Surgery 165 (2019) 373–380

Contents lists available at ScienceDirect

Surgery

journal homepage: www.elsevier.com/locate/surg

Presented at the Academic Surgical Congress 2018

Predicting ICU readmission among surgical ICU patients: Development and validation of a clinical nomogram☆

Luke A. Martin, MD[a], Julie A. Kilpatrick, BS[a], Ragheed Al-Dulaimi, MD, MPH[b], Mary C. Mone, RN, BSE[a], Joseph E. Tonna, MD[a], Richard G. Barton, MD, FACS[a], Benjamin S. Brooke, MD, PhD, FACS[a,*]

[a] Department of Surgery, University of Utah School of Medicine, Salt Lake City, UT
[b] Department of Internal Medicine, University of Utah School of Medicine, Salt Lake City, UT

ARTICLE INFO

Article history:
Accepted 25 June 2018
Available online 29 August 2018

ABSTRACT

Background: Unplanned intensive care unit readmission within 72 hours is an established metric of hospital care quality. However, it is unclear what factors commonly increase the risk of intensive care unit readmission in surgical patients. The objective of this study was to evaluate predictors of readmission among a diverse sample of surgical patients and develop an accurate and clinically applicable nomogram for prospective risk prediction.
Methods: We retrospectively evaluated patient demographic characteristics, comorbidities, and physiologic variables collected within 48 hours before discharge from a surgical intensive care unit at an academic center between April 2010 and July 2015. Multivariable regression models were used to assess the association between risk factors and unplanned readmission back to the intensive care unit within 72 hours. Model selection was performed using lasso methods and validated using an independent data set by receiver operating characteristic area under the curve analysis. The derived nomogram was then prospectively assessed between June and August 2017 to evaluate the correlation between perceived and calculated risk for intensive care unit readmission.
Results: Among 3,109 patients admitted to the intensive care unit by general surgery (34%), transplant (9%), trauma (43%), and vascular surgery (14%) services, there were 141 (5%) unplanned readmissions within 72 hours. Among 179 candidate predictor variables, a reduced model was derived that included age, blood urea nitrogen, serum chloride, serum glucose, atrial fibrillation, renal insufficiency, and respiratory rate. These variables were used to develop a clinical nomogram, which was validated using 617 independent admissions, and indicated moderate performance (area under the curve: 0.71). When prospectively assessed, intensive care unit providers' perception of respiratory risk was moderately correlated with calculated risk using the nomogram (ρ: 0.44; $P < .001$), although perception of electrolyte abnormalities, hyperglycemia, renal insufficiency, and risk for arrhythmias were not correlated with measured values.
Conclusion: Intensive care unit readmission risk for surgical patients can be predicted using a simple clinical nomogram based on 7 common demographic and physiologic variables. These data underscore the potential of risk calculators to combine multiple risk factors and enable a more accurate risk assessment beyond perception alone.

Published by Elsevier Inc.

Introduction

Unplanned readmission to the intensive care unit (ICU) within 72 hours of ICU discharge has been identified as a measure of care quality and used to evaluate hospital performance among payers and policymakers.[1-3] ICU readmission rates vary within published studies but may occur in up to 14% of patients.[4-8] Readmitted ICU patients are known to have worse outcomes with up to 10 times higher in-hospital mortality and significantly increased

☆ This study was presented at a plenary session of the 2018 Academic Surgical Congress in Jacksonville, FL, February 1, 2018.

* Corresponding author: Associate Professor of Surgery Section Chief, Health Services Research, Department of Surgery, University of Utah School of Medicine, 30 North 1900 East, 3C344 SOM, Salt Lake City, UT 84132-2301. Tel.: 801-581-8301; fax: 801-581-3433.
E-mail address: benjamin.brooke@hsc.utah.edu (B.S. Brooke).

https://doi.org/10.1016/j.surg.2018.06.053
0039-6060/Published by Elsevier Inc.

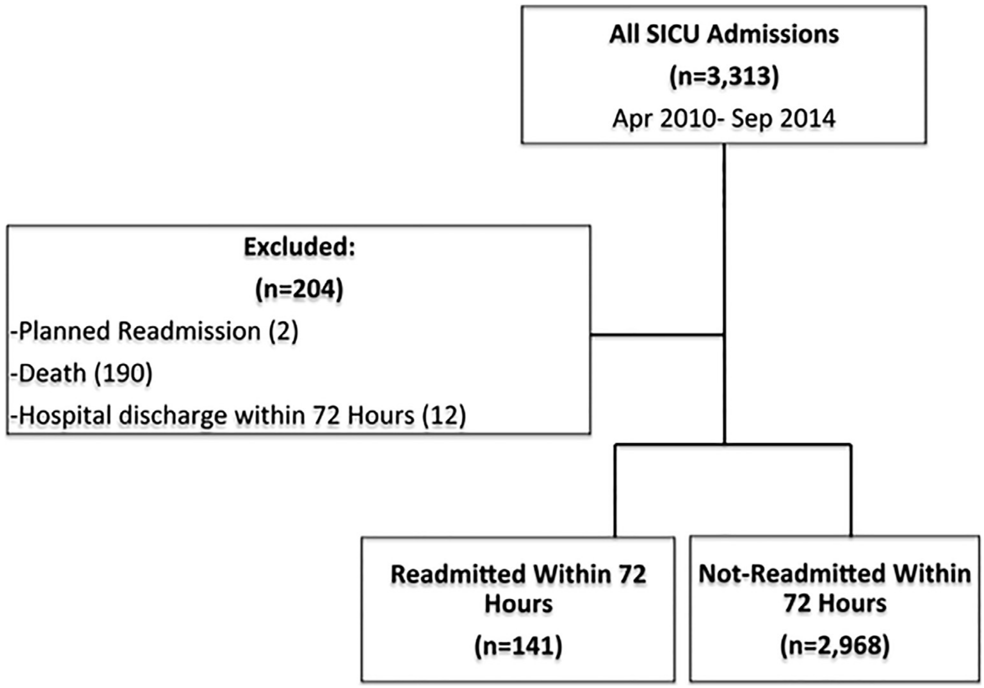

Fig. 1. Selection of patient cohort for development of surgical intensive care unit (SICU) readmission prediction model. The reasons for cohort exclusion and corresponding occurrence frequencies are shown.

