A Prognostic Model for 6-Month Mortality in Elderly Survivors of Critical Illness

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Background: Although 1.4 million elderly Americans survive hospitalization involving intensive care annually, many are at risk for early mortality following discharge. No models that predict the likelihood of death after discharge exist explicitly for this population. Therefore, we derived and externally validated a 6-month postdischarge mortality prediction model for elderly ICU survivors.

Methods: We derived the model from medical record and claims data for 1,526 consecutive patients aged ≥ 65 years who had their first medical ICU admission in 2006 to 2009 at a tertiary-care hospital and survived to discharge (excluding those patients discharged to hospice). We then validated the model in 1,010 patients from a different tertiary-care hospital.

Results: Six-month mortality was 27.3% and 30.2% in the derivation and validation cohorts, respectively. Independent predictors of mortality (in descending order of contribution to the model's predictive power) were a do-not-resuscitate order, older age, burden of comorbidity, admission from or discharge to a skilled-care facility, hospital length of stay, principal diagnoses of sepsis and hematologic malignancy, and male sex. For the derivation and external validation cohorts, the area under the receiver operating characteristic curve was 0.80 (SE, 0.01) and 0.71 (SE, 0.02), respectively, with good calibration for both ($P = 0.31$ and 0.43).

Conclusions: Clinical variables available at hospital discharge can help predict 6-month mortality for elderly ICU survivors. Variables that capture elements of frailty, disability, the burden of comorbidity, and patient preferences regarding resuscitation during the hospitalization contribute most to this model's predictive power. The model could aid providers in counseling elderly ICU survivors at high risk of death and their families.

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Abbreviations: APACHE = Acute Physiology and Chronic Health Evaluation; AUC = area under the receiver operating characteristic curve; CCI = Charlson Comorbidity Index; DNR = do not resuscitate; GoF = Hosmer-Lemeshow Goodness-of-Fit; SAPS = Simplified Acute Physiology Score

Adults older than 65 years of age now comprise more than one-half of all ICU admissions in the United States.¹ Approximately 1.4 million elderly (aged ≥ 65 years) Medicare beneficiaries are discharged each year after receiving intensive care.² With technological advances, many critically ill elderly adults now survive what were previously fatal illnesses,^{3,4} but outcomes can be poor. Among the 33% of elderly ICU patients discharged to skilled-care facilities, nearly one-half are rehospitalized and 25% to 65% die within 6 months.^{2,5}

While predictive models exist for ICU survivors of prolonged mechanical ventilation and elders hospitalized without intensive care,^{6,7} there are no existing clinical prediction tools to help predict outcome

explicitly for elderly ICU survivors. A validated prediction model for postdischarge mortality in elderly ICU survivors could (1) risk-stratify patients for clinical trials of novel preventative, rehabilitative, and therapeutic interventions; (2) help determine appropriate levels of postacute care; and (3) aid providers in addressing expectations and end-of-life care with these patients and their families.

We aimed to derive and externally validate a prediction model for 6-month mortality among elderly ICU survivors. We hypothesized that including markers of frailty and disability as well as patient preferences regarding resuscitation in our model would be important in predicting 6-month mortality. Withholding life-supporting therapies often indicates

anticipated impending death and has been shown to be associated with mortality at least 60 days after ICU admission.⁸ Furthermore, patient preferences regarding resuscitation are not considered in widely used ICU mortality prediction models.^{9,10} Frailty is a measurable clinical phenotype of increased vulnerability to adverse health outcomes due to age or disease-associated decreased physiologic reserves.¹¹ While disability, comorbidity, and frailty are casually related, each is independent of the other, occurs frequently, and is important clinically.¹² For community-dwelling elders, frailty accurately predicts falls, hospitalizations, dependency, and mortality, independent of comorbidities and disability.^{11,12} Both premorbid disability and loss-of-functional independence immediately after critical illness are independent predictors of post-discharge mortality.^{13,14} Therefore, evaluating markers of frailty and disability in ICU survivors might help explain why some older patients recover better than expected and others fare far worse.¹⁵

