious condition treated by both generalist and specialist physicians, few methods exist to help quantatitively estimate prognosis. As a result, clinicians must rely on published mortality rates from clinical trials or other studies, in which patient populations may differ from those encountered in clinical practice.

Knowledge of mortality predictors can be used to generate predictive models that can aid clinicians' decision making, in particular by identifying patients who are at high or low risk of death.[7-11] Such risk-assessment methods have been developed for acute myocardial infarction but not for heart failure.[7,12,13] Risk prediction models may be used in patient counseling to initiate the discussion about end-of-life issues and also may be used for quality-of-care out-

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come assessment. Patients at low risk could be potentially discharged from the hospital early, whereas those at high risk could benefit from intensive or specialized care units.

Previous work in heart failure risk determination focused primarily on risk adjustment in elderly Medicare populations.[14-16] These prior models are complex and arguably difficult for clinicians to use in routine practice. Furthermore, transportability of previous models may be limited because the variables that comprise these models are not routinely collected.[15,16] Our objective was to develop and externally validate a method to predict mortality risk in heart failure patients based on information routinely available to clinicians at hospital presentation such as demographic features, vital signs, and patient comorbid conditions. We hypothesized that the model could effectively stratify the risk of death among heart failure patients at both 30 days and 1 year.

METHODS

Patients

We identified newly admitted patients with a primary diagnosis of heart failure (*International Classification of Diseases, Ninth Revision, Clinical Modification* code 428) using the Canadian Institutes of Health Information hospital discharge abstract as described previously.[17,18] Of the patients identified, we further refined the cohort by only including patients with a clinical heart failure presentation who met modified Framingham heart failure criteria.[3,19-21] We excluded patients who developed heart failure after admission (ie, in-hospital complication), patients transferred from another acute care facility, those aged 105 years or older, nonresidents, and those with an invalid health card number.

Using these methods, 2624 patients from 34 hospitals in Ontario, Canada, from April 1, 1999, to March 31, 2001, were identified as part of the Enhanced Feedback for Effective Cardiac Treatment (EFFECT) study. The hospitals included teaching hospitals and community-based institutions from both rural and urban locales. This sample comprised the mortality model derivation cohort. Similarly, we identified a cohort of 1407 heart failure patients from 14 different hospitals in Ontario from a prior period (April 1, 1997, to March 31, 1999), which comprised an independent model validation cohort. Hospitals included in this study had a minimum yearly volume of more than 100 heart failure patient admissions during the years of sampling. From these hospitals, patients were sampled at random for abstraction of clinical data and subsequent follow-up. Institutional review board approval was obtained from each participating institution prior to the study.

Data Collection and Variable Definitions

Potential candidate variables were identified based on review of the literature, clinical relevance, and routine availability in the initial hours of hospital presentation.[14-16,22-25] Variables selected for abstraction were further guided by the consensus of a Canadian expert panel of heart failure specialists.[26] The potential candidate variables were either presentation features (eg, vital signs) or other data abstractable from the clinical record up to the first 24 hours of hospital presentation (eg, laboratory values, preexisting comorbid conditions) and were classified as demographic characteristics, presenting clinical and laboratory features, or preexisting comorbid conditions. Comorbidity data were subcategorized according to the disease moieties of the Charlson comorbidity index.[24] These included cancer, dementia, diabetes mellitus, chronic obstructive pulmonary disease, cerebrovascular disease, peripheral vascular disease, cirrhotic liver disease, prior myocardial infarction, and renal indices (serum blood urea nitrogen and creatinine concentrations). Hyponatremia and hypokalemia were defined by the lower limit of the normal biochemical range. We also collected information when available on left ventricular function via echocardiography, radionuclide angiography, or cardiac catheterization.