hospital durations of stay compared with nonreadmitted patients.[4,9-11] In addition, the financial burden of unplanned ICU care to health care systems has been found to be significant.[12]

The factors leading to unplanned ICU readmissions have not been clearly delineated, particularly among surgical patients. Although cardiac and respiratory causes have been identified as primary reasons for readmission among medical patients, it is unclear to what extent these factors influence readmission during the postoperative period.[13-15] As such, ICU readmission risk prediction models developed using medical patients are limited when applied to surgical patient populations. Moreover, existing risk-prediction models have not been found to be clinically useful because of their complexity of design, requirement to collect additional laboratory tests or variables, large amounts of missing data leading to selection bias, and lack of external validation.[7,16-19]

To effectively reduce and prevent surgical ICU readmissions, a simplified method is needed to accurately identify surgical patients at high risk for readmission before they leave the ICU and should be easily interpreted by ICU providers. We sought a generalized risk prediction model that could be applied to all patients in the surgical ICU, irrespective of the type of postoperative procedure or surgical condition they are admitted for. The purpose of this study was to develop and validate a clinical nomogram for predicting ICU readmission risk among a diverse surgical population using variables that are collected on the majority of patients. We hypothesize that a clinical nomogram can help improve the identification of patients with elevated risk before they leave the surgical ICU and allow the potential to implement targeted interventions for optimizing health status.

Methods

Data sources and study population

After obtaining Institutional Review Board approval, we identified all patients admitted to the surgical ICU (SICU) at a single academic medical center from April 2010 until July 2015 from an institutional database. This SICU database is prospectively maintained and captures many demographic, physiologic, and clinical risk factor variables associated with critical care management of individual patients. Data are collected by trained staff and clinical research coordinators. The SICU contains 24 beds and is located in a tertiary care, high-volume academic medical center geographically situated in the Intermountain West, with a level 1 trauma center and geographic catchment area representing 10% of the continental United States. The patient population cared for in this SICU includes postoperative patients from a wide spectrum of surgical specialties (eg, general surgery, transplant, trauma, and vascular surgery) as well as patients admitted for critical care management of surgical conditions.

Outcome measure: 72-hour ICU readmission

The primary outcome for this study was readmission to the SICU within 72 hours of SICU discharge to an in-hospital setting. This specific endpoint has been defined by the Society of Critical Care Medicine as a measure that reflects quality of ICU care or the ICU discharge process.[1] Patients were excluded from analysis if their SICU readmission was planned. In addition, patients were excluded if death occurred during their initial SICU stay, if they were directly transferred to an outside facility, or if they were discharged from the hospital within 72 hours after initial discharge from the SICU (Fig. 1).

Candidate predictor variables

We evaluated a comprehensive assortment of 179 patient-level variables collected during the index SICU admission that might be used to predict readmission within 72 hours. These included patient demographic characteristics, preadmission comorbidities, ICU admission diagnosis, laboratory values, vital signs and physiologic parameters, and medications. Laboratory data, vital signs, and other physiologic parameters were evaluated for the 48-hour period before discharge from the SICU during the index admission.

