Predicting Discharge to a Long-Term Acute Care Hospital After Admission to an Intensive Care Unit

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Background Long-term acute care hospitals are an option for patients in intensive care units who require prolonged care after an acute illness. Predicting use of these facilities may help hospitals improve resource management, expenditures, and quality of care delivered in intensive care.

Objective To develop a predictive tool for early identification of intensive care patients with increased probability of transfer to such a hospital.

Methods Data on 1967 adults admitted to intensive care at a tertiary care hospital between January 2009 and June 2009 were retrospectively reviewed. The prediction model was developed by using multiple ordinal logistic regression. The model was internally validated via the bootstrapping technique and externally validated with a control cohort of 950 intensive care patients.

Results Among the study group, 146 patients (7.4%) were discharged to long-term acute care hospitals and 1582 (80.4%) to home or other care facilities; 239 (12.2%) died in the intensive care unit. The final prediction algorithm showed good accuracy (bias-corrected concordance index, 0.825; 95% CI, 0.803-0.845), excellent calibration, and external validation (concordance index, 0.789; 95% CI, 0.754-0.824). Hypoalbuminemia was the greatest potential driver of increased likelihood of discharge to a long-term acute care hospital. Other important predictors were intensive care unit category, older age, extended hospital stay before admission to intensive care, severe pressure ulcers, admission source, and dependency on mechanical ventilation.

Conclusions This new predictive tool can help estimate on the first day of admission to intensive care the likelihood of a patient’s discharge to a long-term acute care hospital. (American Journal of Critical Care. 2014;23:e46-e53)
The economic impact of and demand for critical care services in the United States are intensifying. From 2000 to 2005, annual critical care expenditures increased from $57 billion to $82 billion. In 2005, critical care services accounted for approximately 4% of national health care expenditures and 0.7% of the US gross domestic product. Part of the increased costs and demand for intensive care unit (ICU) services are due to a subgroup of critically ill patients who survive acute illness and require prolonged life-support care. These patients, also termed chronically critically ill, represent a problem of growing importance. Chronically critically ill patients account for only 5% to 10% of all ICU admissions but for approximately 40% of total ICU expenditures.

The increasing costs and demand for critical care services in the United States have resulted in greater emphasis on efficient ICU resource management and improvement in quality of care. Development of care practices for chronically critically ill patients is a considerable challenge not only for ICU clinicians but also for the health system as a whole.

Our primary objective in this study was to develop a predictive algorithm for early identification of ICU patients with a high probability of discharge to an LTACH. We hypothesized that sufficient accuracy could be achieved by using predictor variables that were available within the first 24 hours of ICU admission. Formerly, no such predictive instrument has existed. Although experienced ICU clinicians may use various clinical characteristics and laboratory results to estimate the future need for LTACH transfer, this clinical assessment can be influenced by multiple biases. A predictive tool permits the clinical care team to make decisions based on and supported by objective data rather than subjective intuition. Individualized prediction of discharge to an LTACH may allow for strategic planning to improve ICU resource management and quality of care. In addition, early and objective identification of ICU patients with the greatest likelihood of LTACH transfer could facilitate LTACH referrals, encourage preparation of patients and their families, and decrease financial issues for the patients and the hospitals.

Methods

Sample Selection

This retrospective study was conducted at an academic tertiary care center with 215 adult ICU beds. Approval was granted by the appropriate institutional review board; informed consent was not required. Data for development of the model were obtained from the medical records of 1967 patients 18 years or older who had been admitted to an ICU between January 2009 and June 2009.

Variables

A team of clinicians and research staff developed a list of 21 demographic, ICU admission, and medical variables that they thought had empirical or theoretical relevance to discharge to an LTACH (see Table).
Demographic variables included age, sex, and body mass index. ICU admission was summarized by 4 variables: length of stay before ICU admission, source of admission, ICU category, and type of ICU admission. Length of stay before ICU admission was defined as the number of days the patient stayed in the hospital directly before being admitted to the ICU. Source of admission was the site from which the patient was transferred to the ICU: (1) the emergency department, (2) the hospital unit or operating room, or (3) a skilled nursing facility, an LTACH, or another hospital. ICU category was defined as the...

