Developing Clinical Prediction Models for 30-day Readmission in the General and Medically Complex Pediatric Populations

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Abstract

Hospital readmissions negatively impact patient quality of life and incur substantial healthcare costs. To target resources to prevent readmission, this study sought to develop clinical prediction models for 30-day readmission in the general pediatric population and for children with medical complexity (CMC).

Sociodemographic and clinical characteristics were extracted from electronic health records for pediatric patients aged 6 months to 18 years admitted at an urban academic medical center between October 1, 2010 and July 31, 2016. Factors associated with unplanned 30-day readmission on univariate screen were candidates for the multivariable logistic regression models. Using backward selection, we derived a model predicting readmission utilizing characteristics obtainable at admission ("model at admission"). A second model was derived including variables available by hospital discharge ("model at discharge"). Model performance was assessed using c-statistic and calibration curves, and bootstrap resampling was performed for internal validation. CMC-specific models were developed and evaluated by repeating these procedures in the subgroup of medically complex children.

Of the 7,068 general pediatric index admissions during the study, 313 (4.4%) had an unplanned readmission within 30 days. The model at admission included the following variables: non-English language, prior admissions, prior emergency department (ED) visits, number of home medications, medical complexity, technology assistance, and medical versus surgical admission (c-statistic 0.68). The model at discharge included all these variables plus length of stay, weekday discharge, and discharge disposition (c-statistic 0.69). For the CMC subgroup, of 2,296 index admissions, 188 (8.2%) had

readmissions. The CMC model at admission included prior admissions, prior ED visits, number of complex chronic conditions and medical versus surgical admission (c-statistic 0.65). When including variables available at discharge, the model also included length of stay, weekday discharge, and discharge disposition (c-statistic 0.67). Patients in the highest risk quartiles had 3.6 to 4.5 times higher readmission rates compared with patients in the lowest risk quartiles for all models. Bootstrap samples had similar c-statistics, and slopes did not suggest substantial overfitting in any model.

In conclusion, easily obtainable clinical characteristics are useful in identifying children at particularly high risk for readmission. These high risk children may be an appropriate target for interventions to prevent readmissions. Future proposals will involve external validation of the models and will explore whether the models can be used to target resources aimed at decreasing readmissions.

Dedication

This work is dedicated to my family. To my parents, John and Jeri Cerullo, who have always taught me to dream big and let nothing hold me back. To my husband, Tim Leary, and children, Jack and Anya, for being my greatest inspirations as well and my greatest supporters in pursuit of those dreams. I love you all "too much". I would not be the person, the scientist, or the mother I am today without you.

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List of Abbreviations

AIC	Akaike information criterion
CCC	Complex chronic condition
CMC	Children with medical complexity
DRG	Diagnostic related group
ED	Emergency department
EHR	Electronic health record
ICU	Intensive care unit
LOS	Length of stay
VIF	Variance inflation factor

Chapter 1: Introduction

Hospital readmissions affect millions of Americans annually, negatively impact the quality of life of patients and their caregivers, and incur substantial healthcare costs.[1] The most recent report from the Agency of Healthcare Research and Quality indicates that while readmission rates in adults are declining, readmissions among pediatric patients are increasing.[1]

Studies in adults have suggested that preventable readmissions can occur in response to inadequate care received during admission, poor discharge planning, or inadequate follow-up care or care coordination.[2,3] Because of this, readmission rates are being used as a quality indicator and have become a focus of reimbursement reform, in both adult and pediatric populations.[4–8] Indeed, states are increasingly instituting reimbursement penalties for pediatric readmissions, in an attempt to control rising pediatric readmission rates and child healthcare costs.[9–15] Inasmuch, developing a clinical prediction model for 30-day readmissions may help identify patients at highest risk, allowing for targeting of interventions and resources to reduce readmission rates, associated healthcare costs and reimbursement penalties. Recently, national leaders in the study of pediatric readmissions identified the current lack of prediction models as a contributor to the inability to improve pediatric readmission rates, stating "without accurate prediction models to prospectively identify children at high risk of preventable readmission who may benefit from enhanced discharge support, quality improvement leaders must weigh costs and benefits of transition interventions to prevent readmission across the board."[16]

Prediction and prevention of hospital readmission may be particularly desirable for the field of pediatrics, within which there is a rising population of children with medical complexity at high risk for readmission. Recent advances in the biomedical and social sciences have allowed children to live for extended periods with what may previously have been fatal conditions.[17] This has led to a growing population of children with medical complexity (CMC), who are relatively medically fragile, requiring more intensive care and technology-assistance, such as those with congenital heart disease or chronic respiratory failure with ventilator-dependence.[18] In comparison to the general pediatric population, CMC rely even more on effective functioning of family, social and health system networks to improve their care and outcomes.[19] Although representing only 1% of the pediatric population, CMC have disproportionately high healthcare utilization and healthcare costs.[20–23] Medically complex children accounted for 10% of all hospital admissions in 2006, and this number was rising; they also used approximately one quarter of pediatric hospital days because of their longer lengths of stay.[21] Thirty day readmission rates are also disproportionately high in this population, reportedly reaching as high as 24%.[22,24] Not surprisingly then, CMC account for nearly one third of all child healthcare costs, with the majority attributable to inpatient hospitalization and readmissions representing the highest proportion of subsequent costs (27%).[22,23]

A number of prior studies have attempted to characterize risk factors for hospital readmission in a general pediatric population, inclusive of children with and without medical complexity.[6,25–32] Medical complexity has consistently been identified as a significant risk factor for readmission, while other factors such as age, race, sex, insurance status, income, language, and discharge timing have been inconsistently

evaluated or identified as significant. In a secondary analysis, one recent study by Sills and colleagues found that addition of social determinants of health to a readmission risk model consisting of age, sex, and chronic conditions achieved a c-statistic of 0.708.[25] Although this study provided a robust evaluation of risk factors associated with pediatric readmissions, their models did not evaluate some known risk factors for readmission (e.g., language, home medications, prior hospital use, or home health care), nor were they intended for use in clinical practice, as evident by the lack of development of a practical application for the models.

Fewer association studies have evaluated risk factors for hospital readmission specifically among children with medical complexity.[33–38] Age, number of complex chronic conditions, technology assistance, number of medications, length of stay, timing of outpatient follow-up, and home medical services have been shown to be significant protective or risk factors for readmission in CMC. None of these studies, however, evaluated risk factors for readmission in the larger general pediatric population from which the CMC came, so it remains unclear whether the CMC-specific risk factors differ from those in their broader populations.

