Clinical Risk Prediction Tools in Patients Hospitalized With Heart Failure

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Heart failure (HF) is a significant cause of morbidity, mortality, and health care expenditures. Patients hospitalized with HF are at particularly high risk for mortality. The mortality rates reported for patients hospitalized with HF, although high, can vary significantly. There are a large number of individual variables that are predictive of prognosis in patients hospitalized with HF. Investigators have developed and validated clinical risk models to allow health care providers to more reliably identify HF patients at lower, intermediate, and higher risk for mortality based on admission patient characteristics, vital signs, physical examination findings, laboratory and diagnostic study results, and biomarkers. Use of clinical risk prediction tools may be helpful in triaging patients hospitalized with HF and guiding medical decision making. This article discusses the mortality predictors and risk stratification models for patients hospitalized with HF, and provides a perspective on the value of integrating these risk tools into clinical practice.

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KEY WORDS

Heart failure • Mortality • Hospitalization • Risk prediction • Models

Heart failure (HF) results in considerable morbidity, mortality, and financial burden on the health care system. HF leads to over 1 million hospitalizations in the United States each year and translates into an annual estimated cost of $39.6 billion.[1,2] The in-hospital mortality rates reported for patients hospitalized with HF has varied greatly, ranging from 2% to 20%.[3,4] Prognosis is also reported to be very poor after discharge. The mortality risk after HF hospitalization has been reported to be as high as 11.3% at 30 days and 33.1% at 1 year.[1] These statistics emphasize the need for clinically practical methods of risk prediction for patients hospitalized with HF as well as the need to develop and implement more effective strategies to manage HF.

Risk Prediction Models

In clinical practice, risk models may be useful to inform patient triage and treatment decisions.[3,4] In patients hospitalized with HF, those estimated to be at lower risk may be managed with less intensive monitoring and therapies available on a telemetry unit or hospital ward, whereas patients estimated to be at higher risk may require more intensive management in an intensive or coronary care unit. Despite the large number of patients impacted and the mortality risk, until recently, integrated models for the risk stratification of patients hospitalized with HF were not available. The ability to predict short-term mortality risk could inform clinical decision making, as a wide range of HF therapies are available, some of which are invasive and expensive. Thus, objective prognostic information could guide appropriate application of expensive monitoring and treatments, and lead to improvements in the quality of care delivered to patients hospitalized with HF.[3,4]

A number of individual variables that are associated with increased mortality among patients hospitalized with HF have been identified. These include patient age, sex, race, ischemic etiology, comorbid conditions (eg, cerebrovascular disease, dementia, chronic obstructive pulmonary disease [COPD], hepatic cirrhosis, and cancer), systolic blood pressure (SBP), heart rate, respiratory rate, left ventricular ejection fraction (LVEF), serum sodium concentration, serum creatinine concentration, blood urea nitrogen (BUN), hemoglobin, B-type natriuretic peptide (BNP) or N-terminal pro-BNP, and cardiac troponin, among many others.[3-12] Because multiple risk factors can exist in the same patient, to be meaningful, risk factor analysis must consider factors in combination rather than isolation.[3] Because many studies tended to treat these factors as isolated entities, they had not produced a clinically practical way of integrating various factors to stratify risk in HF patients. A number of recent studies have developed and validated predictive risk models to allow clinicians to reliably identify patients at low, medium, and high risk for mortality based on patient characteristics, vital signs, diagnostic studies, laboratories, and biomarkers at the time of admission (Table 1). These models have been shown to be able to discriminate mortality risk well in HF patients with reduced LVEF as well as those with preserved LVEF.

ADHERE In-Hospital Mortality Risk Tool

Acute Decompensated Heart Failure National Registry (ADHERE) data were used to develop and validate a practical and user-friendly method of risk stratification for in-hospital mortality in patients admitted with HF that could be applicable to the bedside.[3] Overall, in-hospital mortality was 4.1%. In ADHERE, of 39 variables, BUN level $\geq$ 43 mg/dL, serum creatinine level $\geq$ 2.75 mg/dL, and SBP $<$ than 115 mm Hg were independent predictors of high risk for in-hospital mortality in a classification and regression trees (CART) analysis.[3] The mortality risk varied more than 10-fold (2.1%-21.9%) based on the patient's initial SBP, BUN, and creatinine levels (Figure 1). With this validated risk tool, low-, intermediate-, and high-risk patients could be readily identified.

