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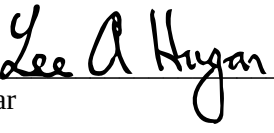

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4/3/14

Date

Predicting Prolonged Length of Stay after Elective Colectomy: Development of a Clinical Decision Support System Using ACS NSQIP Data

By

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By

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Bachelor of Science, The Pennsylvania State University, 2008

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An abstract of
a thesis submitted to the Faculty of the
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Abstract

Predicting Prolonged Length of Stay after Elective Colectomy: Development of a Clinical Decision Support System Using ACS NSQIP Data

By Lee Anthony Hugar

The objective of this project was to develop a Clinical Decision Support System (CDSS) tool to assist surgical teams in postoperative and discharge decision-making at the point of care. Risk factors associated with prolonged postoperative length of stay (pLOS) following colectomy have not been validated nor used in the development of predictive models. CDSS help physicians better integrate real-time clinical data when making decisions; like when and how to discharge complex surgical patients. No tools currently exist to help physicians make evidence-based decisions regarding length of stay and discharge for patients after elective colectomy. This was a retrospective analysis of American College of Surgeons National Surgical Quality Improvement Program data. We determined factors significantly associated with pLOS at our main academic hospital, tested the performance of these factors on an independent cohort via logistic regression modeling, and developed a clinical risk scoring system for pLOS (the pLOS Risk Score). Demographic variables associated with pLOS include age, disseminated cancer, ≥ 3 comorbidities, prior abdominal surgery, and preoperative admission > 1 day. Included laboratory and intraoperative risk factors were elevated international normalized ratio, operative time, blood loss, and open approach to colectomy. External validation of the model yielded an area under the ROC curve of 0.81 and allowed us to predict pLOS with 59% sensitivity, 85% specificity, and 77% accuracy using a cut point of > 24% predicted risk. Prolonged length of stay following elective colectomy can be accurately predicted and translated in to a useful CDSS tool.

Predicting Prolonged Length of Stay after Elective Colectomy: Development of a Clinical Decision Support System Using ACS NSQIP Data

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INTRODUCTION

Length of hospital stay is increasingly used as a measure of health care quality (1,2). In surgical patients, it has been shown to be associated with increased incidence of postoperative morbidities such as surgical site infections (3). Length of stay may also be a good measure of value in procedure-based episodes of care, due to significant effects on hospital costs and the socioeconomic burden on patients' families.

One study of colorectal surgery patients suffering postoperative complications determined that increased cost was mainly attributable to the increased length of stay or intensive care unit expenditures (4). Other studies quote that surgical care pathways aiming to decrease the physiologic stress of surgery and resultant hospital stay may save $2300 US per patient (5). Furthermore, according to a recent systematic review, such pathways have decreased the rate of minor postoperative complications (6).

BACKGROUND

Clearly, postoperative length of stay, cost, and the quality of patient care are intimately linked. As a result, Clinical Decision Support Systems (CDSS)—defined as any electronic or computer-based tool that collates and integrates patient specific health information to assist and advise physicians at the point of care (7)—can be enormously useful. In surgery, CDSS may impact the postoperative phase of patient care, have the potential to improve patient counseling, and facilitate the study of factors affecting outcomes such as length of stay. In fact, we already have the ability to calculate the estimated risk of complications and estimated postoperative stay using web-based tools like the American College of Surgeons National Surgical Quality Improvement Program (ACS NSQIP) Surgical Risk Calculator (8,9).

The surgical community needs a CDSS that can target patients at high risk for tumultuous postoperative recovery, prolonged stay, and readmission. Prolonged length of stay (pLOS) is an alternative to predicting the exact length of stay after surgery. It is defined as a postoperative length of stay greater than the 75^{th} percentile among a patient sample. Current surgical literature has suggested risk factors that may be significantly associated with pLOS after colorectal surgery (10–12). These factors include advanced age, male gender, type of colorectal procedure performed, and patient comorbidities. While some concordance exists between risk factors identified by these studies, no consensus has been made. This may be attributable to the fact that researchers have not validated proposed risk factor models for pLOS or measured their predictive ability. As a result, it would be useful to provide surgeons with a tool that integrates length of stay into the discharge decision-making process at the point of care. The risk of pLOS may be a good candidate outcome for CDSS aimed at stratifying patients into subsets that may 1) truly benefit from tightly coordinated postoperative care or 2) be unharmed by an early discharge.

The current study aims to determine factors associated with pLOS for patients undergoing colectomy at our institution, to test the performance of a predictive logistic regression model for pLOS on an independent cohort, and to develop a CDSS tool for predicting pLOS. We evaluate

pre- and intraoperative variables in order to develop a clinical risk scoring system that surgical teams can use at the point of care; on postoperative day (POD) 0.

METHODS

Data source and patient selection

This study was designed as a retrospective cohort analysis of patients undergoing elective colectomy at Emory University Hospital between 2009 and 2013. The local ACS NSQIP database was queried for patients with the following primary Current Procedure Terminology (CPT) codes for colectomy (44140, 44141, 44143, 44144, 44145, 44146, 44147, 44150, 44151, 44160, 44204, 44205, 44206, 44207, 44208, and 44210). We limited our sample to patients undergoing elective surgeries for the following indications—premalignant, malignant, inflammatory bowel or diverticular disease—in an effort to limit heterogeneity and increase potential generalizability of our clinical risk scoring system. Each observation included in the analysis was assigned a four-digit number between 0 and 1 using a random number generator and the dataset was sorted on this variable. Patients with random numbers in the lower two terciles were assigned to the Training set and those above this cutoff were assigned to the Validation set (Figure 1).

Outcome of interest and risk factors

The primary outcome of interest was prolonged length of stay (pLOS), defined as a postoperative length of stay greater than the 75^{th} percentile for the entire cohort; an established cut point in colorectal surgery and otolaryngology (10,11,13). We assigned each observation a value of 0 (not a prolonged stay) or 1 (prolonged stay) for this binary variable.

All standard NSQIP variables were retrieved; including patient demographics and comorbidities, preoperative laboratory values, and operative data. This data was collected by a fully trained surgical clinical reviewer (SCR) using standard ACS NSQIP procedures and definitions. The NSQIP participant user guide may be referenced for full definitions of each variable (14). A single reviewer supplemented NSQIP data with estimated blood loss (EBL), which was manually collected from the electronic medical record. Variables were classified as preoperative

demographics, preoperative laboratory values, or intraoperative factors. Age was categorized as < 65, 65 to < 75, 75 to < 85, and ≥ 85, based on other studies using NSQIP data (9). Additional demographic variables that we re-categorized included functional status (dependent vs not dependent), medically treated diabetes, presence of ≥3 comorbidities, preoperative admission > 1 day, and American Society of Anesthesiologists (ASA) physical status classification >2. We investigated the association of pLOS with preoperative laboratory values as continuous risk factors, to understand how patients differed on average, and as categorical risk factors, to understand the proportion of different biologic states among patients with and without pLOS. Variables for low albumin, elevated creatinine, low hematocrit, elevated INR, thrombocytopenia, and thrombocytosis were created based off of low- or high- normal values provided by our hospital's laboratory.