Despite this background, and national leaders stating the need for prediction models to help hospitals quantify the likelihood of patient readmission in real time, a clinical prediction model for 30-day readmission, developed for use in clinical practice in the pediatric population, remains absent from the literature.[16] A clinical prediction model would allow knowledge of readmission risk factors to be applied in a practical manner to identify individual children at highest risk for readmission, allowing for the targeting of interventions and resources to reduce readmissions and associated healthcare costs. This

study therefore aimed to develop clinical prediction models for 30-day readmission in both the general pediatric population and the subpopulation of CMC, capable of use following admission for targeting of inpatient interventions, care coordination or discharge planning, or for use at discharge for directing outpatient services.

Chapter 2

Developing Clinical Prediction Models for 30-day Readmission in the General and Medically Complex Pediatric Populations

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2.1. INTRODUCTION

Hospital readmissions affect millions of Americans annually, negatively impact the quality of life of patients and their caregivers, and incur substantial healthcare costs.[1] Consequently, readmission rates have been used as a quality indicator and a focus of reimbursement reform, in both adult and pediatric populations.[4–8] Indeed, states are increasingly instituting reimbursement penalties for pediatric readmissions, in an attempt to control the rise of child healthcare costs.[9–15]

These issues are particularly relevant within the current landscape of pediatric healthcare, with a growing subgroup of children with medical complexity (CMC) at especially high risk for readmission. Recent advances in medical care and social services have allowed children to live for extended periods with what may previously have been fatal conditions.[17] This population of CMC, such as those with congenital heart disease or chronic respiratory failure with ventilator-dependence, are relatively medically fragile and require more intensive care and technology-assistance compared with their peers.[18] Although CMC represent only 1% of the pediatric population, studies show that their healthcare utilization is disproportionately high, with increased rates of admission, longer lengths of stay, greater technology-dependence, higher hospital charges, and 30-day readmission rates reportedly as high as 24%.[20–24]

Some prior association studies have attempted to determine risk factors for hospital readmission in a general pediatric population, defined as inclusive of children with and without medical complexity.[6,25–32] Medical complexity has consistently been identified as a significant risk factor for readmission, while other factors such as age, race, sex, insurance status, income, language, and discharge timing have been inconsistently

evaluated or identified as significant.[6,25–27,29,30,32] Fewer studies have evaluated risk factors for readmission specifically for CMC, but without concurrent study of the larger general pediatric population from which the CMC came, it is unclear whether CMC-specific risk factors differ from those in their broader populations.[33–38]

While prior association studies have provided some insight into potential drivers of pediatric readmissions, a clinical prediction model for 30-day readmission, developed for use in clinical practice, remains absent from the literature. Such a prediction model may help to identify children at highest risk for readmission, aiding in the targeting of interventions and resources to reduce readmission rates and associated healthcare costs and reimbursement penalties. Given their relatively high rates of readmission, a CMC-specific prediction tool may be particularly useful for such targeting of resources. This study therefore aimed to develop clinical prediction models for 30-day readmission, both in the general pediatric population and the subpopulation of CMC, capable of use during admission for targeting of inpatient interventions, care coordination or discharge planning, or for use at discharge for targeting outpatient services.

2.2. METHODS

2.2.1. Study Design

The study utilized a retrospective cohort design. For the general pediatric population, the index admission was defined as the first hospitalization occurring between October 1, 2010 and July 31, 2016. For the subgroup of children with medical complexity, the index admission was redefined as the first admission within that same time window during which the patient met criteria for medical complexity.[39] The primary

outcome (dependent variable) was unplanned readmission within 30 days of the index admission discharge date.

2.2.2. Subject Characteristics

Eligible patients were six months to 18 years old, admitted to an urban academic medical center between October 1, 2010-July 31, 2016. We excluded any pregnancy-related or psychiatric admissions utilizing pregnancy and childbirth and mental health diagnostic related groups (DRGs).[6,34,40] We excluded admissions ending in death (not at risk for readmission outcome), discharges against medical advice (inadequate opportunity to implement care plan and discharge instruction), or discharge to hospice (terminally ill patients have different goals of care compared to non-hospice peers). The subgroup of CMC was determined through application of the widely utilized complex chronic conditions (CCC) taxonomy.[39] This taxonomy uses ICD-9 and ICD-10 codes to identify children with medical complexity based on the presence of a complex chronic condition within 11 broad medical categories such as neurological, cardiovascular, or gastrointestinal. We then determined whether there was a readmission to the same hospital within 30 days of index admission discharge. Utilizing the methodology of Berry and colleagues, we excluded planned readmissions for chemotherapy and planned pediatric procedures.[6,40]

2.2.3. Data Sources and Predictors

All patient data were extracted from a prospectively collected hospital data set maintained by the academic center for determination of quality metrics, augmented by the number of home medications at admission which was extracted directly from the electronic health record (EHR). Independent variables, selected *a priori* based on clinical

judgment and literature review, included sociodemographic factors (age, race, sex, non-English primary language, insurance, neighborhood per capita income), measures of hospital utilization (any admissions and any emergency department (ED) visits in the six months leading up to index admission), clinical measures (medical complexity, technology assistance, complex chronic condition category, number of complex chronic conditions, number of home medications at admission, and admission type) and hospitalization and discharge characteristics (any intensive care unit (ICU) use, length of stay (LOS), discharge disposition, and day of week of discharge during index admission).

Neighborhood per capita income was determined from zip codes. Admission type was dichotomized as either medical or surgical, defined by the admitting service team. Medical complexity, technology assistance, complex chronic condition categories, and number of complex chronic conditions were determined through application of the complex chronic conditions taxonomy.[39] Discharge disposition was categorized as discharge to home, to home with services, or to another facility.

2.2.4. Statistical Analysis

Descriptive statistics were used to determine the frequencies of clinical and demographic characteristics in the study population. Univariate logistic regression was then used to test the association between each independent variable and the primary outcome (unplanned 30-day readmission). The assumption of linearity was checked for continuous variables. Independent variables reaching a p-value <0.2 were considered as candidates for the multivariable models. We first constructed a model utilizing only characteristics obtainable at admission ("model at admission"), using multivariable logistic regression and backward selection with Akaike information criterion (AIC).[41] To

determine whether hospitalization and discharge specific factors improved model performance, a second model was then developed including variables available at discharge. To derive the second model ("model at discharge"), hospitalization and discharge factors passing univariate screening were forced into the final "model at admission".

Hypothesizing that proxies of social or medical support may have different effect on readmission for medically complex versus non-complex children, we assessed effect modification by medical complexity on selected factors (i.e. language, insurance, income, and discharge disposition), which were forced into the final models when needed to determine the significance of their interaction. We checked for collinearity among final model variables using the variance inflation factor (VIF) and assessed for potential influence points.[42] Final model performance was then determined using c-statistic and calibration curves, and internal validation was performed using a bootstrapping algorithm with 500 samples.[43–45]

To facilitate use in clinical practice, the β-coefficient of each variable in the final model was multiplied by a constant factor and rounded to the nearest integer to create a point system; points obtained for each variable were then added to derive a readmission risk score per patient We evaluated the risk score distribution in our study population using descriptive statistics to determine the proportion of total admissions and readmissions within each risk score level. Risk score discriminative performance was determined using c-statistic.