### Table
Descriptive statistics and univariate analysis of model development cohort

<table>
<thead>
<tr>
<th>Variable</th>
<th>Discharged to LTACH (n = 146)</th>
<th>Discharged to non-LTACH (n = 1582)</th>
<th>ICU death (n = 239)</th>
<th>P (LTACH vs non-LTACH)</th>
<th>P (LTACH vs ICU death)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age, a years</td>
<td>64.7 (55.2, 74.5)</td>
<td>62.6 (52.5, 73.3)</td>
<td>66.9 (56.5, 76.5)</td>
<td>.15</td>
<td>.22</td>
</tr>
<tr>
<td>Sex b</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>67 (45.9)</td>
<td>631 (39.9)</td>
<td>116 (48.5)</td>
<td>.16</td>
<td>.61</td>
</tr>
<tr>
<td>Male</td>
<td>79 (54.1)</td>
<td>951 (60.1)</td>
<td>123 (51.5)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BMI a (missing, n = 184)</td>
<td>26.6 (23.2, 32.4)</td>
<td>27.6 (24.3, 31.7)</td>
<td>27.4 (23.1, 33.8)</td>
<td>.28</td>
<td>.52</td>
</tr>
<tr>
<td>LOS before ICU admission, c days</td>
<td>0 (0, 62)</td>
<td>0 (0, 60)</td>
<td>0 (0, 44)</td>
<td>&lt;.001</td>
<td>.49</td>
</tr>
<tr>
<td>Source of admission b (missing, n = 12)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ED</td>
<td>21 (14.4)</td>
<td>307 (19.4)</td>
<td>60 (25.1)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>General care area/or</td>
<td>34 (23.3)</td>
<td>590 (37.3)</td>
<td>36 (15.1)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SNF/LTACH/hospital transfer</td>
<td>91 (62.3)</td>
<td>674 (42.6)</td>
<td>142 (59.4)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ICU category b</td>
<td></td>
<td></td>
<td></td>
<td>&lt;.001</td>
<td>.11</td>
</tr>
<tr>
<td>Cardiovascular</td>
<td>12 (8.2)</td>
<td>443 (28.0)</td>
<td>7 (2.9)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coronary</td>
<td>36 (24.7)</td>
<td>584 (36.9)</td>
<td>77 (32.2)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Heart failure</td>
<td>6 (4.1)</td>
<td>56 (3.5)</td>
<td>10 (4.2)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medical</td>
<td>48 (32.9)</td>
<td>253 (16.0)</td>
<td>81 (33.9)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neurosurgical</td>
<td>22 (15.1)</td>
<td>118 (7.5)</td>
<td>24 (10.0)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Surgical</td>
<td>22 (15.1)</td>
<td>128 (8.1)</td>
<td>40 (16.7)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Type of ICU admission b</td>
<td></td>
<td></td>
<td></td>
<td>&lt;.001</td>
<td>.28</td>
</tr>
<tr>
<td>Planned</td>
<td>9 (6.2)</td>
<td>373 (23.6)</td>
<td>9 (3.8)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unplanned</td>
<td>137 (93.8)</td>
<td>1209 (76.4)</td>
<td>230 (96.2)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MAP, a mm Hg (missing, n = 244)</td>
<td>80.0 (70.5, 89.9)</td>
<td>83.0 (74.0, 95.0)</td>
<td>75.0 (63.9, 90.0)</td>
<td>.02</td>
<td>.01</td>
</tr>
<tr>
<td>Pressure ulcers (≥stage 3): yes b</td>
<td>18 (12.3)</td>
<td>14 (0.9)</td>
<td>9 (3.8)</td>
<td>&lt;.001</td>
<td>.001</td>
</tr>
<tr>
<td>Mechanical ventilation: yes b</td>
<td>81 (55.5)</td>
<td>413 (26.1)</td>
<td>142 (59.4)</td>
<td>&lt;.001</td>
<td>.45</td>
</tr>
<tr>
<td>FiO&lt;sub&gt;2&lt;/sub&gt;, % (missing, n = 18)</td>
<td>40 (30, 50)</td>
<td>30 (27, 40)</td>
<td>50 (33, 80)</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>PaO&lt;sub&gt;2&lt;/sub&gt;, mm Hg (missing, n = 783)</td>
<td>113 (82, 176)</td>
<td>120 (91, 166)</td>
<td>124 (90, 176)</td>
<td>.45</td>
<td>.35</td>
</tr>
<tr>
<td>Dopamine: yes b</td>
<td>4 (2.7)</td>
<td>16 (1.0)</td>
<td>11 (4.6)</td>
<td>.08</td>
<td>.43</td>
</tr>
<tr>
<td>Dobutamine: yes b</td>
<td>1 (0.7)</td>
<td>18 (1.1)</td>
<td>3 (1.3)</td>
<td>.99</td>
<td>.99</td>
</tr>
<tr>
<td>Epinephrine: yes b</td>
<td>9 (6.2)</td>
<td>71 (4.5)</td>
<td>15 (6.3)</td>
<td>.36</td>
<td>.96</td>
</tr>
<tr>
<td>Norepinephrine: yes b</td>
<td>38 (26.0)</td>
<td>193 (12.2)</td>
<td>90 (37.7)</td>
<td>&lt;.001</td>
<td>.02</td>
</tr>
<tr>
<td>Dialysis: yes b</td>
<td>19 (13.0)</td>
<td>54 (3.4)</td>
<td>26 (10.9)</td>
<td>&lt;.001</td>
<td>.53</td>
</tr>
<tr>
<td>Creatinine, a mg/dL (missing, n = 10)</td>
<td>1.2 (0.8, 2.2)</td>
<td>1.0 (0.8, 1.3)</td>
<td>1.5 (0.9, 2.7)</td>
<td>&lt;.001</td>
<td>.02</td>
</tr>
<tr>
<td>Total bilirubin, a mg/dL (missing, n = 204)</td>
<td>0.5 (0.4, 0.9)</td>
<td>0.6 (0.4, 0.9)</td>
<td>0.7 (0.4, 1.3)</td>
<td>.10</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Albumin, a g/dL (missing, n = 204)</td>
<td>3.1 (2.4, 3.5)</td>
<td>3.4 (2.8, 3.9)</td>
<td>2.9 (2.3, 3.5)</td>
<td>&lt;.001</td>
<td>.24</td>
</tr>
<tr>
<td>Platelet count, a K/µL (missing, n = 101)</td>
<td>200 (147, 268)</td>
<td>192 (141, 253)</td>
<td>183 (113, 265)</td>
<td>.43</td>
<td>.11</td>
</tr>
</tbody>
</table>

