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An Efficient Risk Adjustment Model to Predict Inpatient Adverse Events after Surgery

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Abstract

Background—Risk adjustment is an important component of surgical outcomes and quality analyses. Current models include numerous preoperative variables; however, the relative contribution of these variables may be limited. This research seeks to identify a model with the fewest number of variables necessary to perform an adequate risk adjustment to predict any inpatient adverse event for use in resource-limited settings.

Methods—All patients from the National Surgical Quality Improvement Program (NSQIP) database from 2005 to 2010 were included. Outcomes were inpatient mortality or any surgical complication captured by NSQIP. Models were built by sequential addition of preoperative risk variables selected by their area under the receiver operator characteristic curve (AUC).

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Disclosures The ACS NSQIP and its participating hospitals are the source of data used in this research; they have not verified, and are not responsible for, the statistical validity of the data analysis or conclusions of the authors.

Results—Among 863,349 patients, the single variable with the highest AUC was American Society of Anesthesiologists (ASA) classification (AUC = 0.7127). AUC values reached 0.7923 with five variables (ASA classification, wound classification, functional status prior to surgery, albumin, and age) and 0.7945 with six variables. The sixth variable was one of the following: alkaline phosphatase, weight loss, principal anesthesia technique, gender, or emergency status. The model with the highest discrimination that did not require laboratories included ASA classification, functional status prior to surgery, wound classification, and age (AUC = 0.7810). Including all 66 preoperative variables produced little additional gain (AUC = 0.8006).

Conclusions—Six variables are sufficient to develop a risk adjustment tool for inpatient surgical mortality and morbidity. This research has important implications for the field of surgical outcomes research by improving efficiency of data collection. This limited model can aid the expansion of risk-adjusted analyses to resource-limited settings worldwide.

Introduction

Currently, the most widely used surgical outcomes database in the USA, the American College of Surgeons (ACS) National Surgical Quality Improvement Program (NSQIP), collects a total of 135 variables on each patient, including 66 preoperative variables and 21 postoperative adverse events over a 30-day follow-up period [1]. As the number of peri-operative variables increases, the burden of data collection on participating hospitals becomes commensurately prohibitive in resource-constrained settings. Despite the NSQIP Small and Rural program, which provides an avenue for nonurban hospitals to participate if they perform fewer than 1,680 'NSQIP-eligible' cases per year, there are many hospitals that do not routinely engage in robust quality initiatives [2]. Globally, low- and middle-income countries (LMICs) similarly lack infrastructure and resources to participate in risk-adjusted outcomes measurement.

Previous research has demonstrated that a limited model based on a few preoperative risk variables may be sufficient to perform an adequate risk-adjusted analysis for five general surgery procedures, including colectomy, ventral hernia repair, bariatric surgery, cholecystectomy, and pancreatectomy [3]. Our own previous research expanded on this idea to develop a broad risk-adjustment tool for use in resource-limited settings that included all patients, regardless of procedure, and restricted the analysis to inpatient outcomes in order to further reduce the cost of 30-day postoperative data collection. We found that fewer than four preoperative risk variables were sufficient to perform an adequate risk-adjusted analysis for inpatient mortality [4]. However, while mortality is obviously an important surgical outcome, mortality alone is not sufficient as a quality indicator because of low overall surgical mortality rates and low volumes of procedures in which mortality is an appropriate quality indicator [5]. Nonfatal complications also carry significant human and financial costs and should not be disregarded.

This study thus seeks to identify a model with the fewest number of variables necessary to perform an adequate risk adjustment for any inpatient adverse event, including postoperative complications or death. Our objective is to develop an efficient, cost-effective model that may be tested for use in resource-limited settings.

Materials and methods

We utilized all available NSQIP data from 2005 to 2010. This nationally validated program measures over 135 variables on each patient, including 30-day postoperative outcomes. The 2005–2006 database included information from 121 hospitals, while data from 2010 included information from 237 hospitals [1]. This dataset was chosen for its breadth of preoperative and postoperative variables collected for each patient.

Patients were determined to have an adverse event after surgery if they experienced death or at least one of the following complications as captured by NSQIP before discharge: superficial surgical site infection (SSI); deep incisional SSI; organ space SSI; wound disruption; pneumonia; unplanned intubation; pulmonary embolism; ventilator >48 h; progressive renal insufficiency; acute renal failure; urinary tract infection; stroke/ cerebrovascular accident with neurological deficit; coma >24 h; peripheral nerve injury; cardiac arrest requiring cardiopulmonary resuscitation; myocardial infarction; bleeding requiring transfusions; graft, prosthesis, or flap failure; deep vein thrombosis or thrombophlebitis; sepsis; or septic shock.

