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Accurate preoperative prediction of unplanned 30-day postoperative readmission using 8 predictor variables

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ABSTRACT

Background: Unplanned postoperative readmissions are associated with high costs, may indicate poor care quality, and present a substantial opportunity for healthcare quality improvement. Patients want to know their risk of unplanned readmission, and surgeons need to know the risk to adequately counsel their patients. The Surgical Risk Preoperative Assessment System tool was developed from the American College of Surgeons National Surgical Quality Improvement Program dataset and is a parsimonious model using 8 predictor variables. Surgical Risk Preoperative Assessment System is applicable to >3,000 operations in 9 surgical specialties, predicts 30-day postoperative mortality and morbidity, and is incorporated into our electronic health record.
Methods: A Surgical Risk Preoperative Assessment System model was developed using logistic regression. It was compared to the 28 nonlaboratory variables model from the American College of Surgeons National Surgical Quality Improvement Program 2012 to 2017 dataset using the c-index as a measure of discrimination, the Hosmer-Lemeshow observed-to-expected plots testing calibration, and the Brier score, a combined metric of discrimination and calibration.
Results: Of 4,861,370 patients, 188,150 (3.98%) experienced unplanned readmission related to the index operation. The Surgical Risk Preoperative Assessment System model's c-index, 0.728, was 99.3% of that of the full model's, 0.733; the Hosmer-Lemeshow plots indicated good calibration; and the Brier score was 0.0372 for Surgical Risk Preoperative Assessment System and 0.0371 for the full model.
Conclusion: The 8 variable Surgical Risk Preoperative Assessment System model detects patients at risk for postoperative unplanned, related readmission as accurately as the full model developed from all 28 nonlaboratory preoperative variables in the American College of Surgeons National Surgical Quality Improvement Program dataset. Therefore, unplanned readmission can be integrated into the existing Surgical Risk Preoperative Assessment System tool providing moderately accurate prediction of postoperative readmission.

Introduction

Unplanned hospital readmissions related to the index operation are an important concern for patients and providers. Readmissions are associated with high costs, may indicate poor care quality, and present a substantial opportunity for healthcare quality

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improvement.[1,2] Healthcare improvement programs use readmission rates as a marker of quality and the Centers for Medicare and Medicaid Services impose monetary penalties on hospitals for excessive readmissions.[3] Methods to identify patients at increased risk for readmission could direct preventive interventions to decrease unplanned, related readmissions.

There are few easy-to-use, generalized, and validated prediction models for the preoperative identification of patients at risk for adverse postoperative outcomes, including mortality, morbidity, and unplanned 30-day readmission. The American College of Surgeons National Surgical Quality Improvement Program (ACS NSQIP) Surgical Risk Calculator is an online multifactorial prediction tool for adverse outcomes, including hospital readmission. However, this tool requires manual data entry of 22 predictor variables and is not integrated into the electronic health record (EHR).[4] These characteristics make the routine use of the tool impractical in busy surgical clinic settings.

We have developed and implemented the Surgical Risk Preoperative Assessment System (SURPAS), which uses just 8 preoperative predictor variables to estimate the risk of 11 adverse outcomes across a broad spectrum of surgical specialties. The 8 predictor variables included in the model are Current Procedural Terminology (CPT)–specific readmission rate for the adverse outcome being predicted, work Relative Value Unit (wRVU; as a measure of the complexity of the surgical procedure), American Society of Anesthesiologists physical status classification (ASA class), inpatient versus outpatient operation, primary surgeon specialty, functional health status before surgery, patient age, and elective versus emergent surgery status.[5–7] We have shown that these 8 predictor variables for mortality, morbidity, and 6 complication clusters have discrimination (c-indexes) very similar to models with up to 28 predictor variables.[7]

The purpose of this study is to determine whether the 8 variable SURPAS prediction model can predict a new outcome, unplanned, related readmission, as effectively as a model using 28 preoperative predictor variables available in the ACS NSQIP dataset. We hypothesized that the SURPAS predictive model can successfully estimate the risk in the preoperative setting of unplanned, related 30-day readmission after surgery and will demonstrate similar discrimination and calibration as that of the ACS NSQIP 28 nonlaboratory variables model.

Methods

Data source

Data from the 2012 to 2017 ACS NSQIP participant use file dataset were used to build the prediction models. The ACS NSQIP data contain preoperative patient characteristics, perioperative data, and 30-day postoperative outcomes.[8–11] These data, representing events and measurements occurring preoperatively to 30 days after surgery, are collected by manual chart review and direct contact with patients and their families by trained Surgical Clinical Reviewers. Collected data represent 9 surgical specialties: general, vascular, orthopedic, thoracic, plastic, urology, otolaryngology, gynecology, and neurosurgery. The primary outcome variable was unplanned postoperative readmission, defined as a postoperative hospital readmission within 30 days of the index operation, to the same or another hospital for which there is no evidence that a readmission was planned at the time of the index operation. Relation of the readmission to the index operation is a separate variable in the ACS NSQIP dataset, as judged by the nurse reviewer. Six of the 8 SURPAS predictor variables came directly from the ACS NSQIP database. The other 2 predictor variables, wRVU and CPT-specific readmission rate, are derived variables. wRVU is obtained from a table look-up once the CPT code of the operation is specified. CPT-specific readmission rate is a calculated variable using the ACS NSQIP dataset and equal to the number of related unplanned