We performed a univariate analysis to test for associations between pLOS and preoperative demographic, preoperative laboratory, and intraoperative variables. Chi square tests and Fisher's exact tests were used to test the null hypothesis that the proportions of risk factors did not differ between patients with and without pLOS. For continuous variables, these hypotheses were tested using Student's T tests for normally distributed means and Wilcoxon rank sums test for highly skewed measures. Variables that were present in greater than 10% of the test cohort were considered candidates for multivariate modeling if they met the inclusion criteria of $p \leq 0.2$. The significance level for univariate and multivariate analyses was set to $\alpha=0.05$.

Risk prediction model

We performed multivariable logistic modeling on the Training set to find independent predictors of pLOS. We used a hierarchical model building process previously reported in the pLOS literature (13). First, separate multivariate models were built using only demographic, laboratory, or intraoperative data. This was done in order to find factors within each variable category that were independently and significantly associated with prolonged LOS. A variety of selection

techniques—forward, backward, and stepwise—were used, with entry and exit criteria of $\alpha < 0.1$ and $\alpha < 0.05$, respectively. One variable (patient age category) was considered fixed for the demographics-specific model since it is widely accepted as a risk factor among surgical patients.

Second, these separate models were combined in a hierarchical fashion. We began with a model including significant demographic variables and added to it the significant laboratory variables. Laboratory variables were retained if a likelihood ratio (LR) test comparing a model with and without laboratory factors was significant. Intraoperative variables were then added to the model containing demographic and laboratory variables. Again, a LR test was used to determine if these intraoperative variables were independently significant and contributed to the model. This hierarchical order of model building was based on the belief that each variable category has a different strength of predicting an outcome of interest. We believe that patient demographics and comorbidities would have the smallest impact on pLOS. The effect of demographics would be trumped by a patient's biological state implied by laboratory values and be further outweighed by what occurred intraoperatively. Adding variables to the model with increasingly large impacts on the outcome preserves the predictive ability of "less powerful" variables by preventing their exclusion from the final model. This hierarchical construction allowed our final model to accommodate risk factors from all variable categories, by preventing potential risk factors from removal based on p-values alone. We arrived at a final multivariable predictive model once a full complement of independent demographic, laboratory, and intraoperative predictors of pLOS were found.

Parameter estimates obtained from running this final model on the Training set were internally and externally validated. We used a "jack-knife" technique to perform internal validation. This process fits the model using *n-1* patients, estimating the predicted probability of the outcome for the excluded patient. This process is repeated *n* times to arrive at a validated estimate of a model's predictive ability without sacrificing sample size or power. The model was externally

validated on the Validation set. Receiver operating characteristic (ROC) curves were estimated for each set. We chose a classification rule by determining a cut-point for the predicted probability of pLOS that resulted in an acceptable sensitivity and specificity and constructed classification tables for both cohorts using this rule. We then calculated sensitivity, specificity, and accuracy for predicting pLOS using the final model and chosen cut point. We also evaluated the ability of the cut point using Youden's J statistic and the Briar score. Youden's J is a unified summary of the sensitivity and specificity of a test; calculated by subtracting 1 from the sum of the sensitivity and specificity. The Briar Score is a measure of accuracy for probabilistic predictions which is derived from the mean squared difference between the predicted probability assigned to an outcome and the actual outcome. Predictive models with Briar scores closer to zero are most accurate (15).

Clinical risk scoring system

A pLOS Risk Score was developed using each variable in the final model and the parameter estimates obtained from internal validation. Our methodology was based on the development of Framingham Heart Study clinical risk scores for 10-year risk of developing heart disease (16). A referent profile (W^{ij}) and base category (W_{iRef}) was chosen for each variable. The distance between levels within each factor and the base was calculated and converted in to regression units by multiplying by the parameter estimate (β_i). This was divided by a constant (B) to arrive at the point value for each risk factor. Continuous risk factors needed to be categorized for this process. Estimated blood loss was categorized as ≤100 mL, 101-600 mL, 601-1000 mL, and >1000 mL, since physicians can reliably categorize EBL into one of these broad categories (17). Operative time was divided into <3 hours, 3 to <6 hours, 6 to <9 hours, and ≥9 hours. The risk of pLOS associated with each possible point total was calculated using Formula 1. The expression $\sum_{i=0}^{p} \beta i X i$ approximates to the sum of the model intercept (β_0), base values of each continuous

risk factor times their parameter estimates ($W_{iRef}*\beta_i$), and the constant times the point total (B*Point total).

Formula 1

$$\hat{p} = {1}\Big/{(1 + e^{-\sum_{i=0}^{p} \beta i X i})}$$

$$= {1}\Big/{(1 + e^{-(\beta(0) + \mathrm{W(EBLRef)}*\beta(\mathrm{EBL}) + \mathrm{W(OpTimeRef)}*\beta(\mathrm{OpTime}) + B(Point\ total))})}$$

Classification performance of the clinical risk scoring system in both cohorts was measured using the previously defined cut point. The distribution of points for patients with and without pLOS and their average totals were visualized with box plots. All statistical analysis was performed using SAS 9.3 (SAS Institute, Cary, NC).

RESULTS

A total of 417 patients underwent elective colectomy for premalignant, malignant, inflammatory bowel, or diverticular disease at our institution between 2009 and 2013. The 75th percentile for postoperative length of stay was 10 days and patients with stays > 10 days will be referred to as having had a pLOS. This percentile also corresponds to a gap between two local maxima of a histogram for length of stay (Figure 2).

Preoperative demographics and comorbidities of patients with and without pLOS are shown in Table1. The proportion of patients with disseminated cancer, diagnosed bleeding disorder, ≥ 3 comorbidities, prior major abdominal surgery, and ASA classification >2 was significantly greater among patients with pLOS. The average number of comorbidities and length of preoperative admission was also greater. The distribution of surgical indications differed between groups. Those with pLOS were more likely to have required a colectomy for malignant or inflammatory bowel disease. The association between pLOS and preoperative laboratory values is shown in Table 2. Those with pLOS had significantly lower levels of albumin (3.4 ± 0.7 vs. 3.6 ± 0.5 g/dL) and a greater proportion with albumin levels < 3.2 g/dL (33 vs. 20%). Median hematocrit was 3% lower among patient with pLOS, as was the proportion with hematocrit < 33% (44 vs. 27%). The median international normalized ratio (INR) significantly differed and, while this is likely of little clinical significance, those with pLOS were more likely to have an elevated INR > 1.2 (16 vs. 4%). Preoperatively, those with pLOS were also more likely to be thrombocytopenic and fulfill Systemic Inflammatory Response Syndrome (SIRS) criteria. Preoperative demographic and variables that also met the modeling inclusion criteria of $p \leq 0.2$ included gender, presence of ascites within 30 days preoperatively, dyspnea, preoperative transfusion and median alkaline phosphatase (71 ± 36 vs. 68 ± 28 IU/L).