MATERIALS AND METHODS

Patients and Data Sources

We created a derivation cohort of patients from Columbia University Medical Center (Columbia) and an external validation cohort of patients from Weill Cornell Medical Center (Cornell). While both of these hospitals are affiliated with the New York-Presbyterian Health System, they serve distinct local patient populations and have independent health-care providers managed by separate departments of medicine and divisions of critical care. The independent cohorts were constructed from consecutive patients aged ≥ 65 years who (1) had their first Columbia or Cornell medical-ICU admission between January 1, 2006, and December 31, 2009, (2) no previous ICU admissions at Columbia or Cornell in 2005, and (3) survived to hospital discharge (excluding discharge to hospice). We chose to focus on patients admitted to the medical ICUs, rather than surgical or coronary ICUs because

these patients are less likely to have an elective intensive care admission and tend to have higher hospital and long-term mortality. Additional inclusion and exclusion criteria are described in Figure 1 and in e-Appendix 1.

We used administrative data compiled for submission to Medicare and the University Health Consortium¹⁶ and data abstracted from electronic medical records for all hospitalizations involving an ICU admission at Columbia and Cornell from 2005 through 2009 for patients aged ≥ 65 years. The dataset contained claims data in the form of *International Classification of Diseases, Ninth Revision*, clinical modification codes, demographic data including admission source and discharge location, hospital and ICU length of stay, laboratory test values, and do-not-resuscitate (DNR) orders placed during the hospitalization. Death dates were determined from the National Death Index.

Data Abstraction and Measurements

We chose potential predictive factors of 6-month mortality based on clinical relevance and previous studies.^{2,5,6,17} We grouped these factors into six broad categories: demographic variables (sex, race), principal diagnosis for hospitalization, comorbidities (Charlson Comorbidity Index [CCI]), ICU-related interventions (mechanical ventilation, cardiopulmonary resuscitation, and hemodialysis), patient preferences regarding resuscitation (DNR order during the hospitalization), and surrogate markers of frailty and/or disability (age, admission from a skilled-care facility, hospital length of stay, and discharge to a skilled-care facility). Details of the methods of classification and grouping of these variables are available in e-Appendix 1 and e-Tables 1, 2, and 3.

Statistical Analyses

Summary analyses were performed on demographic and hospital admission variables and are expressed as mean $\pm$ SD or median and interquartile range as appropriate. We generated the predication model using logistic regression with the primary outcome defined as death within 6 months after the date of hospital discharge. We used generalized additive models with Lowess smoothing functions to evaluate the linearity of associations between continuous variables and the predicted probability of death after hospitalization at 6 months. Continuous variables that did not vary linearly with the outcome were changed into categorical variables that reflected the nonlinear variation (Charlson comorbidity score and hospital length of stay).¹⁸ The method of model derivation is described in e-Appendix 1. We derived the contribution of each risk factor to the final model's predictive power by calculating the difference in the log likelihoods between full and various reduced models (Fig 2).^{19,20}

We derived and validated a model post hoc to (1) determine whether the contribution of surrogate markers of frailty and/or disability to the predictive power of the model was affected by estimates of severity-of-illness from laboratory predictors at ICU admission and prior to hospital discharge, and (2) whether these laboratory predictors would improve our model's performance. We calculated modified Simplified Acute Physiology Score (SAPS) II using the worst values of the component serum laboratory tests (sodium, potassium, urea, bilirubin, WBC count, and bicarbonate concentrations)¹⁰; vital signs and the Glasgow coma were not used in estimating severity-of-illness because they were not recorded in the electronic medical record during the study period. Age and comorbidities are part of the SAPS II, but these variables were already separately considered in the model. We also performed a post hoc sensitivity analysis using an alternative claims-based definition of sepsis²¹ that is described in e-Appendix 1.

We used the area under the receiver operating characteristic curve (AUC) to examine the ability of the models to discriminate

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FIGURE 1. Derivation and validation cohorts. *First medical ICU admission specifically refers to the first Columbia or Cornell medical ICU admission with no previous Cornell or Columbia ICU admission in 2005.

between patients who died and those who survived. We examined the models' calibration by using the Hosmer-Lemeshow Goodness-of-Fit (GoF) χ^2 test statistic for 10 equally sized groups. To correct for optimism and internally validate the model, we repeatedly fit the model with a recommended 100 bootstrap samples to calculate the average AUC.²² To externally validate the model, we measured the AUC and calculated the GoF test statistic for the model in an independent sample of elderly ICU survivors at a different tertiary-care hospital (Cornell).