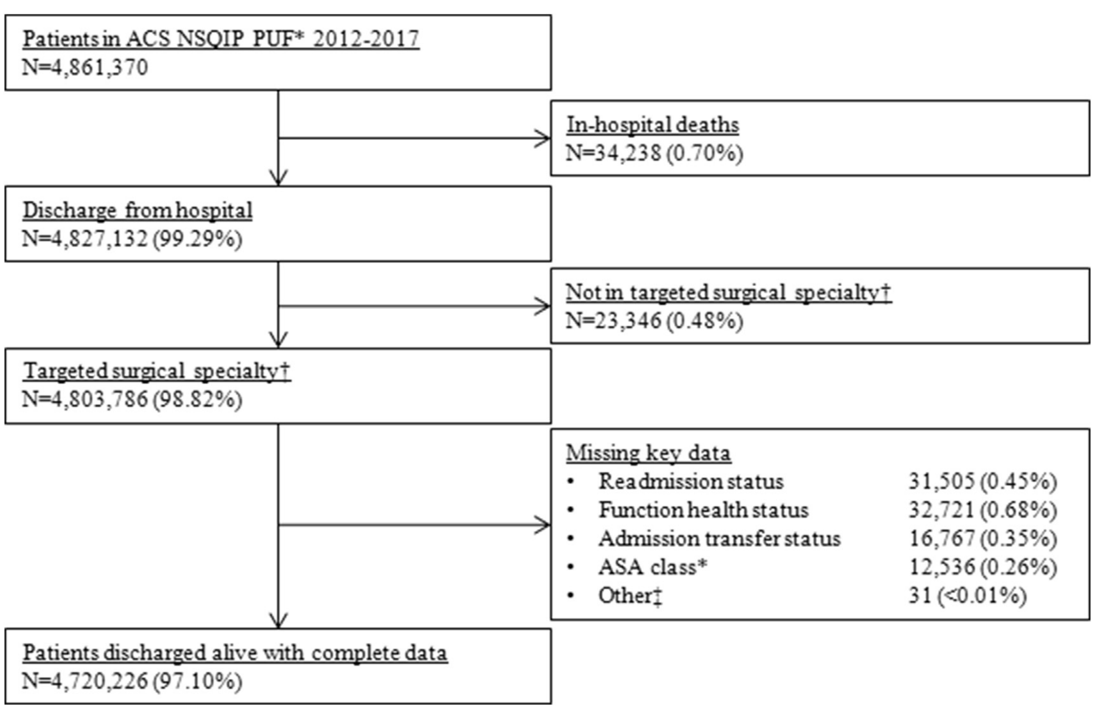


Fig 1. STROBE (Strengthening the Reporting of Observational Studies in Epidemiology). Diagram of patient exclusions and missing data. ACS/NSQIP PUF, American College of Surgeons National Surgical Quality improvement program participant use file. †Cardiac surgery, interventional radiology, other and unknown surgeon specialty were excluded. ‡Others includes sex, age, cigarette smoker within 1 year, ventilator dependent within 48 hours, acute renal failure with rising creatinine to >3 mg/dL within 24 hours, steroid use for chronic condition, >10% loss of body weight within 6 months, transfusion of pack red blood cells within 72 hours before surgery, and emergency operation.

readmissions divided by the total number of operations for the given CPT code of the operation, times 100. This research protocol was evaluated by the Colorado Multiple Institutional Review Board and deemed exempt from review as it uses deidentified data.

Statistical analyses

A Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) diagram was used to delineate excluded observations, reasons for exclusion, and the final sample size of the analytical cohort (Fig 1).[12] Patients were excluded owing to death before discharge from the index hospitalization, unplanned readmission occurring >30 days after the index operation, unplanned readmission not related to the index operation, secondary readmission without a primary admission at the time of the index operation being recorded, operations not performed by 1 of the 9 surgical specialties collected by the ACS NSQIP Essentials dataset, or missing values for 1 or more of the 8 predictor variables in the SURPAS model.

Preliminary analyses were performed using 28 preoperative variables (Table I) to determine which factors showed a bivariable association with unplanned related 30-day hospital readmission. The bivariable association between each of these variables and unplanned related 30-day readmission was tested using a χ^2 test for categorical predictor variables or an unpaired *t* test for continuous variables.

Because the SURPAS 8-predictor variable model had previously been shown to have nearly as good discrimination (c-index) and calibration (Hosmer-Lemeshow analysis) as using all 28 preoperative ACS NSQIP variables in predicting postoperative mortality and morbidity,[7] we were interested in determining whether this was also true for predicting postoperative unplanned, related readmission. We used stepwise, forward selection logistic regression analysis with *P* values of .05 for entry into and exit from the model to develop the prediction model for unplanned related 30-day readmission using all 28 of the nonlaboratory preoperative ACS NSQIP variables (Table I). This was termed *the full model*. Laboratory values were excluded from the analysis because they are not collected routinely, their absence is not random, and as our previous analyses have shown, there was no appreciable difference between the logistic regression prediction models with and without laboratory variables.[6] For the 8-variable SURPAS model, we used the set of predictor variables previously reported from logistic regression analyses for mortality and morbidity with unplanned, related readmission as the dependent variable.[7]