Data abstraction from hospital records was conducted by highly experienced cardiology nurse abstractors using a computerized instrument with preprogrammed range checks. Reliability for abstraction of categorical variables was high. For prior myocardial infarction, reliability was 0.94 using crude agreement and $\kappa = 0.88$; chronic obstructive pulmonary disease, 0.92 and $\kappa = 0.80$; cancer, 0.97 and $\kappa = 0.89$; and dementia, 0.97 and $\kappa = 0.82$.[27] Deaths occurring up to 1 year after hospital admission were identified by linkages with the Registered Persons Database, using the patient's encrypted health card number. The primary model outcomes of 30-day and 1-year mortality were used to eliminate biases related to the decision to discharge and its potential relationship with mortality.

Analysis

Candidate variables that were associated with 30-day and 1-year mortality on univariate analysis ($P \leq .20$) were included as potential covariates in a multiple logistic regression model.[28] Variable selection in multivariable modeling was based on clinical and statistical significance.[29] We examined the strength and shape of the relationships of continuous variables with the log odds of death using cubic spline plots.[30] These functions were used to develop and refine the multivariable regression models as used previously.[13] Discrimination of the model was assessed by the area under the receiver operating characteristic (ROC) curve[31] and calibration was assessed using the Hosmer and Lemeshow χ^2 statistic ($P > .05$ for all models).[28] Models for 30-day and 1-year mortality were assessed for possible overfit using linear shrinkage estimators.[30,32] A sensitivity analysis was also conducted to assess the robustness of the model after accounting for reduced left ventricular systolic function (ejection fraction < 0.40).

Score-based prediction rules for mortality at 30 days and 1 year were developed from logistic regression models by using a regression coefficient-based scoring method.[33,34] Integer scores were assigned by dividing risk-factor coeffi-

cients by the age coefficient and rounding up to the nearest unit for continuous variables and up to the nearest 5 points for midpoints of stratified continuous or categorical variables.[35] The overall risk score was calculated by adding each component together. Mortality rates were assessed according to the numeric value of the 30-day and 1-year risk scores. To assess if the prognostic rank of the 1-year risk score was preserved over time, Kaplan-Meier survival curves were constructed and stratified according to 1-year risk score risk quintile and comparisons were performed using the log-rank test.[8]

We validated the 30-day and 1-year mortality models internally using the bootstrap in the derivation dataset by sampling with replacement for 200 iterations.[36-38] We externally validated both regression models by assessing model performance in the validation cohort.

Analyses were conducted using SAS statistical software (Version 8.0; SAS Institute Inc, Cary, NC) and ROC curve analysis was performed using STATA statistical software (Version 7.0; STATA Corp, College Station, Tex). Bootstrap sampling, cubic spline analysis, and ROC curve optimism analysis were conducted using S-plus statistical software (Version 6.0, Insightful Corp, Seattle, Wash).

RESULTS

Description of the Derivation and Validation Cohorts

There were 2624 heart failure patients in the derivation cohort and 1407 patients in the external validation cohort (N=4031 patients). Age and sex distributions in the 2 cohorts were comparable (TABLE 1). Approximately half were women who were on average, older than men (mean [SD] age of women, 78.5 [10.5] years vs 74.1 [11.5] years for men; $P<.001$). Summary statistics of presenting features (vital signs, initial laboratory values) and frequency of comorbid conditions are shown in Table 1. Left ventricular function evaluation was performed in 1618 (61.7%) of the derivation cohort compared with 692 (49.2%) of the validation cohort.

The mortality rates for the derivation cohort were 8.9% (234 deaths) in-hospital, 10.7% (282 deaths) at 30 days, and 32.9% (862 deaths) at 1 year; validation cohort, 8.2% (115 deaths), 10.4% (147 deaths), and 30.5% (429 deaths), respectively. Thus, the mortality rates at 1 year were comparable with those reported in other population-based studies.

