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Complications after discharge predict readmission after colorectal surgery

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Abstract

Background Health care providers, hospitals, and pay-for-performance programs are focused on strategies identifying patients at highest risk for re-admission after colorectal surgery. The study objective was to determine characteristics most associated with re-admission after elective colorectal surgery using a conceptual framework approach.

Methods This is an observational study of Michigan Surgical Quality Collaborative clinical registry data for 8962 colorectal surgery cases between July-2012 and April-2015. Separate mixed models were fit using known re-admission risk factors aligned in categories that may impact re-admissions by different mechanisms. Overall model discrimination was evaluated using Area Under the Curve estimated on a hold-out data set and examining differences in predicted versus observed re-admission across risk quintiles.

Results The overall 30-day re-admission rate was 10.5%. From Model 1 to Model 6, discrimination of re-admission was poor until Model 6 (AUC, 0.56, 0.61, 0.65, 0.63, 0.72, 0.81). Differences for observed re-admission rates comparing 'very low' versus 'very high' risk strata from Model 1 to Model 6 were 6%, 11%, 15%, 14%, 20%, and 30% respectively, and all comparisons were significant ($p < 0.01$). Though there were significant predictors in the first five models, most were no longer significant when additional predictors were included in subsequent models. Complications identified after discharge significantly increased the likelihood of re-admission and were the strongest predictors.

Conclusion Statistical models that include complications identified after discharge predict re-admission. Strategies to reduce re-admission after colorectal surgery should emphasize prevention of complications and more effective interventions to manage and ameliorate evolving complications identified after discharge.

Keywords Re-admission predictors · Colorectal surgery · Conceptual framework

Re-admission after elective and emergent colorectal surgery occurs after 10–30% of cases and has become the focus of incentives aimed at improving quality and reducing cost [1–3]. Governing bodies consider re-admissions a quality metric. Section 3025 of the Affordable Care Act established the Hospital Readmissions Reduction Program that included

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colectomies and instituted financial penalties for hospitals with high re-admission rates, and private payer programs include incentives for reducing re-admissions [4–6].

Decreasing re-admission rates after colorectal surgery depends on understanding the predictors and reasons for re-admissions, 20–35% of which are modifiable or preventable [7–9]. Risk factors for re-admission are complex and change from admission to discharge and follow-up, and studies to date do not include all categories of re-admission predictor variables [10]. Current statistical models to evaluate re-admissions after surgery are variable with respect to the number and type of predictors, with some centered on patient demographics and comorbidities and others focused on post-operative complications [11–15]. There is a need for a comprehensive statistical re-admission predictor model incorporating all known risk factor patient categories.

Conceptual frameworks are analytical approaches that group determinants into hierarchal relationships that provide guidance for multivariate techniques and aid in result interpretation [16]. The goal of the conceptual framework approach in this study is to determine if providers can predict re-admission probabilities given what is known at each level of the surgical experience as well as the specific variables that are most important. Predictors of re-admission may be organized into categories that represent the various patient, surgery, and hospital factors that potentially impact re-admissions. With each succeeding category, providers do not have information about subsequent patient progression and must make decisions based only on what is known to that point. A conceptual framework helps identify the factors that are known at each category throughout the peri-operative process, and multivariate models can be used to determine how well these variables predict re-admission. Interventions aimed at reducing re-admissions can then be made more effective through improved understanding of high-risk predictors of re-admissions at each stage.

This study was designed to evaluate six different cumulative statistical models, beginning with pre-operative patient factors, and accruing predictors through the peri-operative period. The aim of this study was to determine the capacity for re-admission prediction through each patient-related category and at what point in the patient experience this conceptual framework may allow reasonable judgements about the likelihood of re-admission, to aid in the design of interventions designed to decrease re-admissions after colorectal surgery.

Methods

Data source and study sample

The Michigan Surgical Quality Collaborative (MSQC) is a statewide multicenter collaborative of 73 hospitals that maintains a clinical registry that is protocol-driven, externally audited, and regularly validated. Registry cases were selected using a stratified random sampling methodology. The study sample included 8962 patients age ≥ 18 years and American Society of Anesthesiology (ASA) classification < 4. The following current procedural terminology (CPT) codes were used to identify relevant cases: 44140, 44150, 44160, 44145, 44146, 45110, 45540, 45550, 44204, 44205, 44207, 44208, 44210, 45395, 45400, or 45402. The study period was inclusive of operative dates between July 2012 and April 2015. Of these, 3942 underwent an open surgical approach, 4297 were laparoscopic, and 723 were robotic colorectal resections.