We compared results of the parsimonious SURPAS model to the full model using the c-index as a measure of discrimination, the Hosmer-Lemeshow observed-to-expected plots as a measure of calibration, and the Brier score, a combined metric of discrimination and calibration. The c-index is the proportion of all pairs of patients in which one had a readmission and one did not, where the patient with the readmission had a higher probability of readmission compared with the patient who did not have a readmission. The Hosmer-Lemeshow graph subdivides the sample into deciles of risk based upon the patients' probabilities of readmission and then compares the expected to observed rate of readmissions in each decile of risk group. The closer the expected and observed curves are to one another, the better is the calibration of the model. The Brier score is the mean squared difference between readmission coded as 0 or 1 and the probability of readmission. Smaller Brier scores indicate better overall model fit to the data. All statistical analyses were performed using Statistical Analysis Software version 9.4 (SAS, Inc., Cary, NC); Hosmer-Lemeshow plots were generated from Microsoft Excel software, version 2010 (Microsoft Corp., Redmond, WA).

Results

In the 2012 to 2017 ACS NSQIP dataset, 4,861,370 patients were available for analysis. We excluded 34,238 patients (0.70%) owing to death before discharge, 23,346 patients (0.51%) not in the 9 ACS NSQIP surgical specialties, and 83,560 patients (1.72%) with missing values for key variables. This resulted in 4,720,226 patients (97.09% of the original dataset) for the analytic dataset (Fig 1). The unplanned related readmission rate was 3.98% (188,150 of 4,720,226 patients) in the analytical cohort.

We performed bivariable analysis of the association between each of the 28 ACS NSQIP preoperative variables and 30-day unplanned related readmission (Table I). Unplanned related readmission rates were higher for men compared to women (4.31% vs 3.74%); highest for African Americans (4.71%) and lowest for Asian or Pacific Islanders (3.06%); higher after in-patient compared with outpatient operations (5.62% vs 1.65%); highest for vascular surgical operations (6.29%) and lowest for otolaryngology operations (2.27%). Unplanned related readmissions were more frequent with increasing ASA class (I, 1.39%; II, 2.68%; III, 5.46%; IV, 8.32%; V, 7.84%).

The full model for 30-day unplanned, related readmission is presented in Table II. Of the 28 preoperative variables entered into the logistic regression model (Table I), 25 were statistically significant and independent predictors of unplanned, related readmission with a cumulative c-index of 0.733. However, the first 4 predictor variables to enter the model (CPT-specific readmission rate, ASA class, inpatient or outpatient operation, and surgeon specialty) resulted in a cumulative c-index of 0.727, or 99.18% of that of the full model (0.733). The CPT-specific readmission rate variable alone had a c-index of 0.714, or 97.41% of the full model.

The c-index of the SURPAS 8 variable model was 0.728 or 99.31% of the c-index of the full model (0.733; Table III). The Hosmer-Lemeshow analyses of both the full model and the SURPAS model showed good calibration of both models with little difference between the observed and expected event rates by deciles of risk for both the full model and the 8-variable (SURPAS) models (Fig 2, *A* and *B*). The Brier scores were almost identical between the full model (0.0371) and the SURPAS model (0.0372).

Discussion

The parsimonious set of 8 SURPAS variables from the ACS NSQIP dataset estimates the risk of unplanned related readmission within 30 days of surgery with moderate discrimination (c-index 0.728), which was very similar to that of the 28 variable model (0.733).The Hosmer-Lemeshow analysis (plots of observed and expected outcomes by deciles of risk) shows good calibration for both the 8 variable SURPAS model and the full model. These results thus enable us to add 30-day unplanned related readmission as another outcome variable that can be predicted with moderate accuracy by the SURPAS tool.

In both the full model and the SURPAS model, the first few variables entered accounted for a large proportion of the overall c-index of the models. This might prompt the question as to whether we could use even fewer than 8 variables to estimate the risk of readmission. The development of the SURPAS models considered the simultaneous risk estimation of a number of different types of postoperative adverse events. This development found that 8 predictor variables were needed to adequately estimate risk for all of the adverse outcomes simultaneously, and that different predictor variables were most important for different types of adverse outcomes.[7] Therefore, it is important to enter all 8 SURPAS predictor variables to accomplish the goals of the tool.

Table I
Bivariable association of preoperative characteristics with unplanned 30-day readmission