Predictors of Mortality

Results of univariate analysis for all potential predictors are shown in TABLE 2. Multivariable models for 30-day and 1-year mortality are shown in TABLE 3. There was no statistical evidence of overfit as demonstrated by linear shrinkage estimation in both multivariable models. Model predictors of both 30-day and 1-year mortality included age, systolic blood pressure, respiratory rate, hyponatremia, and urea nitrogen concentration. Although low-hemoglobin concentration was predictive of 1-year death, it was not associated with 30-day mortality. Comorbid conditions associated with mortality common to both models included cerebrovascular disease, dementia, chronic obstructive pulmonary disease, cirrhosis, and cancer. Although creatinine elevation was a significant predictor of death, it was correlated with urea nitrogen concentration (Pearson $R=.67$) and was no longer significant when urea nitrogen concentration was entered into the model (Table 3). Notably, although diabetes was associated with decreased mortality in univariate analysis (Table 2), there was no signifi-

Table 1. Clinical Characteristics of the Derivation and Validation Heart Failure Cohorts*

Characteristic	Derivation Cohort (n = 2624)†	Validation Cohort (n = 1407)‡
Age, mean (SD), y	76.3 (11.2)	75.3 (11.8)
Women	1325 (50.5)	711 (50.5)
Vital sign, mean (SD)		
Blood pressure, mm Hg		
Systolic	148 (33)	148 (34)
Diastolic	80 (20)	83 (20)
Heart rate, beats/min	94 (25)	97 (25)
Respiratory rate, breaths/min	26 (7)	27 (8)
Oxygen saturation, %	92 (8)	91 (8)
Serum concentration, mean (SD)		
Hemoglobin, g/dL	12.4 (2.1)	12.4 (2.1)
Leukocyte count, /mm^2	10.2 (5.1)	10.5 (9.4)
Sodium, mEq/L	138 (5)	138 (5)
Potassium, mEq/L	4.3 (0.7)	4.2 (0.6)
Creatinine, mg/dL [µmol/L]	1.45 (0.96) [128 {85}]	1.49 (1.15) [132 {102}]
Urea nitrogen, mg/dL [mmol/L]	29.4 (19.3) [10.5 {6.9}]	27.2 (19.9) [9.7 {7.1}]
Glucose, mg/dL [mmol/L]	164 (81) [9.1 {4.5}]	171 (105) [9.5 {5.8}]
Left ventricular ejection fraction <0.40§	854 (52.8)	330 (47.7)
Comorbid condition		
Prior myocardial infarction	952 (36.3)	533 (37.9)
Atrial fibrillation	795 (30.3)	402 (28.6)
Diabetes mellitus	891 (34.0)	471 (33.5)
Chronic obstructive pulmonary disease	543 (20.7)	371 (26.4)
Cerebrovascular disease	446 (17.0)	310 (22.0)
Peripheral vascular disease	355 (13.5)	254 (18.1)
Peptic ulcer disease	155 (5.9)	155 (11.0)
Liver disease‖	34 (1.3)	26 (1.9)
Dementia	225 (8.6)	118 (8.4)
Cancer	234 (8.9)	207 (14.7)

*Values are expressed as number (percentage) unless otherwise indicated.
†1999-2001.
‡1997-1999.
§Performed in 1618 (61.7%) of the derivation cohort compared with 692 (49.2%) of the validation cohort.
‖Mild liver disease or hepatic cirrhosis.

Table 2. Univariate Predictors of Mortality in Heart Failure Derivation Cohort (n = 2624)