Intraoperative variables are summarized in Table 3. Patients with pLOS were significantly more likely to have open approach to colectomy (79 vs. 45%), total or subtotal colectomy (15 vs. 6%),

creation of an ostomy (20 vs. 8%), longer operative time (5.3 ± 4.6 vs. 3.2 ± 2.7 hours), and increased EBL (300 ± 350 vs. 100 ± 150 mL). Of note, 55% of cases were planned to be laparoscopic-assisted and a minority these had pLOS (14%). The conversion rate of laparoscopic-assisted to open colectomy was 33% in patients with pLOS (11 of 33 cases) and 12% among those without pLOS (24 of 196 cases).

The final predictive model is shown in Table 4 and Table 5. Table 4 shows the odds ratio and confidence intervals for demographic variables controlling for other demographic factors, for INR controlling for demographic factors, and for intraoperative variables controlling for demographic and laboratory factors. INR was the only independently significant laboratory variable when controlling for demographics, confirmed via likelihood ratio test ($p = 0.04$). A likelihood ratio test also showed that open colectomy, EBL, and operative time significantly contributed to a model predicting pLOS ($p < 0.0001$) controlling for demographic and laboratory variables. The parameter estimates for the full model, one controlling for variables from all categories simultaneously, is shown in Table 5. The ROC curve for this model had an adjusted area under the curve (AUC) of 0.79 on internal cross-validation and 0.81 when pLOS was modeled in the Validation set (Figure 2).

The performance of this model at a predicated probability cut point of > 0.24 (25% or greater predicated risk of pLOS) is summarized in Table 6 and Table 7 for internal and external validation, respectively. . We chose a predicated probability cut point of > 0.24—25% or greater predicated risk of pLOS—based on the Training set ROC curve. We determined the predicted probability corresponding to a point on the ROC curve that we perceived to best maximize sensitivity and specificity. The accuracy of this cut point for classifying a patient as being at increased risk of pLOS was practically the same in the Training and Validation sets (78.1% vs. 77.0%). While there proved to be a much lower sensitivity (70.1% vs. 58.5%) in the Validation versus the Training set, the specificity was improved (80.1% vs. 84.7%). Overall, the model and

cut point performed well when externally validated, with a Youden's J statistic of 0.43 and a Brier score of 0.18.

Development of the clinical risk scoring system is shown in Table 8. The final pLOS Risk Score developed from the Training set and the predicted risk associated with certain point totals are shown in Table 9 and Table 10, respectively. Preoperative admission >1 day was the most impactful demographic risk factor. Elevated INR, which would earn a patient 8 points, had a similar impact as most of the remaining demographic variables; ≥ 3 comorbidities (8 points), prior major abdominal surgery (7 points), and presence of disseminated cancer (7 points). It is of note that preoperative admission was the only non-intraoperative risk factor that remained independently significant in a final model including variables from all three categories. A dotted line on Table 10 denotes where a patient's point total places them at an increased predicted risk of pLOS. A point total over 25 corresponds to a predicted risk of pLOS >25%. Table 11 shows how well the pLOS Risk Score performs in the Training and Validation sets compared to the multivariable logistic regression model. Figure 3 shows the median point totals among patients with and without a pLOS for both datasets. Figure 3 shows the median point totals among patients with and without a pLOS for both datasets. Figure 4a shows an ROC curve comparing the Training set to the Validation set, stratified by the presence or absence of postoperative complications. Table 12 shows odds ratios and confidence intervals for parameter estimates from a parsimonious model, one including only significant variables from the final model. Table 4b compares ROC curves for our full final model versus a parsimonious model; one including only significant variables found without using a hierarchical approach.

CONCLUSIONS

The aim of this study was to determine a set of variables associated with prolonged length of stay (pLOS) in a cohort of patients undergoing colectomy at a tertiary care hospital, assess how well these factors predict risk of pLOS, and create a CDSS tool for predicting pLOS that surgical teams can use at the point of care. Our data show that preoperative admission > 1 day, open colectomy, estimated blood loss, and operative time are independently associated with pLOS when controlling for other potential risk factors. Intraoperative factors greatly increased the odds of having a prolonged LOS; 300% greater for an open approach, 10% greater for a 100 mL increase in EBL, and 15% greater for a one hour increase in operative time. A 500 mL increase in EBL or a 3 hour increase in operative time increased the odds of pLOS by around 50% each. Patients admitted > 1 day prior to the date of surgery had 360% greater odds of pLOS compared to those admitted the day of surgery. Hierarchical modeling by variables of the same class—demographic, laboratory, or intraoperative—provided additional factors that, within each variable category, significantly explain patient-specific variation in the risk of pLOS. These additional factors included the presence of disseminated cancer, ≥ 3 comorbidities, prior major abdominal surgery, and elevated INR > 1.2.

Our results differ from other studies that investigated risk factors for pLOS among the colorectal surgery population (10,11,18). Gender, procedure type, and smoking status were not independent predictors of a prolonged stay in our cohort. Differences in study design may be responsible some of this disagreement. Our fellow investigators from the two most powerful pLOS studies used national registries, able to account for hospital- and surgeon-specific factors, and analyzed patient-specific socioeconomic variables (10,11). Some of the risk factors we propose are consistent with those found in other studies, however. Number of comorbidities and open approach to colectomy seems to be uniformly associated with pLOS. For example, open colectomy was associated with a 200% increase in the odds of pLOS for one of these studies (10)

and a 300% increase in the odds for our cohort. With regard to postoperative risk in general, preoperative admission has also been reported as a risk factor (19).

This is a novel study for two reasons. Firstly, we determined the ability of significant variables to predict a patient's risk of pLOS. We measured the ability of our predictive model in a number of ways. The AUC calculated from the internal and external validation cohorts averaged to 0.8 (0.79 in the Training set and 0.81 in the Validation set). Models with AUCs above 0.8 are generally thought to have 'good' discriminatory ability. The Brier score calculated from external validation of the model was 0.18; a reasonable performance and much better than the flip of a coin (Briar score of 0.25) (20). The classification rule we chose classified observations in both the Training and Validation sets with approximately 77% accuracy.

A second novel aspect of this study is that we converted our predictive model into an easy to use, points-based clinical risk scoring system. The pLOS Risk Score ranges from 0 – 88, with a score of > 25 points corresponding to roughly a 25% risk of postoperative stay greater than 10 days. Using this clinical risk scoring system and classification rule of 25 points, our external validation yielded an overall accuracy of 77%; near exact agreement with the predictive ability of a computer-generated logistic regression model.