Unplanned, related readmission (N = 4,861,370)				
Characteristic*	No readmission or planned readmission (n = 4,532,076)		Unplanned readmission (n = 188,150)	
	n or Mean	% or SD	n or Mean	% or SD
Sex				
Female	2,598,329	96.26	101,083	3.74
Male	1,933,747	95.69	87,067	4.31
Race/ethnicity				
American Indian or Alaska Native	26,430	96.22	1,039	3.78
Asian or Pacific Islander	146,655	96.94	4,627	3.06
Black, not of Hispanic origin	441,698	95.29	21,849	4.71
Hispanic origin	263,979	96.61	9,249	3.39
White, not of Hispanic origin	3,016,009	95.87	129,765	4.13
ASA class				
A normal healthy patient (I)	416,498	98.61	5,868	1.39
A patient with mild systemic disease (II)	2,086,589	97.32	57,353	2.68
A patient with severe systemic disease (III)	1,795,851	94.54	103,806	5.46
A patient with severe systemic disease that is a constant threat to life (IV)	229,013	91.68	20,772	8.32
A moribund patient who is not expected to survive without the operation (V)	4,125	92.16	351	7.84
Body mass index category (kg/m^2)				
Underweight (<18.5)	67,089	93.72	4,497	6.28
Normal weight (18.5–24.9)	1,038,070	95.83	45,209	4.17
Over weight (25.0–29.9)	1,392,607	96.29	53,688	3.71
Obese class I (30.0–34.9)	968,310	96.18	38,487	3.82
Obese class II (35.0–39.9)	511,943	96.04	21,108	3.96
Obese class III (>40.0)	466,067	95.56	21,636	4.44
Transfer status				
Admitted directly from home	4,366,057	96.14	175,300	3.86
Admitted from another acute care hospital	127,446	93.33	9,108	6.67
Admitted from a chronic care facility	38,573	91.16	3,742	8.84
Primary surgeon specialty				
General surgery	2,102,370	95.42	100,870	4.58
Gynecology surgery	358,811	97.24	10,179	2.76
Neurosurgery	231,718	95.55	107,86	4.45
Orthopedic surgery	996,539	97.49	25,703	2.51
Otolaryngology	126,528	97.73	2,935	2.27
Plastic surgery	132,225	97.38	3,557	2.62
Thoracic surgery	53,768	94.33	3,231	5.67
Urologic surgery	253,885	95.37	12,336	4.63
Vascular surgery	276,232	93.71	18,553	6.29
Inpatient/outpatient operation				
Outpatient	1,909,590	98.35	32,094	1.65
Inpatient	2,622,486	94.38	156,056	5.62
Emergency operation	390,035	94.76	21,551	5.24
Diabetes mellitus				
None	3,851,275	96.33	146,760	3.67
Oral medication versus none	432,799	95.23	21,692	4.77
Insulin versus none	248,002	92.64	19,698	7.36
Cigarette smoker (within 1 year)	797,257	95.19	40,303	4.81
Dyspnea (within 30 days)				
None	4,289,548	96.16	171,394	3.84
With moderate exertion	225,193	93.67	15,213	6.33
At rest	17,335	91.83	1,543	8.17
Functional health status before surgery				
Independent	4,421,494	96.13	177,779	3.87
Partially dependent	91,880	91.41	8,632	8.59
Totally dependent	18,702	91.49	1,739	8.51
Ventilator dependent (within 48 hours before surgery)	9,224	93.69	621	6.31
History of chronic obstructive pulmonary disease	189,942	92.49	15,432	7.51
Ascites (within 30 days before surgery)	13,458	90.86	1,353	9.14
Congestive heart failure (within 30 days before surgery)	31,338	90.45	3.307	9.55
Blood pressure >140/90 mm Hg or taking antihypertensive medication	2,009,769	95.06	104,493	4.94
Acute renal failure (rising creatinine to >3 mg/dL within 24 h before surgery)	12.917	90.49	1,357	9.51
Dialysis or hemofiltration (within 2 weeks before surgery)	53,949	90.98	5,349	9.02
Disseminated cancer	95,203	90.83	9,609	9.17
Open wound with or without infection	122,929	91.34	11,661	8.66
Steroid use for chronic condition	156,684	92.18	13,289	7.82
>10% loss of body weight (within 6 months before surgery)	50,721	89.86	5,722	10.14
Bleeding disorder requiring hospitalization	175,445	91.81	15,654	8.19
Transfusion of pack red blood cells (within 72 hours before surgery)	35,933	91.12	3,500	8.88
Age, mean (SD)	56.33	16.78	60.07	16.41
Work relative value units, mean (SD)	16.18	8.75	20.60	10.76
CPT event rate, mean (SD)	3.87	3.14	6.62	4.35

SD, standard deviation.
* All comparisons are frequency and row percent unless otherwise specified. All *P* values were <.001. For categorical variables, the χ^2 test was done; for continuous variables, the unpaired *t* test was done.

Table II
Multivariate association of preoperative characteristics with unplanned, related readmission variables included in the full model