Six-variable models were built using a list of all pre-operative variables included in the NSQIP database, a total of 66 variables, to predict any inpatient adverse event, including any complication or death (Table 1). All continuous variables were kept as such, except for age, which was grouped into 10-year categories.

We performed two separate analyses to determine both discriminatory values of each preoperative variable as well as their contribution to the model's goodness of fit (GOF).

For the discrimination analysis, we performed a six-step process to add each additional variable sequentially. For each step, a logistic regression was performed to predict any adverse event (complication or death). After each regression, the area under the receiver-operator characteristic curve (AUC) for each model was calculated. The AUC is a discriminative measure to identify how well a model separates two groups (i.e. patients with vs. without adverse events). An AUC value of 0.5 indicates that the model separates the two groups no better than chance, whereas an AUC value of 1.0 indicates that the model completely separates the two groups. The AUC statistic is actually the percentage of randomly selected pairs that are correctly predicted by the model. Thus, the AUC allows us to determine which model can more accurately discriminate between the two groups of interest [6–9].

In step 1, a simple logistic regression was performed with each variable to predict in-hospital adverse events. The variable with the highest AUC was chosen and used as the basis for step 2. In step 2, all other variables were added to the top variable chosen from step 1. Multivariate logistic regression with inpatient adverse event as the outcome was performed again for each variation of this two-variable model, and AUC values were found. The models with the top five AUC values were chosen and used as the basis for step 3. The method for steps 3–6 was the same as in step 2: each additional variable was added to the five models chosen from the previous step, multivariate logistic regression was performed, and the AUC value was found. The five models with the highest AUC value became the basis for the next step. This process was repeated until we created models with six variables each (Fig. 1).

This analysis was repeated for each outcome individually to ensure that the same risk factors would predict specific outcomes in addition to our aggregate measure of any adverse event.

For the GOF analysis, we assessed the unique and relative contributions of each variable to the total GOF of our final six-variable model. McFadden's Pseudo R^2 values, based on likelihood statistics, were used to assess GOF in the following calculations. A Pseudo R^2 value ranges from 0 to 1, with a value of 1 indicating that the model fits the data perfectly or explains all the variance. To estimate the unique contribution of a variable to the GOF of the model, we calculated the difference between the Pseudo R^2 of the final six-variable model and a nested five-variable model with the variable of interest removed. The difference between the models represents the unique contribution of the variable removed. Model redundancy is an estimate of the GOF explained by more than one variable (i.e. shared variance) and was calculated as the difference between the Pseudo R^2 of the final six-variable model and the sum of the unique contribution values. Relative contribution for each variable was then calculated as the unique contribution divided by the Pseudo R^2 of the six-variable model. In other words, the relative contribution is the fraction of the final model's Pseudo R^2 explained by the variable removed. p values for the GOF analysis were calculated using the likelihood ratio test for nested models.

Statistical analysis was performed using STATA 64-bit special edition, version 11.2 (Stata Corp, College Station, TX, USA).

Results

Data from a total of 863,349 patients from 2005 to 2010 from the NSQIP database were included (Table 2). Over9.9 % of patients had at least one complication, and the mortality rate was 1.8 %. Mean age was higher among those with complications (63.4 years) and highest among those who died (70.8 years). Less than half of those who died or had complications were women (47.7 and 49.6 %, respectively), while women made up more than half of those without complications (57.4 %).

Discrimination analysis found that the single-variable model with the highest AUC value was the ASA physical status classification (AUC = 0.7127; Table 3). The six-variable model achieved an AUC of 0.7949. ASA classification, wound classification, functional status prior to surgery, albumin, and age emerged as the top five variables. Other variables within the six-variable models included alkaline phosphatase, weight loss, principal anesthesia technique, sex, and emergency status. Including all 66 preoperative variables resulted in an AUC value of0.8006 (Pseudo R^2 = 0.2116), only a fraction higher than the value achieved with only six variables (Fig. 2).

