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A Tool to Predict Readmission to the Intensive Care Unit in Surgical Critical Care Patients—The RISC Score

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Abstract

Background: Readmission to the Intensive Care Unit (ICU) is associated with a high risk of in-hospital mortality and higher health care costs. Previously published tools to predict ICU readmission in surgical ICU patients have important limitations that restrict their clinical implementation. We sought to develop a clinically intuitive score that can be implemented to predict readmission to the ICU after surgery or trauma. We designed the score to emphasize modifiable predictors. **Methods:** In this retrospective cohort study, we included surgical patients requiring critical care between June 2015 and January 2019 at Beth Israel Deaconess Medical Center, Harvard Medical School, MA, USA. We used logistic regression to fit a prognostic model for ICU readmission from a priori defined, widely available candidate predictors. The score performance was compared with existing prediction instruments. **Results:** Of 7,126 patients, 168 (2.4%) were readmitted to the ICU during the same hospitalization. The final score included 8 variables addressing demographical factors, surgical factors, physiological parameters, ICU treatment and the acuity of illness. The maximum score achievable was 13 points. Potentially modifiable predictors included the inability to ambulate at ICU discharge, substantial positive fluid balance (>5 liters), severe anemia (hemoglobin <7 mg/dl), hyperglycemia (>180 mg/dl), and long ICU length of stay (>5 days). The score yielded an area under the receiver operating characteristic curve of 0.78 (95% CI 0.74-0.82) and significantly outperformed previously published scores. The performance of the underlying model was confirmed by leave-one-out cross-validation. **Conclusion:** The RISC-score is a clinically intuitive prediction instrument that helps identify surgical ICU patients at high risk for ICU readmission. The simplicity of the score facilitates its clinical implementation across surgical divisions.

Keywords

readmission to the intensive care unit, score development, surgical intensive care unit, functional mobility, fluid balance, hyperglycemia, anemia

Introduction

Readmission to the intensive care unit (ICU) is associated with 4-fold higher odds of in-hospital mortality, prolonged length of hospital stay and increased healthcare costs.[1-4] ICU readmission has been identified as an ICU performance indicator by the Task Force on Safety and Quality of the European Society of Intensive Care Medicine[5] and the Society of Critical Care Medicine.[6] Only a few modifiable predictors of ICU readmission are known.[7,8]

Previously published tools to predict ICU readmission in surgical ICU patients were difficult to externally validate and implement.[9,10] Additionally, most were developed either in small cohorts or in specific sub-cohorts of surgical critical care patients.[11-14] and all lacked recently introduced modifiable factors associated with ICU readmission such as mobility level at ICU discharge.[9-13,15]

We sought to develop a score to predict readmission to the ICU in all surgical ICU patients, including cardiac surgery, that is easily applicable, transparent and can be calculated at the bedside. We further compared the score to 2 previously developed, applicable prediction instruments.[12,13]

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Methods

After approval of the study by the institutional review board (protocol number: 2020P000126, Committee on Clinical Investigations, Beth Israel Deaconess Medical Center, Boston, MA), we included patients admitted to a surgical ICU (SICU) at Beth Israel Deaconess Medical Center, Boston, MA, USA between June 2015 and January 2019. We excluded patients who died, patients who were transitioned to comfort measures only during their index ICU stay, and patients who had an American Society of Anesthesiologists (ASA) physical status classification of VI. Data were collected from multiple hospital databases that comprise patient, surgery, anesthesia, ICU and outcome-related data (Supplemental Material, Section 1).

Definition of Outcome and Candidate Predictors

The primary outcome was readmission to the ICU within the same hospitalization.[12,15] Candidate predictors were a priori defined based on literature review focusing on newly introduced predictors that are potentially modifiable, e.g. after-hours discharge, fluid balance and functional mobility. Functional mobility is particularly amenable to intervention. At BIDMC, nurses and physical therapists assess the Johns Hopkins Highest Level of Mobility multiple times a day. At the beginning of each day, a mobility goal for the day is set in order to allow constant improvement of a patient's functional mobility. An increase of 1 score point value per day is the goal for patients in the ICU. We only included easily accessible and broadly available data in order to facilitate external validation. A list of candidate predictors and definitions is presented in Supplemental Material, Section 2.

Score Development

A multivariable logistic regression model was used to predict ICU readmission. All candidate predictors were included as independent variables in the model. Stepwise elimination was performed with a cutoff p-value of ≤ 0.05 for retaining predictors in the model. Bootstrapping with 100 samples was performed to eliminate predictors not contributing to the model's fit. Additionally, we conducted a penalized maximum likelihood estimation to address possible overfitting of the model. Penalized likelihood, or regularization, methods can be used in statistics to 1) decrease model complexity and 2) reduce variance in parameter estimates. The original likelihood function and the penalty function are combined to compute parameter estimates by maximizing the new objective function. Candidate predictors that remained significant were weighted. Subsequently, to arrive at an integer score, the beta coefficient of respective predictors was divided by the overall smallest beta coefficient of all remaining significant predictors. After rounding the calculated value to the nearest integer, we arrived at the respective score point value. We performed internal validation of the model utilizing *leave-one-out cross-validation*. Beta values are estimated for all but one observation of the training set, followed by assessment of model-performance for the left-out observation. This is repeated for every single observation in the cohort (Supplemental Material, Section 3). This allows us to assess apparent model performance examining variations in the parameter estimates and model fit for out of sample predictions.

