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RESEARCH ARTICLE

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Development and prospective validation of a model estimating risk of readmission in cancer patients

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Introduction: Hospital readmissions among cancer patients are common. While several models estimating readmission risk exist, models specific for cancer patients are lacking.

Methods: A logistic regression model estimating risk of unplanned 30-day readmission was developed using inpatient admission data from a 2-year period (n = 18 782) at a tertiary cancer hospital. Readmission risk estimates derived from the model were then calculated prospectively over a 10-month period (n = 8616 admissions) and compared with actual incidence of readmission.

Results: There were 2478 (13.2%) unplanned readmissions. Model factors associated with readmission included: emergency department visit within 30 days, >1 admission within 60 days, non-surgical admission, solid malignancy, gastrointestinal cancer, emergency admission, length of stay >5 days, abnormal sodium, hemoglobin, or white blood cell count. The c-statistic for the model was 0.70. During the 10-month prospective evaluation, estimates of readmission from the model were associated with higher actual readmission incidence from 20.7% for the highest risk category to 9.6% for the lowest.

Conclusions: An unplanned readmission risk model developed specifically for cancer patients performs well when validated prospectively. The specificity of the model for cancer patients, EMR incorporation, and prospective validation justify use of the model in future studies designed to reduce and prevent readmissions.

KEYWORDS
cancer, hospital readmission, statistical model

1 | INTRODUCTION

The Centers for Medicare and Medicaid Services (CMS) and other health payers require hospitals to improve value-based care, and reducing hospital readmissions is an important area of emphasis. It is estimated that nearly 20% of CMS patients are readmitted within 30 days of index hospitalization; in turn, preventable readmissions may account for as much as $12 billion in CMS costs each year.[1,2] While causes of readmission are multifactorial, some readmissions may reflect suboptimal quality of care during the initial hospital stay.[3–5] Addressing preventable readmissions is important because readmissions are associated with worse health outcomes. For instance, median survival after pancreatectomy for cancer decreases by nearly half for any patient readmitted within 1 year of the operation.[6,7]

Hospital readmission is common for cancer patients, and cancer diagnosis is a risk factor for readmission in some models.[8–10] Not surprisingly, complications of therapy represent common reasons for readmission in cancer patients, such as infection or other gastrointestinal complications after complex abdominal operations and allogeneic hematopoietic cell transplantation.[11–13] While many readmissions may be unavoidable, an analysis at one cancer hospital found that at least 20% of readmissions in cancer patients were potentially preventable.[14] After complex surgical procedures such as hepatic or pancreas resection, potentially preventable readmissions for symptoms such as dehydration or poor pain control represent up to one third of all readmissions.[15,16]

The use of models to predict which patients are at high risk for readmission may allow targeted delivery of interventions to avoid readmission. Many such models have been developed and typically estimate risk using data from the electronic medical record (EMR) or hospital administrative data sources.[10,17–23] Some models are designed for broad groups of hospital inpatients and others have been designed specifically for patients with congestive heart failure,[24–29] coronary artery disease or intervention,[30–33] stroke,[34] pneumonia, and COPD.[35,36]

Readmission risk models specific to the cancer patient population are lacking. Cancer-specific readmission models are needed because cancer patients are at increased risk of conditions like venous thromboembolism, malnutrition/cachexia, and profound immunosuppression, any of which may increase the risk of hospitalization. As such, risk factors for readmission among cancer patients and levels of risk may not be adequately captured in previous "all-comer" readmission models. Therefore, the purpose of the current study was to develop and prospectively validate a cancer-specific model to estimate risk of unplanned readmission at a tertiary cancer hospital.

2 | METHODS

2.1 | Study site and data collection

The study site is a National Cancer Institute (NCI)-designated comprehensive cancer center with a 306-bed freestanding cancer hospital. The study site's Department of Quality and Patient Safety provided a Quality Data Release for this project. A list of 196 variables possibly associated with readmission was developed by several authors and extracted from the EMR for all inpatient admissions between January 1, 2012 and December 31, 2013. Variables independently associated with readmission, clinically relevant, and known at the time of discharge from the index hospitalization, were further evaluated for possible inclusion in the readmission models.