Variable	30-Day Mortality OR (95% CI)	30-Day Mortality *P* Value	1-Year Mortality OR (95% CI)	1-Year Mortality *P* Value
Age, y (per 10-unit increase)	1.83 (1.59-2.10)	<.001	1.69 (1.55-1.84)	<.001
Men	0.81 (0.63-1.04)	.10	0.84 (0.71-0.99)	.03
Vital sign				
Systolic blood pressure, mm Hg (per 10-unit increase)	0.85 (0.81-0.88)	<.001	0.89 (0.86-0.91)	<.001
Heart rate, beats/min (per 10-unit increase)	1.01 (0.96-1.06)	.76	0.99 (0.96-1.02)	.48
Respiratory rate, breaths/min (per 5-unit increase)	1.13 (1.04-1.22)	.002	1.07 (1.02-1.13)	.009
Oxygen saturation, % (per 5-unit increase)	0.99 (0.92-1.07)	.78	1.02 (0.96-1.07)	.59
Serum concentration				
Hemoglobin <10.0 g/dL	1.73 (1.25-2.36)	<.001	2.07 (1.65-2.60)	<.001
Sodium <136 mEq/L	1.69 (1.30-2.20)	<.001	1.61 (1.34-1.94)	<.001
Potassium <3.5 mEq/L	0.66 (0.38-1.08)	.12	0.68 (0.49-0.93)	.02
Creatinine >2.0 mg/dL [>177 µmol/L]	2.47 (1.84-3.29)	<.001	2.90 (2.33-3.63)	<.001
Urea nitrogen, mg/dL (per 10-unit increase)	1.32 (1.26-1.39)	<.001	1.37 (1.30-1.44)	<.001
Comorbid condition				
Prior myocardial infarction	0.98 (0.75-1.26)	.86	1.22 (1.03-1.44)	.02
Atrial fibrillation	1.21 (0.93-1.57)	.15	1.13 (0.94-1.34)	.19
Diabetes mellitus	0.75 (0.57-0.98)	.04	0.81 (0.68-0.96)	.02
Chronic obstructive pulmonary disease	1.51 (1.14-2.00)	.004	1.30 (1.07-1.58)	.009
Cerebrovascular disease	1.51 (1.11-2.02)	.007	1.47 (1.19-1.81)	<.001
Peripheral vascular disease	1.21 (0.85-1.69)	.28	1.38 (1.09-1.73)	.007
Peptic ulcer disease	0.95 (0.54-1.58)	.86	1.17 (0.83-1.63)	.37
Mild liver disease	1.52 (0.23-5.67)	.59	1.76 (0.56-5.31)	.31
Cirrhosis	2.21 (0.73-5.54)	.12	3.45 (1.53-8.24)	.004
Dementia	3.77 (2.71-5.19)	<.001	2.99 (2.27-3.96)	<.001
Cancer	1.81 (1.28-2.52)	<.001	1.86 (1.45-2.38)	<.001

Abbreviations: CI, confidence interval; OR, odds ratio.

Table 3. Multivariable Predictors of Mortality

Variable	30-Day Model OR (95% CI)	30-Day Model *P* Value	1-Year Model OR (95% CI)	1-Year Model *P* Value
Age, y (per 10-unit increase)	1.70 (1.45-1.99)	<.001	1.61 (1.46-1.77)	<.001
Vital sign				
Systolic blood pressure, mm Hg (per 10-unit increase)	0.84 (0.80-0.88)	<.001	0.88 (0.85-0.90)	<.001
Respiratory rate, breaths/min (per 5-unit increase)	1.23 (1.12-1.36)	<.001	1.15 (1.08-1.24)	<.001
Serum concentration				
Sodium <136 mEq/L	1.53 (1.14-2.05)	.005	1.46 (1.19-1.80)	<.001
Hemoglobin <10.0 g/dL	NA	NA	1.37 (1.05-1.78)	.02
Urea nitrogen, mg/dL (per 10-unit increase)	1.55 (1.42-1.71)	<.001	1.49 (1.39-1.60)	<.001
Comorbid condition				
Cerebrovascular disease	1.43 (1.03-1.98)	.03	1.36 (1.08-1.71)	.01
Dementia	2.54 (1.77-3.65)	<.001	2.00 (1.47-2.72)	<.001
Chronic obstructive pulmonary disease	1.66 (1.22-2.27)	.002	1.41 (1.13-1.75)	.003
Hepatic cirrhosis	3.22 (1.08-9.65)	.04	5.80 (2.23-15.11)	<.001
Cancer	1.86 (1.28-2.70)	.001	1.85 (1.40-2.43)	<.001

Abbreviations: CI, confidence interval; NA, not applicable to 30-day model; OR, odds ratio.

cant effect after adjustment for other factors in the multivariable model ($P>.20$ for both models). The univariate analysis suggested that women had greater risk of death than men; however, the sex disparities were not significant after adjustment for age ($P>.40$ for both models).