Statistical significance was defined as a two-tailed $P < 0.05$. Analyses were performed with Stata 12.0 (StataCorp LP). The study was approved by the Institutional Review Boards of Columbia University (AAA1-0232) and Weill Cornell Medical Center (1107011796-WCMC).

The model equation to calculate the % predicted 6-month mortality is described in e-Appendix 1. Rather than creating a scoring system, a Web-based calculator to determine the predicted risk of death within 6 months after hospital discharged based upon the model is available at <http://www.r-calc.com/R-Calc/ExistingFormulas.aspx>. The calculator is compatible with Internet Explorer and Safari web-browsers using a computer or other mobile devices.

RESULTS

Patient Characteristics

There were 1,526 and 1,010 patients in the derivation and validation cohorts, respectively. The cohorts were similar in age (median 78 years for both), sex, hospital and ICU length of stay, and proportion

discharged to skilled-care facilities without hospice services (56% and 49%, respectively). The proportion of patients admitted to the ICU from a skilled-care facility was 14% and 8% in the derivation and validation cohorts, respectively (Table 1).

The 6-month mortality was 27.3% in the derivation cohort and 30.2% in the validation cohort. Patients discharged home had lower 6-month mortalities than those discharged to skilled-care facilities in the two cohorts: 21% and 13% vs 39% and 40%, respectively.

The derivation and validation cohorts had similar distributions of nonneoplastic principal diagnoses (Table 2). However, more patients in the validation cohort had a principal diagnosis of cancer (8.4% vs 5.2%). The distribution of CCI scores was similar in both cohorts with the majority of patients having a CCI score between 2 and 5. DNR was ordered during the hospitalization for 23.1% of derivation cohort subjects, and for 8.7% of validation cohort subjects.

Univariable and Multivariable Results

The predictor variables in the final 6-month mortality prediction model are shown in Table 3. Univariable associations with 6-month mortality for predictor variables are presented in e-Table 4 (principal diagnoses)

FIGURE 2. Independent percent contribution of predictor variables from the logistic regression model used to predict 6-mo mortality in elderly (≥ 65 y) ICU survivors that includes SAPS-II laboratory scores derived from the first 24 h after ICU admission and during the last 3 d of hospitalization. We determined the contribution of each risk factor to the final model's predictive power by dividing the difference in the $-2 \log$ likelihood between the null model and a final model without the variable of interest by the difference in the $-2 \log$ likelihood between the null and final model.¹⁹ We then normalized these results to determine the percent contribution of each predictor variable when added last to the model.²⁰ Comorbidity Score represents the Charlson Comorbidity Index. Admission Source represents admission from a skilled-care facility or other short-term acute care hospital. DNR = do not resuscitate; SAPS = Simplified Acute Physiology Score.

and e-Table 5 (demographic and hospitalization characteristics, and DNR status). Of all the principal diagnoses that were evaluated in the initial multivariable model, only sepsis and hematologic malignancies remained independently associated with 6-month mortality.

From the derivation and validation cohorts 1,344 of 1,526 and 749 of 1,010 subjects, respectively, had complete laboratory data to calculate SAPS II laboratory scores for post hoc analyses. The effect estimates of the post hoc model that includes SAPS II laboratory scores for the derivation cohort are described in e-Table 6. The independent percentage contribution of each variable to the predictive power of the post hoc model across derivation cohort patients is shown in Figure 2. DNR preference accounted for the greatest amount of predictive power (27.9%). Surrogate markers of frailty and disability, including admission from another hospital or skilled-care facility, hospital length of stay, and discharge to a skilled-care facility together accounted for 29.1% of the predictive ability of the model. After adjusting for other covariates, increasing age, another surrogate marker of frailty and disability, accounted for 5.8% of the model's predictive ability. The CCI accounted for 14% of the model's predictive power. The SAPS II laboratory score derived from the first 24 h after ICU admission had a statistically nonsignificant contribution of 0.7%, whereas the SAPS II laboratory score derived from the last 3 days of hospitalization

contributed to 9.9% of the predictive power of the model. Comparing models with and without the estimates of severity of illness using SAPS II laboratory scores, surrogate markers of frailty and disability collectively accounted for a similar amount of the predictive power of the model when SAPS II laboratory scores were included (34.9%) compared with when the SAPS II laboratory scores were not included (34.3%) ($P = 0.81$). The remaining variables, including principal diagnoses, mechanical ventilation, and sex, accounted for 12.6% of the predictive power of the post hoc model combined.