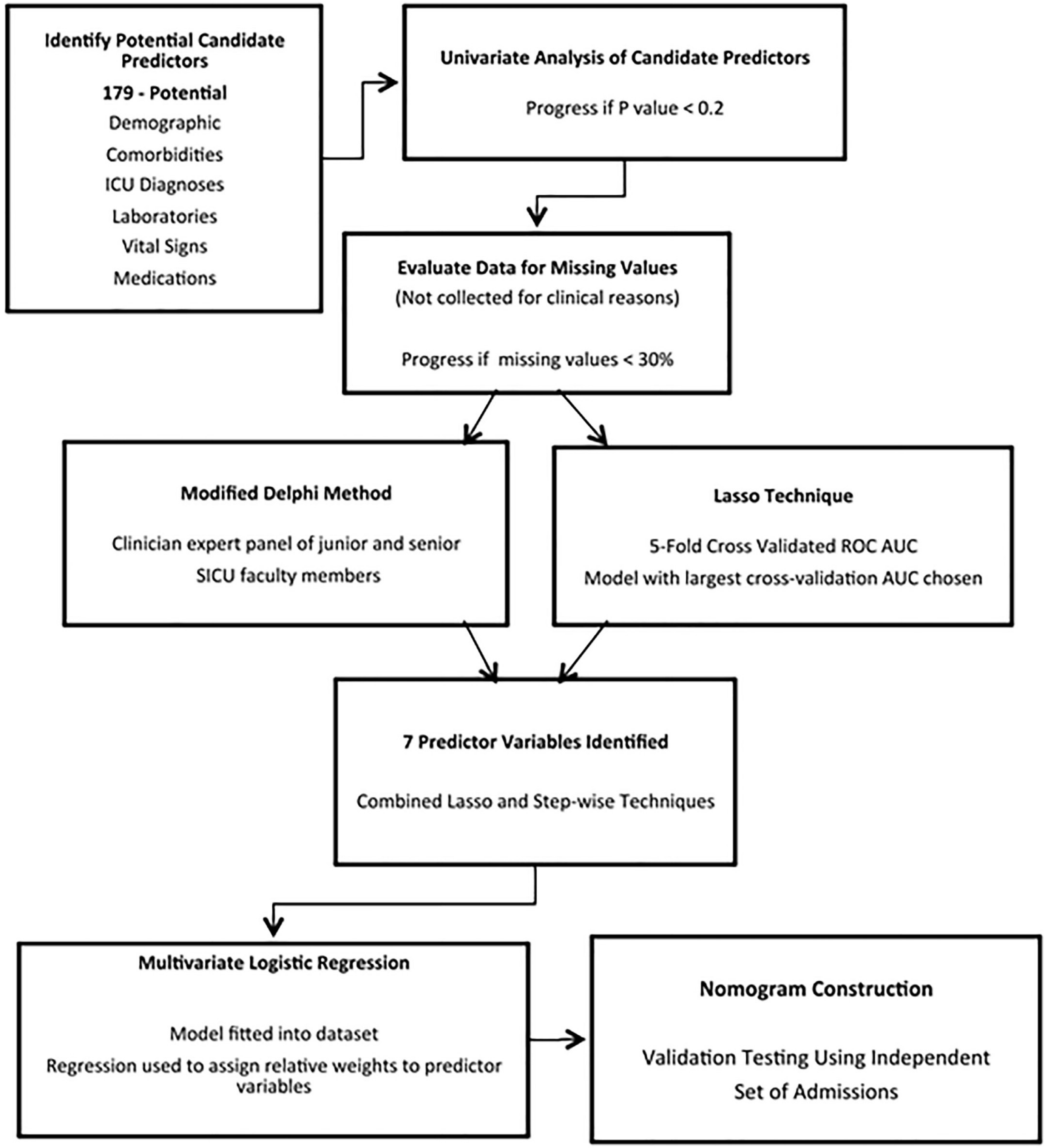

Fig. 2. Sequence of events for development of surgical intensive care unit (SICU) readmission prediction model and construction of clinical nomogram. This shows individual stepwise and parallel pathways of model construction and validation.

We evaluated several pre-ICU covariates, such as the surgical specialty admitting the patient and operation type, but other variables were appraised only if they were collected during the course of SICU care. We only considered variables for the model that were routinely collected for clinical reasons on the majority of SICU patients and would reflect a patient's physiologic state at the time he or she was being considered for SICU discharge.

Model development

Model development was undertaken using a combination of variable screening and lasso regression (Fig. 2). All patients who received care in the SICU from May 2010 until September 2014 were included. Univariate analysis on the primary outcome was performed for each of the potential predictors ($n = 179$), and those

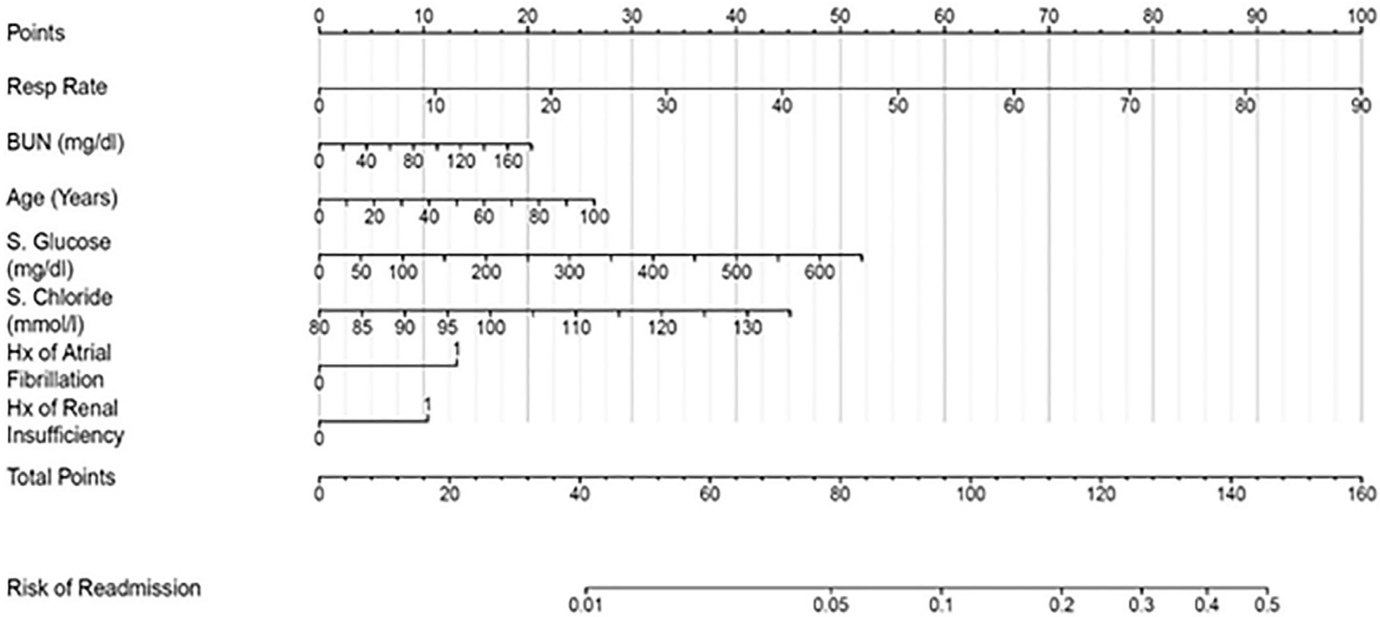

Fig. 3. Surgical intensive care unit readmission clinical nomogram. Values for each variable are individually plotted and corresponding point values assigned from the point scale (*top*). These point values are then totaled and plotted on the total point scale (*bottom*), which is used to assign a corresponding value for risk of readmission. *BUN*, blood urea nitrogen; *Hx*, history; *S*, serum.