Risk Scores

Multivariable risk scores for prediction of both 30-day and 1-year mortality were calculated (TABLE 4). Both scores were normally distributed with mean (SD) scores of 91 (26) at 30 days and 102 (27) at 1 year. Risk categories were assigned in 30-point increments to correspond with 1 or 2 SDs of risk above or below average based on the SDs of the 30-day and 1-year scores. The magnitude of the scores had prognostic implications (FIGURE). Stratification by quintile of risk score revealed a gradation in risk of mortality. The 30-day mortality rate was 0.8% for quintile 1 (with a corresponding score <69); 3.6%, quintile 2 (score, 69-82); 6.3%, quintile 3 (score, 83-96); 12.6%, quintile 4 (score, 97-113); and 30.5%, quintile 5 (score, 114-195). Similarly, a graded increase in risk occurred with 1-year score quintiles. The 1-year mortality rate was 9.0% for quintile 1 (with a corresponding score <80); 17.7%, quintile 2 (score, 80-93); 29.1%, quintile 3 (score, 94-107); 42.1%, quintile 4 (score, 108-123); and 66.3%, quintile 5 (score, 124-198). Assignment of 1-year risk scores at baseline maintained their prognostic implications at all time points up to 1 year of follow-up on Kaplan-Meier analysis ($P<.001$ between-risk quintiles).

Model Validation

In the derivation set (n=2624), the area under the ROC curve was 0.80 for 30-day mortality and 0.77 for 1-year mortality. When the 30-day model was applied to in-hospital mortality in the derivation set, the area under the ROC curve was 0.82. In the external validation set (n=1407), the discriminative ability of the models were maintained with an area under the ROC curve of 0.79 for 30-day mortality and 0.76 for 1-year mortality. The bootstrap-

corrected area under the ROC curve was 0.79 for the 30-day mortality model and 0.76 for the 1-year mortality model. Predicted and observed mortality rates in the validation cohort were in close agreement across the entire spectrum of risk (Figure).

Effect of Left Ventricular Systolic Function

At both 30 days and 1 year, the presence of left ventricular systolic dysfunction was associated with increased mortality risk when compared with patients without systolic dysfunction (adjusted OR, 1.98 [95% CI, 1.25-3.16] at 30 days [$P = .004$] and 1.55 [95% CI, 1.19-2.02] at 1 year [$P = .001$]). After adjustment for left ventricular systolic dysfunction, the coefficients of model covariates remained similar to models without such adjustment. There were no significant interactions between left ventricular systolic function and comorbid conditions. When we accounted for the presence of systolic dysfunction, the discriminative ability of the mortality models improved for in-hospital mortality (ROC curve area, 0.84), 30-day mortality (ROC curve area, 0.81), and 1-year mortality (ROC curve area, 0.78).

COMMENT

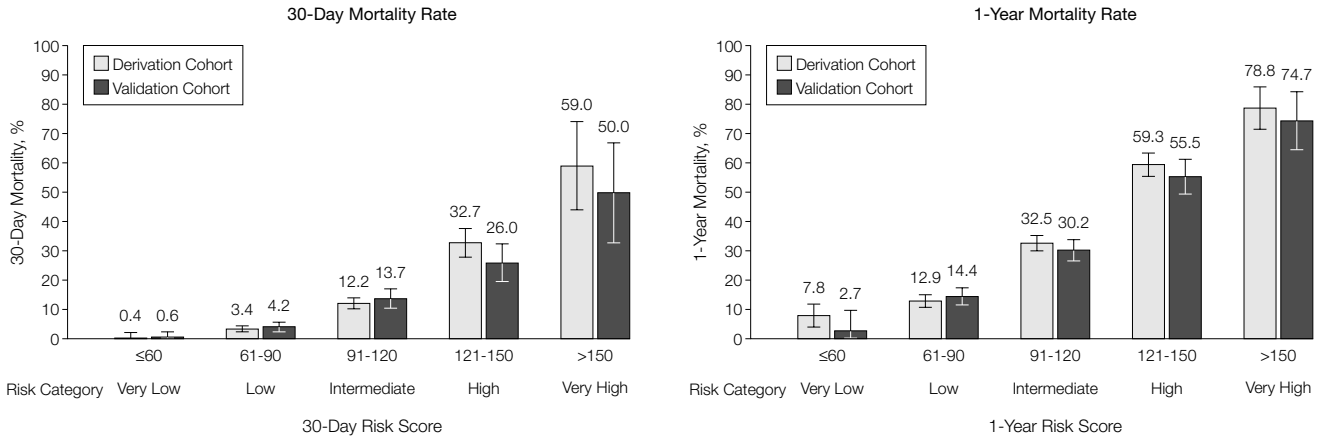
We found that a simple model using data available in the initial hours of hospital presentation predicted mortality in hospitalized heart failure patients at 30 days and 1 year. Both mortality models included acute physiological parameters and chronic disease comorbidities. Important acute physiological variables including hyponatremia, respiratory rate, blood pressure, and selected comorbid conditions including dementia, cirrhosis, and cancer were as-