Outcome and explanatory variables

The primary outcome variable was re-admission within 30-days of operation. Explanatory variables were grouped into six categories representing patient factors related to the surgical experience. These included demographics, general-health-factors and comorbidities, patient surgery factors, in-hospital complications, utilization and discharge, and post-discharge complications.

Statistical approach

Fifty-six predictor variables were grouped into re-admission risk categories: (1) patient demographics, (2) general-health-factors/comorbidities, (3) patient surgery factors, (4) in-hospital complications, (5) utilization and discharge, and (6) post-discharge complications. Differences in predictor variables between re-admission groups are presented as observed frequencies and unadjusted percent.

Separate models were fit for each of the six categories of the conceptual framework. For the statistical analysis, we used generalized linear mixed models with all candidate patient covariate predictors modeled as fixed effects. Random effects were surgeon and hospital. A separate model was fit for categories that included all variables from the prior categories. Measures of association were reported as adjusted odds ratios with 95% confidence intervals. Associations were flagged as significant if p values were less than 0.05 (*), 0.01 (**), or 0.001 (***).

With this approach, each of the six models includes all available potentially relevant information known up to that category. The number of predictors for each model represents the cumulative total of predictors contributing to that stage and preceding stages for each patient. The number of modeled predictor variables ranges from a low of 3 for Model 1 (Demographics) to 56 for Model 6 (Post Discharge Complication). No step-wise procedure was used; the models retained all predictors from the prior model regardless of significance.

Overall prediction

Of interest is the out-of-sample predictive accuracy of each variable category. Toward this end, the data were randomly separated into a "training" sample consisting of 75% of data and a "test" sample consisting of the remaining 25%. The model was fit to the training sample and then used to predict re-admissions on the test set. This was done to avoid overstating the predictive accuracy due to predicting the same data points used to find the best model. Discriminatory power was then tested in two ways. First, the area under the curve (AUC) was determined using predictions from the test sample based on the model fit to the training data. Comparisons between successive AUC curves were made using the Delong test. Second, test sample cases were classified into risk quintiles based on the predicted probabilities from the mixed models, and actual re-admission rates for the test set were then compared to their predicted quintiles. A Chi square test was used to determine if the re-admission rates were significantly different between the lowest and highest quintiles.

Results

The overall re-admission rate was 10.5% (10.6% in the training data and 10.4% in the test data). A brief depiction of the 6 Models is shown in Fig. 1. Full results for each of the six re-admission models that reveal both unadjusted re-admission rates and adjusted odds ratios with 95% confidence intervals are depicted in a Supplemental File because of the large number of variables. Table 1 reveals a detailed summary of the six patient re-admission predictor categories and contributing predictors. Table 2 provides the adjusted odds ratios for variables that were included in at least one model. These adjusted odds ratios come from fitting the models to the training data only. Figures 2 and 3 show the predictive performance of the models from Table 2 on the test set.

The results show that the variables most associated with likelihood of re-admission change as the patient predictor categories progress. In the first model, patients of black race were significantly more likely than white patients to experience re-admission (OR 1.03, 95% CI 1.00–1.05). However, this difference was no longer significant once additional predictors were included in subsequent models. Most notably, as shown in Fig. 2, the AUC for Model 1 is 0.556, reflecting poor discrimination.

The second model adds in general-health-factors. ASA class III patients are significantly more likely than ASA class I and II patients to experience re-admission. This difference remains statistically significant until the last model where significance is reduced by the inclusion of post-discharge complications. The other significant general health factor variables were disseminated cancer, steroid use, and recent weight loss greater than 10%. Each of these were associated with a greater risk of re-admission. The AUC for the second model was 0.610, a significant improvement over Model 1($p = 0.004$).

The third model includes patient surgery factors. While ASA class III remains significant, the other general-health-factors that were significant in Model 2 become non-significant. A post-operative diagnosis of diverticular disease and fistulas was associated with a statistically significant decrease in re-admission risk. Although no other variables were significant, the addition of the patient surgery factor variables raised the AUC to 0.653, which is a significant improvement over the prior model ($p = 0.002$).