Unplanned, related readmission				
Step	Characteristic*	Odds ratio (95% CI)	Cumulative c-index	Maximal c-index, %
1	CPT-specific readmission rate	1.132 (1.130–1.134)	0.714	97.41%
2	ASA class		0.720	98.36%
	II (a patient with mild systemic disease) vs I (a normal healthy patient)	1.327 (1.290–1.364)		
	III (a patient with severe systemic disease) vs I (a normal healthy patient)	1.777 (1.727–1.829)		
	IV (a patient with severe systemic disease that is a constant threat) vs I (a normal healthy patient)	1.901 (1.840–1.965)		
	IV (a moribund patient who is not expected to survive) vs I (a normal healthy patient)	1.565 (1.393–1.758)		
3	Inpatient/outpatient operation	1.978 (1.950–2.006)	0.725	98.91%
4	Surgeon specialty		0.727	99.18%
	Gynecology versus general	1.061 (1.038–1.085)		
	Neurosurgery versus general	1.007 (0.986–1.029)		
	Ortho versus general	0.733 (0.722–0.745)		
	ENT versus general	0.976 (0.940–1.014)		
	Plastics versus general	1.116 (1.078–1.156)		
	Thoracic versus general	0.871 (0.839–0.903)		
	Urology versus general	1.028 (1.007–1.049)		
	Vascular versus general	0.763 (0.750–0.777)		
5	Bleeding disorder requiring hospitalization	1.312 (1.288–1.337)	0.728	99.32%
6	History of severe chronic obstructive pulmonary disease	1.258 (1.234–1.282)	0.729	99.45%
7	Diabetes mellitus		0.729	99.45%
	Oral medication versus none	1.017 (1.002–1.033)		
	Insulin versus none	1.204 (1.184–1.225)		
8	Steroid use for chronic condition	1.356 (1.331–1.383)	0.730	99.59%
9	Race/ethnicity		0.731	99.72%
	American Indian or Alaska Native versus Hispanic	1.030 (0.964–1.101)		
	Asian or Pacific Islander versus Hispanic	0.868 (0.836–0.900)		
	Black, not of Hispanic origin versus Hispanic	1.094 (1.066–1.122)		
	Null/unknown versus Hispanic	0.910 (0.887–0.933)		
	White, not of Hispanic origin versus Hispanic	1.044 (1.022–1.068)		
10	Functional health status before surgery		0.731	99.72%
	Partially dependent versus independent	1.259 (1.228–1.291)		
	Totally dependent versus independent	1.107 (1.050–1.168)		
11	Dialysis	1.340 (1.300–1.383)	0.732	99.86%
12	Hypertension requiring medication	1.110 (1.098–1.122)	0.732	99.86%
13	Cigarette smoker (within 1 year)	1.120 (1.107–1.134)	0.732	99.86%
14	Disseminated cancer	1.217 (1.189–1.244)	0.732	99.86%
15	Body mass index category		0.732	99.86%
	Null/unknown versus normal weight (18.5–24.9)	0.945 (0.911–0.980)		
	Underweight (<18.5) versus normal weight (18.5–24.9)	1.040 (1.006–1.074)		
	Overweight (25.0 – 29.9) versus normal weight (18.5–24.9)	0.978 (0.965–0.991)		
	Obese class I (30.0 – 34.9) versus normal weight (18.5–24.9)	1.023 (1.008–1.037)		
	Obese class II (35.0 – 39.9) versus normal weight (18.5–24.9)	1.050 (1.032–1.069)		
	Obese class III (>40.0) versus normal (18.5–24.9)	1.099 (1.079–1.119)		
16	Ventilator	0.553 (0.508–0.602)	0.733	100.00%
17	Dyspnea		0.733	100.00%
	At rest versus none	1.117 (1.058–1.180)		
	With moderate exertion versus none	1.119 (1.098–1.140)		
18	Open wound at time of surgery	1.081 (1.057–1.106)	0.733	100.00%
19	Emergency operation	1.065 (1.048–1.082)	0.733	100.00%
20	History of congestive heart failure	1.160 (1.116–1.205)	0.733	100.00%
21	Work relative value units	0.998 (0.997–0.999)	0.733	100.00%
22	>10% loss body weight in 6-month before surgery	1.086 (1.054–1.118)	0.733	100.00%
23	Transfer status		0.733	100.00%
	Acute care hospital versus from home	0.973 (0.951–0.996)		
	Chronic care facility versus from home	1.108 (1.067–1.151)		
24	Ascites (within 30 days)	1.089 (1.028–1.154)	0.733	100.00%
25	Sex (male versus female)	1.011 (1.001–1.021)	0.733	100.00%

The cumulative c-index is that with all variables up to and including the Step in the model, the percent maximal c-index is the percent of the maximal c-index (0.733) accounted for by the cumulative c-index of that step. The y-intercept was −4.8466.
CI, confidence interval; *ENT,* otolaryngology; *OR,* odds ratio.
* All *P* values are < .02.

We found that 3.98% of patients in this ACS NSQIP data set from 2012 to 2017 experienced an unplanned, related readmission. The unplanned related readmission rate for 2012 was 5.51% (29,235 of 530,120), which is virtually identical to the 5.7% reported by Merkow et al based on their analysis of 498,875 procedures from the same dataset for calendar year 2012.[13] Other large studies report much higher readmission rates in selected higher risk patients. Tsai et al reported a median risk-adjusted composite 30-day readmission rate of 13.1% for 479,471 discharges from 3,004 hospitals for patients undergoing 6 major surgical procedures likely to have greater risk for readmission (coronary-artery bypass grafting, pulmonary lobectomy, endovascular repair of abdominal aortic aneurysm, open repair of abdominal aortic aneurysm, colectomy, and hip replacement) than the broad range of surgical procedures of

Table III
Multivariate association of the 8 SURPAS preoperative variables with unplanned 30-day readmission: Variables included in the SURPAS model