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This model is appealing because it uses only three variables to classify patients as low, intermediate, or high risk.[3] However, it does not allow more precise characterization of individual risk, and it does not include all variables that significantly inform outcomes. In a multivariate analysis of the same dataset, SBP, heart rate, serum

TABLE 1

Clinical Risk Prediction Tools in Patients Hospitalized With Heart Failure

Study	Data Source	N	Time Period	Mortality Rate	Higher Mortality Risk	Lower Mortality Risk
Clinical Quality Improvement Network Investigators[8]	Registry	4606	1992-1993	19% in-hospital	Age Use of magnesium Use of nitrates	ACE inhibitors Warfarin Aspirin β-blockers Calcium channel blockers
EFFECT[5]	Registry	4031	1997-2001	8.9% in-hospital/ derivation cohort; 8.2% in-hospital/ validation cohort; 10.4%-10.7% at 30 days; 30.5%-32.9% at 1 year	Age Higher respiratory rate Hyponatremia Low hemoglobin Increased BUN Cerebrovascular disease Dementia COPD Cirrhosis Cancer	Higher SBP
OPTIME-CHF[9]	Clinical trial	949	1997-1999	9.6% 60-day mortality	Age NYHA class IV vs I-III BUN	Higher SBP Higher serum sodium
ADHERE[3]	Registry	33,046 (derivation cohort); 32,229 (validation cohort)	2001-2003	4.2% (derivation); 4.0% (validation) in-hospital mortality	BUN $>$ 43 mg/dL Serum creatinine $\geq$ 2.75 mg/dL	SBP $\geq$ 115 mm Hg
OPTIMIZE-HF[6]	Registry	48,612	2003-2004	3.8% in-hospital mortality	Higher serum creatinine Low serum sodium Age Higher heart rate Liver disease Prior CVA/TIA Peripheral vascular disease White race Left ventricular systolic dysfunction Chronic obstructive pulmonary disease	Higher SBP Higher serum sodium Higher diastolic blood pressure Hyperlipidemia Smoking within previous year No known HF prior to admission HF as primary cause of admission
GWTG-HF[11]	Registry	26,837 (derivation cohort); 11,501 (validation cohort)	2005-2007	2.9% in-hospital mortality	Higher age COPD Higher heart rate Higher BUN	Higher SBP Higher serum sodium

ACE, angiotensin-converting enzyme; ADHERE, Acute Decompensated Heart Failure National Registry; BUN, blood urea nitrogen; COPD, chronic obstructive pulmonary disease; CVA, cerebrovascular accident; EFFECT, Enhanced Feedback for Effective Cardiac Treatment; HF, heart failure; GWTG-HF, Get With the Guidelines-Heart Failure; NYHA, New York Heart Association; OPTIME-CHF, Outcomes of a Prospective Trial of Intravenous Milrinone for Exacerbations of Chronic Heart Failure; OPTIMIZE-HF, Organized Program to Initiate Lifesaving Treatment in Hospitalized Patients with Heart Failure; SBP, systolic blood pressure; TIA, transient ischemic attack.