The fourth model considers in-hospital complications. Both variables that were significant in Model 3 remain significant and of the same magnitude. In-hospital sepsis is also significant, though it is associated with a significant decrease in re-admissions. The remaining variables included

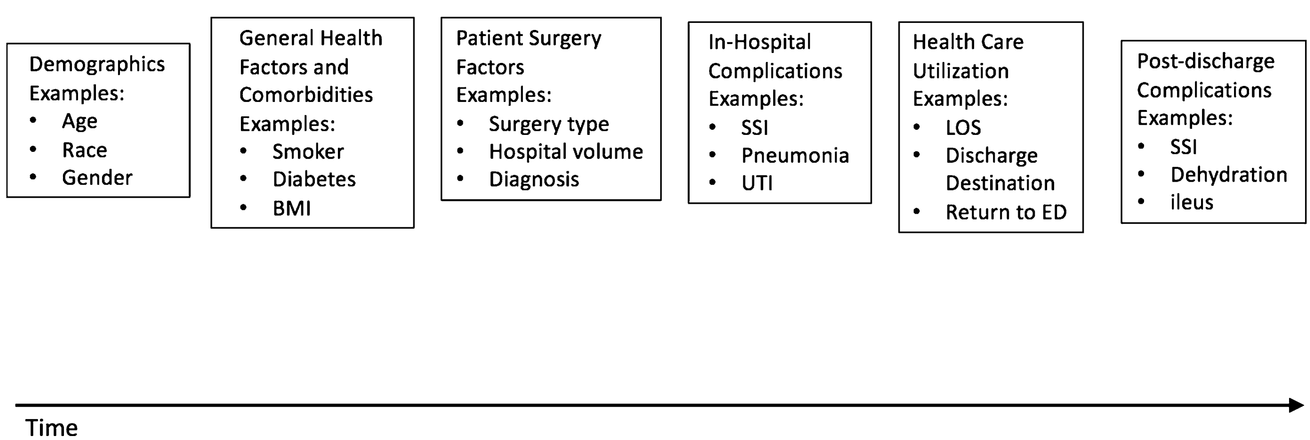

Fig. 1 Conceptual framework predictor categories

Table 1 Summary of six models of surgical journey stages and contributing predictors

Surgical journey stage	Predictor variables (levels)	Number of predictor variables	
		By stage	Cumulative total
Patient demographics	Age ≥ 65 years, male, race (white, black, other)	3	3
General health factors and comorbidities	Obese, smoker, alcohol use, functional status not independent, ASA Class III, comorbidities count (0–1, 2–3, 4–5, 6+), diabetes, ventilator, hypertension, congestive heart failure, peripheral vascular disease, disseminated cancer, steroid use, body weight loss > 10%, bleeding disorder	15	18
Patient surgery factors	Preoperative LOS > 3 days, surgical priority (emergent, urgent, elective), surgical approach (open, laparoscopic, laparoscopic converted, robotic, robotic converted), high case volume hospital, high case volume surgeon, ostomy, surgery type [anterior resection (LAR), abdominoperineal resection (APR), total colectomy, partial colectomy], estimated blood loss < 100 mL, surgical site infection prevention bundle (App IV prophylactic ABX, postop normothermia, oral ABX with Mech. bowel prep., postop day 1 glucose ≤ 140 mg/dL, operative duration < 100 min.), post-operative ICD9 Dx (colorectal cancer, colorectal adenomas/polyps, other neoplasms, diverticular Dz and fistulas, inflammatory bowel Dz), pain score ≥ 8 on post-operative day-1	11	29
In-hospital complications	Surgical site infection (superficial incisional, deep incisional, organ/space), pneumonia, pulmonary embolism, acute renal insufficiency and/or failure, urinary tract infection (symptomatic, catheter-associated), cardiac arrest req. CPR, myocardial infarction, cardiac arrhythmias, transfusions within 72 h. postop, deep vein thrombosis req. therapy, sepsis, C-difficile	12	41
Utilization and discharge	Post-operative LOS > 10 days, discharge destination (home, nursing home), ED visit	3	44
Post-discharge complications	Anastomotic leak (antibiotics only, percutaneous drainage, reoperation—new anastomosis, reoperation—proximal diversion, reoperation—end stoma), surgical site infection (superficial incisional, deep incisional, organ/space), pneumonia, pulmonary embolism, acute renal insufficiency and/or failure, urinary tract infection (symptomatic, catheter-associated), cardiac arrest req. CPR, myocardial infarction, cardiac, arrhythmias, deep vein thrombosis req. therapy, sepsis, C-difficile	12	56

in this category were not significant, and the addition of several non-significant variables reduced the AUC relative to Model 3 at 0.639. There was no significant difference in AUC between Models 3 and 4 ($p = 0.085$).