Unplanned/related readmission				
Step	Characteristic*	Odds ratio (95% CI)	Cumulative c-index	Maximal c-index, %
1	CPT-specific readmission rate†	1.138 (1.136–1.140)	0.714	98.08%
2	ASA class		0.720	98.90%
	II (a patient with mild systemic disease) versus I (a normal healthy patient)	1.456 (1.416–1.497)		
	III (a patient with severe systemic disease) versus I (a normal healthy patient)	2.204 (2.143–2.267)		
	IV (a patient with severe systemic disease that is a constant threat) versus I (a normal healthy patient)	2.652 (2.569–2.738)		
	IV (a moribund patient who is not expected to survive) versus I (a normal healthy patient)	1.914 (1.707–2.145)		
3	Inpatient/outpatient operation	2.001 (1.973–2.030)	0.725	99.59%
4	Primary surgeon specialty (general surgery is comparator value)		0.727	99.86%
	Gynecology versus general	1.034 (1.012–1.056)		
	Neurosurgery versus general	1.001 (0.980–1.022)		
	Ortho versus general	0.733 (0.722–0.744)		
	ENT versus general	0.951 (0.916–0.988)		
	Plastics versus general	1.080 (1.043–1.118)		
	Thoracic versus general	0.908 (0.875–0.941)		
	Urology versus general	1.000 (0.980–1.020)		
	Vascular versus general	0.848 (0.833–0.862)		
5	Functional health status before surgery		0.727	99.86%
	Partially dependent versus independent	1.378 (1.346–1.411)		
	Totally dependent versus independent	1.147 (1.090–1.206)		
6	Work relative value unit	0.996 (0.995–0.996)	0.728	100.00%
7	Emergency operation	1.019 (1.003–1.035)	0.728	100.00%
8	Age in years	1.000 (1.000–1.001)	0.728	100.00%

The cumulative c-index is that with all variables up to and including the step in the model, the percent maximal c-index is the percent of the maximal c-index (0.728) accounted for by the cumulative c-index of that step. The y-intercept was −4.7992.
AASA class, American Society of Anesthesiology physical status classification; *CI,* confidence interval; *ENT,* otolaryngology; *OR,* odds ratio.
* All *P* values are < .01 except for age which had a *P* value of .51. CPT codes with <100 patients were omitted because of increasing variance with small numbers of cases.
† The CPT-specific readmission rate, calculated from the ACS participant use file, is mean readmission rate for all patients undergoing the surgical procedure specified by the CPT code.

patients in the ACS NSQIP.[14] In a single-institution study of 1,142 patients entered into the ACS NSQIP, Kassin et al reported a readmission rate of 11.8%, with preoperative disseminated cancer, dyspnea, and open wound being associated with increased risk.[15] Wilson et al analyzed the national administrative database of academic health centers and reported readmission rates for four major procedures: colectomy, 15.8% of 103,129; lung resection, 9.7% of 73,558; gastric bypass, 8.9% of 62,010; and abdominal aortic surgery, 14.3% of 17,997.[16] Thus, readmission rates are quite variable by type of operation, which is one reason why CPT-specific readmission rate was the number one predictor variable in both the full and SURPAS models.

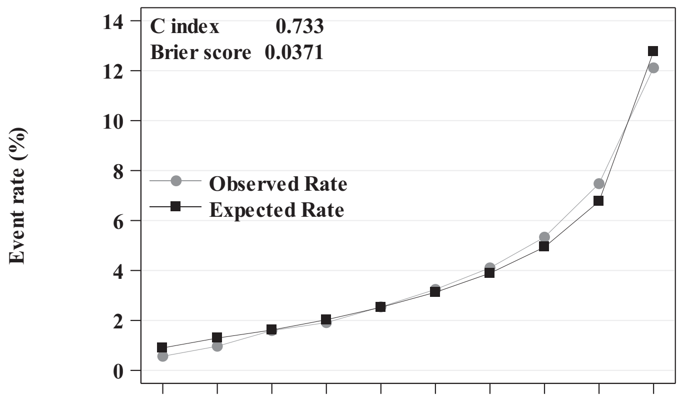
There are relatively few studies in the literature that have published prediction models for unplanned readmission after surgery in a broad surgical population. One example is the aforementioned ACS NSQIP risk calculator, which includes the outcome of unplanned readmission. This is an open access tool which utilizes 22 predictor variables and is completed manually online.[17] SURPAS has advantages over this tool because it is parsimonious in requiring only eight risk variables (of which 2 are prepopulated and entry of 5 data items accounts for 6 variables), and it has been successfully integrated into the EHR. SURPAS has been designed with a printable risk report, previously published,[18] which helps guide providers during the risk discussion and helps patients visualize their risk compared to the average patient undergoing the same operation.

Our prior studies have demonstrated that between a quarter and half of complications after high risk operations become clinically apparent after discharge and these are correlated with unplanned readmissions.[19,20] Most of these complications resulting in unplanned, related readmission are infectious in nature.[21] Most readmissions occur within the first 2 weeks after major surgery.[19,20] Intervention to reduce unplanned readmissions relies on accurate and early identification of complications.

Identification of patients at high risk of readmission, and other associated complications as done by SURPAS, has the potential to heighten awareness by providers, patients, and their families, thereby facilitating early intervention to mitigate these outcomes. Use of emerging statistical techniques to screen post discharge data may further identify patients showing increased risk of complications that can lead to readmission if unaddressed.[22] Although expensive and labor intensive, interventions such as multidisciplinary care management with telephone and home visits have been shown to decrease readmission rates by about 50% for vascular patients.[23] Early clinical follow-up with the surgical or primary care provider for those patients at high risk for readmission may also decrease readmission.[24–27] Improved education of patients and families about signs and symptoms of common postoperative complications, how to manage these issues, and how to contact providers has the potential to decrease unplanned readmissions.