This analytic procedure was repeated for the subgroup of CMC, substituting number of complex chronic conditions for the binary medical complexity variable as the measure of medical complexity in the models.

All statistical analyses were performed using R statistical software version 3.4.2 (RStudio version 1.1.383; the stats package was used for model development and the rms package was used for model evaluation and validation). This study was approved by the Tufts Medical Center Institutional Review Board.

2.3. RESULTS

There were 11,151 pediatric admissions during the period under study. After application of exclusion criteria, 7,068 index admissions for unique pediatric patients remained, and 313 (4.4%) had unplanned 30-day readmissions (Figure 2.1). There were a total of 2,296 index admissions for children with medical complexity, with 188 (8.2%) resulting in unplanned 30-day readmissions.

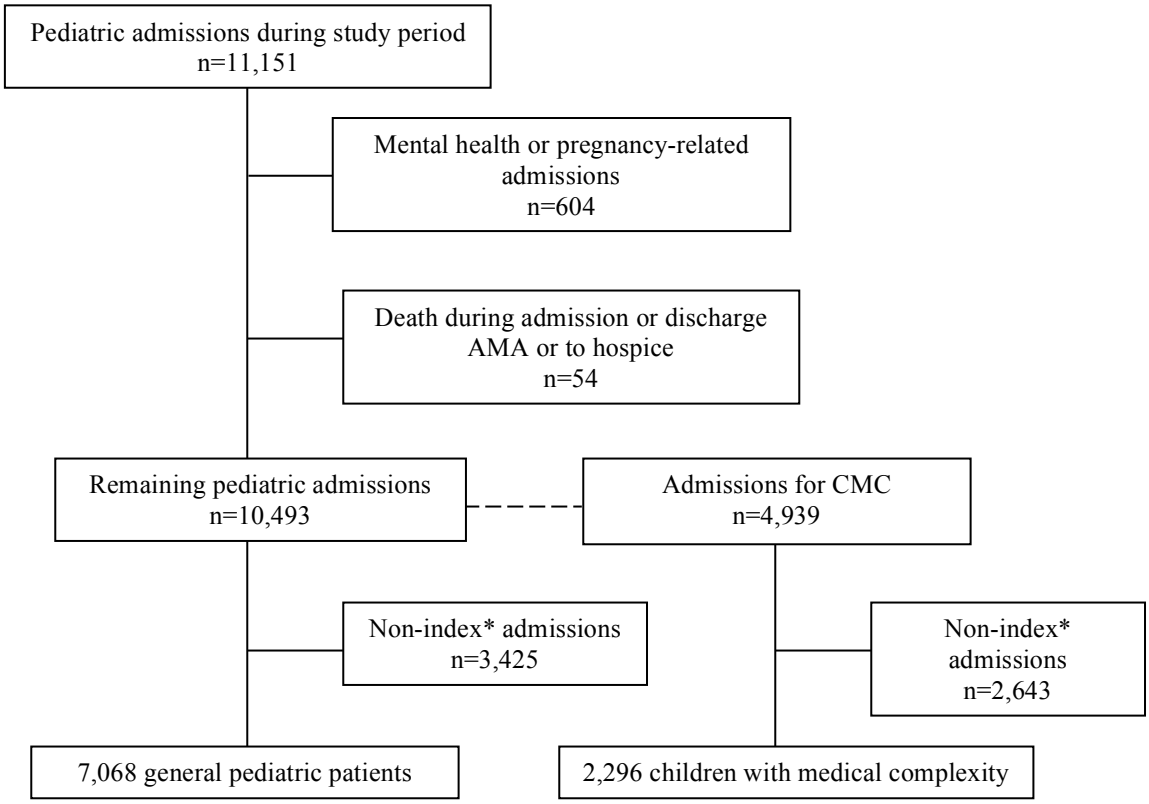
2.3.1. Demographic and Clinical Characteristics

Among our study patients, mean age was 7.9 years, 56% were male, 89% were English-speaking, and 62% had private insurance (Table 2.1). Approximately one third of the study population was medically complex, with neurological, cardiovascular, and gastrointestinal complex chronic conditions being the most common.

2.3.2. Model Development

A complete case analysis was performed, as missing data were minimal (~1%) and limited to the income and medication variables (Table 2.1).

Figure 2.1. Flow diagram of the study cohort



*For the general pediatric population, index admission defined as the first eligible admission per patient during the study timeframe; for the subgroup of children with medical complexity (CMC), index admission defined as the first eligible admission during the study timeframe where the patient met criteria for medical complexity

Table 2.1. Sociodemographic and clinical characteristics of the study cohort

Characteristic	General pediatric population (n=7068 patients)	Subgroup of children with medical complexity (n=2296 patients)
Sociodemographic factors		
Age		
6 months to <2 years	1129 (16)	437 (19)
2-5 years	2022 (29)	500 (22)
6-12 years	1912 (27)	625 (27)
13-18 years	2011 (28)	734 (32)
Race/Ethnicity		
Non-Hispanic White	4055 (57)	1370 (60)
Non-Hispanic Black	745 (11)	243 (11)
Asian	702 (10)	191 (8)
Hispanic	1355 (19)	432 (19)
Other	211 (3)	50 (3)
Male	3972 (56)	1286 (56)
Non-English primary language	743 (11)	237 (10)
Insurance		
Private	4402 (62)	1410 (61)
Public	2580 (37)	872 (38)
Uninsured	86 (1)	14 (<1)
Neighborhood per capita income	$30,520[$22,728-37,587]	$30,520[$22,714-37,424]
Missing data	21	8
Clinical factors		
Any admissions in prior 6 months	508 (7)	333 (15)
Any ED visits in prior 6 months	558 (8)	203 (9)
Number of home medications at admission		
0-3	6216 (89)	1770 (78)
4-7	534 (8)	301 (13)
≥8	224 (3)	196 (9)
Missing data	94	29
Medical complexity	2157 (31)	2296 (100)
Neurological CCC*	523 (7.4)	550 (24)
Cardiovascular CCC*	473 (6.7)	492 (21)
Gastrointestinal CCC*	393 (5.6)	419 (18)
Other CCC*	1736 (25)	1835 (80)
Number of complex chronic conditions*		
0	4911 (69)	0
1	1504 (21)	1621 (71)
2	420 (6)	439 (19)
≥3	233 (3)	236 (10)
Technology assistance	518 (7)	545 (24)
Admission type		
Surgical	2834 (40)	856 (37)
Medical	4234 (60)	1440 (63)
Hospitalization and discharge factors		
ICU use	2567 (36)	1087 (47)
Disposition to		
Home, no services	5925 (84)	1706 (74)
Home with services	938 (13)	468 (20)
Other facility	205 (3)	122 (5)
LOS in days		
0-1	3022 (43)	668 (29)
2-5	3335 (47)	1172 (51)
≥ 6	711 (10)	456 (20)
Weekday discharge	5201 (74)	1746 (76)