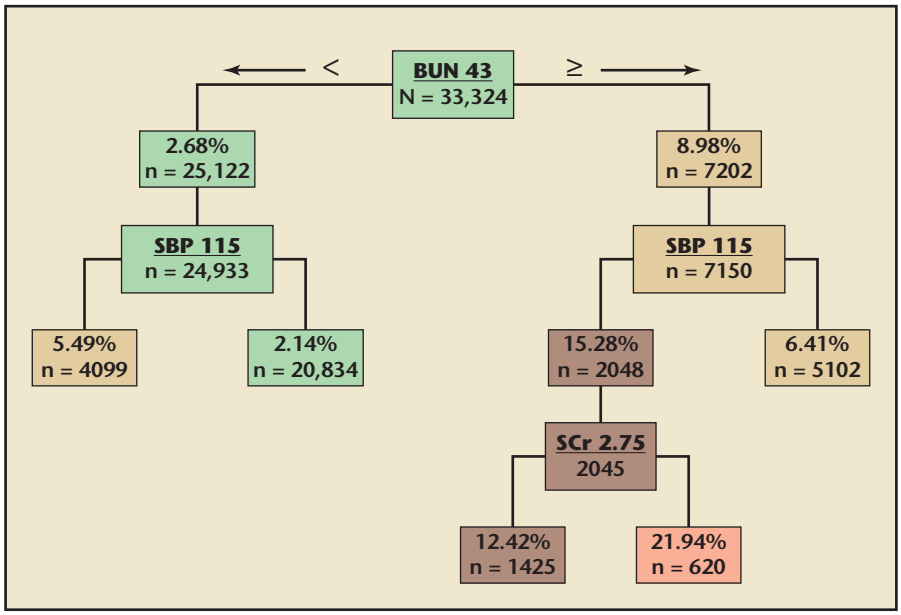

Figure 1. Acute Decompensated Heart Failure National Registry (ADHERE) in-hospital mortality risk prediction tool. Predictors of in-hospital mortality and risk stratification identified in ADHERE using classification and regression tree analysis. Each node is based on available data from registry patient hospitalizations for each predictive variable presented. Percentages indicate crude mortality for each terminal node. BUN, blood urea nitrogen; SBP, systolic blood pressure; SCr, serum creatinine. Data from Fonarow GC et al.[3]

creatinine, serum sodium, and liver disease were highly predictive of in-hospital mortality. Multivariate logistic regression identified BUN, SBP, heart rate, and age as the most significant mortality risk predictors, and adding as many as 24 additional predictors did not meaningfully increase the accuracy of this model.[3] Based on the C statistics, the accuracy of the CART model (0.67) was moderately less than that of the more complicated logistic regression model (0.76). Nevertheless, the ADHERE risk tree provides clinicians with a validated, practical bedside tool for mortality risk stratification.

In a subsequent analysis of > 100,000 hospitalizations from ADHERE, CART analysis identified elevated BUN, lower SBP, low sodium, older age, elevated creatinine, presence of dyspnea at rest, and absence of chronic β-blocker use as mortality risk factors.[12] Among these variables, the two main contributors to higher mortality (the top splits in the tree) were BUN > 37 mg/dL and SBP ≤ 125 mm Hg. When the CART analysis was carried out in HF patients with preserved LVEF (LVEF ≥ 0.40) and those with reduced LVEF separately, elevated BUN and lower SBP were confirmed as the most important mortality predictors within each group. In addition, increased heart rate was identified as a mortality predictor in patient episodes of HF with preserved LVEF, but not in patient episodes of HF with reduced LVEF.[12] Thus, mortality risk can be reliably predicted for both preserved and reduced LVEF HF patients equally well.

OPTIMIZE-HF In-Hospital Mortality Risk Prediction Tool

Data from the Organized Program to Initiate Lifesaving Treatment in Hospitalized Patients with Heart Failure (OPTIMIZE-HF) were applied to develop and validate a mortality risk tool for patients hospitalized with HF.[6] A total of 45 potential predictor variables were used in a stepwise logistic regression model for in-hospital mortality gathered from 48,612 patients enrolled in 259 hospitals. A scoring system was developed to predict mortality. Multivariable predictors of mortality included age, heart rate, SBP, sodium, creatinine, HF as primary cause of hospitalization, and presence/absence of left ventricular systolic dysfunction (Table 2).[6] Increased risk of in-hospital mortality was associated with several comorbid conditions, including liver disease, past cerebrovascular events, peripheral vascular disease, and COPD. Hyperlipidemia and current/recent smoking were associated with a lower risk of in-hospital mortality. Diabetes, sex, and coronary artery disease were not

Data from the OPTIMIZE-HF were applied to develop and validate a mortality risk tool for patients hospitalized with HF.