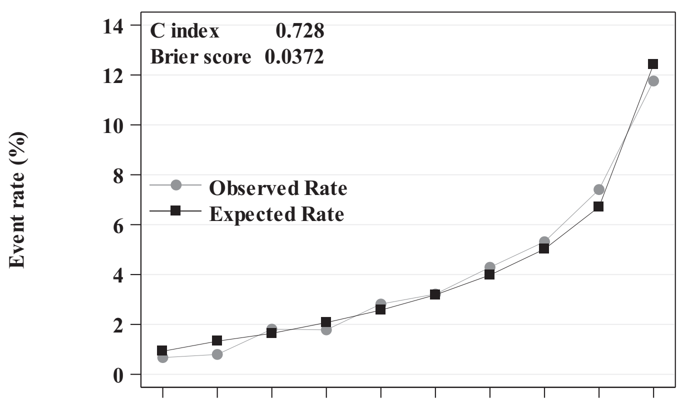
SURPAS was developed to provide the surgeon with a relatively easy tool in the EHR (Epic Systems, Verona, WI) to help with the consent process for surgery with the patient, and to identify patients at high risk for postoperative complications so that interventions might be made to mitigate the risk. The patient is a given a graphic display to show their risk versus the national average for the given CPT code, which has been previously published.[18] It is a system that uses ACS NSQIP data, but which is independent from the purposes of the ACS NSQIP, which are to provide hospitals with risk-adjusted surgical outcomes so that they can compare their performance to other participating hospitals. We have used an outside vendor under contract with UCHealth to build the SURPAS tool in our EHR (AgileMD, San Francisco, CA). The authors do not have any financial interests in SURPAS. The SURPAS tool includes look-up tables for wRVU and CPT-specific readmission rates. The only variables needing input include CPT code of the planned operation (SURPAS has a search engine to help with this),

A Full 28Variable Model



Decile of risk	1	2	3	4	5	6	7	8	9	10
Observed	0.6	1.0	1.6	1.9	2.5	3.2	4.1	5.3	7.5	12.1
Expected	0.9	1.3	1.6	2.0	2.5	3.1	3.9	4.9	6.8	12.8
Difference	0.3	0.3	0.0	0.1	0.0	0.1	0.2	0.4	0.7	0.7

B Eight Variable SURPAS Model



Decile of risk	1	2	3	4	5	6	7	8	9	10
Observed	0.7	0.8	1.8	1.8	2.8	3.2	4.3	5.3	7.4	11.8
Expected	0.9	1.3	1.6	2.1	2.6	3.2	4.0	5.0	6.7	12.4
Difference	0.3	0.5	0.2	0.3	0.2	0.0	0.3	0.3	0.7	0.7

Fig 2. Hosmer-Lemeshow partition graphs with fit statistics for (*A*) the full 28 variable model and (*B*) the 8 variable (SURPAS) model. The observed, expected, and difference between the observed and expected readmission rates are shown below each graph.

ASA class, functional health status, inpatient or outpatient, patient age, specialty of the primary surgeon, and emergency operation (yes or no).

Strengths of this study include the following: (1) use of a contemporary large dataset on patients who have undergone a broad range of procedures; (2) inclusion of a broad set of surgical specialties; (3) use of high-quality ACS NSQIP data subject to audit; and (4) utilization of medically relevant predictor variables across a national sample. Advantages specific to the SURPAS tool include the following: (1) the 8 predictor variables are already being collected in SURPAS for the prediction of postoperative mortality and morbidity; and (2) SURPAS is currently implemented in the EHR at the University of Colorado Hospital.

Potential limitations include the following: (1) the absence of socioeconomic variables, which have been shown to be related to surgical readmission risk and generally worse surgical outcomes[28–30]; and (2) the ACS NSQIP database probably overrepresents university medical centers and large community hospitals in contrast to smaller regional and rural hospitals. Future work should include a prospective evaluation of the external validity of the SURPAS prediction model for unplanned, related readmission, and demonstration of the use of the prediction model in conjunction with interventions can reduce postoperative readmissions.

We demonstrated that the 8 independent predictor variables currently collected by the SURPAS tool can accurately estimate the risk of unplanned, related readmission within 30-days of operation, with similar discrimination and calibration as that of a model using all 28 nonlaboratory preoperative variables included in the ACS NSQIP database.

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Conflict of interest/Disclosure

The authors report no proprietary or commercial interest in any product mentioned or concept discussed in this article.