Score Characterization and Performance Assessment

C-statistics were assessed (area under the receiver operating characteristic curve, ROC-AUC) and the Brier Score (average squared difference between patients' predicted probability and the actual outcome) was calculated. Youden's index[16] was used to determine the optimal cutoff to differentiate between high and low risk patients. The corresponding positive and negative predictive values were then calculated to characterize the performance of the RISC-score at the cutoff value.

Secondary Analyses

We compared the predictive value of the RISC-score to 2 other established ICU readmission prediction nomograms published by Frost et al. in 2010[12] and Martin et al. in 2019.[13] Comparison of C-statistics was conducted using the *roccomp* command in Stata in a sub-cohort with available data for the calculation of all 3 scores. Finally, we performed a decision curve analysis to assess the possible net benefit gained by applying the different scores. The net benefit is defined as the proportion of true positive subtracted by the proportion of false negatives weighted by the odds of the respective risk threshold.[17]

Exploratory Analyses

Due to the strong predictive value of anemia and its association with bleeding, we categorized readmission reasons (Supplemental Material, Section 5) and assessed the discrimination of RISC for bleeding-related readmissions using this category as an independent outcome.

Sensitivity Analyses

We conducted several sensitivity analyses to confirm the robustness of our findings. C-statistics were used to confirm primary findings. We conducted multiple imputation with chained equations to address missing data for predictors. To address possible bias derived from the outcome, we conducted sensitivity analyses; 1) excluding patients who died on the ward after discharge from the index ICU stay; 2) using a composite outcome of readmission to the ICU or in-hospital death after ICU discharge and 3) limiting the outcome to ICU readmission within 10 days after ICU discharge rather than ICU readmission any time prior to discharge from hospital.

Statistical Analyses

Variables were expressed as mean $\pm$ standard deviation, median (interquartile range) or frequency (%) if not otherwise

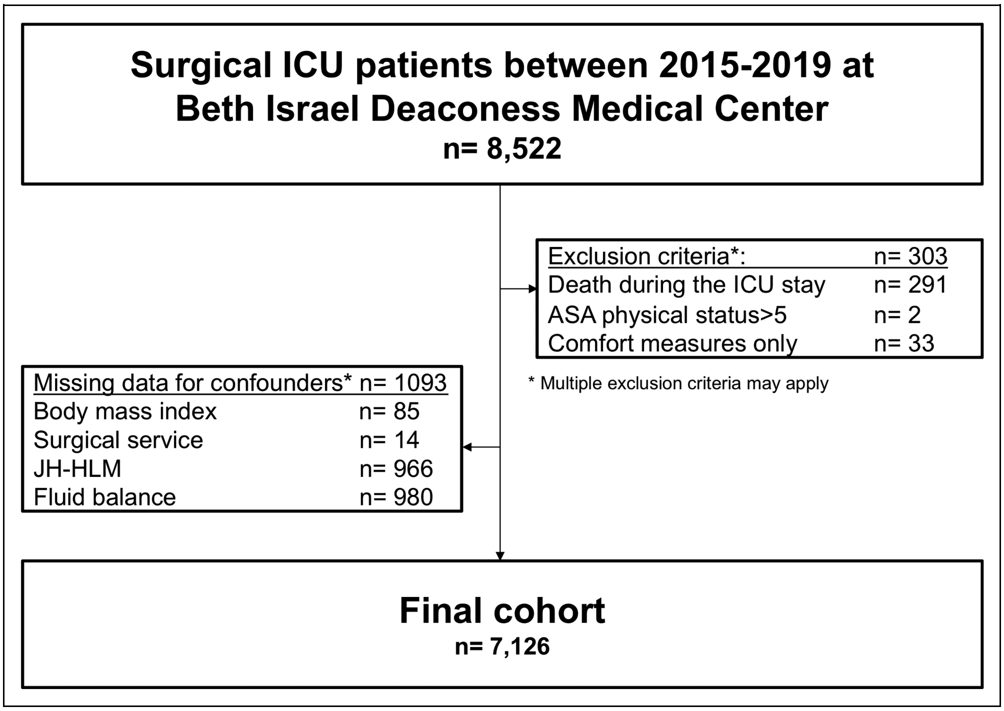

Figure 1. Study flow. Abbreviations: ASA American Society of Anesthesiologists, JH-HLM Johns Hopkins Highest Level of Mobility, ICU Intensive Care Unit.

specified. We managed the database and conducted all statistical analyses in Stata 15 (Statacorp, College Station, Texas). Figures were created using Prism 8 (GraphPad Software, San Diego, California).

Results

We included 7,126 cases in the final study cohort. 168 (2.4%) SICU patients were readmitted to the ICU. Figure 1 shows the study flow. Cohort characteristics are presented in Table 1.

Score Development

We identified 8 independent predictors of ICU readmission derived from stepwise backward elimination (Figure 2). Final predictors included: *demographics and surgical factors* such as sex and surgical service, *factors describing the acuity of illness*: APACHE II-Score at ICU admission of >20 as well as 5 potentially modifiable predictors including *physiological parameters within 24 h before discharge:* severe anemia (<7 mg/dl), hyperglycemia (>180mg/dl) and factors of *ICU treatment*: A positive fluid balance >5 liters over the operation and the ICU stay, the inability to ambulate 10 steps or more within 24 hours prior to discharge and the duration of the ICU stay >5 days. Score points for single predictors ranged from -3 to 3, with a minimum of -3 and a maximum of 13 overall achievable score points. The median of RISC in the cohort was 3 points with an interquartile range of 1 to 5 score points.