When the analysis was performed for each specific outcome separately (a total of 21 adverse events), ASA class, albumin, and international normalized ratio (INR) were among the top five models for 21, 18, and 11 outcomes, respectively (Table 4). The average AUC among these models was highest among ASA classification (AUC = 0.7041).

In examining the relative contribution of the variables to the GOF of our top six-variable models, ASA class was the largest contributor to the explanatory power (16.69 %), with functional status prior to surgery and wound classification the next highest contributors (8.12 and 7.20 %, respectively; Table 5). However, there is also a large amount of shared variance in the model (60.41 %).

Discussion

This research demonstrates that it is possible to develop a risk-adjustment tool based on a few variables to predict inpatient adverse events, including complications or death. This study adds to the literature in several ways. First, by including all patients, irrespective of type of procedure, and restricting the analysis to inpatient outcomes, these models are ideal for use in resource-limited settings in which the number of procedures performed may be few and collecting 30-day outcomes is unrealistic. Second, this model considers both mortality and morbidity, as any robust tool to evaluate quality requires inclusion of nonfatal adverse events. The potential implications for quality improvement programs in LMICs are vast when we consider that rates of morbidity and mortality are up to tenfold higher in LMICs than in high-income countries [10].

Third, in contrast to previous research, this study also offers several different models with comparable discriminatory ability, allowing choice as to which variables to include based on information availability and ease of data collection (Table 3). Different settings may find that one model is more useful and appropriate than another. For example, rural US hospitals may not regularly collect alkaline phosphatase or albumin on all surgical patients, but they may routinely collect other laboratory variables included in these models. Alternatively, in LMICs, where laboratory data may be unavailable or prohibitively expensive, the following four variables – ASA classification, wound classification, functional status prior to surgery, and age – may be more appropriate, as they provide the highest discrimination without requiring laboratory testing. Importantly, these data offer several choices of risk-adjustment models that provide comparable discrimination.

Although these findings must be validated in a variety of settings, this research allows for comparison of risk-adjusted surgical outcomes over time within a single hospital or between hospitals, and can serve as the backbone for developing a common risk-adjustment tool to expand surgical outcomes research globally. Valid risk adjustment is critical to performance comparisons across hospitals, and prevents hospitals that accept the sickest patients from being improperly identified as low performing. This model also enables more robust evaluation of various interventions in their ability to impact surgical outcomes. For example, comparing risk-adjusted outcomes before and after the implementation of an intervention at a particular hospital, such as the use of mosquito nets for hernia repairs or a pulse oximeter, can more accurately evaluate effectiveness at achieving desired outcomes. This has particular significance in LMICs, in which there is a dearth of prospective clinical trials, particularly in the field of surgery.

Interestingly, the results of this risk-adjustment tool in predicting inpatient adverse events are similar to those in our previous model predicting inpatient mortality [4]. While the AUC values are slightly lower in the adverse events model, most variables are the same. The differences are that the model predicting any adverse event includes alkaline phosphatase, body mass index (BMI), and sex, but does not include disseminated cancer status. These results are also similar to findings by Dimick et al [3]. When examining models that predicted 30-day outcomes for five procedures separately (cholecystectomy, ventral hernia repair, gastric bypass, pancreatectomy, and colectomy), the most important variables in predicting both mortality and morbidity included functional status, ASA class, congestive heart failure, wound class, emergent surgery, dyspnea, ascites, and albumin [3]. Dialysis, gender, hypertension, and weight loss were also important in predicting mortality, whereas bleeding disorders, BMI, and diabetes were important in predicting morbidity [3].

Other studies support the concept that a few variables may be sufficient for adequate risk adjustment. Rubinfeld et al. [11] found that the AUC decreased from 0.767 using all variables to 0.750 using only five variables, a statistically insignificant change, when predicting morbidity using the ACS-NSQIP from 2005 to 2008. Similarly, Birkmeyer et al. [12] found a high correlation between a 5-variable and a 20-variable model. They recommend that new versions of the NSQIP have ten or fewer ‘core’ variables, selected according to their contribution to discrimination (AUC) and the extent to which they explain morbidity or mortality. However, none of these models were explored for the explicit purpose of applying risk-adjustment methodologies to LMICs.

This research has several strengths. By utilizing the NSQIP database, we were able to obtain a very large sample size. The NSQIP database also includes a variety of complications that are collected prospectively with reliable accuracy. An additional strength was including the novel method of assessing relative contribution, which further quantifies the risk factors most likely to influence outcomes. The results of the relative contributions correlate with our findings insofar as ASA classification, functional status, and wound classification were found to be the three largest contributors to both the discrimination (AUC) and the GOF of the model.