Abbreviations: BMI, body mass index; ED, emergency department; FiO<sub>2</sub>, fraction of inspired oxygen; ICU, intensive care unit; K, 1000; LOS, length of stay; LTACH, long-term acute care hospital; MAP, mean arterial pressure; OR, operating room; PaO<sub>2</sub>, partial pressure of oxygen in arterial blood; SNF, skilled nursing facility.

SI conversions: For total bilirubin, to convert from mg/dL to µmol/L, multiply by 17.104. For creatinine, to convert from mg/dL to µmol/L, multiply by 88.4.

Values in columns 2, 3, and 4 are expressed as median (lower quartile, upper quartile).

Values in columns 2, 3, and 4 are expressed as number of cases (percentage of column header population).

Values in columns 2, 3, and 4 are expressed as median (minimum, maximum).
admitting ICU (cardiovascular, coronary, heart failure, medical, neurosurgical, surgical). Type of ICU admission indicated whether or not the admission was planned or anticipated by the care team (ie, discussed in notes before the admission or treatment intervention). The remaining 14 physiological and laboratory variables were measures of medical status during the first 24 hours of ICU admission. The response variable, discharge disposition, was collapsed into 3 categories: LTACH, home or other care facilities (ie, non-LTACH), and death in the ICU. Other care facilities encompassed skilled nursing facilities as well as acute and chronic rehabilitation facilities.