TABLE 2

Organized Program to Initiate Lifesaving Treatment in Hospitalized Patients With Heart Failure In-Hospital Mortality Risk Prediction Model

Variable	Wald χ-Square	Adjusted Odds Radio	95% Confidence Interval	*P* Value
Serum creatinine: per 0.3-mg/dL increase up to 3.5 mg/dL	335.5	1.18	1.16-1.20	< .0001
Systolic blood pressure: per 10-mm Hg increase up to 160	107.0	0.83	0.80-0.86	< .0001
Age: per 10-year increase	108.5	1.34	1.26-1.41	< .0001
Heart rate: per 10 beats/min increase between 65 and 110 beats/min	55.1	1.18	1.13-1.24	< .0001
Sodium: per 3-mEq/L decrease below 140 mEq/L	39.1	1.15	1.10-1.20	< .0001
Sodium: per 3-mEq/L decrease above 140 mEq/L	6.6	0.87	0.78-0.97	.0100
Heart failure as primary cause of admission	10.7	0.72	0.60-0.88	.0011
Liver disease	11.5	2.33	1.43-3.80	.0007
Prior cerebrovascular accident/transient ischemic attack	18.6	1.37	1.19-1.58	< .0001
Peripheral vascular disease	12.9	1.32	1.13-1.54	.0003
Diastolic blood pressure: per 10-mm Hg increase up to 100 mm Hg	12.9	0.90	0.85-0.95	.0003
Hyperlipidemia	11.1	0.80	0.71-0.91	.0009
Smoker within past year	12.5	0.70	0.58-0.85	.0004
No known heart failure prior to this admission	10.5	0.65	0.51-0.85	.0012
Black race	11.1	0.71	0.57-0.87	.0009
Left ventricular systolic dysfunction	14.0	1.28	1.13-1.46	.0002
Chronic obstructive pulmonary disease	6.32	1.19	1.04-1.35	.0120
Angiotensin-converting enzyme inhibitor at admission	7.67	0.84	0.75-0.95	.0056
β-blocker at admission	17.3	0.77	0.68-0.87	< .0001

Data from Abraham WT et al.[6]

significant predictors of in-hospital mortality. This model had good discrimination and excellent reliability. The bootstrapped resampling indicated that discrimination remained high with a C statistic of 0.75 (95% confidence interval [CI], 0.74-0.77).[6] Further, this risk tool was applied to admission data for patients hospitalized with HF and enrolled in a previously published randomized controlled trial. The OPTIMIZE-HF nomogram performed well in this highly selected clinical trial-based patient population, with a C statistic of 0.76. Having performed well in both clinical trial populations and real-world registry datasets, this model may be particularly useful in HF clinical trial design and development of improved in-hospital HF treatment strategies. Additional OPTIMIZE-HF models were developed and validated to predict 60- to 90-day postdischarge mortality and mortality/rehospitalization risk.[7] It has proven to be more difficult to develop models with good discrimination of rehospitalization risk, with C statistics in the 0.58 to 0.64 range.[7]

GWTG-HF In-Hospital Mortality Risk Tool

Data from the national American Heart Association's Get With the Guidelines-Heart Failure (GWTG-HF) program were used to derive and validate a predictive model for in-hospital mortality in patients hospitalized with HF.[11] In this study, a cohort of 38,338 patients admitted to 197 participating hospitals were divided

Data from the national American Heart Association's GWTG-HF program were used to derive and validate a predictive model for in-hospital mortality in patients hospitalized with HF.

into derivation (n = 26,837) and validation (n = 11,501) samples. Multivariable logistic regression using generalized estimating equations were employed to identify predictors of in-hospital mortality in the derivation sample from candidate demographic, medical history, and laboratory variables collected at admission. The model was validated by assessing model performance in the validation sample. Older age, low SBP, elevated heart rate, low serum sodium, elevated BUN, and presence of COPD predicted an increased risk of death (Table 3).[11] Age, SBP, and BUN contributed most substantially to the overall point score, whereas heart rate, the presence of COPD, and serum sodium contributed relatively few points to the overall score. Additional factors known to be associated with mortality, including reduced LVEF, depression, hemoglobin, and serum creatinine, were considered but did not contribute to model discrimination beyond those variables included in the model. The model had good discrimination in the derivation and validation datasets (C statistic = 0.75 in each). The predicted probability of in-hospital mortality varied by more than 11-fold across quintiles (range, 0.6%-7.0%) and corresponded with the observed mortality rates in each quintile. The model also had similar discrimination in both patients with preserved and reduced LVEF. This American Heart Association GWTG-HF risk score using commonly available clinical variables provides clinicians with a validated practical bedside tool for in-hospital mortality risk stratification that may be applicable to a broad spectrum of patients hospitalized with HF.[11]