Model Performance

The model's discrimination and calibration for predicting 6-month mortality in the derivation and validation cohorts are described in Table 4. The AUC for the derivation cohort was 0.80 (SE, 0.01). The average AUC after bootstrap resampling decreased marginally to 0.79 (SE, 0.01), suggesting that the model is internally valid. The model retained adequate discrimination in the external validation cohort with an AUC of 0.71 (SE, 0.02). We excluded patients with principal or comorbid diagnoses of cancer in the derivation and validation cohorts, and refit the model to ensure that discrimination did not depend upon elderly ICU survivors dying from cancer. We found that discrimination improved to 0.81 (SE, 0.01) and 0.73 (0.02) in the derivation and validation cohorts

Table 1—Demographics, Hospital Admission Characteristics, and 6-Month Postdischarge Mortality of Elderly Patients in the MICU

Characteristic	Derivation (n = 1,526)	Validation (n = 1,010)
Demographics		
Age, median (IQR), y	78 (71-85)	78 (71-84)
Male	684 (44.8)	512 (50.7)
Race		
White	527 (34.5)	a
Black	288 (18.9)	a
Hispanic	432 (28.3)	a
Other	187 (12.3)	a
Unknown	92 (6.0)	a
Prehospitalization residence		
Home	1,170 (76.7)	851 (84.3)
Other hospital	137 (9.0)	75 (7.4)
Skilled-care facility	219 (14.4)	84 (8.3)
Length of stay		
MICU days, median (IQR)	3 (2-7)	4 (2-7)
Hospital days, median (IQR)	12 (7-22)	14 (8-25)
Discharge locations		
Discharged home	679 (44.5)	512 (50.7)
Discharge to skilled care	847 (55.5)	498 (49.3)
6-month postdischarge mortality		
Overall	417 (27.3)	305 (30.2)
Discharged home	86 (12.7)	108 (21.1)
Discharged to skilled care	331 (39.1)	197 (39.6)

Data are given as No. (%) unless otherwise indicated. IQR = interquartile range; MICU = medical ICU.

*Race and ethnicity were not readily available in analyzable form.

when cancer patients were excluded. The model was well calibrated in the derivation and validation cohorts based upon its calibration plots (Fig 3) and GoF test *P* values of 0.31 and 0.43, respectively.

For reference, we compared the performance of our model in this study to the performance of the Acute Physiology and Chronic Health Evaluation (APACHE) and Study to Understand Prognoses and Preferences for Outcomes and Risks of Treatment (SUPPORT) models in other studies. The discrimination and calibration of our model at predicting 6-month mortality is similar to that of the SUPPORT model,²⁵ and better than that of the APACHE II model when the APACHE II model was used to predict postdischarge mortality in a different cohort of ICU survivors (Table 4).²⁴

The performance of the post hoc model that includes SAPS II laboratory scores is described in e-Table 7. After incorporating SAPS II laboratory scores from the first 24 h after ICU admission and the last 3 days of hospitalization into the model, model discrimination did not change for the derivation cohort (AUC, 0.80 to 0.80 [SE, 0.01]), and improved marginally for the validation cohort (AUC, 0.71 to 0.72 [SE, 0.02]). Model calibration remained adequate in both cohorts.

DISCUSSION

The Institute of Medicine has prioritized comparative effectiveness research that promises to improve coordination of end-of-life care with skilled care for the elderly,²⁷ and one of the key research priorities of the 2012 Multisociety Taskforce for Critical Care Research in America is to identify outcome measures and improvement strategies for care through the acute and chronic stages of critical illness and into recovery.²⁸ To this end, we derived and externally validated a model to predict 6-month mortality among elderly medical ICU survivors. The model uses demographic variables, patient preferences regarding resuscitation, and clinical characteristics that are easily measured at the time of hospital discharge, and does not require recording of physiologic variables either during the first day of ICU admission or on hospital discharge. The most important elements of the model are those variables that reflect frailty, disability, patient preferences regarding resuscitation that connote a perceived poor prognosis, and the burden of comorbidity, suggesting that we should prospectively measure these variables to better identify and risk-stratify elderly ICU survivors for interventions aimed at improving care after critical illness.