While postoperative complications may not have figured into our risk estimation, the events of a patient's postoperative course could indeed affect length of hospitalization and, therefore, our results. Prior studies have shown that postoperative complications double a patient's average length of stay (21) and, along with intraoperative processes, have the greatest effect on a patient's risk for pLOS (22). Cohen et al recently investigated how stratifying patients by the presence of complications or estimated preoperative morbidity risk affects the variability of postoperative stay. In this study, the presence of a complication greatly increased variability. Cohen et al concluded that, while these occurrences increase the average length of stay, the effect varies across complication type and their effect on patients is not modifiable (23).

It is possible that our model could be detecting the prevalent risk factors among those suffering complications and subsequently having prolonged hospital stays. Furthermore, it could be that pLOS is a surrogate for postoperative complications. This would render our collection of risk factors useless in predicting pLOS in patients that did not suffer a discrete adverse event. Due to the large variation complications can introduce into a patient's postoperative stay, we preformed sub-analyses on the Validation set for patients with and without any postoperative complications (Figure 5. a). Fewer than 40% of our cohort suffered a postoperative complication, a composite outcome defined as the development of at least one of the following; deep venous thrombosis, pulmonary embolism, myocardial infarction, urinary tract infection, pneumonia, surgical site infection (superficial, organ space, or deep), wound disruption, sepsis, septic shock, or placement on a ventilator for > 48 hours postoperatively. The model performed just as well among patients without any complications (AUC = 0.85) as it did in the entire Validation cohort. We were able to predict pLOS with 50% sensitivity and 91% specificity at the predicted probability cut point of > 24%. The model did not perform as well overall (AUC = 0.64) among patients suffering postoperative complications, but the classification rule had a much greater sensitivity at 68% and a specificity of 64%.

It has also been shown that simplified models using NSQIP data can perform equally compared to a more complex counterpart (24). We were able to adequately predict pLOS using a parsimonious model controlling for age that included only preoperative admission > 1 day, open colectomy, estimated blood loss, and operative time (Figure 5.b). This version of our pLOS model preforms just as well in the Validation set as the full model (AUC= 0.82 vs. 0.81).

This study does have limitations. First, we did not account for some potential risk factors of pLOS. Since this was a single site study, we could not account for the effect of institutional variation on pLOS. We also did not account for important socioeconomic variables such as level of education, income, living situation, or social support and marital status. Since surgeons

performing colectomy at our institution have not adopted a uniform postoperative clinical care pathway, provider-specific variation is sure to exist and this was also left unaccounted. While we did address how our model performs among patients that did and did not suffer postoperative complications, we do not have a solution for accounting for the added variation these events may contribute towards postoperative length of stay. However, our main objective was to provide surgical teams with a CDSS able to estimate a patient's risk of pLOS on POD 0. Since complications occur over a broad range of postoperative time periods—immediately, acutely, and sub-acutely—we cannot account for this added variation if the pLOS Risk Score is to function as a true CDSS tool. Designing a method to calculate post-test probability of pLOS after a complication may be a useful future initiative.

Second, our model has not been validated in other surgical populations or for different procedural-based episodes of care. As a result, it may not be generalizable to other institutions or for procedures other than colectomy. At most, we may generalize our findings to patients undergoing elective colectomy at academic, tertiary care facilities. We understand that studies using local data may have limited generalizability. However, it is possible that models created with national datasets may be less relevant to each individual institution when compared with models using local data. The performance of our model and the pLOS Risk Score should be investigated with additional studies, potentially using a national dataset like the ACS NSQIP Participant Use Data Files. Along similar lines, the definition of pLOS will differ from cohort to cohort. We are unsure how our model will perform in populations with varying distributions in length of stay.

A third shortcoming is in the validation of our predictive model itself, as the sensitivity precipitously drops at higher predicted probability cut points. Throughout our study, we used a cut point of > 24% predicted risk of pLOS. This was able to correctly classify 70% patients with pLOS in the Training set, but misclassified nearly half of these patients in the Validation cohort.

The sensitivity of a cut point around 25% predicted risk was 58.5% using both the multivariable logistic regression model and the pLOS Risk Score. It is not ideal to misclassify nearly half of the patients we mean to detect with this risk score. However, providers are currently forced to make decisions based on clinical expertise and the values of their patients. The addition of a CDSS, especially one with a high specificity, may improve upon current methods of discharge decision-making.

The discharge decision-making process is complex and the amount of data presented to surgical teams is daunting. Our group has started to determine which factors play into the discharge decision-making process; patient age, functional status, vital signs, red and white cell count, social support, and others (25). In addition, a recent systematic review collated various attempts to predict risk of 30-day readmission (26). This outcome is not easily predicted, as most models performed poorly. Other studies have shown that patients readmitted with complications may have been discharged too early (21). Clinical decision-support systems (CDSS) may assist physicians in sorting through this data and making complex decisions. Clinical risk scoring systems and risk prediction models are important forms of CDSS, the use of which is lacking in general surgery. As a CDSS, the pLOS Risk Score could significantly impact decision-making at the point of care by prompting the initiation of early and appropriate discharge planning, better managing patient expectations, or selecting patients for rigorous nutrition or physical rehabilitation regimens during the postoperative period. If this tool were validated on other cohorts and proven to assist surgical teams during the postoperative period, low risk patients could begin recovering in the comfort of their homes earlier, at risk patients would receive the added care they need, and the health care system would cut down on overall costs. Future studies will need to focus on determining the impact of estimated risk of pLOS on hospital costs, patient satisfaction, and readmission rates.

CDSS help physicians quickly make complex management decisions appropriate for the individual patient. As patient-centered care becomes the banner under which all health related activities are to be performed, we must strive to tailor our decisions based on the evidence at hand. Improving the efficiency and quality of health care is a top initiative among stakeholders in the field (1,2,27) and we have seen that quality postoperative care and efficient postoperative care are not mutually exclusive (6,28). Prolonged length of postoperative hospital stays (pLOS) can be particularly taxing on patients, families, surgical provider teams, and hospital resources. Validating risk factors for pLOS among patients undergoing colorectal procedures is the first step in bringing surgeons closer to applying evidence to discharge decision making for this patient population. The pLOS Risk Score may have a role in positively affecting surgical outcomes, patient satisfaction, and the cost of care.