This study is not without limitations. By including every complication as an adverse event without differentiating between more or less serious complications, and also by including all patients regardless of type of operation, this model may not be helpful if one were only interested in examining nuanced outcomes from a certain field of surgery or a certain operation. In addition, this model only considers certain adverse events without characterizing the severity of these events, such as with the Clavien–Dindo classification of complications, since this is not available in NSQIP [13]. It is quite possible that more severe outcomes would have different risk profiles. However, our results do provide a model that can be used to analyze outcomes across a breadth of surgical procedures considering a range of adverse events. In fact, the risk variables that are important in predicting adverse events for all procedures combined are the same as those for subspecialty surgeries reported by Dimick et al. [3], described above. This may actually increase the usefulness of our model in resource-limited settings, where surgeons often perform a broad range of procedures and no one procedure has a large enough sample size to provide enough power for analysis. Thus, a broad approach to understanding general trends and outcomes may be a more achievable starting point until resources allow for more nuanced outcomes research.

Some may question the validity and reliability of the subjective variables ASA class and functional status prior to surgery. However, evidence suggests that ASA class and functional status can be consistently classified and that inter-rater reliability has improved since the implementation of NSQIP, likely due to data collection training and ongoing support [14, 15]. Other research argues that ASA class and functional status are the most important variables in many risk-adjustment models for a variety of outcomes and procedures [3, 16–18].

In conclusion, six or fewer variables may be sufficient to perform an adequate risk-adjusted analysis to predict inpatient adverse events after surgery. While our previous research demonstrated that a model with four variables is sufficient to predict inpatient mortality, this research expands the concept to include adverse events. Importantly, we find that, although the AUC values are slightly lower, the same preoperative variables are important for adequate risk-adjusted analyses. This is especially significant for performing surgical outcomes research in resource-limited settings, in which extensive data collection is not feasible. With minimal training, it is possible that existing hospital personnel at small or resource-limited hospitals, both in developed countries and in LMICs, can easily and cheaply collect three or four variables to participate in wide-scale surgical outcomes research.

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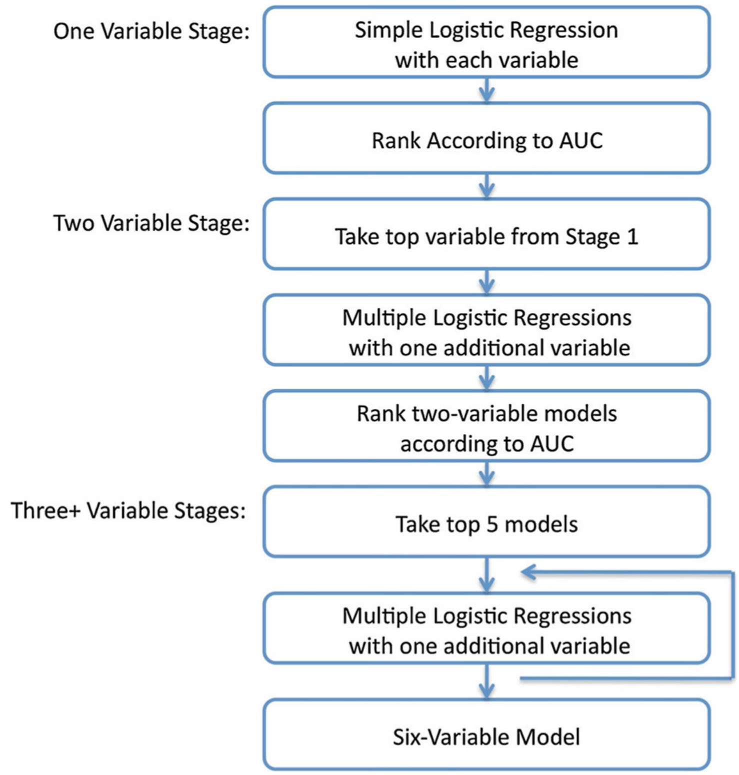