The fifth model adds in variables related to health care services utilization at or after discharge. Those discharged to home were less likely to be readmitted, whereas those who had a subsequent ED visit were more likely to be admitted. In addition, two patient surgery factor variables from Model 3 became significant for the first time, with robotic converted cases and those with recent significant weight loss more likely to be readmitted in Model 5. The AUC increases substantially up to 0.722, which is a significant improvement vis-à-vis Model 4 ($p < 0.001$).

Finally, the sixth model adds in post-discharge complications. These are complications that become clinically apparent and are identified after discharge. Note that a single observation (one patient) can have multiple complications. Nearly all the post-discharge complications are predictors of re-admission, and most with very strong effects. Overall, the sixth model shows that patient health status in the weeks following discharge is a strong predictor of the likelihood of re-admission. The AUC for the model is 0.814, which is again a significant improvement over Model 5 ($p < 0.001$).

Fifty-five percent of the post-operative complications identified after discharge resulted in re-admission (Supplemental File). The most common complications identified after discharge associated with re-admission were related to infection/sepsis (surgical site infections, anastomotic leaks, sepsis, urinary tract infections). Cardiopulmonary complications were less commonly associated with re-admission.

Figure 3 shows the information value of the conceptual framework models for predicting patient risk strata for re-admission in the study sample. Though the AUC for Model 1 suggested poor predictor capacity for patient demographics (0.556), Fig. 3 shows that patient demographics discriminated a 1.85-fold (13%/7%) increase in average re-admission rate between the lowest and highest quintiles (Model 1). After including patient health factors, the difference between the lowest and highest quintiles increases to 3.2-fold (16%/5%) (Model 2). Modeled patient surgery factors result in a modest increase in discrimination (Model 3).

Table 2 Adjusted odds ratios for significant predictors of re-admission after colorectal surgery

Variable	Adjusted odds ratios (95% confidence interval)					
	Demographics	General health factors	Patient surgery factors	In-hospital complications	Utilization discharge	Post discharge
Race: black	**1.03 (1, 1.05)****	1.02 (1, 1.05)	1.02 (0.99, 1.04)	1.02 (0.99, 1.04)	1.01 (0.99, 1.03)	1.01 (0.99, 1.03)
Obese		0.99 (0.97, 1)	0.99 (0.97, 1)	0.99 (0.97, 1)	0.99 (0.97, 1)	**0.98 (0.96, 0.99)*****
ASA class III		**1.04 (1.02, 1.05)*****	**1.03 (1.01, 1.04)*****	**1.03 (1.01, 1.04)*****	**1.02 (1, 1.04)***	1.01 (0.99, 1.03)
Disseminated cancer		**1.05 (1, 1.1)***	1.03 (0.99, 1.08)	1.03 (0.99, 1.08)	1.03 (0.98, 1.08)	1.03 (0.99, 1.07)
Steroid use		**1.05 (1.02, 1.09)*****	1.03 (0.99, 1.07)	1.03 (1, 1.07)	1.02 (0.99, 1.05)	0.99 (0.96, 1.02)
Body weight loss > 10%		**1.05 (1.01, 1.09)***	1.04 (1, 1.08)	1.04 (1, 1.08)	**1.04 (1, 1.08)***	1.03 (1, 1.07)
Surgical approach: robotic converted			1.1 (1, 1.21)	1.09 (0.99, 1.2)	**1.11 (1.01, 1.22)***	1.06 (0.98, 1.15)
Postop ICD9 Dx: diverticular Dz and fistulas			**0.96 (0.93, 0.98)*****	**0.96 (0.93, 0.98)*****	**0.96 (0.93, 0.98)*****	**0.97 (0.95, 1)***
Deep incisional SSI (in hospital)				1.08 (0.99, 1.19)	1.07 (0.98, 1.18)	**1.13 (1.04, 1.22)*****
Urinary tract infection: catheter-associated (in hospital)				1.1 (0.99, 1.21)	1.09 (0.98, 1.2)	**1.1 (1.02, 1.17)***
Sepsis (in hospital)				**0.91 (0.86, 0.96)*****	**0.91 (0.86, 0.96)*****	**0.91 (0.87, 0.96)*****
Discharge destination: home					**0.94 (0.93, 0.96)*****	**0.97 (0.95, 0.99)*****
ED visit					**1.23 (1.2, 1.26)*****	**1.13 (1.11, 1.16)*****
Anastomotic leak: antibiotics only						**1.53 (1.38, 1.7)*****
Anastomotic leak: percutaneous drainage						**1.27 (1.14, 1.42)*****
Anastomotic leak: reoperation—end stoma						**1.24 (1.15, 1.34)*****
Superficial incisional SSI (post discharge)						**1.21 (1.16, 1.26)*****
Deep incisional SSI (post discharge)						**1.58 (1.47, 1.7)*****
Organ/space SSI (post discharge)						**1.8 (1.69, 1.91)*****
Pneumonia (post discharge)						**1.26 (1.13, 1.4)*****
Pulmonary embolism (post discharge)						**1.84 (1.64, 2.06)*****
Acute renal insufficiency and/or failure (post discharge)						**1.91 (1.75, 2.07)*****
Urinary tract infection: symptomatic (post discharge)						**1.21 (1.13, 1.29)*****