with P values $< .2$ were selected. Next, each selected predictor was analyzed with regard to frequency of missing (not collected for clinical reasons) data. Those candidate predictors with missing values for less than 30% of the development population were selected to ensure that the model is based on variables routinely collected in ICU patients. A total of 62 variables were then evaluated by a modified Delphi method approach to select the most clinically relevant predictors among this set, based on feedback from experienced SICU staff physicians, nurses, and researchers. In parallel to the modified Delphi approach, we performed least absolute shrinkage and selection operator (lasso) regression on the 62 variables selected from univariate screening, where the optimal model was selected using 5-fold validated area under the receiver operating characteristic area under the curve (ROC-AUC) as the measurement of model accuracy. The optimal lasso model was refined by clinical input to yield the final SICU readmission model. This model was then fit to the whole data set and multivariate logistic regression was used to assign relative weights. A nomogram was created to display these predictor variables and their corresponding points and risk of readmission (Fig. 3).

Model validation

Validation of the SICU readmission predictive nomogram was performed in several sequential steps. First, we validated the nomogram on an independent set of patients from the same SICU retrospectively identified between October 2014 through June 2015. Any patient overlapping from the development period into the validation period was excluded from the validation set. Model discrimination was assessed using the ROC-AUC, along with sensitivity, specificity, and positive predictive values (PPV). The model's goodness of fit of was assessed using the Hosmer-Lemeshow test, and multicollinearity among predictor variables was assessed using the variance inflation factors test. Second, we prospectively validated the nomogram among SICU patients admitted between June and August 2017 on risk of ICU readmission. ICU providers were surveyed after surgical ICU rounds to determine perception of individual risk factors, blinded to risk calculator results. Survey questions asked ICU providers to categorize each patient in terms of risk for ICU readmission (high, medium, or low) and to list individual risk factors perceived to place patients are risk for readmission. Finally, we compared the performance of the nomogram for predicting surgical ICU readmissions to other established ICU risk models, including the Stability and Workload Index for Transfer (SWIFT) score and the Sequential Organ Failure Assessment (SOFA) score.[16]

Statistical analyses

Patient demographic and clinical characteristics, SICU laboratory vales, and vital measures were summarized as means with standard deviation and medians with interquartile range (IQR) for continuous variables or count (%) for categorical variables. For continuous variables with an approximately normal distribution, t tests were used; otherwise Wilcoxon rank sum tests were used for nonparametric data. For categorical variables, a χ^2 or Fisher exact test (when any expected cell count was less than 5) was used. The Hanley and McNeil tests of equality were used to compare ROC areas between different models. The correlation between calculated risk scores and risk perceived by ICU providers was analyzed using the Spearman rank correlation test. Statistical analyses were conducted using R software Version 3.1.2 (R Foundation for Statistical Computing, Vienna, Austria), and all tests were 2-tailed.

Results

A total of 3,313 patients were admitted to the SICU between April 2010 and September 2014, and after applying exclusion criteria, 3,109 patients were used for development of the predictive model (Fig. 1). The included patients were admitted to the general surgery (34%), transplant (9%), trauma (43%), and vascular surgery (14%) services, and about half the patients had undergone a surgical procedure before their index admission. The characteristics of these patients are shown in Table 1. The primary outcome, SICU readmission within 72 hours of SICU discharge, occurred in 141 patients (5%). The reasons for SICU readmission were classified as

Table 1
Characteristics of surgical ICU patients used in the development and validation of nomogram for ICU readmission risk prediction.

Variables	*Development Cohort* N = *3,109% (n)*	*Validation Cohort* N = *577% (n)*
Reason for ICU Admission		
Status postoperative	48 (1,480)	56 (324)
CV Monitoring	33 (1,019)	36 (205)
CNS Monitoring	10 (296)	1 (5)
Respiratory	5 (151)	4 (21)
Bleeding	4 (123)	3 (17)
Peripheral vascular monitoring	1 (29)	0 (0)
Other	<1 (11)	<1 (4)
Admitting service		
Trauma surgery	43 (1,326)	39 (225)
General surgery	34 (1,053)	30 (175)
Vascular surgery	14 (449)	12 (68)
Transplant surgery	9 (281)	19 (109)
Operative status on admission		
Nonoperative	49 (1,538)	44 (252)
Status post–emergency procedure	35 (1,097)	47 (269)
Status post–elective procedure	15 (474)	10 (56)
Severity of illness		
Mechanically ventilated	47 (1,451)	45 (262)
Open abdomen	5 (166)	7 (43)
APACHE II, median (IQR)	13 (9, 18)	14 (11, 20)
Discharged to		
Floor	60 (764)	76 (436)
Stepdown unit	30 (388)	14 (78)
Home	5 (58)	5 (30)
Other ICU	4 (51)	3 (17)
Long-term acute care	1 (16)	3 (15)

CNS, central nervous system; *CV,* cardiovascular.

respiratory (33%), cardiovascular (22%), bleeding (15%), postoperative (12%), infectious (9%), neurologic (4%), other (4%), or major metabolic/endocrine (1%). The in-unit mortality rate for the readmitted cases used for nomogram development was 5.0% (7 of 141), and overall hospitalization mortality was 9.4% (12 of 128, accounts for multiple readmissions). Among all patients admitted to the SICU during the study period (before applying exclusion criteria), the in-hospital mortality rate was 9.1%; the in-unit mortality rate among those not readmitted was 6.0%. Among patients readmitted to the SICU, the in-unit mortality was 8.0% and in-hospital mortality was 12.9%.