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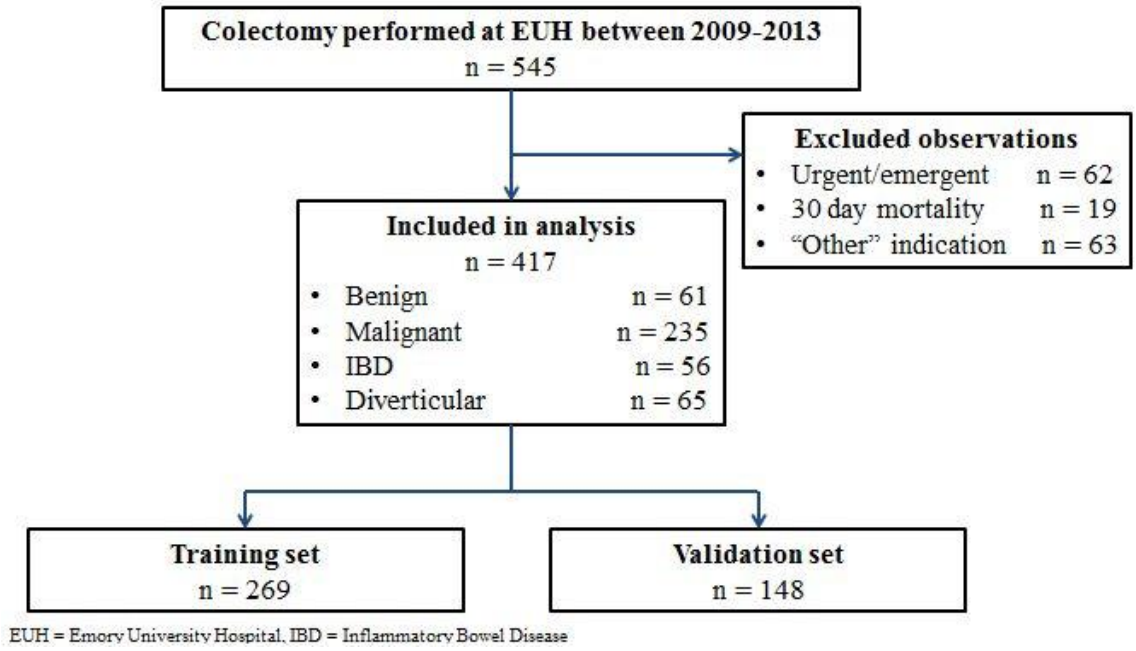
FIGURES AND **TABLES**

Figure 1



EUH = Emory University Hospital, IBD = Inflammatory Bowel Disease

Figure 2

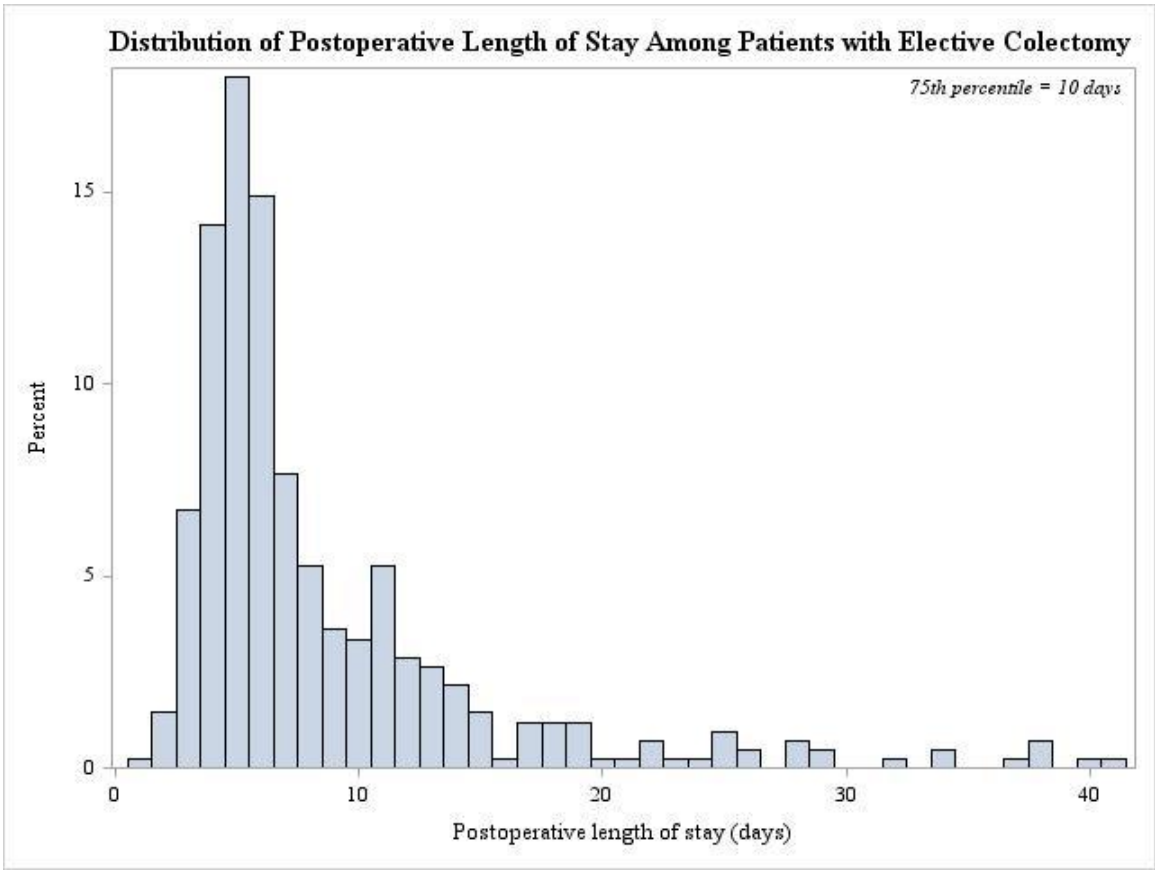

Distribution of Postoperative Length of Stay Among Patients with Elective Colectomy
75th percentile = 10 days
Percent
0
5
10
15
0
10
20
30
40
Postoperative length of stay (days)

Table 1

Table 1: Summary of preoperative demographic variables in a sample of patients undergoing elective colectomy