Table 4. Heart Failure Risk Scoring System*

Variable	No. of Points	
	30-Day Score†	1-Year Score‡
Age, y	+Age (in years)	+Age (in years)
Respiratory rate, min (minimal 20; maximum 45)§	+Rate (in breaths/min)	+Rate (in breaths/min)
Systolic blood pressure, mm Hg‖		
≥180	−60	−50
160-179	−55	−45
140-159	−50	−40
120-139	−45	−35
100-119	−40	−30
90-99	−35	−25
<90	−30	−20
Urea nitrogen (maximum, 60 mg/dL)§¶	+Level (in mg/dL)	+Level (in mg/dL)
Sodium concentration <136 mEq/L	+10	+10
Cerebrovascular disease	+10	+10
Dementia	+20	+15
Chronic obstructive pulmonary disease	+10	+10
Hepatic cirrhosis	+25	+35
Cancer	+15	+15
Hemoglobin <10.0 g/dL (<100 g/L)	NA	+10

Abbreviation: NA, not applicable to 30-day model.
*An electronic version of the risk scoring system is available at: http://www.ccort.ca/CHFriskmodel.asp.
†Calculated as age + respiratory rate + systolic blood pressure + urea nitrogen + sodium points + cerebrovascular disease points + dementia points + chronic obstructive pulmonary disease points + hepatic cirrhosis points + cancer points.
‡Calculated as age + respiratory rate + systolic blood pressure + urea nitrogen + sodium points + cerebrovascular disease points + dementia points + chronic obstructive pulmonary disease points + hepatic cirrhosis points + cancer points + hemoglobin points.
§Values higher than maximum or lower than minimum are assigned the listed maximum or minimum values.
‖Increases were protective in both mortality models. Points are subtracted for higher blood pressure measurements.
¶Maximum value is equivalent to 21 mmol/L. Score calculated using value in mg/dL.

Figure. Mortality Rates Stratified by 30-Day and 1-Year Risk Scores



Score categories were assigned according to 30-point increments corresponding to unit SD increments above and below the intermediate range (91-120). Error bars indicate 95% confidence intervals for the mortality rates in each category.

sociated with an increased risk of death. Abnormal renal function, as measured by blood urea nitrogen was also a strong predictor of death. The risk score provides a simple method to stratify a patient's risk of death at the time of initial hospital presentation into very low (≤60 points), low (61-90 points), high (121-150 points), and very high (>150 points) risk categories relative to an intermediate (91-120 points) risk group at average risk.