Patient demographic characteristics, preadmission comorbidities, and a selection of all candidate predictors ($n = 179$) are shown in Table 2. From these candidate variables, the 7 final predictors were identified: age, blood urea nitrogen, serum chloride, serum glucose, history of chronic atrial fibrillation before initial SICU admission, history of chronic renal insufficiency before initial SICU admission, and respiratory rate (Table 3). The most recently collected value before ICU discharge for each of these variables was used in the model, and values that occurred more than 48 hours before ICU discharge were not considered. The final development model used to construct the SICU readmission nomogram had an AUC of 0.70, sensitivity of 48.3%, specificity of 91.3%, and PPV of 52.9%. In addition, there was no evidence of multicollinearity or overspecification among predictor variables.

The derived nomogram for predicting ICU readmission is shown in Fig. 3. The mathematical equation for calculating readmission risk can be broken into 3 steps. *Step 1*: Calculate Y_1, where $Y_1 = (-9.284491) + 0.04883$ X (Respiratory Rate) + 0.011588 X (Age [years]) + 0.036104 X (Serum Chloride [mEq/L]) + 0.004967 X (Blood Urea Nitrogen [mg/dL]) + 0.580153 X (History of Atrial Fibrillation [value = 1 for "yes" OR value = 0 for "no"]) + 0.458202 X (History of Renal Insufficiency [value = 1 for "yes" OR value = 0 for "no"]) + 0.003519 X (Serum Glucose [mg/dL]). *Step 2:* Calculate Y_2 where $Y_2 = e^{y1}$. *Step 3:* Calculate probability of readmission, where Probability = Y_2 / $(1 + Y_2)$.

Validation of the nomogram was determined using both retrospective and prospective patient cohorts. First, a total of 617 independent patients admitted to the SICU between September 2014 and August 2015 were used to validate the nomogram. Among this cohort, 39 patients (6.3%) were readmitted to the SICU within 72 hours after discharge. The SICU readmission nomogram had moderate discrimination in the validation cohort with an AUC of 0.71, sensitivity of 49.1%, specificity of 92.2%, and PPV of 56.5%. In comparison, the SWIFT and SOFA scores were found to have poor discrimination for predicting readmissions among surgical patients in the same cohort with significantly lower (both $P < .01$) AUCs of 0.58 and 0.56, respectively (Fig. 4). Next the nomogram was prospectively assessed among 130 patients admitted to the SICU between June and August 2017. Among this cohort, there were 7 (5.4%) readmissions. The median (IQR) calculated risk based on the nomogram was 3.7% (2.8%–5.3%), which was significantly higher for patients who were readmitted versus not readmitted (5.3% vs 3.6%; $P < .01$).

The perception of readmission risk for surgical patients was weakly correlated with the calculated risk for ICU readmission (ρ: 0.345; $P < .01$). The most common perceived risk factors that kept patients in the ICU were respiratory issues (50.5%), hemodynamic instability (14.2%), and kidney failure (12.4%). ICU provider's perception of respiratory risk was moderately correlated with a patient's respiratory rate or ventilator status (ρ: 0.44; $P < .001$), although perception of electrolyte abnormalities (ρ: 0.02; $P = .75$), hyperglycemia (ρ: 0.01; $P = .82$), renal insufficiency (ρ: 0.04; $P = .50$), or risk of arrhythmias (ρ: 0.02; $P = .76$) were not correlated with measured values.

Discussion

Unplanned readmissions within 72 hours are recognized as a marker of ICU care quality, and there has been a focus on identifying risk factors for readmission and preventing readmissions among at risk patients.[1-3,20,21] Unfortunately, current ICU

Table 2
Characteristics of surgical ICU patients in study cohort used for model derivation, stratified by readmission status.

Variable	Readmission status		
	Yes N = *141 (5%)*	*No* N = *2968 (95%)*	P
Demographic characteristics			
Age (y), median*	60	55	<.01
Male, %	59	62	.40
Race, %			.19
White	85	80	
African American	3	40	
Asian/Pacific Islander	2	2	
Latin/Hispanic	4	5	
Unknown	7	7	
Other	2	5	
Physician-reported documented comorbidities			
Hypertension, %	48	36	<.01
Type 2 diabetes, %	23	15	.01
Renal insufficiency, %*	13	7	.02
Chronic atrial fibrillation,%*	15	7	<.01
Coronary artery disease, %	11	10	.54
COPD, %	8	5	.21
Congestive heart failure, %	6	4	.14
ICU-related events			
Delirium, %	31	16	<.01
Atrial fibrillation/flutter, %	5	4	.36
Acute respiratory distress syndrome, %	1	1	1
Acute renal failure, %	5	4	.76
Hepatic failure, %,	2	0	.03
Gastrointestinal bleeding, %	1	1	.68
Total parenteral nutrition, %	18	8	<.01
Laboratory values			
Serum sodium, median (IQR)	140 (136, 142)	138 (136, 1,414)	<.01
Blood urea nitrogen, median* (IQR)	22 (14, 35)	16 (11, 26)	<.01
Serum potassium, median (IQR)	4 (3.8, 4.3)	4 (3.8, 4.3)	.87
Anion gap, median (IQR)	7 (6, 9)	7 (5, 9)	.57
Serum chloride, median (IQR)*	109 (105, 112)	107 (104, 111)	.01
Serum glucose, median (IQR)*	123 (106, 154)	118 (101, 141)	.04
Serum creatinine, median (IQR)	0.9 (0.6, 1.3)	0.8 (0.7, 1.1)	.32
Vital signs			
Systolic blood pressure, median (IQR)	126 (111.5, 143)	124 (112, 137)	.20
Diastolic blood pressure, median (IQR)	65 (57, 75)	67 (58, 76)	.18
Mean arterial pressure, median (IQR)	85 (75, 95)	84 (75, 94)	.95
Heart rate, median (IQR)	93 (82, 106.5)	88 (77, 100.8)	.01
Respiratory rate, median (IQR)*	21 (17, 26)	18 (16, 22)	<.01
ICU intravenous medications			
Dexmedetomidine, %	6	4	.2
Propofol, %	48	38	.03
Fentanyl, %	45	37	.04