EFFECT Mortality Risk Prediction Tool

The Enhanced Feedback for Effective Cardiac Treatment (EFFECT) study database of 4031 community-based patients presenting with HF to multiple hospitals in Ontario, Canada, from 1997 to 2001 was used to

TABLE 3

Get With the Guidelines-Heart Failure In-Hospital Mortality Risk Score

SBP	Points
50-59	35
60-69	33
70-79	31
80-89	30
90-99	28
100-109	26
110-119	24
120-129	23
130-139	21
140-149	19
150-159	17
160-169	16
170-179	14
180-189	12
190-199	10
200-209	9
210-219	7
220-229	5
230-239	3
240-249	2
≥ 250	0

Heart Rate	Points
< 75	0
75-105	4
> 105	8

Age	Points
< 20	0
20-29	3
30-39	5
40-49	8
50-59	11
60-69	13
70-79	16
80-89	19
90-99	21
100-109	24
≥ 110	26

COPD	Points
Yes	2
No	0

BUN	Points
0-9	0
10-19	2
20-29	4
30-39	5
40-49	7
50-59	9
60-69	11
70-79	12
80-89	14
90-99	16
100-109	18
110-119	19
120-129	21
130-139	23
140-149	25
> 150	26

Sodium	Points
< 135	3
135-140	0
> 140	1

Total Score	Probability of Death
13-38	< 1%
39-54	1%-5%
55-60	> 5%-10%
61-65	10%-15%
66-68	15%-20%
69-72	20%-30%
73-76	30%-40%
77-80	40%-50%
≥ 81	> 50%

BUN, blood urea nitrogen; COPD, chronic obstructive pulmonary disease; SBP, systolic blood pressure.
Data from Peterson PN et al.[11]

identify predictors of mortality and to develop and to validate a model using information available at hospital presentation.[5] In-hospital, 30-day, and 1-year all-cause mortality rates for the cohort were 8.9% in-hospital, 10.7% at 30 days, and 32.9% at 1 year. Predictors of mortality at both 30 days and 1 year included older age, lower SBP, higher respiratory rate, higher BUN, and hyponatremia. Comorbid conditions associated with mortality included cerebrovascular disease, COPD, hepatic cirrhosis, dementia, and cancer. A risk index was developed to stratify the risk of death and identify 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.[5] 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. Thus among community-based HF patients, factors identifiable within hours of hospital presentation predicted mortality risk at 30 days and 1 year.[5]

Other HF Risk Models

The Outcomes of a Prospective Trial of Intravenous Milrinone for Exacerbations of Chronic Heart Failure (OPTIME-CHF) study found that, in 949 patients with decompensated HF, the variables at presentation that predicted death at 60 days were older age, lower SBP, New York Heart Association class IV symptoms, elevated BUN, and decreased sodium.[9] Hospitalization data have been used to develop a risk score for HF readmission. This risk score, which is based on 16 parameters, was moderately predictive in the derivative cohort, but it has not been independently validated in a second cohort. Medicare claims data from 1998 to 2001 were used to develop and validate a hierarchical regression model to predict hospital risk-standardized 30-day mortality rates using medical chart review data.[13] This model was then compared with an administrative claims model. The final model included 24 variables. The model had a C statistic of 0.70. This administrative claims-based model produced estimates of risk-standardized state mortality that appeared to be a reasonable surrogate for estimates derived from a medical record model.[13] Because this model is based on administrative claims data it cannot be readily applied at the bedside. However, this model may be useful in facilitating quality assessment and improvement efforts and is in use by the Center for Medicare and Medicaid Services to publicaly report hospital 30-day mortality risk standardized mortality rates for HF.