This study is consistent with prior investigations of heart failure mortality risk. The adverse prognostic impact of increasing comorbidity burden, using the Charlson comorbidity index,[24] has been described.[17] However, we found that a subset of comorbid conditions had the greatest independent impact on mortality in community-based patients, and the relative contributions of the comorbid conditions to mortality differed substantially in comparison with the Charlson comorbidity index.[24] Evidence of respiratory distress was associated with mortality, which also concurs with findings from other studies[39] and guidelines[40] that advise hospitalization in the presence of increased respiratory rate. Systemic hypotension and shock have been identified by others as mortality predictors.[39,41] However, our findings extend prior observations and concur with those of Goldberger et al,[42] who also reported a similar pattern of blood pressure effect on mortality in patients presenting with acute pulmonary edema. Although higher blood pressure was protective in an acute clinical presentation, our findings should not be interpreted as suggesting that maintaining higher blood pressure long term by avoiding the use of drug therapies is beneficial. Rather, the effects observed may relate to an acute protective mechanism from factors influencing cardiac output or vascular tone, which have yet to be elucidated.

Our model was designed to be independent of left ventricular function information because these data may not be available in the early hours of hospital presentation. This design allows for broader utility because community-based heart failure studies have found that many patients do not undergo left ventricular function evaluation during the hospital stay.[43] Therefore, our study did not exclude heart failure patients without documented ventricular function. Exclusion of this subset could bias parameter estimates because patients who have had echocardiographic assessment may have a better prognosis.[20] Nonetheless, when we assessed the robustness of our models in the subset who had left ventricular function assessed, the estimated ORs were not materially altered.

The present model differs from other models used to predict heart failure mortality in a number of important ways. A unique difference is prediction of mortality at both early and later times. Two other models were designed to predict mortality at 30 days, but none were intended to predict mortality at 1 year.[14,15] Second, based on the number of variables required, it has greater parsimony than most other predictive risk models. Only the Time-Insensitive Predictive Instrument model is simpler because it contains only 4 variables[23]; however, the instrument was developed for hospital mortality assessment and did not include comorbid conditions. Finally, the variables in the current model can be easily obtained and are not dependent on specialized laboratory tests, making it less susceptible to problems arising from missing data.[44]

Several reports have alluded to the need for tools to quantitively estimate prognosis in heart failure patients.[45,46] A recent international survey found that the treatment aim of symptom relief held greater importance to physicians for elderly patients, while delay of death was thought to be more important for younger patients.[45] The study implied that if prognosis was poor, physicians should consider symptom relief as their primary aim. Previously, the best estimates of risk from heart failure were either from the average mortality rates across all patients or the physician's best guess of prognosis.[46] However, physicians may underestimate or overestimate prognosis in heart failure patients based on memorable clinical experiences.[47] In contrast to anecdotal experience, the heart failure index is an objective stratification of mortality risk. The index could be used as a framework to discuss prognosis and provides evidence to support rational decision making about end-of-life care in heart failure patients who are at highest risk.[48-50] It could also potentially be used as an aid in making decisions about patient disposition (ie, discharge, or admission to ward or intensive/cardiac care units).

Our study has a number of limitations. Because this was a retrospective study, our results are dependent on the accuracy of recorded data. Despite this limitation, however, the model covariates (eg, vital signs, laboratory results) are likely to be accurately documented in medical records.[51] Another possible limitation is misclassification of comorbid conditions based on underreporting in the medical record because coexisting but undiagnosed conditions may not be recognized or because of variability in abstraction. However, this would result in true effects that are larger because it would tend to bias results toward the null. Finally, this study included hospitalized patients and may not have direct applicability to the ambulatory chronic heart failure population as examined previously.[52,53]

In conclusion, significant predictors of mortality in heart failure patients presenting to the hospital include age, presentation vital signs, routine biochemistry, and comorbid conditions. A simple model and corresponding risk index predicted risk of 30-day and 1-year mortality in a broad sample of hospitalized heart failure patients using data available at hospital presentation. The risk index provides estimates of risk that may assist clinicians in counseling patients and families and guides clinical decision making.

Author Contributions: Dr Lee had full access to all the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis. *Study concept and design:* Lee, Liu, Naimark, Tu.

Acquisition of data: Lee, Tu.
Analysis and interpretation of data: Lee, Austin, Rouleau, Liu, Naimark.
Drafting of the manuscript: Lee.
Critical revision of the manuscript for important intellectual content: Lee, Austin, Rouleau, Liu, Naimark, Tu.
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