Statistical Analysis

All statistical analyses were performed by using SAS, version 9.2 (SAS Institute Inc) and R statistical software, version 2.12 (R Foundation for Statistical Computing). Univariate analyses to compare the LTACH group with the non-LTACH and ICU-death groups were performed by using the Mann-Whitney test, Pearson $\chi^2$ test, or Fisher exact test, as appropriate. Differences were considered significant at $P \leq .05$.

With all 21 established variables (see Table), a multiple ordinal logistic regression model was developed to predict the outcome of LTACH discharge. A simultaneous approach (ie, all variables entered at a single step) was implemented, rather than a stepwise procedure, for analysis as recommended by Harrell et al. Missing data in the development cohort were estimated by using the mice (multivariate imputation by chained equations) function in R statistical software, generating several imputations by using Gibbs sampling. The coefficients from the resulting multiple logistic regression model were used to construct a paper-based graphic calculation tool, called a nomogram, by using the design library of R statistical software. Points for each predictor were determined by rescaling the regression coefficients to adapt to a user-friendly 100-point scale. Variable importance in the final model was ascertained from the relative potential contribution of points, as deduced from the nomogram and the length of the axis. Variables with longer axes have greater potential predictive effect in the model.

Internal validation of the model with the original development data was determined by using the bootstrapping technique to correct for overfitting bias. During this process, a random bootstrap sample of the original data was generated from the cohort and the model was applied to this sample to yield predicted results. This technique was repeated 1000 times to obtain a bias-corrected estimate of the model’s predictive accuracy. Discrimination of the model was quantified by using the concordance index (ie, the area under the receiver operating characteristic curve). The concordance index ranges from 0.5 (random discrimination) to 1.0 (perfect discrimination) and represents the ability of the model to accurately assign a higher probability to the patient discharged to LTACH for a randomly selected pair of patients with one discharged to LTACH and the other not. Typically, predictive tests are considered of clinical value when the concordance index is greater than 0.70. Calibration, an additional measure of model performance, illustrates how well the model’s predictions agree with the observed outcomes. Calibration was assessed graphically by plotting predicted vs actual probabilities for discharge to LTACH. A model with perfect predictions generates a calibration curve that lies on the 45° line.

The predictive tool was externally validated with an independent cohort of 950 ICU patients at the same institution admitted between January 2011 and March 2011. The sample size of the validation cohort was estimated to provide greater than 80% statistical power to conclude a concordance index of the validation data set (assumed to be approximately 0.80 on the basis of the data for the development cohort) is significantly greater than 70%. Discrimination of the model on the external validation sample was quantified with the concordance index, and calibration was assessed graphically.

Using the nomogram (Figure 1) to calculate the predicted probability of LTACH discharge requires the following steps: (1) locate the patient’s category or value on the axis corresponding to the respective predictor variable; (2) draw a vertical line upward to the points axis to determine how many points are assigned for that characteristic in the model; (3) repeat this process for the remaining predictor variable axes, determining the points for each predictor independently; (4) sum the points achieved for all predictors; (5) locate this summed point value on the total points axis and draw a vertical line down to the probability axis to calculate the patient’s predicted probability of having the model’s primary end point (ie, discharge to an LTACH).

Results

Of the 1967 ICU patients in the development cohort, 146 (7.4%) were discharged to an LTACH and 1582 (80.4%) were discharged home or to other care facilities; 239 (12.2%) died in the ICU.
The median ICU length of stay for patients transferred to an LTACH was 12.5 days (25th-75th percentile [interquartile range], 3.75-22 days). Conversely, patients discharged home or to other care facilities had a median ICU length of stay of 2 days (interquartile range, 1-3 days) \((P < .001)\) and patients who died in the ICU had a median ICU length of stay of 3 days before death (interquartile range, 1-7 days) \((P < .001)\). Of note, the percentage of extended ICU stays (ie, ≥15 days) among the LTACH discharge group (45.2%, 66 of 146 patients) was significantly greater \((P < .001)\) than the percentage among the other discharge groups (home or other care facilities, 1.6%, 25 of 1582 patients; death in the ICU, 13.0%, 31 of 239 patients), emphasizing the disparity in hospital resources required by an LTACH discharge patient. The Table summarizes the characteristics of the study cohort by discharge disposition and presents the results of univariate analysis.