Table 2 (continued)

Variable	Adjusted odds ratios (95% confidence interval)					
	Demographics	General health factors	Patient surgery factors	In-hospital complications	Utilization discharge	Post discharge
Urinary tract infection: catheter-associated (post discharge)						**1.37 (1.23, 1.53)*****
Cardiac arrest req. CPR (post discharge)						**0.63 (0.51, 0.78)*****
Myocardial infarction (post discharge)						**1.94 (1.57, 2.4)*****
Cardiac arrhythmia (post discharge)						**1.5 (1.26, 1.78)*****
Deep vein thrombosis req. therapy (post discharge)						**1.47 (1.35, 1.59)*****
Sepsis (post discharge)						**1.33 (1.24, 1.43)*****
C-difficile (post discharge)						**1.37 (1.25, 1.49)*****

Bold values are statistically significant

Estimates based on models fit to training data only. Baseline category for race is white. Baseline category for ASA is class == 2. Baseline for ICD9 diagnoses is all diagnoses other than diverticulitis, fistulas, colorectal cancer, colorectal adenomas/polyps, other neoplasms, and inflammatory bowel disease that were captured by inclusion criteria CPT codes. Baseline for comorbidities count is 0–1. Baseline category for surgical priority is elective. Baseline category for surgical approach is open

$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

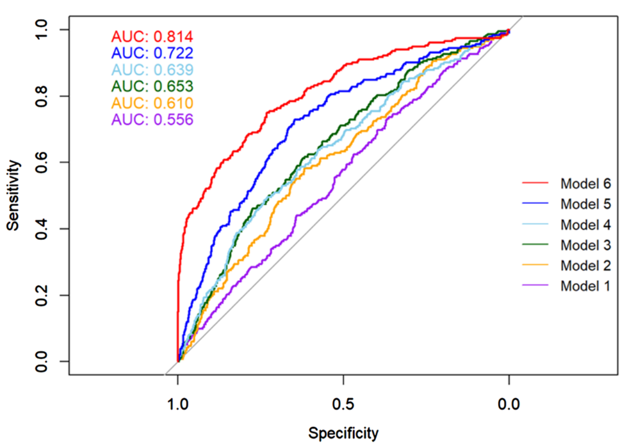

Fig. 2 Receiver operating curves (ROC) and area under the curve (AUC) for predicted re-admission in six models of surgical journey stages

In-hospital complications in total do not make a substantially meaningful, independent contribution to re-admission risk strata (Model 4). Utilization/Discharge events contribute to the prediction of re-admission risk strata until post-discharge complications are included. The difference between the lowest and highest quintiles increased to a sixfold (24%/4%) difference (Model 5). With post-discharge complications, the difference between the lowest and highest quintiles demonstrates a 16-fold (32%/2%) difference (Model 6).

Discussion

This conceptual framework analysis of 8962 patients in a large protocol-driven regional database undergoing open and minimally invasive colorectal surgery showed that re-admission risk factors in earlier conceptual framework models that include patient demographics, comorbidities, surgery-related factors, and utilization resources do not effectively predict re-admissions. Post-operative complications identified post-discharge are the best predictors of re-admissions, and the conceptual framework approach is not predictive of these complications until they occur. Some predictors significant in earlier patient surgical experience models lost significance in later models because of the introduction of subsequent intervening significant predictors.