Admission from or discharge to a skilled-care facility, hospital length of stay, and increasing age likely capture elements of frailty and/or disability and do not just reflect comorbidities, severity of illness, or patient preferences regarding resuscitation because these potential confounders were included in the prediction model. Furthermore, work suggests that the need for skilled care, longer hospital length of stay, and increasing age are all associated with frailty and/or disability, independent of comorbidity and severity of illness.^{11,12,29-31} Frailty predicts the need for long-term care,^{12,29} and frailty and disability are highly prevalent in nursing home patients.³⁰ Frail adults have decreased physiologic reserves and hence may suffer greater severity of illness and may require more time for recovery that could increase hospital length of stay.³¹ Frailty and disability are increasingly common with advancing age, independent of comorbidities.¹¹

Validated measures of disability (Activities of Daily Living³²), frailty (Fried frailty criteria¹¹), and other functional measures that have been used to identify frailty (gait speed³³) were not available in our dataset. To the best of our knowledge, there is only one frailty index retrospectively derived from administrative data using a cohort of older adult outpatients in The Netherlands, and this index uses measures of comorbidity to predict adverse outcomes.²⁹ Therefore, we considered our surrogate measures of frailty and/or disability to be the best available to us in our administrative and electronic medical records data.

Table 2—Clinical Characteristics of MICU Survivors

Characteristic	Derivation (n = 1,526)	Validation (n = 1,010)
Charlson Index Score		
Overall, median (IQR) [range]	2 (1-4) [0-11]	1 (0-3) [0-15]
0-1	576 (37.7)	375 (37.1)
2-5	816 (53.4)	505 (50)
6-7	91 (6.0)	92 (9.1)
≥ 8	43 (2.8)	38 (3.8)
Principal diagnosis		
Sepsis	334 (21.9)	197 (19.5)
Diagnoses each with < 1% prevalence, combined	300 (19.7)	227 (22.4)
Respiratory failure	159 (10.4)	118 (11.7)
GI hemorrhage	121 (7.9)	79 (7.8)
Any malignancy	77 (5.0)	88 (8.4)
Hematologic malignancy	12 (0.78)	29 (2.9)
Solid malignancy	65 (4.3)	56 (5.5)
Acute myocardial infarction	64 (4.2)	16 (1.6)
Diverticulosis and diverticulitis	53 (3.5)	32 (0.32)
Pneumonia	50 (3.3)	38 (3.8)
Congestive heart failure exacerbation	47 (3.1)	26 (2.6)
Aspiration pneumonitis	42 (2.8)	17 (1.7)
Acute renal failure	41 (2.7)	48 (4.8)
Complication of device or transplant	38 (2.5)	26 (2.6)
Arrhythmia	24 (1.6)	5 (0.5)
Complication of surgery or medical care	22 (1.4)	25 (2.5)
Intestinal obstruction without hernia	20 (1.3)	1 (0.1)
Pulmonary heart disease	19 (1.2)	8 (0.8)
Biliary disease	19 (1.2)	3 (0.3)
Hip fracture	18 (1.2)	8 (0.8)
Diabetes with complications	17 (1.1)	8 (0.8)
Asthma exacerbation	17 (1.1)	3 (0.3)
Liver disease	17 (1.1)	10 (1.0)
COPD or bronchiectasis exacerbation	14 (1.0)	4 (4.0)
Acute stroke	13 (1.0)	26 (2.6)
Mechanical ventilation		
All	588 (38.5)	361 (35.7)
≤ 96 h	236 (15.5)	179 (17.7)
> 96 h without prolonged MV	235 (15.4)	126 (12.5)
Prolonged MV	117 (7.7)	56 (5.5)
Other critical care interventions		
CPR	42 (2.8)	23 (2.3)
Hemodialysis	138 (9.0)	78 (7.7)
DNR ordered during hospitalization		
DNR	352 (23.1)	88 (8.7)

Data are given as No. (%) unless otherwise indicated. DNR = do not resuscitate; MV = mechanical ventilation; prolonged MV = > 96 h with tracheostomy. See Table 1 for expansion of other abbreviations.