Values reported as n(%) or median[25th-75th percentile]
Emergency department (ED); Intensive care unit (ICU); Length of stay (LOS)
*CCC: complex chronic condition; values for CCC categories differ slightly between the general pediatric population and medically complex subgroup, because for CMC, index admission was defined as the first admission during which the patient met criteria for medical complexity

General Pediatric Population

Of the 7,068 general pediatric patients, 6,974 complete cases were utilized in the logistic regression analyses. Table 2.2 presents the univariate and multivariable associations with 30-day readmission. On unadjusted analyses, age and non-English language were the only demographic variables meeting our *a priori* inclusion criteria (p-value <0.2). Multiple clinical measures were found to have a univariate association with unplanned readmission: any admissions in the prior six months, any ED visits in the prior six months, number of home medications, medical complexity, technology assistance, and medical (vs. surgical) admission type (all p-values <0.001). Hospitalization and discharge characteristics associated with unplanned readmission included discharge disposition, LOS, and weekday discharge (all p-values <0.05)

After backward selection, the multivariable regression model at admission included non-English language, any admissions in the prior six months, any ED visits in the prior six months, number of home medications, medical complexity, technology assistance and medical (vs. surgical) admission type. The c-statistic of the model was 0.68.

When incorporating hospitalization and discharge characteristics, the model at discharge added discharge disposition, LOS, and weekday discharge to the model at admission, and resulted in a similar c-statistic of 0.69.

In both multivariable prediction models, medical complexity conveyed the highest adjusted odds ratio (aOR) for readmission; patients with medical complexity had over twice the odds of readmission compared with noncomplex patients (Table 2.2). There was no evidence of effect modification by medical complexity on language, income,

Table 2.2. Univariate and multivariable associations with 30-day readmission in the general pediatric population

	Univariate Screen		Final multivariable model at admission[a]	Final multivariable model at discharge[b]
	Unadjusted OR (95% CI)	p-value	Adjusted OR (95% CI)	Adjusted OR (95% CI)
Admission characteristics				
Age				
6 months to <2 years	Reference	0.01*		
2-5 years	0.61 (0.44 to 0.84)			
6-12 years	0.64 (0.46 to 0.89)			
13-18 years	0.65 (0.47 to 0.9)			
Race				
White	Reference	0.42		
Black	0.89 (0.59 to 1.3)			
Asian	0.98 (0.65 to 1.43)			
Hispanic	1.09 (0.81 to 1.45)			
Other	0.41 (0.12 to 0.98)			
Male	1.09 (0.86 to 1.37)	0.48		
Non-English primary language	1.3 (0.92 to 1.8)	0.13	1.33 (0.93 to 1.86)	1.32 (0.92 to 1.84)
Public insurance	1.12 (0.89 to 1.41)	0.34		
Neighborhood per capita income (per $10,000 increase)	0.94 (0.85 to 1.04)	0.25		
Any admissions in prior 6 months	2.34 (1.67 to 3.22)	<0.001	1.6 (1.11 to 2.24)	1.64 (1.14 to 2.31)
Any ED visits in prior 6 months	2.16 (1.55 to 2.95)	<0.001	1.84 (1.3 to 2.55)	1.88 (1.32 to 2.61)
Number of home medications at admission				
0-3	Reference	<0.001	Reference	Reference
4-7	1.46 (0.97 to 2.12)		0.97 (0.64 to 1.42)	0.99 (0.65 to 1.45)
≥8	3.67 (2.41 to 5.43)		1.71 (1.07 to 2.63)	1.61 (1 to 2.52)
Medical complexity	2.97 (2.36 to 3.74)	<0.001	2.43 (1.88 to 3.14)	2.17 (1.66 to 2.83)
Technology assistance	2.76 (2 to 3.73)	<0.001	1.38 (0.95 to 1.98)	1.22 (0.83 to 1.77)
Medical admission	1.69 (1.33 to 2.17)	<0.001	1.61 (1.25 to 2.13)	1.54 (1.19 to 2)
Hospitalization and discharge characteristics				
ICU use	0.98 (0.77 to 1.23)	0.84		
Disposition to				
Home, no services	Reference	<0.001		Reference
Home with services	2.12 (1.6 to 2.77)			1.35 (0.98 to 1.83)
Other facility	2.3 (1.33 to 3.74)			1.11 (0.61 to 1.91)
LOS in days				
0-1	Reference	<0.001		Reference
2-5	1.27 (0.98 to 1.65)			1.04 (0.79 to 1.36)
≥6	3.08 (2.23 to 4.22)			1.77 (1.22 to 2.55)
Weekday discharge	1.35 (1.04 to 1.82)	0.03		1.18 (0.89 to 1.59)

Odds ratio (OR); Confidence interval (CI); Emergency department (ED); Intensive care unit (ICU); Length of stay (LOS)

[a] Multivariable logistic regression model utilizing admission characteristics with p<0.2 on univariate screen, backward selected using Akaike Information Criterion

[b] Multivariable logistic regression model at discharge added hospitalization and discharge characteristics passing univariate screen to the model at admission

* Passed univariate screen but eliminated from model by backward selection

insurance, or discharge disposition (all interaction term p-values >0.05). Measures of prior hospital utilization were also significant risk factors for readmission, with any admissions in the preceding six months imparting approximately 1.6 times the odds of readmission, and any ED visits in the preceding six months approximately 1.8 times the odds of readmission in both models. Number of home medications at admission also significantly affected readmission likelihood, as patients with eight or more home medications had 1.6 to 1.7 times the odds of readmission compared to patients with 0-3 medications. Although only included in the model at discharge, length of stay was also associated with higher likelihood of readmission, as patients with LOS greater than five days had about 1.8 times the odds of readmission compared to patients with a short stay of zero to one day.

Subgroup Analysis of Children with Medical Complexity

Of the 2,296 CMC in our cohort, 2,267 complete cases were utilized in the regression analyses. Table 2.3 summarizes the univariate and multivariable associations with 30-day readmission. Sociodemographic factors meeting the *a priori* univariate screen cut-off with p-value <0.2 included age and public insurance. Many clinical characteristics were also associated with unplanned readmission on univariate analysis, including any admissions in the prior six months, any ED visits in the prior six months, number of home medications at admission, number of complex chronic conditions, technology assistance, and medical (vs. surgical) admission type (all p-values <0.05). Hospitalization and discharge characteristics passing the univariate screen included discharge disposition and LOS (both p-values <0.001), and weekday discharge (p-value 0.07).