Although the variables retained in specific HF models vary, multiple evaluations have demonstrated the prognostic value of SBP and indices of renal function (Table 1). In EFFECT, higher BUN and lower SBP were significant and independent predictors of both 30-day and 1-year mortality. In ADHERE, SBP, BUN, and creatinine were the three variables most predictive of in-hospital mortality. In OPTIME, SBP and BUN were significant and independent predictors of death or rehospitalization. Thus, the assessment of blood pressure and determining renal function are essential in risk stratifying patients presenting with HF.

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The use of biomarkers as prognostic indicators for patients hospitalized with HF has been of interest. Several studies have suggested that markers of myocardial damage such as cardiac troponin I and T are elevated in patients hospitalized with HF in the absence of an acute coronary syndrome and provide prognostic information.[14] Admission BNP and N-terminal pro-BNP has been shown to predict in-hospital and postdischarge mortality, independent of other prognostic variables.[15] Other biomarkers for HF that are predictive of mortality have also been identified.[16,17] These biomarkers can be used in conjunction with the clinical risk tools or, as more data become available, integrated into the risk models. Further, these biomarkers can be followed serially as patients transition from the inpatient to outpatient setting, allow for dynamic risk assessment, and potentially be used to titrate HF therapy.[16,17]

There have also been risk tools developed for outpatients with HF.[18,19] The Seattle Heart Failure Model was derived in a cohort of 1125 HF patients with the use of a multivariate Cox model.[18] This model predicted 1-, 2-, and 3-year survival in HF patients using characteristics relating to clinical status, therapy, and laboratory parameters. For the lowest score, the 2-year survival was 92.8% compared with 88.7%, 77.8%, 58.1%, 29.5%, and 10.8% for scores of 0, 1, 2, 3, and 4, respectively.[18] The overall C statistic was 0.73. This model also allowed estimation of the benefit of adding medications or devices to an individual patient's therapeutic regimen.[18] However, this model did not perform well when applied to patients hospitalized with HF.

Clinical Applicability of Risk Models for HF

To have any potential influence on management and clinical outcomes, risk scores need to be utilized in clinical practice. A potential disadvantage of multivariate-generated risk scores is their complexity.[3,4] The number of parameters and mathematical functions involved frequently requires access to a computer or electronic calculator to generate the score and determine risk, making them potentially impractical for bedside assessment.[3] Even when converted to point scores, the tools derived from a multivariate model still require a nomogram reference to convert the point score to risk. CART methodology can detect interactions among variables and yields a decision tree that is relatively easy to apply at the bedside.[3,4] In the ADHERE CART analysis, three variables were found to be the most significant predictors of in-hospital mortality risk. In a simple two- to three-step process, these variables permit identification of patients with low, intermediate, or high risk for in-hospital mortality. The CART-based analysis of the ADHERE registry has created a simple tool to predict in-hospital mortality that is easy to use, can be readily applied at the bedside, and has good discriminative ability. For clinicians with bedside access to computers or personal digital assistants, using logistic regression model calculation or point score determination for prediction of HF patient risk may be preferred.[4]

Role in Clinical Management

An accurate understanding of prognosis is fundamental to many clinical decisions in patients hospitalized with HF. However, it has been previously reported that less than one-fifth of a clinician cohort caring for patients with HF believed they could accurately predict death, and clinicians frequently incorrectly estimate risk in patients with HF.[20] In general, clinicians substantially overestimate the risk of mortality, which potentially results in overutilization of critical care resources. Clinical risk tools may allow clinicians to estimate risk much more precisely than clinical judgment only and can be employed at the point of care to help quantify patient risk.[11] This may better facilitate patient triage, closer in-hospital monitoring, and earlier cardiology/HF specialist consultation, and encourage more aggressive use of evidence-based therapy in the highest-risk patients. Alerting physicians to the existence of this risk is a strategy with the potential to help them target interventions to reduce short-term mortality in this population.[4] Patients judged to be at higher risk may receive higher-level monitoring and earlier, more intensive treatment for HF, whereas patients estimated to be at lower risk may be reassured and managed less intensively.[3,4] Furthermore, high-risk patients can be identified for whom very resource-intensive interventions (heart transplantation or ventricular assist devices) designed to improve outcomes may be justified (Table 4). Patients identified as being at higher risk for postdischarge mortality can be targeted for earlier physician follow-up, closer monitoring, and more aggressive titration of evidence-based HF medical and device therapies. These HF risk prediction tools may be used to identify intermediate and higher risk patients for whom guidelines recommend referral to HF disease management programs. They may also allow for identification of HF patients who will derive the greatest benefit from implantable hemodynamic monitors, which are currently under investigation. However, for any of these potential uses, these models should be employed to enhance, not replace, physician assessment in patients with HF.[3,4] It is also a critical next step to demonstrate prospectively whether application of risk prediction tools will favorably impact HF patient care and clinical outcomes.