Score Performance

RISC yielded an AUC of 0.78 (95% CI 0.74-0.82) and a Brier Score of 0.022 (reliability <0.001). Performance of the underlying model for RISC in predicting all-cause ICU readmission was confirmed by leave-one-out cross-validation (AUC 0.80, 95% CI 0.77-0.84).

Score dichotomization using Youden's J-statistics was 5 score points, resulting in 5,054 (70.9%) patients classified as low risk and 2,072 (29.1%) classified as high-risk patients. Using this cutoff definition, RISC had good discrimination with a sensitivity of 0.74 and specificity of 0.72. Corresponding characteristics for different score point cutoffs are depicted in further detail in eTable2 in the Supplemental Material.

Secondary Analyses

The scores of Frost et al. and Martin et al. were compared with RISC in predicting ICU readmission in a cohort of 7,009 patients with available data for all scores (98.4% of patients included in the primary cohort) (Figure 3). Individual comparison showed superior discrimination of the RISC-score over Frost et al. and Martin et al. ($p = 0.004$ and $p < 0.001$, respectively).

Decision curve analyses revealed a positive net benefit of the RISC-score for predicted probability thresholds between 0 and 12% (corresponds to RISC-score values of -2 to 9). Further, we found a higher net benefit for the RISC-score compared to previously published prediction models across a broad spectrum of predicted probability thresholds (Figure 4).

Table 1. Patient Characteristics.

Factor	No readmission to the ICU	Readmitted to the ICU
N	6958 (97.6%)	168 (2.4%)
Demographics		
RISC-score, median (IQR)	3 (1, 5)	6 (4, 7)
Age	64 ± 14	64 ± 15
Gender		
Female	2870 (41.2%)	58 (34.5%)
Male	4088 (58.8%)	110 (65.5%)
BMI, mean ± SD	28.76 ± 6.62	29.40 ± 15.56
Admission source		
OR	5887 (84.6%)	108 (64.3%)
ED	156 (2.2%)	9 (5.4%)
Floor	879 (12.6%)	47 (28.0%)
Outside facility	36 (0.5%)	4 (2.4%)
Emergency surgery	1338 (19.2%)	57 (33.9%)
Afterhour Discharge	4432 (63.7%)	130 (77.4%)
ICU Length of stay	4 ± 5	8 ± 9
Comorbidities		
Acute renal failure	327 (4.7%)	19 (11.3%)
Congestive heart failure	1478 (21.2%)	44 (26.2%)
Fall within 3 months	980 (14.1%)	39 (23.2%)
Physiological factors during last 24 h before discharge		
Median Heart Rate during last 24 h	81 (72, 90)	88 (79, 95)
Median RR during last 24h	18 (16, 20)	19 (16, 22)
Hypoglycemia	92 (1.3%)	2 (1.2%)
Hyperglycemia	1906 (27.4%)	59 (35.1%)
Hypothermia	280 (4.0%)	2 (1.2%)
Hyperthermia	93 (1.3%)	3 (1.8%)
Hemogblobin <7mg/dl	96 (1.4%)	8 (4.8%)
Sputum Amount		
No sputum	6166 (88.6%)	136 (81.0%)
Little	180 (2.6%)	6 (3.6%)
Medium	357 (5.1%)	12 (7.1%)
Much	255 (3.7%)	14 (8.3%)
Pain present during last 24 h	3973 (57.1%)	87 (51.8%)
Maximum functional mobility during last 24 hours		
Walking >10 steps	2500 (35.9%)	27 (16.1%)
Impaired functional mobility	4458 (64.1%)	141 (83.9%)
ICU treatment during last 24 h before discharge		
Invasive ventilation during last 24h	1365 (19.6%)	19 (11.3%)
IV propofol	1051 (15.1%)	11 (6.5%)
IV dexmedetomidine	295 (4.2%)	3 (1.8%)
IV antipsychotics	63 (0.9%)	1 (0.6%)
IV benzodiazepines	254 (3.7%)	10 (6.0%)
Restrains during last 24h	1924 (27.7%)	72 (42.9%)
Delirium within 24h	549 (7.9%)	26 (15.5%)
Acuity of illness		
APACHE II	18.11 ± 6.14	20.77 ± 6.76
Surgical Service		
Neurosurgery	681 (9.8%)	15 (8.9%)
Cardiac	3125 (44.9%)	28 (16.7%)
General	1335 (19.2%)	78 (46.4%)
Surgical Oncology	36 (0.5%)	3 (1.8%)
Transplant (Liver and Kidney)	66 (0.9%)	2 (1.2%)
Other	1053 (15.1%)	16 (9.5%)
Thoracic	179 (2.6%)	9 (5.4%)
Trauma/Orthopedic	585 (8.4%)	22 (13.1%)

Sensitivity Analyses

Our primary results remained robust throughout all sensitivity analyses. Imputation of missing data added 1,093 cases that were previously excluded due to missing data. Primary results remained robust throughout all sensitivity analyses (Supplemental Material, Section 4).

Exploratory Analyses

From 168 readmission to the ICU, 15 (8.9%) were related to bleeding. C-statistics revealed that the RISC-score predicted bleeding-related readmission with an excellent AUC of 0.84 (95% CI 0.75-0.94).

Discussion

In this study, we developed a clinically intuitive instrument to help identify patients at high risk of readmission to the ICU. In addition to 3 surgical and demographic predictors, the score included 5 potentially modifiable parameters: functional mobility status, abnormal hematocrit, hyperglycemia, fluid overload and an ICU stay of more than 5 days.