2.2 | Readmission

Since 2011, all readmissions to the site are manually reviewed by experienced case managers and data recorded include reason for readmission, admitting, and readmitting clinical service, planned or unplanned and related or unrelated status. Unplanned readmission was defined as any inpatient admission to the hospital within 30 days of a prior inpatient admission (both admissions at the study site only), excluding planned readmissions such as for inpatient chemotherapy or surgical procedures. Unrelated readmissions, such as readmission for an unrelated diagnosis like motor vehicle crash involving a cancer patient, were also excluded. Potentially preventable readmissions were defined as any readmission within 72 h of index discharge, length of stay less than 3 days at readmission, or any readmission within 30 days for a principle diagnosis of pain, nausea, vomiting, or dehydration.

2.3 | Analysis

During the study period there were 20 405 index admissions. The average patient age was 57 and 52% were female. There were 9656 admissions to surgical services (47%) and the remainder to medical services. A total of 1623 admissions were excluded due to: inpatient death ($n = 229$), death less than 30 days after discharge ($n = 867$), travelled more than 125 miles for care ($n = 524$), and missing data ($n = 3$). Unique patients had between 1 and 20 admissions in the analytic file. Since the unit of analysis for this study was the patient and not the index admission, a single index admission was randomly selected for each unique patient in the data set resulting in 10 789 index admissions available for analysis. The index admissions were split into a modeling set ($n = 6615$) and a testing set ($n = 4174$).

Logistic regression analysis was used to determine factors highly associated with unplanned readmission within 30 days and potentially preventable readmissions. Patients with benign disease or missing cancer types ($n = 1649$) were excluded from the analysis for potentially preventable readmissions, and these 9140 index admissions were also split into a modeling set ($n = 5630$) and testing set ($n = 3510$). Logistic regression models were fit using SAS® v9.4 Proc Logistic with maximum likelihood estimate and backward variable selection. The models were assessed using the c-statistic and Hosmer and Lemeshow Goodness-of-Fit Tests for both the modeling and validation data sets. For the c-statistic, values over 0.70 typically indicate a reasonable model and values over 0.80 indicate a strong model.

The predictive model was implemented in the EMR and risk scores were generated based on each of the two statistical models. The models' estimates of risk were recorded for all inpatient admissions at the day of discharge over a 10-month period (November 2015-August 2016). Patients were stratified into groups based on estimated risk of readmission: low <8%; medium 8-10%; high 10-20%; and very high >20% for the 30-day model and low <8%; medium 8-10%; and high >10% for the potentially preventable model. Actual incidence of unplanned readmission was measured for each risk group.

3 | RESULTS

3.1 | Estimating risk of unplanned readmission within 30 days

During the study period, there were a total of 18 782 eligible inpatient admissions and 5741 total (30.6%) readmissions within 30 days. Among all readmissions, 2478 (13.2%) were classified as unplanned.

TABLE 1 Variables associated with unplanned readmission within 30 days

Demographic variables	Clinical variables	Utilization variables
Gender	Secondary cancer	Emergency admission
Marital status	Gastrointestinal cancer	Discharged to home
Self-pay status	Lung cancer	Length of stay
Dual eligible (Medicare/ Medicaid)	Surgical admission	Chemotherapy admission
	Abnormal heart rate	More than six diagnoses
	Abnormal sodium	Emergency department visit within 30 days
	Abnormal hemoglobin	More than one admission in last 60 days
	Abnormal WBC	
	Solid tumor	

WBC, white blood cell count.

The number of unplanned 30-day readmissions in the initial modeling subset was 475 (8.4%). Variables independently associated with unplanned readmission, clinically relevant, and known at the time of initial discharge spanned a combination of demographic, clinical, and utilization data (Table 1). Factors included in the all cause 30-day unplanned readmission model are listed in Table 2; gastrointestinal cancer diagnosis, length of stay (LOS) more than 5 days, emergency department (ED) visit within 30 days, and more than one hospital admission within 60 days were strongly associated with readmission (all $P < 0.05$). The c-statistic for this model was 0.68 for the modeling subset and 0.70 for the testing set, demonstrating the model to be stable. The Hosmer-Lemeshow statistic was not significant ($P = 0.58$) and therefore no significant lack of fit was observed.