Demographic variable	**pLOS (>10 days)** n = 103	**Non-p LOS (≤10 days)** n = 314	**p**
Age			
Mean ± SD (years)	58 ± 16	58 ± 15	0.83 †
<65, n (%)	65 (63)	206 (65)	0.89
65 to <75, n (%)	20 (19)	62 (20)	0.89
75 to <85, n (%)	15 (15)	40 (13)	0.89
>85, n (%)	3 (3)	6 (2)	0.89
Male gender, n (%)	64 (62)	163 (52)	0.07
Body mass index (kg/m^2), mean ± SD	27 ± 6	27 ± 6	0.58 †
Obese, n (%)	24 (23)	91 (29)	0.26
Non-white race, n (%)	35 (34)	91 (29)	0.34
Dependent functional status, n (%)	4 (4)	11 (4)	0.77 •
Steroid use for chronic condition, n (%)	14 (14)	34 (11)	0.45
Ascites w/in 30 days preoperatively, n (%)	5 (5)	5 (2)	0.07 •
Disseminated cancer, n (%)	27 (26)	25 (8)	**<0.0001**
Diabetes, n (%)	13 (13)	34 (11)	0.62
Dyspnea, n (%)	8 (8)	11 (4)	0.10 •
Current smoker w/in 1 y, n (%)	15 (15)	39 (12)	0.57
History of severe COPD, n (%)	4 (4)	7 (2)	0.48 •
Bleeding disorder, n (%)	9 (9)	10 (3)	**0.03** •
Recent significant weight loss, n (%)	10 (10)	25 (8)	0.58
Total comorbidities			
Median ± IQR	1 ± 2	0 ± 1	**<0.0001** ‡
≥ 3, n (%)	15 (15)	11 (4)	**<0.0001**
Preoperative admission (days), median ± IQR	0 ± 3	0 ± 1	**<0.0001** ‡
Preoperative admission >1 day, n (%)	36 (35)	39 (12)	**<0.0001**
Preoperative transfusion, n (%)	6 (6)	8 (3)	0.12 •
Prior abdominal surgery, n (%)	68 (66)	160 (51)	**0.008**
ASA class >2, n (%)	74 (72)	183 (58)	**0.01**
Indication for colon surgery			
Polyp (premalignant), n (%)	4 (4)	57 (18)	**0.0002**
Malignant, n (%)	67 (65)	168 (54)	**0.0002**
Inflammatory bowel disease, n (%)	21 (20)	35 (11)	**0.0002**
Diverticular disease, n (%)	11 (11)	54 (17)	**0.0002**

pLOS = prolonged length of stay; SD = standard deviation, COPD = chronic obstructive pulmonary disease, IQR = Interquartile range; ASA = American Society of Anesthesiologists; • = Fisher's Exact, † = Student's t, all other tests of significance were Chi-square; Significance level α=0.05. Significant values bolded. Fewer than 3 patients each had the following characteristics; ventilator dependent, congestive heart failure, dialysis, acute renal failure..

Table 2

Table 2: Summary of preoperative laboratory variables in a sample of patients undergoing elective colectomy

Laboratory variable [# of obs. missing]	**pLOS (>10 days)** n = 103	**Non-pLOS (≤10 days)** n = 314	**P**
Albumin (g/dL), mean ± SD [7]	3.4 ± 0.7	3.6 ± 0.5	**0.0007** †
Bilirubin (mg/dL), median ± IQR [7]	0.6 ± 0.4	0.6 ± 0.2	0.85 ‡
Alk. phos. (IU/L), median ± IQR [7]	71 ± 36	68 ± 28	0.15 ‡
AST (IU/L), median ± IQR [6]	23 ± 12	23 ± 9	0.65 ‡
BUN (mg/dL), median ± IQR [1]	11 ± 8	12 ± 6	0.90 ‡
Creatinine (mg/dL), median ± IQR [1]	0.9 ± 0.4	0.9 ± 0.3	0.99 ‡
WBCs (cells/mL), median ± IQR [2]	6.5 ± 3.1	6.2 ± 2.9	0.45 ‡
Hematocrit (%), mean ± SD [2]	34 ± 6	37 ± 5	**0.0001** †
INR, median ± IQR [13]	1.04 ± 0.13	1.02 ± 0.10	**0.004** ‡
Platelets ($x10^3$), median ± IQR [2]	237 ± 119	244 ± 98	0.40 ‡
SIRS w/in 48 h preoperatively, n (%)	16 (16)	11 (4)	**<0.0001**
Low albumin, n (%)	34 (33)	64 (20)	**0.009**
Elevated creatinine, n (%)	16 (16)	36 (11)	0.28
Low hematocrit, n (%)	45 (44)	85 (27)	**0.002**
Elevated INR, n (%)	16 (16)	12 (4)	**<0.0001**
Thrombocytosis, n (%)	5 (5)	8 (3)	0.32 •
Thrombocytopenia, n (%)	16 (16)	24 (8)	**0.02**

pLOS = prolonged length of stay; SD = standard deviation, IQR = interquartile range, AST = aspartate transaminase, BUN = blood urea nitrogen; WBCs = white blood cells; INR = international normalized ratio, SIRS = systemic inflammatory response syndrome; Low albumin (<3.2 g/dL), Elevated creatinine (>1.2 md/dL), Low hematocrit (<33%),), Elevated INR (>1.2), Thrombocytopenia ($<10^5$), Thrombocytosis ($>4.5*10^5$), Elevated PTT (>35 seconds• = Fisher's Exact; † = Student's t test, ‡ = Wilcoxon rank sums, all other tests of significance were Chi-square; Significance level α=0.05. Significant values bolded.

Table 3

Table 3: Summary of intraoperative variables in a sample of patients undergoing elective colectomy

Intraoperative variable [# of obs. missing]	**pLOS (>10 days)** n = 103	**Non-pLOS (≤10 days)** n = 314	**P**
Wound classification			
Clean / Contaminated, n (%)	86 (83)	275 (88)	0.49
Contaminated, n (%)	7 (7)	19 (6)	0.49
Dirty / Infected, n (%)	10 (10)	20 (6)	0.49
Wound classification >2, n (%)	17 (17)	39 (12)	0.29
Open colectomy, n (%)	81 (79)	142 (45)	**<0.0001**
Converted lap to open[1], n (%)	11 (33)	24 (12)	**0.002**
Procedure type[2], n (%)			
Right colectomy, n (%)	48 (47)	151 (48)	0.79
Transverse colectomy, n (%)	6 (6)	9 (3)	0.22 •
Left colectomy, n (%)	12 (12)	30 (10)	0.54
Sigmoid, n (%)	18 (17)	67 (21)	0.40
Low anterior resection, n (%)	19 (18)	48 (15)	0.45
Total/Subtotal, n (%)	15 (15)	18 (6)	**0.004**
Low pelvic anastomosis, n (%)	24 (23)	75 (24)	0.90
Ostomy, n (%)	21 (20)	25 (8)	**0.0005**
Operative time (hours), median ± IQR	5.3 ± 4.6	3.2 ± 2.7	**<0.0001** ‡
EBL (mL), median ± IQR [2]	300 ± 350	100 ± 150	**<0.0001** ‡

pLOS = prolonged length of stay, EBL = estimated blood loss, IQR = interquartile range; • = Fisher's Exact, ‡ = Wilcoxon rank sums, all other tests of significance were Chi-square; Significance level α=0.05. Significant values bolded.
[1]Proportions from 229 cases initiated laparoscopically, [2]Some patients had > 1 segment or discontinuous segments of bowel removed.