* One of 7 identified predictors.
COPD, chronic obstructive pulmonary disease.

Table 3
Logistic regression analysis for predicting ICU readmission.

Variable	*Adjusted odds ratio (95% confidence intervals)*	P
Age	1.012 (1.001, 1.023)	.04
History of renal insufficiency	1.581 (0.903, 2.77)	.11
History of chronic atrial fibrillation	1.786 (1.041, 3.065)	.04
Blood urea nitrogen	1.005 (0.996, 1.014)	.30
Serum glucose	1.004 (1, 1.007)	.06
Respiratory rate	1.05 (1.029, 1.072)	<.001
Serum chloride	1.037 (1.004, 1.07)	.03

risk-prediction models are not clinician friendly and have not been designed specifically for surgical populations. In this study we have developed an ICU risk prediction model with moderate discrimination that can be applied to diverse patients within a surgical ICU setting using variables that are known or measured on the vast majority of patients within 48 hours before discharge. The clinical nomogram may provide clinicians with a rapid and simple method to identify surgical patients at risk for readmission and candidates for targeted interventions before transferring from the SICU. Furthermore, our results indicate that calculating patient risk using this nomogram is likely to be a more accurate method for assessing risk than relying on the perception of ICU providers alone.

Although a number of different models have been developed to predict risk for early ICU readmission after discharge, these models each have limitations. The SWIFT score, developed in 2008, is perhaps the most well-known, clinically useful (5 variables), and widely studied of the previous models. It was originally developed and validated in a medical ICU (AUC 0.75).[22] The SWIFT score has been externally validated in mixed medical-surgical ICU populations with varied results.[23] In one small study of 156 patients in Brazil, its prediction ability was quite good (AUC 0.76).[24] But this high level of prediction ability has not been replicated in larger, mixed medical-surgical populations (AUC 0.58–0.66).[18,23,25] These data agree with our results indicating that the SWIFT score was a

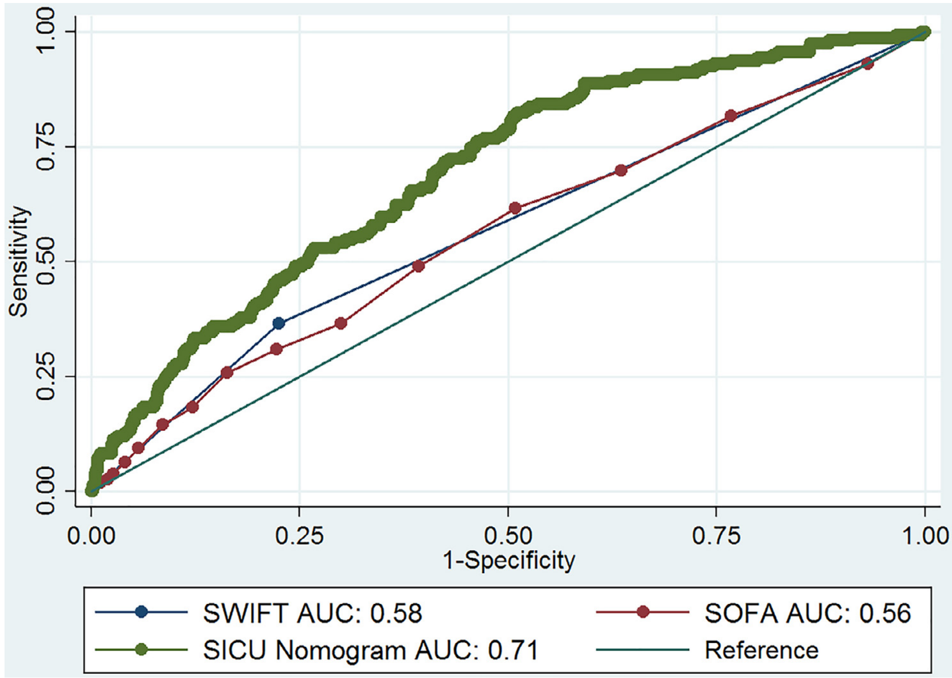

Fig. 4. Predictive ability of surgical intensive care unit (SICU) readmission clinical nomogram as compared to the Stability and Workload Index for Transfer (SWIFT) and the Sequential Organ Failure Assessment (SOFA) models shown by receiving operator characteristic area under the curves (AUC).

poor predictor of ICU readmission when applied exclusively to surgical patient populations.