Table 2.3. Univariate and multivariable associations with 30-day readmission in the subgroup of children with medical complexity

	Univariate Screen		Final multivariable model at admission[a]	Final multivariable model at discharge[b]
	Unadjusted OR (95% CI)	p-value	Adjusted OR (95% CI)	Adjusted OR (95% CI)
Admission characteristics				
Age				
6 months to <2 years	Reference	0.1*		
2-5 years	0.74 (0.48 to 1.15)			
6-12 years	0.66 (0.43 to 1.01)			
13-18 years	0.61 (0.4 to 0.92)			
Race				
White	Reference	0.65		
Black	1.38 (0.86 to 2.15)			
Asian	1.25 (0.72 to 2.07)			
Hispanic	1.1 (0.73 to 1.61)			
Other	0.86 (0.26 to 2.15)			
Male	1.2 (0.89 to 1.63)	0.24		
Non-English primary language	1.3 (0.81 to 2.01)	0.25		
Public insurance	1.23 (0.9 to 1.65)	0.19*		
Neighborhood per capita income (per $10,000 increase)	0.94 (0.81 to 1.08)	0.38		
Any admissions in prior 6 months	2.06 (1.43 to 2.91)	<0.001	1.7 (1.15 to 2.45)	1.7 (1.16 to 2.46)
Any ED visits in prior 6 months	2.43 (1.59 to 3.61)	<0.001	2.04 (1.32 to 3.1)	2.04 (1.31 to 3.11)
Number of home medications at admission				
0-3	Reference	0.01*		
4-7	1.15 (0.73 to 1.76)			
≥8	1.95 (1.23 to 3)			
Number of complex chronic conditions				
1	Reference	<0.001	Reference	Reference
2	1.7 (1.17 to 2.42)		1.73 (1.19 to 2.49)	1.56 (1.06 to 2.26)
≥ 3	2.38 (1.56 to 3.56)		2.3 (1.5 to 3.47)	1.72 (1.08 to 2.69)
Technology assistance	1.4 (1 to 1.94)	0.04*		
Medical admission	1.82 (1.3 to 2.56)	<0.001	1.82 (1.3 to 2.63)	1.75 (1.23 to 2.5)
Hospitalization and discharge characteristics				
ICU use	0.83 (0.61 to 1.12)	0.22		
Disposition to				
Home, no services	Reference	<0.001		Reference
Home with services	2.21 (1.59 to 3.06)			1.69 (1.17 to 2.44)
Other facility	1.7 (0.89 to 3.01)			1.15 (0.58 to 2.13)
LOS in days				
0-1	Reference	<0.001		Reference
2-5	1.22 (0.84 to 1.81)			1.15 (0.78 to 1.72)
≥6	2.13 (1.41 to 3.25)			1.45 (0.9 to 2.33)
Weekday discharge	1.41 (0.98 to 2.08)	0.07		1.23 (0.84 to 1.85)

Odds ratio (OR); Confidence interval (CI); Emergency department (ED); Intensive care unit (ICU); Length of stay (LOS)

[a] Multivariable logistic regression model utilizing admission characteristics with p<0.2 on univariate screen, backward selected using Akaike Information Criterion

[b] Multivariable logistic regression model at discharge added hospitalization and discharge characteristics passing univariate screen to the model at admission

***** Passed univariate screen but eliminated from model by backward selection

The final CMC model at admission included: any admissions in the preceding six months, any ED visits in the preceding six months, number of complex chronic conditions, and medical (vs. surgical) admission. The c-statistic of this model was 0.65.

When considering hospitalization and discharge characteristics, the model at discharge added discharge disposition, LOS, and weekday discharge to the model at admission. The c-statistic remained similar at 0.67.

In both CMC-specific prediction models, prior ED use was highly associated with readmission. Patients with any ED visit in the preceding six months had about twice the odds of readmission compared to patients without for both models (Table 2.3). Degree of medical complexity was also a significant risk factor for readmission, as patients with three or more CCCs had 1.7 to 2.3 times the odds of readmission compared to patients with only one CCC. Admissions in the prior six months (vs. none), medical (vs. surgical) admissions, and discharge disposition home with services (compared to without services) imparted similar 1.7-1.8 increased odds of readmission.

2.3.3. Readmission Risk Scoring Systems

For the general pediatric model at admission (which includes both those with and without medical complexity), Table 2.4 presents the readmission risk scores, with scores ranging from 0-11 depending on individual patient characteristics. Patients with the highest risk scores (≥8) had a readmission rate of 27%, but accounted for less than 1% of total admissions and 5% of total readmissions (Table 2.5). Patients with a score of 4 or greater were almost all (95-100%) medically complex, accounting for 26% of total admissions and 52% of total readmissions. The discriminative performance of the risk scores was identical to that of the final model, with a c-statistic of 0.68. Appendix 4.1

presents the detailed calculation of readmission risk scores, risk scoring systems, and risk score distributions for the general pediatric model at discharge and the CMC-specific models.

Table 2.4. 30-day readmission risk scores for the general pediatric model at admission

Risk factor	**β-coefficient**	**Points***
Non-English primary language	0.29	1
Any admissions in prior 6 months	0.47	1
Any ED visits in prior 6 months	0.61	2
Number of home medications at admission		
0-3	Reference	
4-7	-0.03	0
≥ 8	0.53	2
Medical complexity	0.89	3
Technology assistance	0.32	1
Medical admission	0.48	1
Readmission risk score		**Range 0-11**

Emergency department (ED)

*For clinical purposes, the β-coefficient for each factor was multiplied by 3 and rounded to the nearest integer to derive a point value (see Appendix for further details); points obtained for each factor are added to compute a readmission risk score

Table 2.5. 30-day readmission risk score distribution for the general pediatric model at admission