The nomogram to predict the probability of discharge to an LTACH (Figure 1) shows a relatively high level of discrimination with a bias-corrected concordance index of 0.825 (95% CI, 0.803-0.845). In order to facilitate more efficient and accurate clinical use, the model equation was converted into an online risk calculator that is accessible via the Internet (http://www.r-calc.com/calculator.aspx?calculator_id=QLBsEdEY). Of the 21 variables included in the model, hypoalbuminemia (ie, serum level of albumin <3.5 g/dL) is potentially the most influential predictor of increased likelihood of discharge to an LTACH. ICU categories other than cardiovascular ICU (particularly neurosurgical ICU); older age (ie, ≥65 years); extended hospital length of stay before ICU admission (ie, ≥10 days); presence of stage 3 or higher pressure ulcers; ICU admission from a skilled nursing facility, an LTACH, or another hospital; and early dependency on mechanical ventilation also contribute substantial points (~40 points or higher) to the model, increasing the predicted probability of LTACH discharge. Only extreme values of \(\text{Pao}_2\), serum levels of creatinine or total bilirubin, or platelet count contribute any meaningful amounts to the predicted risk. Sex and requirements for dopamine, dobutamine, and epinephrine during the first 24 hours of ICU admission have minor impacts on the prediction of discharge to an LTACH (ie, contributed a relatively small number of points to the nomogram total score regardless of value).

Figure 2 displays the calibration of the LTACH discharge model: the predicted probability of discharge to an LTACH vs the actual proportion of patients discharged to an LTACH. This plot shows that the model tends to slightly underestimate the
probability of going to an LTACH for many of these patients.

When tested in the external validation sample (6.6% LTACH, 80.1% non-LTACH, 13.3% ICU deaths), the model performed similarly well. The calculated concordance index of the LTACH discharge prediction model was 0.789 (95% CI, 0.754-0.824). The calibration plot of predicted vs actual probability of LTACH discharge for this cohort is shown in Figure 3.

**Discussion**

We used demographic, ICU admission, and ICU clinical data measured during the first 24 hours of ICU admission to construct and validate a predictive model for estimating future use of an LTACH. The model’s discrimination and calibration in the development and validation cohorts indicate it makes it possible to accurately predict the likelihood of LTACH use among ICU patients. The most potentially influential determinants of this outcome included hypoalbuminemia, ICU categories other than cardiovascular ICU; older age; extended hospital length of stay before ICU admission; presence of severe pressure ulcers; ICU admission from a skilled nursing facility, an LTACH, or another hospital; and early requirement for mechanical ventilation. These findings confirm and extend those of previous investigations,18-21 which have shown that in addition to dependency on mechanical ventilation, older age, and greater severity of illness, other considerations are important for assessing disposition of discharge from an ICU.

The model shows a strong, direct association between hypoalbuminemia and the likelihood of discharge to an LTACH. This finding may be explained by the underlying nutritional status, hepatic failure, cirrhosis, and/or acute response to stress or sepsis among critically ill patients.22,23 Several studies24,25 have indicated that hypoalbuminemia is associated with increased mortality, morbidity, ICU length of stay, and resource utilization in critically ill patients. Scheinhorn et al21 found that hypoalbuminemia was common among patients admitted to an LTACH, and previous investigators22,23 emphasized its importance in predicting prolonged mechanical ventilation and chronic critical illness. ICU categories other than cardiovascular ICU contribute substantial points to the model’s predicted risk for discharge to an LTACH. This result most likely occurs because these noncardiovascular ICUs typically receive more unplanned, critically ill ICU patients than does a cardiovascular ICU. A majority of cardiovascular ICU admissions (~65% in a cardiovascular ICU vs ~6% in all other ICUs) are planned, temporary (eg, 24-48 hours) ICU transfers immediately after surgery as a monitoring precaution before the patient is moved to a step-down unit. Finally, the predictive
value of deep-wound pressure ulceration within the LTACH discharge model is supported by the results of other investigations.\textsuperscript{23,27,28} The frequency of pressure ulcers in critically ill patients is a result of multiple comorbid conditions, inability to move, impaired angiogenesis response, and dependency on mechanical ventilation.\textsuperscript{28} Our results suggest that stage 3 or higher pressure ulcers early in the ICU admission are associated with a higher likelihood of discharge to an LTACH.