Fig. 1.
Stepwise methods for creating a 6-variable model based on AUC values

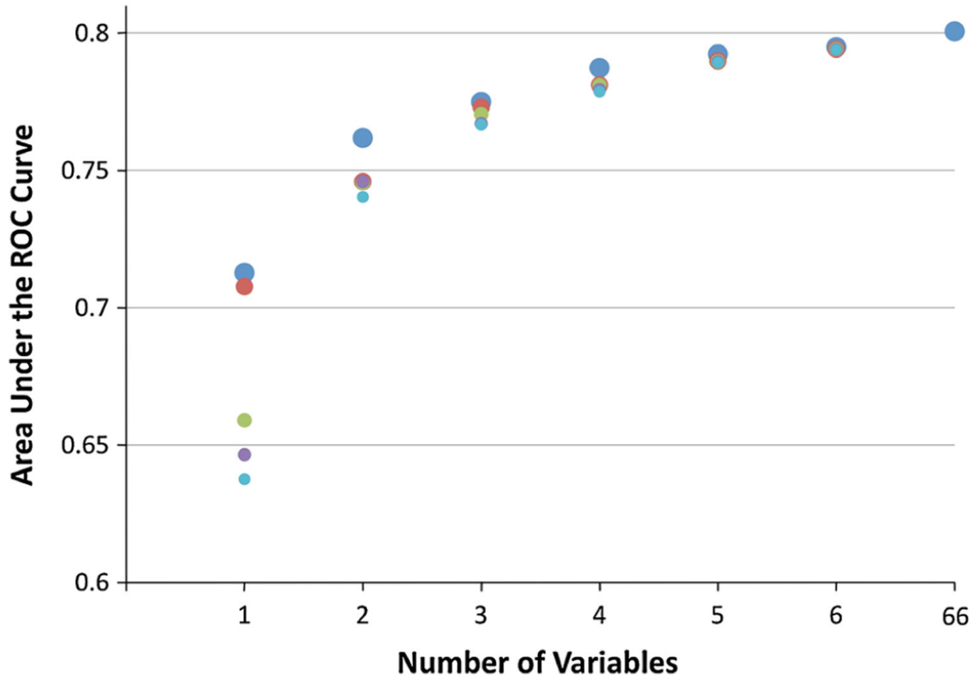

Fig. 2.
Diminishing returns of additional variables on AUC value. AUC values for the top five ranked models within each step are shown

Table 1

All pre-operative National Surgical Quality Improvement Program variables considered in the analysis

ASA classification
Preoperative serum albumin
Functional health status prior to surgery
Preoperative INR of PT values
Preoperative BUN
Preoperative systemic sepsis
Age (in 10-year categories)
Preoperative hematocrit
Preoperative serum creatinine
Pregnancy
Preoperative PT
Emergency case
Preoperative WBC
Preoperative SGOT
Preoperative PTT
Preoperative total bilirubin
Ventilator dependent
Wound classification
Preoperative platelet count
Dyspnea
Functional health status prior to current illness
Hypertension requiring medication
Bleeding disorder
BMI
Mallampati scale
Preoperative alkaline phosphatase
Surgical specialty of surgeon performing procedure
Impaired sensorium
History of severe COPD
Prior operation within 30 days
Wound infection
Ascites
Preoperative serum sodium
Currently on dialysis (preoperation)
Congestive heart failure in 30 days prior to surgery
Previous cardiac surgery
Sex
Acute renal failure
Current pneumonia
Diabetes mellitus with oral agents or insulin

Steroid use for chronic condition
>10 % loss body weight in last 6 months
DNR status
History of revascularization/amputation for peripheral vascular disease
Disseminated cancer
Transfusion >4 units PRBCs in 72 h before surgery
Previous PCI
History of MI 6 months prior to surgery
CVA/stroke with neurological deficit
Rest pain/gangrene
Race (White, Black, Hispanic, Asian or Pacific Islander, American Indian or Alaska Native, other)
CVA/stroke with no neurological deficit
Coma >24 h
History of angina in 1 month before surgery
Chemotherapy for malignancy in <30 days preoperation
History of TIA
Hemiplegia
Principal anesthesia technique
Alcohol >2 drinks/day in 2 weeks before admission
Current smoker within 1 year
Esophageal varices
Paraplegia
Radiotherapy for malignancy in last 90 days
Quadriplegia
Tumor involving CNS
Airway trauma