Currently, 6 prediction instruments for ICU readmission developed for surgical ICU patients exist.[9-14,18] Three are limited by barriers to implementation and data quality,[9,10,18] 3 are limited to certain subpopulations within surgical critical care such as cardiac surgery[11-13] and all 6 were developed without surgical variables and newly introduced modifiable predictors of ICU readmission.[9-13,18]

We chose to include variables in the development of the score based on expert clinical judgment, such as days spent ventilated and the volume of airway secretions. Compared to the RISC-score, machine learning approaches developed by Lin et al.[9] and Desautels et al.[10] face many barriers to implementation and validation in that they use a large number of variables and are difficult to calculate at the bedside. The need for advanced information management systems capable of calculating complex scores from multiple data source inputs could inhibit widespread use of these algorithms. We argue that in order to implement change in clinical practice in the ICU, it is helpful for scores to be relatively simple, with the necessary information easily retrievable for the ICU team. We therefore developed an easily calculated score that does not use a large number of parameters. All of which are easily retrievable for the ICU staff.

Additionally, these machine-learning based algorithms, as well as other instruments[18] were developed using the MIMIC II database which has important limitations including very limited validation and a significant number of physiologically implausible values.[19] By contrast, we have conducted an intensive validation of our database used for score generation.[15]

In another study done in 421 patients undergoing cardiac surgery, Magruder et al. developed a score that is transparent

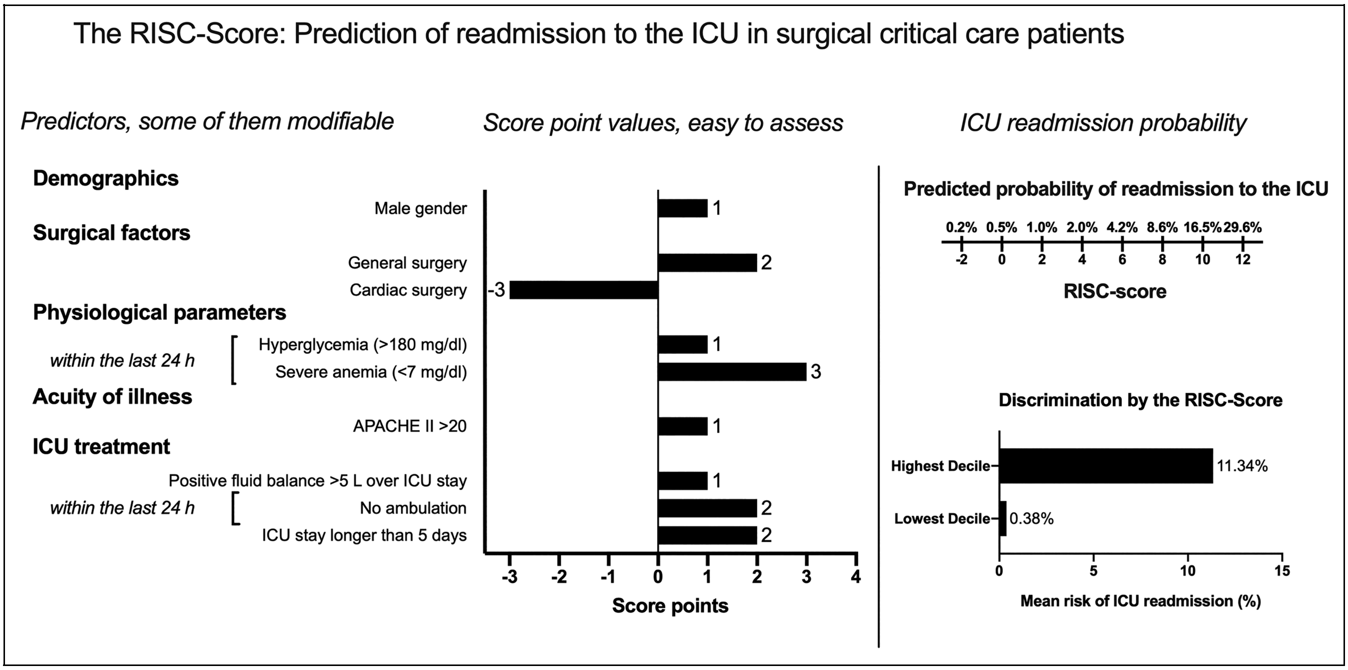

Figure 2. The RISC-score: Summary Figure. The RISC-Score predicts readmission to the ICU in surgical critically ill patients. It focuses on predictors that are modifiable, is easy to assess and can be used for a diverse group of SICU patients including those undergoing cardiac surgery. The figure summarizes the variables included in the RISC-score with corresponding score point values. Additionally, the predicted probabilities of ICU readmission of the highest and lowest decile as discriminated by the RISC-score are shown.

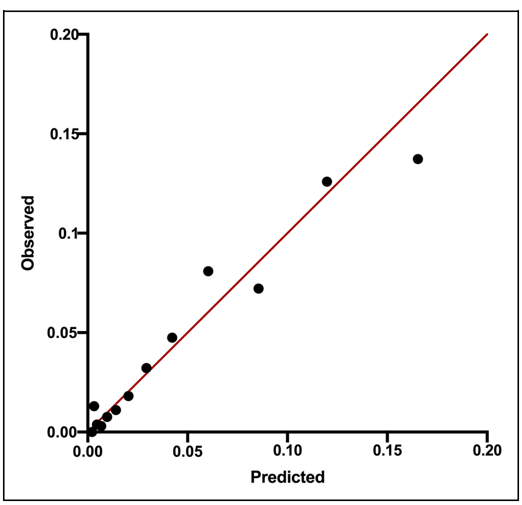

Figure 3. Calibration plot of the RISC-score. Observed over expected fraction of ICU readmissions for observation groups with reference line (red) for the RISC score in the development cohort.