Table 4

Table 4: Summary of hierarchical construction of pLOS predictive model

Variable	Odds ratio	95% CI	P
Age category	1.18	0.81 – 1.73	0.39
Disseminated cancer	5.47	2.19 – 13.68	0.0003
≥ 3 Comorbidities	3.13	1.03 – 9.51	0.05
Preoperative LOS >1	3.94	1.85 – 8.39	0.0004
Prior major abdominal surgery	2.69	1.37 – 5.27	0.004
Preoperative labs			
Elevated INR	3.09	1.07 – 8.91	0.04
Postoperative variables			
Open colectomy	3.10	1.38 – 6.97	0.006
Estimated blood loss (100 mL)	1.10	1.01 – 1.19	0.03
Operative time (hour)	1.15	1.02 – 1.29	0.03

pLOS = prolonged length of stay, CI = confidence interval, INR = international normalized ratio
Likelihood ratio test after adding labs: $\chi^2 = 4.25$, p = 0.04, after intraoperative variables: $\chi^2 = 25.43$, p = 0.00001

Table 5

Table 5: Summary of full pLOS predictive model

Variable	Odds ratio	95% CI	P
Age category	1.15	0.76 – 1.74	0.50
Disseminated cancer	2.02	0.71 – 5.76	0.19
≥ 3 Comorbidities	2.12	0.64 – 7.08	0.22
Preoperative LOS >1	3.62	1.53 – 8.56	0.003
Prior major abdominal surgery	1.96	0.94 – 4.08	0.07
Elevated INR	2.22	0.73 – 6.77	0.16
Open colectomy	3.10	1.38 – 6.97	0.006
Estimated blood loss (100 mL)	1.10	1.01 – 1.19	0.03
Operative time (hour)	1.15	1.02 – 1.29	0.03

pLOS = prolonged length of stay, CI = confidence interval, INR = international normalized ratio
Hosmer and Lemeshow Goodness-of-Fit test: : $\chi^2 = 8.04$, p = 0.43

Figure 2

Receiver Operating Characteristic (ROC) curves for an internally cross-validated and externally validated predictive model for prolonged length of stay among patients undergoing elective colectomy

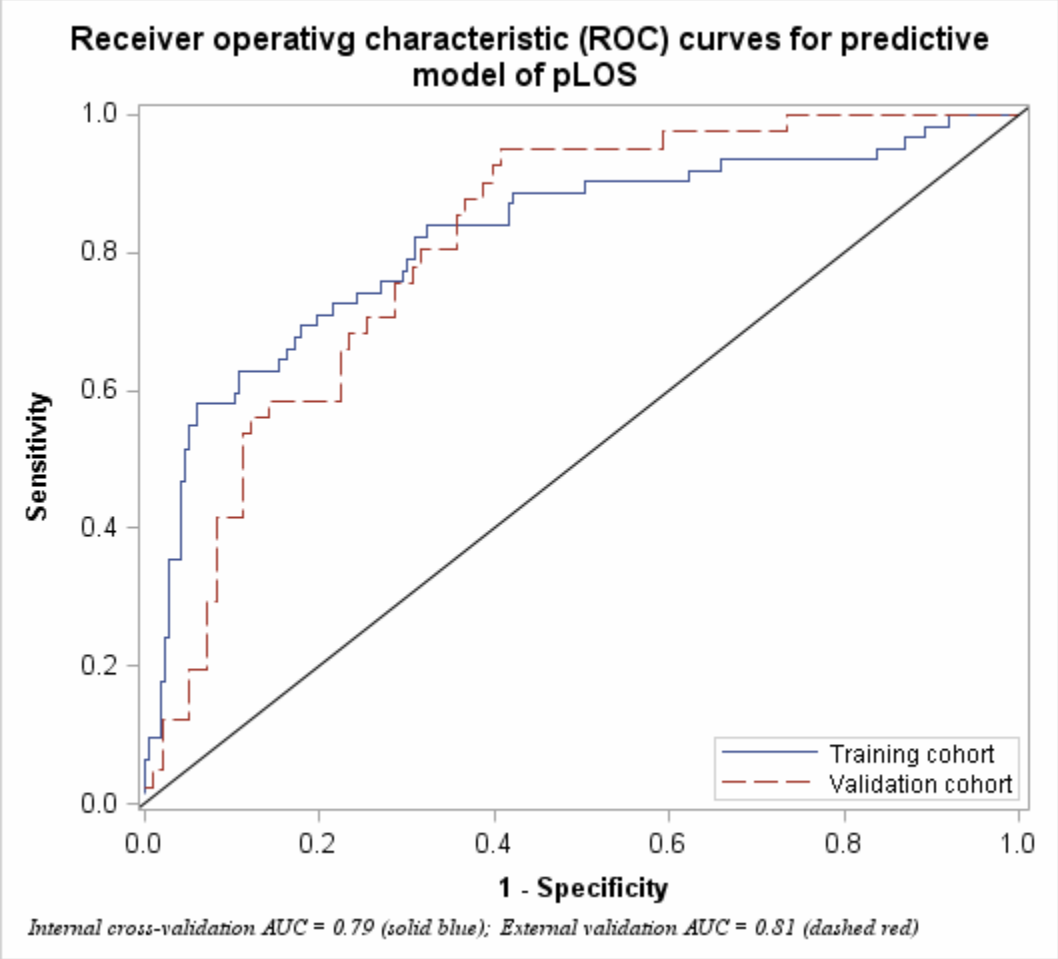


Table 6

Table 6: Predictive ability of model on training set

	pLOS	Non-pLOS
PProb > Cut point	44	43
PProb ≤ Cut point	18	173
Sensitivity	70.1 %	
Specificity	80.1 %	
False pos. rate	49.4 %	
False neg. rate	9.4 %	
Accuracy	78.1 %	

pLOS = prolonged length of stay, PProb = predicted probability, Cut point > 0.24;
Area under ROC curve = 0.82, adjusted for cross-validation = 0.79; Youden's J = 0.50

Table 7

Table 7: Predictive ability of model on validation set

	pLOS	Non-pLOS
PProb > Cut point	24	15
PProb ≤ Cut point	17	83
Sensitivity	58.5 %	
Specificity	84.7 %	
False pos. rate	38.5 %	
False neg. rate	17.0 %	
Accuracy	77.0 %	

pLOS = prolonged length of stay, PProb = predicted probability, Cut point > 0.24;
Area under ROC curve = 0.81, rescaled R^2 = 0.25, Brier score = 0.18, Youden's J = 0.43

Table 8

Table 8: Summary of clinical risk scoring system (pLOS Risk Score) development

Preoperative variables	β_i	W_{ij}	W_{ij}-W_{iRef}	$\beta_i(W_{ij}-W_{iRef})$	$(\beta_i(W_{ij}-W_{iRef}))/B$
Age category	0.1419				
Less than 65		0 *	0	0.00	0
65 to less than 75		1	1	0.14	1
75 to less than 85		2	2	0.28	3
85 or older		3	3	0.43	5
Disseminated cancer	0.7048	0 *	0	0.00	0
		1	1	0.71	7
≥ 3 Comorbidities	0.7529	0 *	0	0.00	0
		1	1	0.75	8
Preoperative LOS >1	1.2863	0 *	0	0.00	0
		1	1	1.29	13
Prior major abdominal surgery	0.6713	0 *	0	0.00	0
		1	1	0.67	7
Preoperative labs					
Elevated INR	0.7975	0 *	0	0.00	0
		1	1	0.80	8
Postoperative variables					
Open colectomy	1.1310	0 *	0	0.00	0
		1	1	1.13	11
Estimated blood loss (100 mL)	0.0919				
100mL or less		0.6 *	0.0	0.00	0
101 mL to 600 mL		3.5	2.9	0.27	3
601 mL to 1 L		8.0	7.4	0.68	7
Greater than 1 L		17.5	16.9	1.55	16
Operative time categories	0.1357				
<3 hours		2.0 *	0.0	0.00	0
3 to <6 hours		4.5	2.5	0.34	3
6 to <9 hours		7.5	5.5	0.75	8
>9 hours		11.7	9.7	1.32	13