The conceptual framework approach addresses the following questions. First, what is known in each demographic and peri-operative predictor category? Second, how well

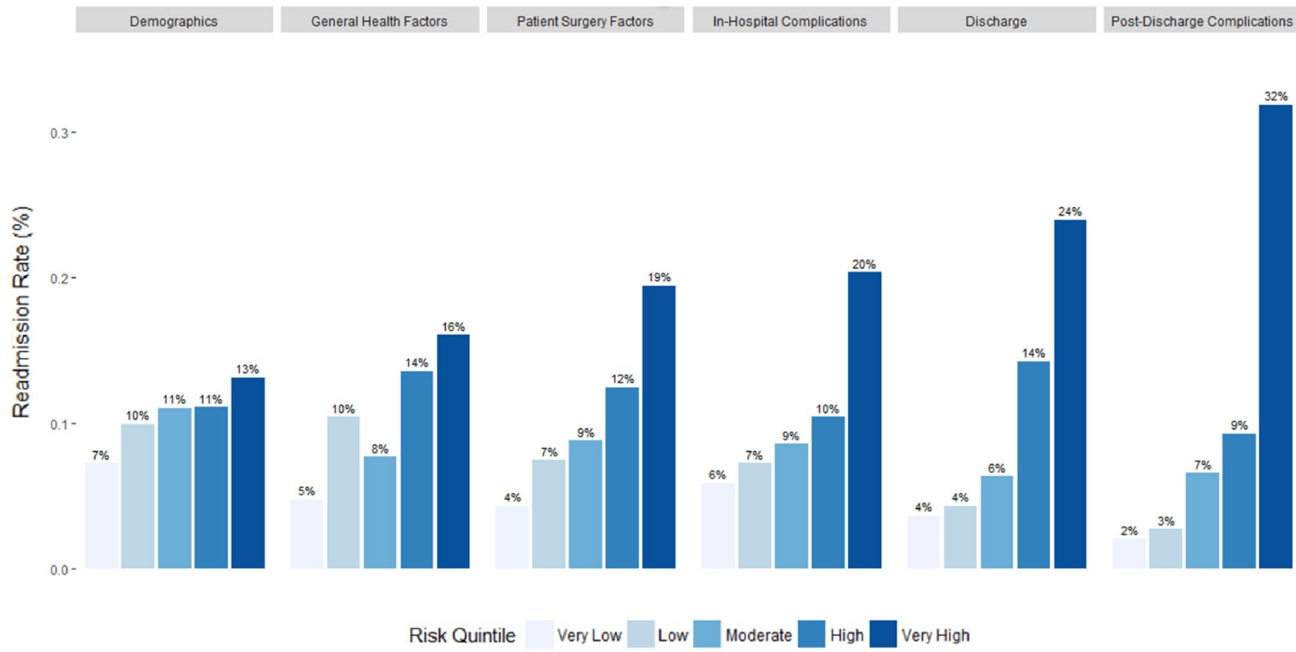

Fig. 3 Observed re-admission rates by predicted risk quintiles for six models of surgical journey stages

does this information predict re-admissions? Third, what are the variables within each category that have strongest predictive power? Patient demographics and health histories are known prior to referral for surgery. While these variables may be associated with re-admission risk down the road, their combined predictive power is likely less than what is known once variables related to patient surgery factors appear—namely information about surgery type and hospital environment. Following surgery, providers document in-hospital complications that may be associated with re-admission following discharge. Finally, resource utilization after surgery as well as complications following discharge become important pieces of information for identifying re-admissions [16].

Previous studies were centered on fewer parts of the peri-operative care continuum with a shorter list of re-admission variables, including some that did not consider complications after discharge [11, 13–15]. Patient demographics like socioeconomic and race equity are the focus of a CMS Medicare initiative [17, 18]. The results of our study revealed that black race is associated with increased risk of re-admission but that explanatory power is reduced by the inclusion of subsequent clinically discriminative variables. The same is true for other re-admission predictors in earlier models like disseminated cancer, steroid use, and weight loss > 10 percent. ASA Class was a significant re-admission predictor through all model categories until Model 6. Diverticular disease as a diagnosis was consistently protective of re-admission through all stages. Complications identified during the index hospitalization prior to discharge were not significant re-admission predictors, in contrast to other studies [14]. Discharge to home significantly decreased, and ED Visits significantly increased, risk for re-admission in all models.

Other investigators have also emphasized the relationship between post-operative complications identified after discharge and re-admissions [11, 13–15]. One found that post-discharge complications had higher odds for re-admission (61-fold) than complications evident prior to discharge (twofold) [13]. Interestingly, sepsis prior to discharge was a predictor protective of re-admission in our study, and this has been confirmed by others [19]. This finding may be related to the extended hospital LOS for patients with these predictors, with some being readmitted beyond the 30-day post-operative period, or mortality precluding the possibility of re-admission. Sepsis prior to discharge was associated with longer hospital LOS in our study – 73.1% of cases had hospital LOS > 10 days compared to 9.1% of cases without sepsis. As expected, sepsis identified after discharge was a re-admission predictor.