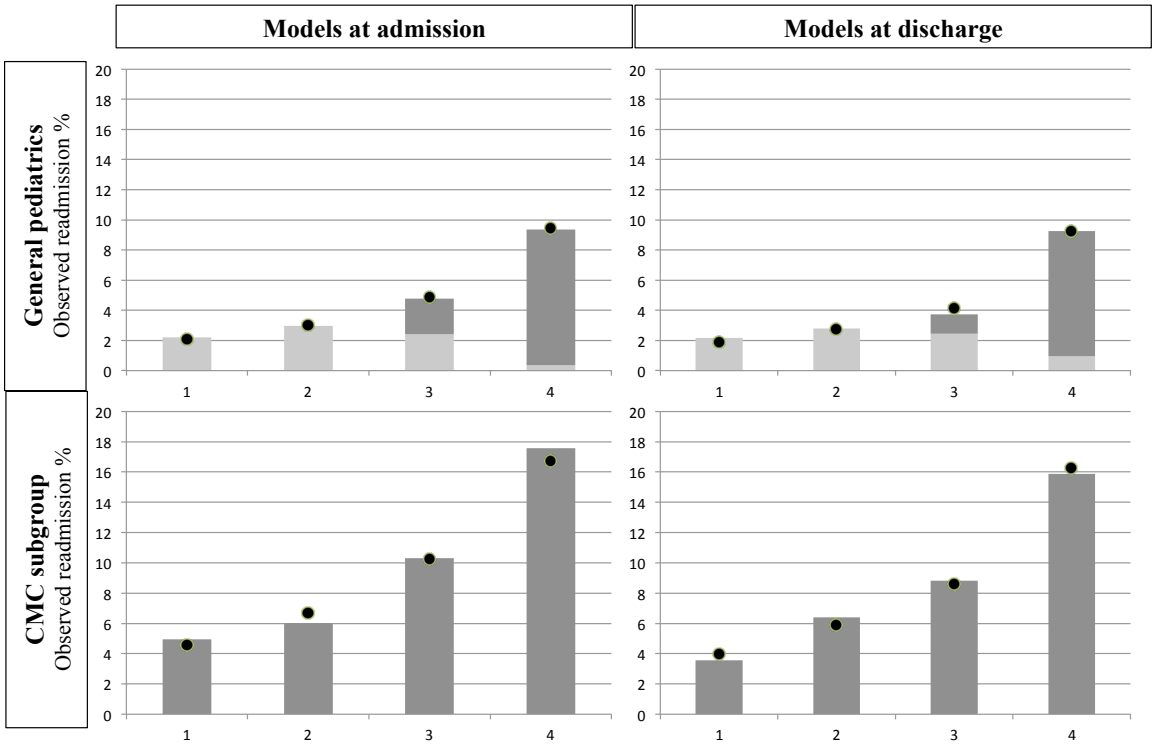
Risk score	Number of patients (total n=6974)*	% children with medical complexity (n)	Cumulative % of admissions	Observed % readmitted	Cumulative % of observed readmissions
8+	59	100 (59)	<1	27	5
7	111	100 (111)	3	17	11
6	180	99 (179)	5	9	16
5	341	99 (339)	10	9	27
4	1123	95 (1062)	26	7	52
3	625	61 (379)	35	4	60
2	481	0	42	4	66
1	2495	0	78	3	91
0	1559	0	100	2	100

*Patients with missing data for number of home medications at admission, who were not included in model development, were also not included in this analysis

2.3.4. Model Diagnostics and Validation

No collinearity was found among the variables included in the final models, and no influential points were detected. Internal validation produced similar c-statistics for all models. Calibration curves (Figure 2.2) did not indicate any particular pattern of risk over- or under-estimation. Patients in the highest quartiles of risk had 3.6 to 4.5 times higher readmission rates compared to patients in the lowest quartiles for all models (observed readmission rates were 2.2% in lowest quartiles vs. 9.3-9.4% in the highest quartiles for the general pediatric models, and 3.6-4.9% in the lowest quartiles vs. 15.9-17.6% in the highest quartiles for the CMC models). For the general pediatric models, the highest quartile of risk consisted of nearly all medically complex patients (96% using the model at admission, and 90% using the model at discharge).

Figure 2.2. Calibration plots by quartiles of 30-day readmission risk for the final models



2.4. DISCUSSION

In this study, we aimed to identify independent risk factors for pediatric readmission and develop novel clinical prediction models and readmission risk scoring systems for use in clinical practice. While the predictive value of individual risk factors differed between the general pediatric population and CMC subpopulation, we found that nearly all of the predictive factors in our models were indicative of degree of medical complexity or illness severity. In both the general pediatric population as a whole and in the medically complex subpopulation, our models were capable of separating patients into quartiles or risk score levels with clinically meaningful differences in the likelihood of readmission.

The level of discrimination achieved by our models (c-statistic 0.65-0.69) is similar to that seen in prior adult and pediatric readmission studies utilizing retrospective data, and reflects the limitations of predicting readmission using data from electronic health records alone.[25,46] In terms of individual risk factors, those included in our final prediction models provide support to the findings obtained from prior association studies.[6,25–27,29,31,32,35,47] In particular, our findings contribute to a body of literature indicating that medical complexity is a primary driver of readmissions.[6,25–27,29,30,32] Our study also demonstrated that weekday discharge did not maintain a statistically significant association with unplanned readmission in multivariable models, consistent with findings from a recent study by Auger et al.[30] Some prior studies have demonstrated that social determinants of health reflected in demographic variables including race, public insurance, or income were predictive of pediatric readmission.[25,26,29,32] Interestingly, none of these had sufficiently significant predictive value for inclusion in

our final models. This difference may potentially be attributed to the location of our study, in a state with long standing state support for disadvantaged families. It may also reflect the relative imprecision of measures of social determinants of health obtained through EHR data compared with direct surveying of patients or family members.

In contrast to prior studies, by developing clinical prediction models and readmission risk scores, our study allows key risk factors to be applied in a practical manner for use in clinical practice or research. Our risks scores could provide practitioners and investigators with an evidence-based approach for identifying the highest risk patients for targeted interventions or resource allocation, with risk score targets tailored to the specific costs, effectiveness, and/or personnel bandwidth for individual interventions. For example, an expensive intervention or one with limited personnel, e.g., dedicated case managers or patient navigators, could benefit from an efficient targeting strategy. As seen in Table 2.5, targeting an intervention at patients with a risk score of 5 or above would focus efforts on only 10% of all general pediatric admissions, yet 27% of all readmissions. Interestingly, approximately half of the study's medically complex patients fell beneath this cut-off. While all medically complex children could be targeted through larger programmatic interventions such as initiation of a complex care coordination program, this approach requires significant resources which may not be attainable by all institutions caring for these children. Risk scores from our CMC-specific models could provide a more efficient approach to target focused clinical interventions specifically aimed at reducing readmission for highest risk patients. Because hospitalization and discharge specific factors added little predictive value to the readmission models, clinicians and investigators could use the models with only

admission characteristics to target interventions in both inpatient and post-discharge settings for a simplified and practical approach.

The risk factors identified by our models could also be used to guide the development of targeted interventions aimed at reducing readmission. For instance, since non-English language was shown to have predictive value for readmission in the general pediatric population, a focused intervention could include the development of written discharge paperwork in the languages most prevalent in the local community, or follow-up phone calls in parents' native languages.