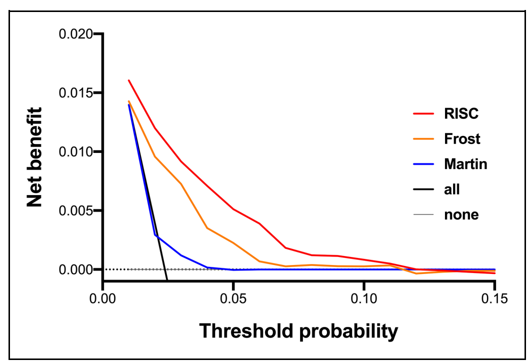

Figure 4. Decision curve analyses depicting the net benefit for the RISC-score, Frost et al. and Martin et al. Results from decision curve analyses: the RISC-score yields a positive net benefit over a broad spectrum of threshold probabilities and outperforms previously published algorithms. x-axis: Threshold probability of ICU readmission at which a patient would be classified as being at high risk for being readmitted to the ICU after discharge, prompting initiation of preventive measures. y-axis: Net benefit of model: proportion of true positive classifications subtracted by proportion of false negatives weighted by the odds of the risk threshold.

and easy to implement. However, it was focused on a small sub-population of cardiac surgical patients and developed with a small sample size.[11] The proportion of patients undergoing elective, standardized fast-track surgeries is higher in this specific sub-cohort than in general surgical ICU patients.[11,15] This characteristic of cardiac surgical patients may explain the lower ICU readmission risk we found for patients undergoing cardiac surgery in our cohort (-3 points in the RISC-score). Scores developed by Martin et al.[13] and Frost et al.[12] focus on surgical ICU patients without cardiac surgical patients. However, in smaller hospitals, cardiac-surgical and non-cardiac surgical patients are often treated by the same intensive care clinical team. Thus, both scores could not be applied to all surgical ICU patients in a given institution. Martin et al. and Frost et al. provide exact details on score calculation and allow easy validation.[14] However, both were developed before newly identified, important predictors of ICU readmission such as functional mobility at ICU discharge were introduced. Our data show that the RISC-score outperformed both scores in the prediction of ICU readmission.

Functional mobility status plays an important role in ICU readmission prediction. Recent studies show that patients who are able to stand but cannot ambulate at least 10 steps before ICU discharge have a 1.2% absolute higher risk of ICU readmission attributable solely to their impaired functional mobility status after adjusting for a variety of known predictors and acuity of illness.[15] This is supported by our data; low functional mobility with inability to ambulate 10 or more steps within 24 hours prior to discharge is given 2 score points, which translates to a more than doubled risk for ICU readmission (OR for ICU readmission with a 2 point increase of the RISC-score: 2.11 [1.87-2.37], p<0.001). The WHO defines *activities* such as functional mobility as the interplay of multiple *body functions and structures*. This integration of *body functions*, including isolated muscle strength and balance, can be improved during the ICU stay as demonstrated in several randomized controlled trials. Based on these trials, we believe that among the potentially modifiable predictors in our score, functional mobility is perhaps the most promising as a target to reduce readmission risk.[20-23] Additionally, unlike strength measures, functional mobility has not shown a ceiling effect in previous studies and therefore allows good discrimination.[15,24] This is supported by our data: only 35% of patients reached a level of ambulation of at least 10 steps within 24 hours prior to discharge.

In the RISC-score, severe anemia with Hb <7 mg/dl within 24 hours prior to discharge was the most important modifiable risk factor for ICU readmission (3 points). This degree of anemia is widely accepted as the lowest threshold to consider for transfusing packed red blood cells in critically ill patients.[25,26] Anemia can lead to tissue hypoxia in patients at high risk for perioperative complications and might be detrimental.[27-29] In addition to serving as a marker for tissue hypoxia, severe anemia might also signal blood loss from surgery, ICU interventions including unnecessary blood sampling, sepsis and undetected bleeding in critically ill patients.[30-32] This is supported by our finding that the RISC-score predicts bleeding-related readmissions with an excellent AUC of 0.84 (95% CI 0.75-0.94). In patients with hemoglobin <7 mg/dl during the 24 hours preceding ICU discharge, clinicians should evaluate possible causes of low hemoglobin such as sources of occult bleeding and consider administration of packed red blood cells. It remains unclear if anemia can be prevented effectively. It may be helpful to limit frequent blood draws and procedures where appropriate by reducing length of stay in the ICU where possible to 5 days or less, which we identified as another independent predictor of ICU readmission.

While many patients have prolonged ICU stays because of ongoing critical illness, studies have demonstrated that a substantial percentage of patients remain in the ICU for longer than necessary because of non-clinical delays such as lack of ward beds. Unnecessary prolongation of exposure to the ICU environment particularly harms healthier patients due to higher frequency of potentially unnecessary interventions and associated complications, such as ongoing blood sampling of approximately 41 ml per day[33] and the increasing risk of anemia over time.[34-39] Our finding highlights a potential benefit of systems that facilitate timely discharge from the ICU when medically appropriate.