INR = International normalized ratio, β_i = parameter estimate, W_{if} = reference values, W_{iRef}, = referent risk factor (denoted by *), B = constant "multiplier",
Intercept = -3.994;

Table 9

Table 9: pLOS Risk Score

Preoperative variables	**Points awarded for risk factor**
Age category	
Less than 65	0
65 to less than 75	1
75 to less than 85	3
85 or older	5
Disseminated cancer	7
≥ 3 Comorbidities	8
Preoperative LOS >1	13
Prior major abdominal surgery	7
Preoperative labs	
Elevated INR	8
Postoperative variables	
Open colectomy	11
Estimated blood loss (100 mL)	
100mL or less	0
101 mL to 600 mL	3
601 mL to 1 L	7
Greater than 1 L	16
Operative time	
<3 hours	0
3 to <6 hours	3
6 to <9 hours	8
>9 hours	13

Table 10

Table 10: Point totals and corresponding risk for pLOS Risk Score

Point total	Estimate of risk (%)
0	2.5
5	4.0
10	6.5
15	10.2
20	15.8
25	23.7
30	33.8
40	58.1
45	69.6
50	79.1
55	86.2
60	91.1

Table 11

Table 11: Predictive ability of pLOS Risk Score

	Training set		Validation set	
	pLOS	Non-pLOS	pLOS	Non-pLOS
PProb > Cut point	41	46	24	15
PProb ≤ Cut point	21	170	17	83
Sensitivity	66.1 % (-4.0)		58.5 % (-0.0)	
Specificity	78.7 % (-1.4)		84.7 % (-0.0)	
False pos. rate	52.9 % (+3.5)		38.5 % (-0.0)	
False neg. rate	11.0 % (+1.6)		17.0 % (-0.0)	
Accuracy	75.9 % (-2.2)		77.0 % (-0.0)	

Cut point > 25 points (predicted risk of pLOS ≥ 25.5%

Figure 3

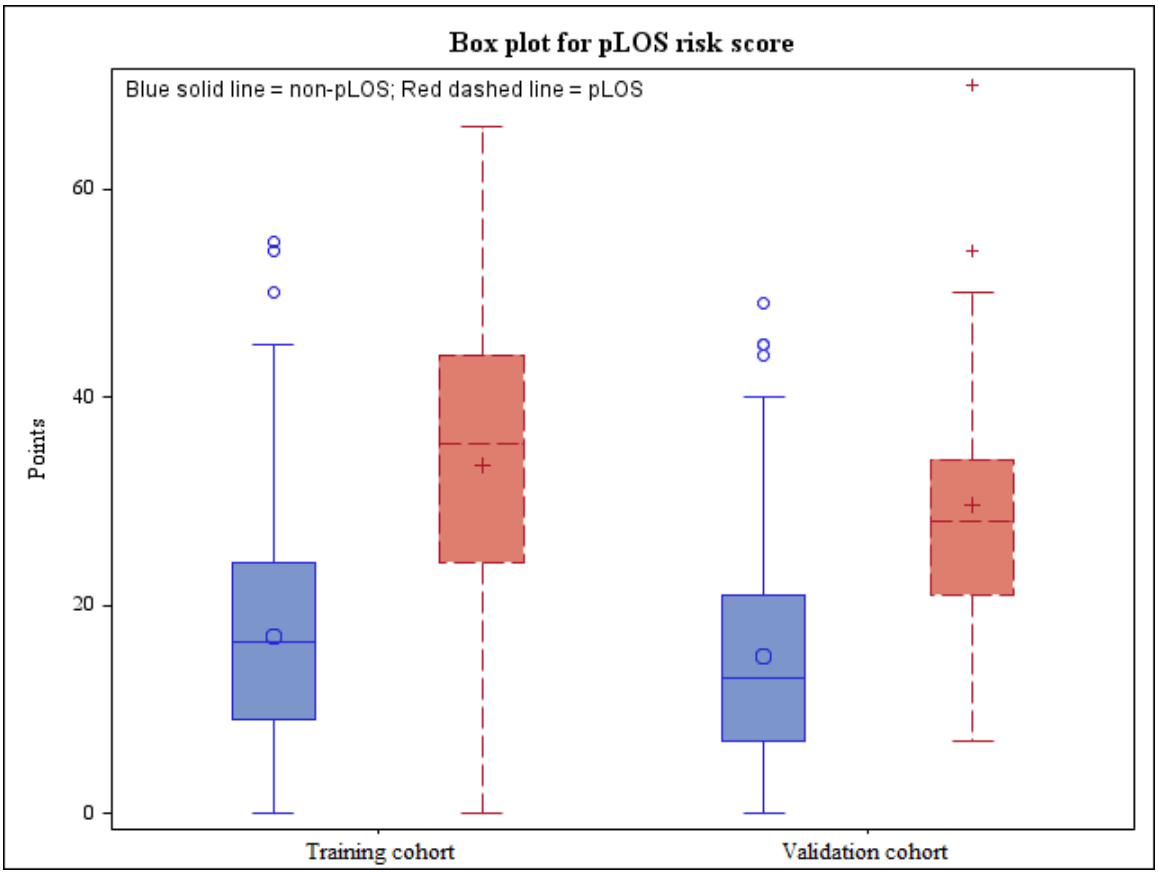


Table 12

Table 12: Summary of parsimonious predictive model

Demographic variables	Odds ratio	95% CI	P
Age category	1.18	0.80 – 1.74	0.41
Preoperative LOS >1	4.63	2.23 – 9.60	<0.0001
Open colectomy	4.18	1.92 – 9.10	0.0003
Estimated blood loss (100 mL)	1.10	1.03 – 1.20	0.008
Operative time (hour)	1.18	1.05 – 1.233	0.004

pLOS = prolonged length of stay, CI = confidence interval, INR = international normalized ratio
Hosmer and Lemeshow Goodness-of-Fit test: : $\chi^2 = 13.22$, $p = 0.11$

Figure 4

Receiver Operating Characteristic (ROC) curves for an internally cross-validated and externally validated predictive model for prolonged length of stay among patients undergoing elective colectomy