Severity of illness ICU scoring systems such as SOFA, SAPS (Simplified Acute Physiology Score), TISS-28 (Therapeutic Intervention Scoring System), and APACHE II (Acute Physiology and Chronic Health Evaluation) have also been evaluated for their ability to predict ICU readmission.[16,18,26] Although these severity of illness scores were not designed for this purpose, prediction ability results have been similar to that of the SWIFT scoring model. A 2015 paper by Rosa et al[18] evaluated SOFA and TISS-28 scores in 1,277 patients in a mixed medical-surgical ICU calculated on the day of discharge, with resulting AUCs of 0.65 and 0.74 ($P = .58$). Nevertheless, we found the SOFA score to be a very poor predictor of surgical ICU readmission in our cohort with an AUC of only 0.56. It is also worth noting that use of these severity of illness scores often mandates collection of a large number of variables, some of which seem irrelevant to a patient ready to leave the ICU (eg, pulmonary artery catheter use, TISS-28). Furthermore, these severity of illness scores often include laboratory values that are not routinely drawn shortly before ICU discharge (eg, arterial pH, APACHE II) making them less clinically useful prospectively and introducing potential selection bias when they are required for analysis in retrospective studies. In addition to these more well-known scoring systems, models with higher complexity have also been examined with limited gains in prediction ability. Fialho et al[19] created models that included calculated means of continuously monitored variables such as heart rate and SpO_2 (AUC 0.72). Although Ouanes et al[17] achieved an AUC of 0.74, their final model is limited in terms of rapid use at the bedside in the ICU given that it uses a computer-generated multivariate equation that requires imputation of multiple calculated variables, including SAPS II (admission), central venous catheter (while in ICU), systemic inflammatory response syndrome (discharge), SOFA (discharge), and discharge at night.[17]

Intensive care unit readmission risk prediction tools gain clinical relevance only if they are accurate and easy to implement at the bedside by already busy clinical providers. The graphic nomogram (Fig. 3) developed in this study takes just minutes to use at the bedside and provides a numeric risk for ICU readmission. Moreover, the model used to calculate the nomogram risk score can be incorporated into available electronic health record applications that generate automatic risk scores based on patient variables. Whether a graphic or electronic health record version of the nomogram is used, the numeric risk of readmission provided by the model should be interpreted in the context of a surgical ICU setting overall and targeted rates of readmission, and consideration should be given to the institutional costs of additional ICU days.

On an individual patient level, the nomogram was designed to be used as an adjunctive measure to clinical judgment during ICU rounds, helping to identify patients at high risk for ICU readmission who subjectively appear ready for ICU discharge. Identifying patients with higher than normal ICU readmission risk allows providers to then see what variables are weighing the risk model most heavily. Although not every risk factor in the model is directly amenable to intervention, some variables such as respiratory rate allow the potential for targeted interventions such as additional respiratory therapy to reduce this risk. Moreover, the nomogram allows ICU patients to be risk stratified when ICU bed shortages mandate selecting patients who are least likely to deteriorate when they arrive on the floor. Delaying SICU discharge for patients with elevated risk may in turn either directly or indirectly improve their clinical outcome by way of either preventing a clinical deterioration altogether or by having it occur in a more closely monitored setting where immediate interventions can be taken to mitigate the clinical consequences. As our data indicate, patient risk is not always perceived by ICU providers and can be highlighted by the nomogram before discharge. It has been well documented that patients who leave the ICU and are readmitted have worse clinical outcomes, and among all patients examined during this period, those who were readmitted within 72 hours had an 8% unit mortality rate, more than a 30% increase compared with a rate of 6% among those who were not readmitted within 72 hours.[4,9-11]

The tool may also be used on a unit level when bed needs for a new admission necessitates transfer out of the least sick patients. In this circumstance, it may be used to help identify the patients at lowest risk for ICU readmission. The component variables of the nomogram developed in this study are available in virtually all ICU patients, which is unique advantage to this model compared with previous scoring systems. Furthermore, this feature limited selection bias during model development, which has been an issue with some prior models and discourages the collection of additional laboratory values (eg, PaO_2) that would not otherwise be drawn in a patient who appears ready for ICU discharge.

There are several limitations of this study to discuss. First, the development of the nomogram only included patients from the surgical ICU in a single tertiary care medical center where readmission rates are low. Validation of the predictive nomogram across other sites with a SICU will be warranted to assess external validity and ensure adequate power. Furthermore, this nomogram would likely not be applicable to medical and mixed ICUs given that development and validation occurred using a surgical patient population. Second, the nomogram is limited by its moderate prediction ability, which is likely influenced by the heterogeneity of different surgical specialty patients included in the development model. Focusing on a more homogenous patient cohort may improve the predictive power of the model but could lose generalizability. Moreover, the AUC of the development and validation cohorts is consistent with other published ICU readmission risk prediction models. Finally, our study was not designed to determine whether patients received interventions based on perceived or calculated risk of readmission and whether this resulted in improved morbidity or mortality. However, this is the topic of a future prospective clinical study.

In conclusion, unplanned readmission within 72 hours of SICU discharge for surgical ICU patients can be predicted using a nomogram based on 7 common demographic and physiologic variables. The unique advantages offered by this model are its construction and validation in a diverse but exclusively surgical population and that the 7 variables are generally available daily in all ICU patients. The nomogram is designed to be clinically applicable to a broad spectrum of surgical patients before they leave the ICU and to assist in identifying patients who may benefit from targeted interventions to optimize health status before leaving the ICU setting. In addition, it may help stratify patients when ICU bed shortages mandate selecting patients who are most likely to deteriorate in status when they arrive on the hospital ward.