TABLE 2 Model variables used to estimate unplanned readmission within 30 days

Variable	Odds ratio estimate	95% Confidence interval
Gastrointestinal cancer	1.539	1.217-1.945
Surgical admission	0.586	0.470-0.731
Emergency admission	1.358	1.106-1.667
LOS > 5 days	1.657	1.389-1.977
Solid tumor	1.283	1.012-1.628
Abnormal sodium	1.263	1.022-1.560
Abnormal hemoglobin	1.461	1.114-1.916
Abnormal WBC	1.218	1.014-1.464
ED visit in last 30 days	1.686	1.180-2.409
More than one admission in last 60 days	1.606	1.317-1.957

LOS, length of stay; WBC, white blood cell count; ED, emergency department.

TABLE 3 Model variables used to estimate potentially preventable readmission

Variable	Odds ratio estimate	95% Confidence interval
Gastrointestinal cancer	2.293	1.636-3.215
Surgical admission	0.612	0.450-0.831
LOS > 5 Days	1.556	1.159-2.090
Abnormal sodium	1.682	1.214-2.331
More than one admission in last 60 days	1.416	1.005-1.997

LOS, length of stay.

3.2 | Estimating risk of potentially preventable readmission

There were a total of 186 (3.3%) potentially preventable readmissions in the modeling subset. Factors included in the model for potentially preventable readmission are listed in Table 3. Again, there were strong associations with potentially preventable readmission and gastrointestinal cancer diagnosis, LOS more than 5 days, and more than one hospital admission within 60 days. Abnormal sodium (either hyponatremia or hypernatremia) was also associated. The c-statistic for this model was 0.65 for the modeling set and 0.57 for the test set, demonstrating that the model had less predictive power and less stability than the more general unplanned readmission model. The Hosmer-Lemeshow statistic was not significant ($P = 0.77$) and therefore no significant lack of fit was observed.

3.3 | Prospective confirmation of model performance

The actual number of unplanned readmissions within 30 days observed prospectively over 10 months was 1289 out of 8616 total admissions (15%). The proportion of readmissions in each model risk category increased as estimated risk increased (Figure 1). Specifically, actual incidence of 30-day unplanned readmission for the four risk categories from lowest to highest estimated risk was 9.6%, 14.9%, 19.1%, and 20.7%. There were 465 potentially preventable readmissions observed prospectively over 10 months out of 8616 total admissions (5.4%). The proportion of readmissions in each potentially preventable model risk category also increased as estimated risk increased. Specifically, actual incidence of potentially preventable unplanned readmission was 4.8%, 6.7%, and 7.1% from lowest to highest estimated risk.

4 | DISCUSSION

This study describes the development of logistic regression models to estimate the risk of unplanned 30-day and of potentially preventable readmissions in cancer patients. Within each model, an increasing estimate of risk by subgroup was associated with an increase in actual

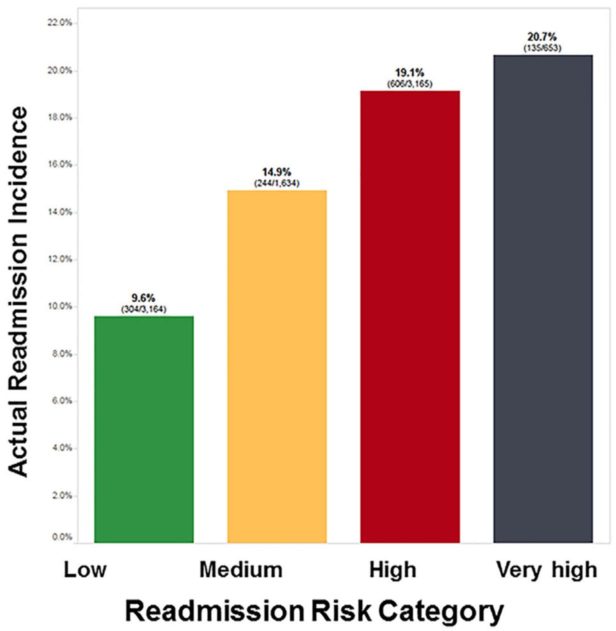

FIGURE 1 Actual incidence of 30-day unplanned readmission for 8616 patients recorded prospectively over 10 months, stratified by risk model categories (Green = low minimal <8%; Yellow = medium 8-10%; Red = high 10-20%; Black = very high >20%)

readmissions when the model was tested prospectively. Performance of the potentially preventable model was inferior to the 30-day model. To our knowledge, this is the first readmission risk model specific to cancer patients that has been prospectively validated with real-time data capture through incorporation into an EMR.