Though the conclusion that post-operative complications after discharge drive re-admissions is not novel, our study differs from other re-admission predictor analyses in that we tested a comprehensive list of known re-admission predictors and compared six different models of variable re-admission profiles, instead of relying on a single multivariate logistic regression model. We sought to determine the discriminatory power of the generalized linear mixed models used on re-admission predictors by first determining the AUC curve using predictors from the test sample, and then by comparing actual re-admission rates for the test set with risk quintiles composed of test sample cases.

This study has limitations inherent to any retrospective database analysis. It relies on accurate data retrieval and coding. Though the MSQC database is comprehensive in the number of predictors and the unique nature of some predictors available for analysis, there may be other data (e.g. ileus, poor pain management) not captured by this database that impacts re-admissions. Re-admission diagnoses depend on the ability of an abstractor to decipher complex hospital coding strategies and because it is not practical to request chart review from 73 Michigan hospitals, more information about re-admission diagnoses was difficult to appreciate in this study. Our data source does not allow determination of which ED visits led to re-admissions and what proportion of re-admissions included an ED visit or were direct re-admissions. We were also unable to assess specific ED visits and cultural, psychosocial, and caregiver support factors that may impact re-admissions [20]. Some anastomotic leak categories were not significant predictors of re-admissions. Like sepsis, if this complication occurred prior to discharge, the extended hospital LOS may have resulted in re-admission after the 30 post-operative days expired. Some of the post-discharge complications were infrequent and may not be sufficiently powered for statistical significance.

It is possible that re-admissions could be underestimated if patients present to another hospital for their re-admission. MSQC actively surveys re-admissions to other hospitals, though, and this may be considered a strength of this clinical registry. It is possible that hospitals and surgeons differ in their complication and re-admission profiles and so these results may not be generalizable to all hospitals and surgeons. We were unable to collect data on socioeconomic and healthcare insurance status. The strength of this study is that the data source is from a protocol-driven, regularly validated database that includes hospitals and surgeons of varied composition with data entered by trained clinicians.

Our goal was to use the conceptual framework approach in a risk-adjusted regional database to identify re-admission predictors that would allow the development of interventions designed to decrease re-admissions. The effectiveness of these interventions could then be studied at the institutional level. This study suggests that re-admissions are difficult to predict until Model 6, when post-operative complications identified after discharge become significant. Other studies using different statistical methods and fewer predictor categories and variables have not recognized post-operative complications identified after discharge as the primary driver of re-admissions [14]. This study, therefore, suggests that prevention strategies may be different than other findings (e.g., complications identified prior to discharge) may have suggested.

Understanding that the relevant post-operative complications will be identified after discharge, the focus of re-admission efforts should be preparing for and intervening sooner in the complication process, and on resource utilization designed to attenuate the severity of modifiable complications before they become re-admissions. We have implemented interventions within our established Enhanced Recovery Pathway prior to discharge in preparation for discharge, as well as within the first week after discharge designed to decrease re-admissions and targeted toward the most common complications identified after discharge that result in re-admissions at our institution. This is the subject of our current institutional study.

We recognize that there may be other re-admission model options. Other investigators are collecting retrospective and prospective data and implementing multiple statistical model strategies with a plan to convene Delphi panel participants in an effort to develop a re-admission risk prediction tool [20].

Conclusions

The conceptual framework approach confirms that post-operative complications after colorectal surgery that become apparent after discharge are most predictive of re-admissions. This model does not allow prediction of re-admissions until complications after discharge occur and is therefore not optimally predictive prior to discharge. Efforts to decrease surgical complications through standardized Enhanced Recovery Pathways and developing interventions that identify modifiable complications before they become re-admissions may be the best re-admission reduction strategy at this time.