Hyperglycemia on the day of ICU discharge (serum glucose level of 180 mg/dl or above) predicts ICU readmission. The data on the efficacy of intensive insulin-therapy in reducing adverse outcomes is equivocal. Van de Berghe et al. in 2001[40] showed a significant decrease in mortality with tight glucose control between 80 and 110 mg/dl compared to only intervening if serum glucose rose above 215 mg/dl. Follow up-studies with an even more aggressive approach showed that tight glucose control increased the risk of severe hypoglycemia (<40 mg/dl) and complications.[41] Of note, the target serum glucose of control groups in these follow up studies was 140-180 mg/dl in order to maintain equipoise in light of previous trial results. Over time, maintaining blood glucose below 180mg/dl became the standard of care, with subsequent trials demonstrating that further reduction in blood glucose targets was detrimental and an intermediate target glucose level of 110- 180 mg/dl might be the preferable target range for ICU patients.[42,43] Our data support the current consensus; the RISC-score shows a significant increase in the likelihood of ICU readmission if hyperglycemia above 180 mg/dl occurs within 24 hours prior to ICU discharge. Moderate glucose control is necessary and recommended.[44,45] Our findings indicate that maintaining moderate glucose control with target glucose <180 mg/dl might help to prevent readmissions to the ICU in surgical critical care patients.

Another potentially modifiable predictor of ICU readmission is an excessively positive fluid balance of more than 5 liters over the course of the operation and subsequent ICU stay. Acid-base disturbances and impaired gas exchange due to tissue edema are consequences of fluid overload, increasing the risk of adverse outcomes such as mortality, respiratory complications and acute renal failure.[46,47] Strategies that limit fluid administration and promote diuresis have been widely adopted and have been demonstrated to improve outcomes in patients undergoing thoracic and abdominal surgery[48,49] and in patients suffering from complications of surgery such as pneumonia, sepsis or acute respiratory distress syndrome.[50]

The observational design of the study with model development based on data on file confers risks of unmeasured bias, such as unidentified predictors due to misclassified data and measurement errors. The outcome measure, readmission to the ICU, was validated by chart review to minimize these risks. Additionally, to further reduce the risk of measurement and recording errors, only datapoints that were electronically validated by the clinical care team were used to generate physiological predictors, minimizing possible bias.

Currently, the RISC-score has not been externally validated. However, cross-validation was performed on the underlying model with excellent results and the score was developed in a large cohort of cardiac and non-cardiac surgical patients to ensure generalizability. The studied cohort comprises a wide variety of surgical ICU patients including trauma, surgical oncology, transplant (kidney and liver), cardiac surgery, general surgery and neurosurgery patient populations admitted to an ICU at an academic tertiary care center. The score is therefore most applicable to these patient populations. By contrast, since our hospital does not care for burn, pediatric or heart transplant patient populations, our instrument cannot be applied to these patient cohorts. Our score will be implemented into the ICU systems at Beth Israel Deaconess Medical Center, Harvard Medical School, which will facilitate future prospective studies of interventions to reduce ICU readmission.

Conclusion

We developed a score to predict ICU readmission in surgical ICU patients which was well-calibrated with good discrimination. The RISC-score outperformed previously developed prediction instruments by utilizing newly introduced modifiable predictors. The score is applicable in both cardiac and non-cardiac surgical patients admitted to the ICU.

Authors' Note

Matthias Eikermann is also affiliated with Klinik für Anästhesiologie und Intensivmedizin, Universitätsklinikum Essen, Essen, Germany. Study concept and design: MH, SDG, BT, ME. Acquisition of data: MH, SDG, ME. Analysis and interpretation of data: All authors. Drafting of the manuscript: MH, SDG, BT, ME. Critical revision of the manuscript for important intellectual content: All authors. Statistical analysis: MH, SDG, XX. Study supervision: ME. Questions regarding dataset availability will be answered by the corresponding author on reasonable request. This study was approved by the institutional review board of Beth Israel Deaconess Medical Center, Harvard Medical School (protocol number: 2020P000126, Committee on Clinical Investigations). The need for informed consent was waived.

Declaration of Conflicting Interests

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Supplemental Material

Supplemental material for this article is available online.