Our finding that surrogate measures of frailty and/or disability account for nearly one-half of the predictive power of our model is consistent with previous work showing that functional measures predict hospital outcomes among older adults who have not been critically ill.^{7,34}

The widely accepted Fried frailty index for community-dwelling elders has not yet been evaluated in elderly ICU survivors,¹¹ but has been shown to improve prediction of surgical outcomes in older adults.³⁵ Measuring frailty in elderly ICU survivors may help differentiate between those who are more likely to die and those with greater capacity to recover. Disability that is not preexisting or due to frailty may help identify those with greater potential resiliency. Comorbidity is traditionally defined as the total burden of preexisting illness unrelated to a patient's principal diagnosis.³⁶ However, mechanistically, comorbid conditions may be both a risk factor for and a result of critical illnesses that lead to multiorgan failure (eg, septic shock). Therefore, measuring comorbidity prior to hospital discharge will potentially better

Table 3—Multivariable Model of Predictors of 6-Mo Mortality for Elderly MICU Survivors Using the Derivation Cohort

Variable	OR	95% CI	P Value
Demographics			
Male	1.32	1.01-1.73	.042
Age, per y	1.03	1.01-1.04	.002
Hospital length of stay			
1-7 d	1.0	...	...
8-21 d	1.24	0.85-1.80	.26
> 21 d	2.08	1.34-3.24	.001
Admission source			
Home	1.0	...	...
Outside hospital	1.40	0.91-2.17	.14
Skilled-care facility	2.19	1.53-3.12	< .001
Discharge location			
Home	1.0	...	...
Skilled-care facility	2.39	1.73-3.30	< .001
Principal diagnosis^a			
Diagnoses each with < 1% prevalence, combined	1.0	...	...
Sepsis	1.49	1.10-2.00	.010
Acute stroke	3.42	0.93-12.5	.064
Hematologic malignancy	5.48	1.57-19.2	.008
Solid malignancy	1.25	0.64-2.46	.52
Mechanical ventilation			
No MV	1.0	...	...
MV ≤ 96 h	1.06	0.73-1.54	.76
MV > 96 h (− trach)	1.13	0.78-1.63	.53
MV > 96 h (+ trach)	1.60	1.0-2.59	.057
Charlson Comorbidity Score			
0-1	1.0	...	...
2-5	1.85	1.38-2.47	< .001
6-7	2.30	1.32-4.00	.003
≥ 8	7.2	3.33-15.5	< .001
DNR ordered during hospitalization			
Full code	1.0	...	...
DNR	3.52	2.63-4.71	< .001

Trach = tracheostomy. See Table 1 and 2 legends for expansion of other abbreviations.

^aORs of principal diagnoses represent the odds of death in patients with the listed principal diagnosis compared with those with principal diagnoses each with < 1% prevalence, combined.

Table 4—Performance of the Multivariable Model in the Derivation and Validation Cohorts

6-Mo Mortality After Hospital Discharge	Discrimination AUC (SE)	Calibration GoF χ^2_{10} , <i>P</i> Value
Derivation cohort	0.80 (0.01)	.31
Internal validation with bootstrap resampling 100 times for optimism-correction	0.79 (0.01)	...
External validation cohort	0.71 (0.02)	.43
Excluding cancer patients		
Derivation cohort (n = 1,276)	0.81 (0.01)	.15
Validation cohort (n = 729)	0.73 (0.02)	.83
Reference prediction models		
APACHE IV: Predicting in-hospital mortality in own derivation cohort ²³	0.88	.08
APACHE II: Predicting postdischarge mortality in a cohort of ICU survivors discharged to skilled care ²⁴	0.63	< .01
SUPPORT: Predicting 6-month mortality on the third day of ICU admission in own derivation cohort ²⁵	0.79	> .2

A higher *P* value represents better calibration because it represents the probability that the predicted number of deaths within 6 mo is consistent with the observed number of deaths within 6 mo, over deciles of risk. *P* values > .20 are considered indicative of excellent calibration.²⁶ APACHE = Acute Physiology and Chronic Health Evaluation; AUC = area under the receiver operating characteristic curve; GoF χ^2_{10} = Hosmer-Lemeshow Goodness of Fit χ^2 test statistic with 10 degrees of freedom.

characterize the longer-term effect of critical illness on mortality. Future studies should carefully measure frailty, disability, and comorbidity in this population to establish the relationships between these factors and outcomes after hospital discharge and to determine the mechanisms that contribute to these associations.