The strengths of our study include a large sample size, the utilization of sociodemographic and clinical variables routinely captured by health systems in our models, allowing for practical use in real time, robust methods to identify patients with medical complexity, and exclusion of planned readmissions, not always accomplished in readmission studies.[46] By creating a model using only characteristics obtainable at admission, our study predictions are not limited to use in a post-discharge setting, but could also be used to guide discharge planning or to target either inpatient or outpatient interventions. Our study has several limitations. Given that this study was performed with pediatric patients hospitalized at one urban academic center, our findings may not be generalizable to patients in different geographic locations or different hospital systems. Although internal validation did not suggest substantial overfitting, external validation would be necessary to establish generalizability. Our methods also could not determine whether patients were readmitted to another institution, or whether they died outside of the hospital within 30 days of discharge, potentially resulting in misclassification error. Variables considered for our models were limited to those available in the electronic

health record, so we were unable to assess more contextually complex medical or social drivers of readmission, which could provide motivation for future qualitative work.

2.5. CONCLUSION

This study determined which characteristics independently predict 30-day readmission among pediatric patients discharged from a tertiary care center, and the resultant clinical prediction models and readmission risk scores may aid in the identification of patients who are at highest risk for readmission. Our findings could facilitate strategic targeting of interventions to decrease the risk of these costly readmissions, which may improve readmission outcomes and patient/family experiences, while decreasing healthcare utilization and healthcare costs. Future proposals could involve prospective studies utilizing and validating the prediction models, qualitative studies to determine more nuanced reasons behind readmissions, and development and evaluation of interventions to improve care transitions and care coordination to reduce pediatric readmissions.

Chapter 3: Discussion

In this study, we aimed to fill a critical gap in our understanding of 30-day readmission in the general and medically complex pediatric populations by developing novel clinical prediction models and readmission risk scoring systems. Our study contributes knowledge of key risk factors for pediatric readmission to the body of prior readmission association studies. The risk factors determined by our study to predict readmission in the general pediatric population and/or subpopulation of children with medical complexity (prior admissions, prior ED visits, number of home medications, medical complexity, number of complex chronic conditions, technology assistance, medical admission, non-English language, discharge with services, length of stay, and weekday discharge) were largely indicative of higher degree of medical complexity or illness severity. These results support administrators and policy makers arguing strongly for increased resource allocation for complex care coordination programs or home medical services, to better support transitions of care for our most complex and vulnerable patients. In fact, presentation of our preliminary study results to the Tufts pediatric administration helped them make the business argument for initiation of a complex care coordination program to Tufts Medical Center hospital administrators, who subsequently approved the proposal. Our work also determined that non-English language has predictive value for readmission in the general pediatric population. Clinicians can now use this knowledge to guide the development of targeted interventions such as standardized discharge paperwork in the most prevalent languages in the surrounding communities, or discharge follow-up phone calls in the parents' native languages.

Our research went a step further than prior readmission association studies by creating predictive models and readmission risk scores, allowing knowledge of risk factors to be applied and utilized by clinicians and investigators to determine highest risk patients for targeted resource allocation, targeted interventions, or to risk stratify patients in future research proposals. Some prior studies have demonstrated improved readmission rates through use of large programmatic interventions such as multifaceted care coordination programs, which require significant resources.[33] Our readmission risk scoring systems and risk score distributions (Tables 2.4 and 2.5, and Appendix 4.1) provide practitioners and clinician-investigators with an evidence-based approach to identifying efficient risk score cut-offs for more focused interventions or resource allocation, depending on local context.

Interestingly, although all four of our predictive models were able to separate patients into quartiles with significantly different risk of readmission, discrimination remained in the 0.65-0.69 range. This level of discrimination is consistent with prior readmission studies utilizing retrospective data, and it likely reflects the complexity of reasons behind readmissions, which cannot be fully captured by the limited data available in medical records.[25,46]

Examining all of the knowledge gained through this study together, while acknowledging its limitations and unresolved questions, three significant potential foci for future research arise:

1. External validation of the prediction models

Our study was limited by its conduct at a single urban academic center with a particular population and social determinants, so results may not be generalizable. An external validation study would be necessary to determine temporal and geographic generalizability and to modify our models if needed to predict readmission more accurately in a broader population. Given the potential for significant differences in resource availability between freestanding children's hospitals and general hospitals, inclusion of data from both types of hospitals, in geographically different regions, would strengthen a future validation study.

2. Collection of qualitative data to augment prior quantitative readmission studies

Our models' c-statistics suggest that quantitative data from medical records do not tell the whole story behind the reasons for readmission. Without speaking directly to patients and their families regarding their perceived reasons for readmission, more contextually complex medical and social drivers of readmission cannot be elicited. Prior and current quantitative research would therefore benefit from augmentation with qualitative data. Future research proposals could involve semi-structured interviews performed with readmitted pediatric patients and families, probing information such as: prior discharge experience, understanding of discharge instructions, perceived readiness to leave the hospital, additional dependent care required of parents, disruption (or lack thereof) of home routine for parents and patient, perceived adequacy (or lack) of home resources, social support structure within the home, and follow-up care. Focus groups could also be considered as an alternative format to semi-structured interviews while eliciting similar information. During focus group sessions, participants have the

additional benefit of hearing each others' responses to semi-structured interview questions, providing opportunity to react to each others' comments, generate greater consensus and potentially accrue insights that would not otherwise have been provided by individual participants. As non-English language has been shown to have predictive value for readmission, in our study as well as other prior quantitative studies, inclusion of non-English speakers in the interview or focus group sessions may provide critical perspectives from an underrepresented and particularly vulnerable group.[26] Qualitative data generated by either approach would provide a more comprehensive understanding of the drivers behind readmission, allowing for identification of promising leverage points for the development of interventions aimed at reducing readmissions. Including qualitative results in the intervention development process may help to make future interventions more effective, patient-centered, and impactful in meaningful ways for our patients and families.

3. Prospective study utilizing the prediction models and readmission risk scores to target interventions and resources

Although external validation may be necessary prior to broader uptake of our models, these models could be used at a local level to target interventions or resources in future studies. Use of the models and risk scores may be particularly advantageous for targeting of interventions that are expensive, or with limited scope, perhaps due to demands of personnel such as dedicated case managers or patient navigators, where efficiency is paramount. As the Floating Hospital for Children at Tufts Medical Center will soon be starting a pediatric complex care coordination program, our readmission risk

scores could also be utilized within our current local context to identify higher risk patients for inclusion in the program, even if not medically complex.

In conclusion, our clinical prediction models for readmission provide insight into independent risk factors for readmission in both the general and medically complex pediatric populations. Future qualitative study, probing patient and family perceived reasons for readmissions, would augment our quantitative results and provide a more comprehensive understanding of drivers of readmission in the pediatric population. Unlike prior studies, our clinical prediction models and accompanying readmission risk scores allow knowledge of readmission risk factors to be applied practically, identifying highest risk patients potentially for targeted interventions, resource allocation, or intensive care coordination and discharge planning. Future research will involve external validation of the models and exploration of whether the models and risk scores can be used to efficiently target interventions and resources aimed at reducing readmissions.