References

1. Cooper LM, Linde-Zwirble WT. Medicare intensive care unit use: analysis of incidence, cost, and payment. *Crit Care Med*. 2004; 32(11):2247-2253. doi:10.1097/01.ccm.0000146301.47334.bd
2. Kramer AA, Higgins TL, Zimmerman JE. The association between ICU readmission rate and patient outcomes. *Crit Care Med*. 2013;41(1):24-33. doi:10.1097/CCM.0b013e3182657b8a
3. Kramer AA, Higgins TL, Zimmerman JE. Intensive care unit readmissions in U.S. hospitals: patient characteristics, risk factors, and outcomes. *Crit Care Med*. 2012;40(1):3-10. doi:10.1097/CCM.0b013e31822d751e
4. Al-Jaghbeer MJ, Tekwani SS, Gunn SR, Kahn JM. Incidence and etiology of potentially preventable ICU readmissions. *Crit Care Med*. 2016;44(9):1704-1709. doi:10.1097/CCM.0000000000001746
5. Rhodes A, Moreno RP, Azoulay E, et al. Prospectively defined indicators to improve the safety and quality of care for critically ill patients: a report from the Task Force on Safety and Quality of the European Society of Intensive Care Medicine (ESICM). *Intensive Care Med*. 2012;38(4):598-605. doi:10.1007/s00134-011-2462-3
6. Nates JL, Nunnally M, Kleinpell R, 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(8):1553-1602. doi:10.1097/CCM.0000000000001856
7. Willsie P, Hunter K, Schorr C, Milcarek B, Rachoin J-S, Cerceo E. 652: Identifying risk factors for ICU readmission. *Crit Care Med*. 2012;40:1-328. doi:10.1097/01.ccm.0000424868.88811.74
8. Vollam S, Dutton S, Lamb S, Petrinic T, Young JD, Watkinson P. Out-of-hours discharge from intensive care, in-hospital mortality and intensive care readmission rates: a systematic review and meta-analysis. *Intensive Care Med*. 2018;44(7):1115-1129. doi:10.1007/s00134-018-5245-2
9. Lin Y-W, Zhou Y, Faghri F, Shaw MJ, Campbell RH. Analysis and prediction of unplanned intensive care unit readmission using recurrent neural networks with long short-term memory. *PLoS One*. 2019;14(7):e0218942. doi:10.1371/journal.pone.0218942
10. Desautels T, Das R, Calvert J, et al. Prediction of early unplanned intensive care unit readmission in a UK tertiary care hospital: a cross-sectional machine learning approach. *BMJ Open*. 2017; 7(9):e017199. doi:10.1136/bmjopen-2017-017199
11. Magruder JT, Kashiouris M, Grimm JC, et al. A predictive model and risk score for unplanned cardiac surgery intensive care unit readmissions. *J Card Surg*. 2015;30(9):685-690. doi:10.1111/jocs.12589
12. Frost SA, Tam V, Alexandrou E, et al. Readmission to intensive care: development of a nomogram for individualising risk. *Crit Care Resusc*. 2010;12(2):83-89.
13. Martin LA, Kilpatrick JA, Al-Dulaimi R, et al. Predicting ICU readmission among surgical ICU patients: development and validation of a clinical nomogram. *Surgery*. 2019;165(2):373-380. doi:10.1016/j.surg.2018.06.053
14. Markazi-Moghaddam N, Fathi M, Ramezankhani A. Risk prediction models for intensive care unit readmission: a systematic review of methodology and applicability. *Aust Crit Care*. 2020; 33(4):367-374. doi:10.1016/j.aucc.2019.05.005