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Compliance with ethical standards

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References

1. Rossi G, Vaccarezza H, Vaccaro CA et al (2013) Two-day hospital stay after laparoscopic colorectal surgery under an

enhanced recovery after surgery (ERAS) pathway. World J Surg 37(10):2483–2489
2. Adamina M, Kehlet H, Tomlinson GA, Senagore AJ, Delaney CP (2011) Enhanced recovery pathways optimize health outcomes and resource utilization: a meta-analysis of randomized controlled trials in colorectal surgery. Surgery 149(6):830–840
3. Thiele RH, Rea KM, Turrentine FE, Friel CM, Hassinger TE, Goudreau BJ, Umapathi BA, Kron IL, Sawyer RG, Hedrick TL, McMurry TL (2015) Standardization of care: Impact of an enhanced recovery protocol on length of stay, complications, and direct costs after colorectal surgery. J Am Coll Surg 220:430–443
4. Wasfy JH, Zigler CM, Choirat C, Wang Y, Dominici F, Yeh RW (2016) Readmission rates after passage of the Hospital Readmissions Reduction Program: a pre-post analysis. Ann Intern Med 366:1364–1366
5. Leape LL (2015) Hospital readmissions following surgery: turning complications into "treasures". JAMA 313(5):467–468
6. Kansagara D, Englander H, Salanitro A, Kagen D, Theobald C, Freeman M, Kripalani S (2011) Risk prediction models for hospital readmission: a systematic review. JAMA 306(15):1688–1698
7. Sutherland T, David-Kasdan JA, Beloff J, Mueller A, Whang EE, Bleday R, Urman RD (2016) Patient and provider-identified factors contributing to surgical readmission after colorectal surgery. J Investig Surg 29:195–201
8. Kwaan MR (2015) Can large database studies help us decrease readmissions after colorectal surgery? Dis Colon Rectum 58(12):1121–1122
9. Hechenbleikner EM, Makary MA, Samarov DV, Bennett JL, Gearhart SL, Efron JE, Wick EC (2013) Hospital readmission by method of data collection. J Am Coll Surg 216(6):1150–1158
10. Nguyen OK, Makam AN, Clark C, Zhang S, Xie B, Valesco F, Amarasingham R, Halm EA (2016) Predicting all-cause readmissions using electronic health record data from the entire hospitalization: model development and comparison. J Hosp Med 11(7):473–480
11. Kerwel TG, Leichtle SW, Asgeirsson T, Hendren SK, Cleary RK, Luchtefeld MA (2014) Risk factors for readmission after elective colectomy: postoperative complications are more important than patient and operative factors. Dis Colon Rectum 57(1):98–104
12. Dawes AJ, Sacks GD, Russell MM, Lin AY, Maggard-Gibbons M, Winograd D, Chung HR, Tomlinson J, Tillou A, Shew SB, Hiyama DT, Cryer HG, Brunicardi FC, Hiatt JR, Ko C (2014) Preventable readmissions to surgical services: lessons learned and targets for improvement. J Am Coll Surg 219(3):382–389
13. Glance LG, Kellermann AL, Osler TM, Li Y, Mukamel DB, Lustik SJ, Eaton MP, Dick AW (2014) Hospital readmission after noncardiac surgery: the role of major complications. JAMA Surg 149(5):439–445
14. Kassin MT, Owen RM, Perez SD, Leeds I, Cox JC, Sadiraj V, Sweeney JF (2012) Risk factors for 30-day hospital readmission among general surgery patients. J Am Coll Surg 215(3):322–330
15. Kelly KN, Iannuzzi JC, Rickles AS, Monson JR, Fleming FJ (2014) Risk factors associated with 30-day postoperative readmissions in major gastrointestinal resections. J Gastrointest Surg 18(1):35–43
16. Victora CG, Huttly SR, Fuchs SC, Olinto MT (1997) The role of conceptual frameworks in epidemiological analysis: a hierarchical approach. Int J Epidemiol 26(1):224–227
17. Jung DH, Palta M, Smith M, Oliver TR, DuGoff EH (2016) Differences in receipt of three preventive health care services by race/ethnicity in Medicare Advantage Plans: tracking the impact of pay for performance, 2010 and 2013. Prev Chronic Dis Sep 8;13:E125. https://doi.org/10.5888/pcd13.160047
18. Tsai TC, Orav EJ, Joynt KE (2014) Disparities in surgical 30-day readmission rates for Medicare beneficiaries by race and site of care. Ann Surg 259(6):1086–1090
19. Prescott HC, Langa KM, Iwashyna TJ (2015) Readmission diagnoses after hospitalization for severe sepsis and other acute medical conditions. JAMA 313(10):1055–1057
20. Copeland LA, Graham LA, Richman JS, Rosen AK, Mull HJ, Burns EA, Whittle J, Itani KMF, Hawn MT (2017) A study to reduce readmissions after surgery in the Veterans Health Administration: design and methodology. BMC Health Serv Res 17:198