Table 2

Patient population

	All **(N = 863,349)**	**No complications** **(N = 761,935, 88.3 %)**	**Complication** **(N = 85,749, 9.9 %)**	**Died** **(N = 15,665, 1.8 %)**
Age [mean (SD)]	57.6 (17.1)	56.7 (17.1)	63.4 (15.5)	70.8 (13.5)
Race [N(%)]				
White	460,085 (78.8)	409,733 (78.9)	41,393 (78.1)	8,959 (80.0)
African American	65,071 (11.2)	56,395 (10.9)	7,244 (13.7)	1,432 (12.8)
Hispanic	41,165 (7.1)	37,789 (7.3)	2,874 (5.4)	502 (4.5)
Asian or Pacific Islander	13,221 (2.3)	11,918 (2.3)	1,065 (2.0)	238 (2.1)
Other or unknown	4,291 (0.7)	3,804 (0.7)	412 (0.8)	75 (0.7)
Female [N(%)]	487,511 (56.5)	437,548 (57.4)	42,491 (49.6)	7,472 (47.7)

Data are presented as N(%) unless otherwise indicated

Table 3

Models predicting inpatient adverse events (mortality or any complication combined) using National Surgical Quality Improvement Program data from 2005 to 2010

No. of variables	Variables	AUC	Pseudo R^2
1	ASA cass	0.7127	0.1100
	Albumin	0.7077	0.0945
	Hematocrit	0.6590	0.0503
	INR	0.6465	0.0197
	Functional status	0.6376	0.0961
2	ASA class, albumin	0.7618	0.1531
	ASA class, wound classification	0.7459	0.1271
	ASA class, hematocrit	0.7455	0.1283
	ASA class, functional status	0.7459	0.1271
	Albumin, functional status	0.7403	0.1098
3	ASA class, albumin, functional status	0.7749	0.1779
	ASA class, wound classification, functional status	0.7730	0.1398
	ASA class, albumin, wound classification	0.7704	0.1446
	ASA class, albumin, emergent	0.7670	0.1563
	ASA class, albumin, age (categories)	0.7666	0.1565
4	ASA class, wound classification, functional status, albumin	0.7873	0.1886
	ASA class, wound classification, functional status, alkaline phosphatase	0.7811	0.1747
	ASA class, wound classification, functional status, age (category)	0.7810	0.1717
	ASA class, albumin, functional status, surgical specialty	0.7794	0.1786
	ASA class, albumin, functional status, emergent	0.7786	0.1802
5	ASA class, wound classification, functional status, albumin, age (category)	0.7923	0.1947
	ASA class, wound classification, functional status, albumin, alkaline phosphatase	0.7898	0.1937
	ASA class, wound classification, functional status, albumin, BMI (category)	0.7896	0.1907
	ASA class, wound classification, functional status, albumin, sex	0.7895	0.1927
	ASA class, wound classification, functional status, albumin, BUN	0.7893	0.1907
6	ASA class, wound classification, functional status, albumin, age (category), alkaline phosphatase	0.7949	0.1980
	ASA class, wound classification, functional status, albumin, age (category), weight loss	0.7941	0.1964

No. of variables	Variables	AUC	Pseudo R^2
	ASA class, wound classification, functional status, albumin, age (category), principal anesthesia technique	0.7941	0.1981
	ASA class, wound classification, functional status, albumin, age (category), sex	0.7940	0.1957
	ASA class, wound classification, functional status, albumin, age (category), emergent	0.7939	0.2022
66	All variables	0.8006	0.2116

Table 4

Individual contributions of risk variables to each complication (a total of 21 complications)

Risk variable	Number of times it was included among the top five variables	Average AUC
ASA classification	21	0.7041
Albumin	18	0.6941
INR	11	0.6585
Age (categorical)	8	0.6442
Functional status 2	8	0.6596
Wound classification	7	0.6628
Hematocrit	7	0.6394
BUN	6	0.6824
Surgeon specialty	5	0.6851
Creatinine	5	0.7008
Sepsis	4	0.6843

Table 5

Relative contribution of variables to goodness-of-fit of the full model containing the six variables below (Pseudo $R^2 = 0.1980$)

Variable	Unique contribution	Relative contribution (%)	*p* value
ASA class	0.0331	16.69	<0.001
Functional status prior to surgery	0.0161	8.12	<0.001
Wound classification	0.0143	7.20	<0.001
Albumin	0.0106	5.36	<0.001
Age (category)	0.0037	1.89	<0.001
Alkaline phosphatase	0.0006	0.33	<0.001
Model redundancy	0.1196	60.41	