15. Hammer M, Grabitz SD, Teja B, Serrano M, Eikermann M; SICU Optimal Mobilization Team (SOMT). Functional mobility recovery predicts readmission to the surgical intensive care unit. *Intensive Care Med*. 2020;46(5):1054-1056. doi:10.1007/s00134-020-05972-0
16. Youden WJ. Index for rating diagnostic tests. *Cancer*. 1950;3(1):32-35. doi:10.1002/1097-0142(1950)3:1<32::aid-cncr2820030106>3.0.co;2-3
17. Van Calster B, Wynants L, Verbeek JFM, et al. Reporting and interpreting decision curve analysis: a guide for investigators. *Eur Urol*. 2018;74(6):796-804. doi:10.1016/j.eururo.2018.08.038
18. Fialho AS, Cismondi F, Vieira SM, Reti SR, Sousa JMC, Finkelstein SN. Data mining using clinical physiology at discharge to predict ICU readmissions. *Exp Syst Appl*. 2012;39(18):13158-13165. doi:10.1016/j.eswa.2012.05.086
19. Maslove DM, Dubin JA, Shrivats A, Lee J. Errors, omissions, and outliers in hourly vital signs measurements in intensive care. *Crit Care Med*. 2016;44(11):e1021-e1030. doi:10.1097/CCM.0000000000001862
20. World Health Organization. *International Classification of Functioning, Disability and Health : ICF : Short Version*. Short Version. World Health Organization; 2001.
21. Schweickert WD, Pohlman MC, Pohlman AS, et al. Early physical and occupational therapy in mechanically ventilated, critically ill patients: a randomised controlled trial. *Lancet*. 2009;373(9678):1874-1882. doi:10.1016/S0140-6736(09)60658-9
22. Schaller SJ, Anstey M, Blobner M, et al. Early, goal-directed mobilisation in the surgical intensive care unit: a randomised controlled trial. *Lancet*. 2016;388(10052):1377-1388. doi:10.1016/S0140-6736(16)31637-3
23. Schaller SJ, Scheffenbichler FT, Bose S, et al. Influence of the initial level of consciousness on early, goal-directed mobilization: a post hoc analysis. *Intensive Care Med*. 2019;45(2):201-210. doi:10.1007/s00134-019-05528-x
24. Latronico N, Herridge M, Hopkins RO, et al. The ICM research agenda on intensive care unit-acquired weakness. *Intensive Care Med*. 2017;43(9):1270-1281. doi:10.1007/s00134-017-4757-5
25. Mazer CD, Whitlock RP, Fergusson DA, et al. Restrictive or liberal red-cell transfusion for cardiac surgery. *N Engl J Med*. 2017;377(22):2133-2144. doi:10.1056/NEJMoa1711818
26. Carson JL, Guyatt G, Heddle NM, et al. Clinical practice guidelines from the AABB: red blood cell transfusion thresholds and storage. *JAMA*. 2016;316(19):2025-2035. doi:10.1001/jama.2016.9185
27. Mazer CD, Whitlock RP, Fergusson DA, et al. Six-month outcomes after restrictive or liberal transfusion for cardiac surgery. *N Engl J Med*. 2018;379(13):1224-1233. doi:10.1056/NEJMoa1808561
28. Hare GMT, Baker JE, Pavenski K. Assessment and treatment of preoperative anemia: continuing professional development. *Can J Anaesth*. 2011;58(6):569-581. doi:10.1007/s12630-011-9498-2
29. Grosso MJ, Boddapati V, Cooper HJ, Geller JA, Shah RP, Neuwirth AL. The effect of preoperative anemia on complications after total hip arthroplasty. *J Arthroplasty*. 2020;35(6S):S214-S218. doi:10.1016/j.arth.2020.01.012
30. Ong B, Rockey DC. The syndrome of a large drop in hematocrit in hospitalized patients: clinical features and gastrointestinal bleeding outcomes. *J Investig Med*. 2014;62(8):963-967. doi:10.1097/JIM.0000000000000109
31. Fecso AB, Samuel T, Elnahas A, et al. Clinical indicators of postoperative bleeding in bariatric surgery. *Surg Laparosc Endosc Percutan Tech*. 2018;28(1):52-55. doi:10.1097/SLE.0000000000000480
32. Tomizawa M, Shinozaki F, Hasegawa R, et al. Low hemoglobin levels are associated with upper gastrointestinal bleeding. *Biomed Rep*. 2016;5(3):349-352. doi:10.3892/br.2016.727
33. Vincent JL. Anemia and blood transfusion in critically ill patients. *JAMA*. 2002;288(12):1499. doi:10.1001/jama.288.12.1499
34. Thevathasan T, Copeland CC, Long DR, et al. The impact of postoperative intensive care unit admission on postoperative hospital length of stay and costs: a prespecified propensity-matched cohort study. *Anesth Analg*. 2019;129(3):753-761. doi:10.1213/ANE.0000000000003946
35. Wunsch H. Is there a starling curve for intensive care? *Chest*. 2012;141(6):1393-1399. doi:10.1378/chest.11-2819
36. Wunsch H, Gershengorn HB, Cooke CR, et al. Use of intensive care services for Medicare beneficiaries undergoing major surgical procedures. *Anesthesiology*. 2016;124(4):899-907. doi:10.1097/ALN.0000000000001024
37. Tiruvoipati R, Botha J, Fletcher J, et al. Intensive care discharge delay is associated with increased hospital length of stay: a multicentre prospective observational study. *PLoS One*. 2017;12(7):e0181827. doi:10.1371/journal.pone.0181827
38. Williams T, Leslie G. Delayed discharges from an adult intensive care unit. *Aust Health Rev*. 2004;28(1):87-96. doi:10.1071/ah040087
39. Kahan BC, Koulenti D, Arvaniti K, et al. Critical care admission following elective surgery was not associated with survival benefit: prospective analysis of data from 27 countries. *Intensive Care Med*. 2017;43(7):971-979. doi:10.1007/s00134-016-4633-8
40. van den Berghe G, Wouters P, Weekers F, et al. Intensive insulin therapy in critically ill patients. *N Engl J Med*. 2001;345(19):1359-1367. doi:10.1056/NEJMoa011300
41. NICE-SUGAR Study Investigators; Finfer S, Liu B, et al. Hypoglycemia and risk of death in critically ill patients. *N Engl J Med*. 2012;367(12):1108-1118. doi:10.1056/NEJMoa1204942
42. Van den Berghe G, Mesotten D, Vanhorebeek I. Intensive insulin therapy in the intensive care unit. *CMAJ*. 2009;180(8):799-800. doi:10.1503/cmaj.090500
43. Griesdale DEG, de Souza RJ, van Dam RM, et al. Intensive insulin therapy and mortality among critically ill patients: a meta-analysis including NICE-SUGAR study data. *CMAJ*. 2009;180(8):821-827. doi:10.1503/cmaj.090206
44. Gunst J, De Bruyn A, Van den Berghe G. Glucose control in the ICU. *Curr Opin Anaesthesiol*. 2019;32(2):156-162. doi:10.1097/ACO.0000000000000706
45. Jacobi J, Bircher N, Krinsley J, et al. Guidelines for the use of an insulin infusion for the management of hyperglycemia in

critically ill patients. *Crit Care Med*. 2012;40(12):3251-3276. doi:10.1097/CCM.0b013e3182653269

46. Shin CH, Long DR, McLean D, et al. Effects of intraoperative fluid management on postoperative outcomes: a hospital registry study. *Ann Surg*. 2018;267(6):1084-1092. doi:10.1097/SLA.0000000000002220
47. Balakumar V, Murugan R, Sileanu FE, Palevsky P, Clermont G, Kellum JA. Both positive and negative fluid balance may be associated with reduced long-term survival in the critically ill. *Critical Care Medicine*. 2017;45(8):e749-e757. doi:10.1097/CCM.0000000000002372
48. Arslantas MK, Kara HV, Tuncer BB, et al. Effect of the amount of intraoperative fluid administration on postoperative pulmonary complications following anatomic lung resections. *J Thorac Cardiovasc Surg*. 2015;149(1):314-320, 321.e1. doi:10.1016/j.jtcvs.2014.08.071
49. Holte K, Foss NB, Andersen J, et al. Liberal or restrictive fluid administration in fast-track colonic surgery: a randomized, double-blind study. *Br J Anaesth*. 2007;99(4):500-508. doi:10.1093/bja/aem211
50. Comparison of two fluid-management strategies in acute lung injury. *N Engl J Med*. 2006;354(24):2564-2575. doi:10.1056/NEJMoa062200