Our findings are especially relevant because of the current initiatives to improve care practices for patients who are chronically critically ill.\textsuperscript{4,10,18,29,30} Early identification of LTACH use may allow clinical care teams to make appropriate arrangements for patients’ care after discharge from the ICU, improve the transition of care, ensure bed availability, and avoid potential delays in patients’ discharge. As emphasized by Zimmerman et al.,\textsuperscript{31} discharge planning started shortly after ICU admission allows for more efficient use of ICU resources. Enhanced ICU bed utilization has a variety of clinical implications, including potentially better outcomes, and far-reaching financial value.\textsuperscript{32}

LTACHs may improve outcomes for chronically critically ill patients through specialized care. These hospitals often embrace a multidisciplinary and rehabilitation-based approach to treatment, providing a setting with experienced health professionals and ample clinical resources for the care of patients who are chronically critically ill.\textsuperscript{4,10,13,34} Votto et al.\textsuperscript{35} reported that the clinical outcomes, including in-hospital mortality and discharges to home, were significantly better for patients transferred to an LTACH than for similar patients who remained in acute care hospitals. Furthermore, patients treated at an LTACH are less likely to be readmitted to an acute care hospital than are those treated in alternative care settings after discharge from an ICU.\textsuperscript{36}

In addition to potential clinical benefits, financial advantages may exist that support the use of LTACHs for chronically critically ill patients. Cost reduction by LTACHs has been achieved by focusing on efficient staff operation and incorporation of care protocols, as well as service and resource standardization.\textsuperscript{35} Votto et al.\textsuperscript{35} compared costs between LTACH-eligible patients transferred and not transferred to an LTACH and concluded that the mean total cost per patient at an LTACH ($36,626) was less than that at an acute care hospital ($59,103). In a study\textsuperscript{37} of critically ill patients with tracheostomies, total Medicare expenses related to the admission (ie, acute and postacute care) were less for patients in an LTACH than for patients in other settings. Conversely, results of a study\textsuperscript{38} examining Medicare claims for a variety of patient types indicated that although patients transferred to an LTACH had decreased costs in the acute setting, their total cost of care was higher than that of patients discharged to other postacute care facilities (eg, skilled nursing facility, rehabilitation facility). Although evidence\textsuperscript{39-41} indicates that LTACH utilization results in considerable cost savings for acute care hospitals, the economic impact of LTACH facilities on US health care expenditures is still undetermined.

Unfortunately, evidence is lacking on the effectiveness of LTACH utilization to treat patients with long-term illnesses. The current interpretation is primarily based on retrospective studies, which may introduce multiple biases. The economic impact of LTACH utilization and whether these facilities actually help improve the long-term outcomes of chronically critically ill patients must be properly evaluated. If compelling evidence supports therapeutic benefits of LTACH usage, implementation of interventions designed to discharge chronically critically ill patients to an LTACH would be a safe approach to providing critical care services in a cost-effective way.

Our study has some notable limitations. Our development and validation cohorts were patients admitted to a single tertiary care institution, a situation that may limit the applicability of the results. In addition, the retrospective design may have introduced ascertainment bias. The study design also restricted our analysis to data contained within the electronic health records, preventing us from including other factors known to influence LTACH utilization, such as payer source, patient and clinician preference, LTACH discharge criteria, bed availability, and geographic limitations.\textsuperscript{10-40}

Conclusions

This study was our first effort at developing a clinical instrument to predict early in a patient’s ICU admission the probability of that patient’s discharge to an LTACH. We think that this predictive tool offers a valuable perspective for patients, patients’ family members, clinicians, and hospitals. When complemented by the clinician’s judgment, as well as feedback from patients and their family members, this risk calculator has the potential to improve the quality of care delivered to chronically critically ill patients while enhancing ICU resource management.
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FINANCIAL DISCLOSURES
None reported.

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