References

1. Glebova NO, Hicks CW, Taylor R, et al. Readmissions after complex aneurysm repair are frequent, costly, and primarily at nonindex hospitals. *J Vasc Surg*. 2014;60:1429–1437.
2. Clement RC, Gray CM, Kheir MM, et al. Will medicare readmission penalties motivate hospitals to reduce arthroplasty readmissions? *J Arthroplasty*. 2017;32:709–713.
3. Joynt KE, Jha AK. A path forward on Medicare readmissions. *N Engl J Med*. 2013;368:1175–1177.
4. Surgeons ACo. ACS NSQIP Surgical Risk Calculator. Available at: https://riskcalculator.facs.org/RiskCalculator/Outcome.jsp. Accessed 25 June 2019.
5. Meguid RA, Bronsert MR, Juarez-Colunga E, Hammermeister KE, Henderson WG. Surgical risk preoperative assessment system (SURPAS): I. Parsimonious, clinically meaningful groups of postoperative complications by factor analysis. *Ann Surg*. 2016;263:1042–1048.
6. Meguid RA, Bronsert MR, Juarez-Colunga E, Hammermeister KE, Henderson WG. Surgical Risk Preoperative Assessment System (SURPAS): II. Parsimonious risk models for postoperative adverse outcomes addressing need for laboratory variables and surgeon specialty-specific models. *Ann Surg*. 2016;264:10–22.
7. Meguid RA, Bronsert MR, Juarez-Colunga E, Hammermeister KE, Henderson WG. Surgical Risk Preoperative Assessment System (SURPAS): III. Accurate preoperative prediction of 8 adverse outcomes using 8 predictor variables. *Ann Surg*. 2016;264:23–31.
8. Birkmeyer JD, Shahian DM, Dimick JB, et al. Blueprint for a new American College of Surgeons: National Surgical Quality Improvement Program. *J Am Coll Surg*. 2008;207:777–782.
9. Henderson WG, Daley J. Design and statistical methodology of the National Surgical Quality Improvement Program: Why is it what it is? *Am J Surg*. 2009;198(5 Suppl):S19–S27.
10. Hall BL, Richards K, Ingraham A, Ko CY. New approaches to the National Surgical Quality Improvement Program: The American College of Surgeons experience. *Am J Surg*. 2009;198(5 Suppl):S56–S62.
11. Ingraham AM, Richards KE, Hall BL, Ko CY. Quality improvement in surgery: The American College of Surgeons National Surgical Quality Improvement Program approach. *Adv Surg*. 2010;44:251–267.
12. von Elm E, Altman DG, Egger M, et al. The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) statement: Guidelines for reporting observational studies. *Int J Surg*. 2014;12:1495–1499.
13. Merkow RP, Ju MH, Chung JW, et al. Underlying reasons associated with hospital readmission following surgery in the United States. *JAMA*. 2015;313:483–495.
14. Tsai TC, Joynt KE, Orav EJ, Gawande AA, Jha AK. Variation in surgical-readmission rates and quality of hospital care. *New Engl J Med*. 2013;369:1134–1142.
15. Kassin MT, Owen RM, Perez SD, et al. Risk factors for 30-day hospital readmission among general surgery patients. *J Am Coll Surg*. 2012;215:322–330.
16. Wilson GC, Cutler QR III, Sutton JM, et al. Factors related to readmission after major elective surgery. *Dig Dis Sci*. 2015;60:47–53.

17. Bilimoria KY, Liu Y, Paruch JL, et al. Development and evaluation of the universal ACS NSQIP surgical risk calculator: A decision aid and informed consent tool for patients and surgeons. *J Am Coll Surg*. 2013;217:833–842.e831–833.
18. Lambert-Kerzner A, Ford KL, Hammermeister KE, Henderson WG, Bronsert MR, Meguid RA. Assessment of attitudes towards future implementation of the "Surgical Risk Preoperative Assessment System" (SURPAS) tool: A pilot survey among patients, surgeons, and hospital administrators. *Patient Safe Surg*. 2018;12:12.
19. Bhagat R, Bronsert MR, Juarez-Colunga E, et al. Postoperative complications drive unplanned readmissions after esophagectomy for cancer. *Ann Thorac Surg*. 2018;105:1476–1482.
20. Bhagat R, Bronsert MR, Ward AN, et al. National analysis of unplanned readmissions after thoracoscopic versus open lung cancer resection. *Ann Thorac Surg*. 2017;104:1782–1790.
21. Glebova NO, Bronsert M, Hammermeister KE, et al. Drivers of readmissions in vascular surgery patients. *J Vasc Surg*. 2016;64:185–194.e183.
22. Colborn KL, Bronsert M, Amioka E, Hammermeister K, Henderson WG, Meguid R. Identification of surgical site infections using electronic health record data. *Am J Infect Control*. 2018;46:1230–1235.
23. Rümenapf G, Geiger S, Schneider B, et al. Readmissions of patients with diabetes mellitus and foot ulcers after infra-popliteal bypass surgery: Attacking the problem by an integrated case management model. *Vasa*. 2013;42:56–67.
24. Antonoff MB, Ragalie W, Correa AM, et al. Results of postdischarge nursing telephone assessments: Persistent symptoms common among pulmonary resection patients. *Ann Thorac Surg*. 2016;102:276–281.
25. Hornick JR, Balderman JA, Eugea R, Sanchez LA, Zayed MA. A telephone call 1 week after hospitalization can identify risk factors for vascular surgery readmission. *J Vasc Surg*. 2016;64:719–725.
26. Sands K, Vineyard G, Livingston J, Christiansen C, Platt R. Efficient identification of postdischarge surgical site infections: Use of automated pharmacy dispensing information, administrative data, and medical record information. *Journal Infect Dis*. 1999;179:434–441.
27. Daneman N, Lu H, Redelmeier DA. Discharge after discharge: Predicting surgical site infections after patients leave hospital. *J Hosp Infect*. 2010;75:188–194.
28. Calvillo-King L, Arnold D, Eubank KJ, et al. Impact of social factors on risk of readmission or mortality in pneumonia and heart failure: Systematic review. *J Gen Intern Med*. 2013;28:269–282.
29. Birkmeyer NJ, Gu N, Baser O, Morris AM, Birkmeyer JD. Socioeconomic status and surgical mortality in the elderly. *Med Care*. 2008;46:893–899.
30. Taylor FC, Ascione R, Rees K, Narayan P, Angelini GD. Socioeconomic deprivation is a predictor of poor postoperative cardiovascular outcomes in patients undergoing coronary artery bypass grafting. *Heart*. 2003;89:1062–1066.

Doctor, have you noticed the first three letters in "diet" are "die"?