Several variables used to estimate risk in these models-specifically LOS, previous emergency department visits, hemoglobin level, sodium level, and surgical admission- are similar to those used in other readmission risk models such as the LACE and HOSPITAL tools.[8,21,37] Other studies have also emphasized the importance of LOS, previous readmissions, and gastrointestinal cancer diagnosis.[2,38] The consistency of these variables across several models is reassuring yet sobering in that many of these variables cannot be modified prior to discharge in an effort to improve a patient's readmission risk.

When measured by the c-statistic, our model for estimating risk of potentially preventable readmissions performed marginally. Many other published models estimating readmission risk demonstrate similar marginal or even poor performance.[18,39] Investigators have described strategies to improve the performance of readmission risk models including adding psychosocial and sociodemographic variables to clinical variables,[30] adding more variables to previously developed models[23] or using a decision tree approach rather than logistic regression or a neural network analysis.[40] One of the highest performing models in the literature with a c-statistic of 0.85 uses only two variables, Charlson score, and polypharmacy.[20] However, this model is specific to patients admitted to a Family Medicine service.

Other investigators have modified existing readmission risk models leading to only modest improvements in performance. For instance, Krumholz et al[27] developed a model for heart failure patients that included patient-reported information on socioeconomic status, health status, and psychosocial characteristics obtained by telephone interview. This was compared with a model that had only clinical and demographic factors. The added variables improved model performance from c-statistic of 0.62 to only 0.65. Another study used data from the full hospital stay to estimate readmission risk in medical patients and compared results from this model to the results from models using data available at time of admission.[21] The addition of hospital stay data did improve model performance, but only modestly-from a c-statistic of 0.64-0.67 to 0.69. We attempted to improve the performance of our original 30-day model by developing a second model estimating the risk of potentially preventable readmissions which also excluded patients with benign primary diagnosis. Nonetheless, the c-statistic for the second model did not improve.

This study has several limitations. The initial variables chosen for analysis were subjectively determined by four of the authors based on prior literature and clinical experience. Also, as there is not yet any standard criteria to define potentially preventable,[41] the authors developed the definition of potentially preventable readmission for use in this study. Alternative approaches to identifying potentially avoidable readmissions such as using the HOSPITAL score that relies on a computerized algorithm to classify admissions as potentially avoidable based on comparison of index admission and readmission diagnosis codes might improve our model or increase its external validity.[8] However, cancer diagnosis or discharge from an oncology service are risk factors for readmission in published models, thus designing a model for cancer patients will likely have constraints in terms of specificity since the patient population itself is at risk. Further, some variables such as surgical procedure type may be important factors for cancer patient readmission risk even if they were not incorporated into this analysis from one hospital. Finally, as we did not include readmissions to other hospitals after index admission at the study site, it is certain we did not capture all readmissions in the study population.

Preventing readmissions is clearly important; beyond improving quality of care and decreasing cost there may also be a benefit to quality of life.[42] Previous efforts at reducing readmissions have included changing hospital processes as well as offering programs designed to address this issue. For instance, the introduction of standardized processes such as oral antibiotic bowel preparation prior to elective colorectal surgery are associated with reductions in infection-related readmissions.[43] In addition, a meta-analysis of randomized studies aimed at preventing readmissions confirmed a “consistent and beneficial” effect of various interventions[44] with such interventions including case management support, patient education, home visits, and augmenting patient capacity for self-care. Capacity for self-care may be one of the most important interventions based on another study which reported that readmitted patients commonly are unable to take all discharge medications as prescribed (20%), feel unprepared for initial discharge (11.8%), and have difficulty performing activities of daily living (10.6%).[45]

The 30-day readmission model for cancer patients developed in this study shows promise and next should be independently validated by an analysis using data from another hospital with the same EMR. Pilot studies are also underway using the model on selected hospital services to guide interventions aimed at readmission prevention for higher risk patients. Interventions include earlier follow-up appointments, increased post-discharge communication, and multidisciplinary discharge rounds. Modifications to the model may be needed based on actual performance during these pilot studies and could include adding socioeconomic and psychosocial variables or developing additional models specific to certain cancer diagnoses or admitting services. There are no further plans for the potentially preventable model at this time given its lower c-statistic. Ultimately, predictive models will hopefully enable implementation of many beneficial interventions to cancer patients with extra health needs or higher risk of complications after hospital discharge.

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