Clinical risk tools may allow clinicians to estimate risk much more precisely than clinical judgment only and can be employed at the point of care to help quantify patient risk.

These models have also been useful in demonstrating that there is a risk-treatment mismatch in HF. Using the EFFECT model, medication administration rates at hospital discharge and 90 days after discharge were assessed in patients in the low-, intermediate-, and high-risk groups.[21] It was shown that the highest-risk HF patients were much less likely to receive evidence-based, guideline-recommended therapies. Low-risk patients were more likely to receive angiotensin-converting enzyme inhibitors or angiotensin receptor blockers and β-blockers when compared with high-risk patients. Use of these models in clinical practice should allow clinicians to better calibrate the use of guideline-recommended therapies in patients with HF to ensure that patients at high risk are treated with every indicated therapy in the absence of contraindications or intolerance. Improved use of evidence-based medical therapy for patients with HF and reduced LVEF should help to reduce the high burden of early

TABLE 4

Evidence-Based Therapies, Monitoring, and Other Potential Interventions for Patients With Heart Failure

Low, Intermediate, High Risk
Angiotensin-converting enzyme inhibitors or angiotensin receptor antagonists
β-blockers (evidence-based)
Aldosterone antagonists
Hydralazine/isosorbide dinitrate
Cardiac resynchronization therapy
Implantable cardioverter defibrillator
Intermediate and High Risk
Heart failure disease management program
Implantable hemodynamic monitors[a]
High Risk
Ventricular assist device
Heart transplantation
Palliative care/hospice

[a]Under investigation. See Hunt SA et al[2] for specific guideline recommendations.

rehospitalization, in addition to lowering mortality risk. Also, these models should prove to be valuable in designing clinical trials to evaluate HF therapies allowing for development of trial inclusion criteria to enroll only patients at high risk for in-hospital mortality (targeted trial design).[6]

Conclusions

In patients hospitalized with HF, the risk of in-hospital, 30-day, and 1-year mortality can be readily and effectively determined using admission clinical, vital sign, and laboratory parameters. On the basis of these parameters, HF patients can be stratified into groups at low, intermediate, and high risk for mortality. Application of these risk prediction tools may help identify HF patients at high risk for mortality who may benefit from more aggressive monitoring, use of medication and device therapy, and other interventions. The continued high mortality for patients hospitalized with HF provides a persuasive indication to apply risk prediction tools to improve the evaluation, management, and outcomes of these patients. ■

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MAIN POINTS

- Patients hospitalized with heart failure (HF) are at particularly high risk for mortality, yet the mortality rates reported for patients hospitalized with HF can significantly vary.
- There are a large number of individual variables that are predictive of prognosis in patients hospitalized with HF.
- Investigators have derived and validated a number of clinical risk models to allow health care providers to more reliably identify HF patients at lower, intermediate, and higher risk for mortality based on admission patient characteristics, vital signs, physical examination findings, laboratory results, diagnostic studies, and biomarkers.
- Use of clinical risk prediction tools may be helpful in triaging patients hospitalized with HF and guiding medical decision making.
- Use of these models in clinical practice may allow clinicians to better calibrate the use of guideline-recommended therapies in patients with HF to better ensure that patients at high risk are treated with every indicated therapy in the absence of contraindications or intolerance.