Acknowledgments

The statistical analysis performed by Dr. Al-Dulaimi was supported in part by the University of Utah Study Design and Biostatistics Center, with funding from the National Center for Research Resources and the National Center for Advancing Translational Sciences, National Institutes of Health, through Grant 5UL1TR001067-02 (formerly 8UL1TR000105 and UL1RR025764)

References

1. Nates JL, Nunnally M, Kleinpell R, Blosser S, Goldner J, Birriel B, et al. ICU admission, discharge, and triage guidelines: a framework to enhance clinical operations, development of institutional policies, and further research. *Crit Care Med*. 2016;44:1553–1602.
2. Guidelines for intensive care unit admission, discharge, and triage. Task Force of the American College of Critical Care Medicine, Society of Critical Care Medicine. *Crit Care Med*. 1999;27:633–638.
3. Cooper GS, Sirio CA, Rotondi AJ, Shepardson LB, Rosenthal GE. Are readmissions to the intensive care unit a useful measure of hospital performance? *Med Care*. 1999;37:399–408.
4. Rosenberg AL, Hofer TP, Hayward RA, Strachan C. Watts CM Who bounces back? Physiologic and other predictors of intensive care unit readmission. *Crit Care Med*. 2001;29:511–518.
5. Brown SE, Ratcliffe SJ, Kahn JM, Halpern SD. The epidemiology of intensive care unit readmissions in the United States. *Am J Respir Crit Care Med*. 2012;185:955–964.
6. Al-Jaghbeer MJ, Tekwani SS, Gunn SR, Kahn JM. Incidence and etiology of potentially preventable ICU readmissions. *Crit Care Med*. 2016;44:1704–1709.
7. Wong EG, Parker AM, Leung DG, Brigham EP, Arbaje AI. Association of severity of illness and intensive care unit readmission: a systematic review. *Heart Lung*. 2016;45:3–9.e2.
8. Renton J, Pilcher DV, Santamaria JD, Stow P, Bailey M, Hart G, Duke G. Factors associated with increased risk of readmission to intensive care in Australia. *Intensive Care Med*. 2011;37:1800–1808.
9. Rosenberg AL, Watts C. Patients readmitted to ICUs: a systematic review of risk factors and outcomes. *Chest*. 2000;118:492–502.
10. Kramer AA, Higgins TL, Zimmerman JE. The association between ICU readmission rate and patient outcomes. *Crit Care Med*. 2013;41:24–33.
11. Fernandez R, Serrano JM, Umaran I, Abizanda R, Carrillo A, Lopez-Pueyo MJ, et al. Ward mortality after ICU discharge: a multicenter validation of the Sabadell score. *Intensive Care Med*. 2010;36:1196–1201.
12. Cooper LM, Linde-Zwirble WT. Medicare intensive care unit use: analysis of incidence, cost, and payment. *Crit Care Med*. 2004;32:2247–2253.
13. Chen LM, Martin CM, Keenan SP, Sibbald WJ. Patients readmitted to the intensive care unit during the same hospitalization: clinical features and outcomes. *Crit Care Med*. 1998;26:1834–1841.
14. Durbin Jr CG, Kopel RF. A case-control study of patients readmitted to the intensive care unit. *Crit Care Med*. 1993;21:1547–1553.
15. Chan KS, Tan CK, Fang CS, Tsai CL, Hou CC, Cheng KC, et al. Readmission to the intensive care unit: an indicator that reflects the potential risks of morbidity and mortality of surgical patients in the intensive care unit. *Surg Today*. 2009;39:295–299.
16. Hosein FS, Bobrovitz N, Berthelot S, Zygun D, Ghali WA, Stelfox HT. A systematic review of tools for predicting severe adverse events following patient discharge from intensive care units. *Crit Care*. 2013;17:R102.
17. Ouanes I, Schwebel C, Francais A, Bruel C, Phillippart F, Vesin A, et al. A model to predict short-term death or readmission after intensive care unit discharge. *J Crit Care*. 2012;27:422.e1–422.e9.
18. Rosa RG, Roehrig C, de Oliveira RP, Maccari JG, Antonio AC, Castro Pde S, et al. Comparison of unplanned intensive care unit readmission scores: a prospective cohort study. *PLoS One*. 2015;11.
19. Fialho AS, Cismondi F, Vieira SM, Reti SR, Sousa JMC, Finkelstein SN. Data mining using clinical physiology at discharge to predict ICU readmissions. *Expert Syst Appl*. 2012;39:13158–13165.
20. Stelfox HT, Bastos J, Niven DJ, Bagshaw SM, Turin TC, Gao S. Critical care transition programs and the risk of readmission or death after discharge from ICU. *Intensive Care Med*. 2016;42:401–410.
21. Metnitz PG, Fieux F, Jordan B, Lang T, Moreno R, Le Gall JR. Critically ill patients readmitted to intensive care units—lessons to learn? *Intensive Care Med*. 2003;29:241–248.
22. Gajic O, Malinchoc M, Comfere TB, Harris MR, Achouti A, Yilmaz M, et al. The stability and workload index for transfer score predicts unplanned intensive care unit patient readmission: initial development and validation. *Crit Care Med*. 2008;36:676–682.
23. Kareliusson F, De Geer L, Tibblin AO. Risk prediction of ICU readmission in a mixed surgical and medical population. *J Intensive Care*. 2015;3:30.
24. Oakes DF, Borges IN, Forgiarini Junior LA, Rieder Mde M. Assessment of ICU readmission risk with the stability and workload index for transfer score. *J Bras Pneumol*. 2014;40:73–76.
25. Kastrup M, Powollik R, Balzer F, Rober S, Ahlborn R, von Dossow-Hanfstingl V, et al. Predictive ability of the stability and workload index for transfer score to predict unplanned readmissions after ICU discharge. *Crit Care Med*. 2013;41:1608–1615.
26. Alban RF, Nisim AA, Ho J, Nishi GK, Shabot MM. Readmission to surgical intensive care increases severity-adjusted patient mortality. *J Trauma*. 2006;60:1027–1031.