While some critical illness constitutes an acute event with minimal sequelae, we now recognize that many patients leave the ICU in a state similar to having a severe chronic disease, with an increased risk of long-term morbidity and mortality.^{2,5} We chose to predict 6-month postdischarge mortality because in the 3 years after intensive care, elderly ICU survivors are most vulnerable to death and readmission during the first 6 months.² Therefore, they may benefit most

from postacute interventions during this early post-acute period. While our model requires further refinement and validation, it ultimately could be used to identify and risk-stratify elderly ICU survivors just prior to hospital discharge for postacute interventions that are rehabilitative (diaphragmatic exercise training to improve ventilator weaning³⁷ and exercise tolerance³⁸), therapeutic (use of pharmaconutrients³⁹ and growth hormone secretagogues, such as ghrelin,⁴⁰ insulin-like growth factor-1,⁴¹ and myostatin antagonists to decrease and prevent muscle loss⁴²), preventative (screening for colonization and subsequent infection with antimicrobial-resistant organisms³⁹), and palliative.⁴³

We also chose to study 6-month postdischarge mortality because Medicare defines hospice eligibility as

FIGURE 3. Comparison of observed and predicted 6-mo mortality for patients divided into five equal-sized groups from the derivation and validation cohorts.

a life expectancy of < 6 months with the usual progression of a disease.⁴⁴ Elderly ICU survivors, their families, and their providers could benefit from greater insight into the patient's prognosis.⁴⁵ While our model should not be used as an adjunct to clinical decision-making until it is further evaluated, it could potentially increase clinicians' confidence in discussing prognosis and the need for hospice care.⁴⁶ By informing discussions of goals of care, our model could indirectly influence whether a patient enrolls in hospice upon discharge from the hospital. Prior studies such as SUPPORT have failed to demonstrate such an effect of information during the ICU stay,²⁵ but these patients, their families, and their providers may use this information differently later in the patient's clinical course after extensive efforts have been made on the patient's behalf, when recovery has stalled, and predicted outcome is poor. Prognoses in the intermediate range may be less likely to impact decision-making, but even intermediate prognoses have still been shown to affect decision-making for seriously ill older patients.⁴⁷

Some strengths of our approach should be emphasized. We derived our model from consecutively admitted elderly ICU patients, regardless of admission diagnosis, making our model potentially more generalizable to elderly ICU patients. Furthermore, our model depends only on variables available near the time of hospital discharge, arguably an important moment to discuss a patient's long-term prognosis and potential need for palliative interventions.

Our study has several limitations. We retrospectively ascertained principal diagnoses from *International Classification of Diseases, Ninth Revision*, clinical modification codes assigned by medical coders and these may not be as accurate as prospectively ascertained principal diagnoses. However, when prospectively assessed ICU admission diagnoses were included in the APACHE III score, they did not improve the explanatory power of the model.⁴⁸ We derived and externally validated our model at two tertiary-care medical centers in New York City, where utilization of acute care in the last 6 months of life is greater than at other major medical centers in the United States.⁴⁹ Our model still needs to be validated in community hospitals and in other geographic regions where case mix and patient care may differ.

In conclusion, we derived and externally validated a 6-month mortality prediction model for elderly ICU survivors using demographic characteristics, patient preferences regarding resuscitation, and clinical variables that are readily available near the time of hospital discharge. Our Web-based model can be easily used by providers to inform discussions with elderly ICU survivors at high risk of death and their families regarding the potential need for end-of-life

care just prior to hospital discharge. While existing critical illness mortality prediction models tend to rely more on physiologic variables during the first 24 h after ICU admission in order to predict in-hospital mortality, the high 6-month mortality for elderly survivors of critical illness suggests that survival to hospital discharge should no longer be the only endpoint for success. Our findings suggest that we should now prospectively measure frailty, disability, and comorbidities prior to hospital discharge to more accurately predict postdischarge mortality and target preventative, therapeutic, rehabilitative, and palliative interventions that will improve critical illness survivorship for the elderly.

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Dr Baldwin: contributed to study concept and design, drafted the article, contributed to data acquisition and analysis, and approved the submission of this version for publication.

Mr Narain: contributed to data acquisition and analysis and critical revision of the article and approved the submission of this version for publication.

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