Chapter 4: Appendix

4.1. Supplementary Material for Manuscript

Table 4.1. Calculation of 30-day readmission risk score for the general pediatric model at admission (c-statistic 0.68)

Variable	**β-coefficient**	**Points***
Non-English primary language	0.29	1
Any admissions in prior 6 months	0.47	1
Any ED visits in prior 6 months	0.61	2
Number of home medications at admission		
0-3	Reference	
4-7	-0.03	0
≥ 8	0.53	2
Medical complexity	0.89	3
Technology assistance	0.32	1
Medical admission	0.48	1
Readmission risk score		**Range 0-11**

*Points calculated by multiplying β-coefficients by a factor of 3 and rounding to the nearest integer. This allowed one or more variables to have a point factor of 1, generating a more continuous distribution of possible risk scores. The multiplication factor of 3 was also capable of differentiating between different levels of the categorical variable, number of home medications at admission.

Table 4.2. Calculation of 30-day readmission risk score for the general pediatric model at discharge (c-statistic 0.68)

Variable	**β-coefficient**	**Points***
Non-English primary language	0.27	1
Any admissions in prior 6 months	0.495	1
Any ED visits in prior 6 months	0.63	2
Number of home medications at admission		
0-3	Reference	
4-7	-0.01	0
≥ 8	0.48	1
Medical complexity	0.78	2
Technology assistance	0.20	1
Medical admission	0.43	1
Discharge disposition to		
Home, no services	Reference	
Home with services	0.30	1
Other facility	0.10	0
LOS in days		
0-1	Reference	
2-5	0.04	0
≥ 6	0.57	2
Weekday discharge	0.17	1
Readmission risk score		**Range 0-13**

*Points calculated by multiplying β-coefficients by a factor of 3 and rounding to the nearest integer. This allowed one or more variables to have a point factor of 1, generating a more continuous distribution of possible risk scores. The multiplication factor of 3 was also capable of differentiating between different levels of the categorical variables, number of home medications at admission, discharge disposition, and length of stay.

Table 4.3. 30-day readmission risk score distribution for the general pediatric model at discharge

Risk score	Number of patients (total n=6974)*	% of patients medically complex (n)	Cumulative % of admissions	Observed % readmitted	Cumulative % of observed readmissions
9+	48	100 (48)	<1	35	5
8	88	99 (87)	2	10	8
7	191	97 (186)	5	15	18
6	277	94 (259)	9	11	27
5	492	78 (384)	16	9	41
4	993	69 (683)	30	5	56
3	1031	37 (381)	45	4	69
2	1898	5 (101)	72	3	87
1	1521	0	94	2	98
0	435	0	100	1	100

*Patients with missing data for number of home medications at admission were not included in model development nor this analysis

Table 4.4. Calculation of 30-day readmission risk score for the CMC model at admission (c-statistic 0.65)

Variable	**β-coefficient**	**Points***
Any admissions in prior 6 months	0.53	1
Any ED visits in prior 6 months	0.71	2
Number of complex chronic conditions 1 2 ≥ 3	 Reference 0.55 0.83	 1 2
Medical admission	0.60	2
Readmission risk score		**Range 0-8**

*Points calculated by multiplying β-coefficients by a factor of 2.5 and rounding to the nearest integer. This allowed one or more variables to have a point factor of 1, generating a more continuous distribution of possible risk scores. The multiplication factor of 2.5 was also capable of differentiating between different levels of the categorical variable, number of complex chronic conditions.

Table 4.5. 30-day readmission risk score distribution for the CMC model at admission

Risk score	Number of patients (total n=2267)*	Cumulative % of admissions	Observed % readmitted	Cumulative % of observed readmissions
7+	8	<1	25	1
6	20	1	20	3
5	67	4	27	13
4	225	14	14	29
3	333	29	13	52
2	925	70	6	82
1	223	79	6	89
0	466	100	4	100

*Patients with missing data for number of home medications at admission were not included in model development nor this analysis

Table 4.6. Calculation of 30-day readmission risk score for the CMC model at discharge (c-statistic 0.67)

Variable	**β-coefficient**	**Points***
Any admissions in prior 6 months	0.53	2
Any ED visits in prior 6 months	0.71	2
Number of complex chronic conditions		
1	Reference	
2	0.44	1
≥ 3	0.54	2
Medical admission	0.55	2
Discharge disposition to		
Home, no services	Reference	
Home with services	0.53	2
Other facility	0.14	0
LOS in days		
0-1	Reference	
2-5	0.14	0
≥ 6	0.37	1
Weekday discharge	0.21	1
Readmission risk score		**Range 0-13**

*Points calculated by multiplying β-coefficients by a factor of 3 and rounding to the nearest integer. This allowed one or more variables to have a point factor of 1, generating a more continuous distribution of possible risk scores. The multiplication factor of 3 was also capable of differentiating between different levels of the categorical variables, number of complex chronic conditions, discharge disposition, and length of stay.

Table 4.7. 30-day readmission risk score distribution for the CMC model at discharge

Risk score	Number of patients (total n=2267)*	Cumulative % of admissions	Observed % readmitted	Cumulative % of observed readmissions
9+	28	1	25	4
8	76	5	30	16
7	113	10	19	27
6	148	16	10	35
5	268	28	9	48
4	285	40	9	63
3	661	70	6	85
2	300	83	5	94
1	281	95	3	98
0	107	100	4	100

*Patients with missing data for number of home medications at admission were not included in model development nor this analysis

4.2. Supplementary Material for Thesis

4.2.1. Internal Validation

To perform internal validation for the final models, we utilized a bootstrapping technique. Five hundred bootstrap samples were randomly selected with replacement from the derivation data set. For the "models at admission", the backward selection procedure with AIC was repeated for each bootstrapped sample utilizing the variables that had passed univariate screening in the derivation set. Ultimately, the final models after backward selection with bootstrapped samples retained the same variables as retained in the derivation set (for the general pediatric model: language, prior admissions, prior ED visits, number of medications, medical complexity, technology assistance, and admission type; for the CMC model: prior admissions, prior ED visits, number of complex chronic conditions, and admission type). For the "models at discharge", an automated stepwise selection approach was not utilized in the model building, so the final

model variables, determined from the derivation set, were forced onto the bootstrap samples. C-statistics were recalculated for each of the bootstrapped models and then averaged. Relative concordance between the bootstrap c-statistics and the original c-statistics suggests validity of our models' predictions for new subjects. The slope (observed probability/predicted probability) for the bootstrap samples can also give an estimation of how overfit a model is to the original derivation data set, with a greater absolute distance from one suggesting more overfitting. As our slopes do not deviate substantially from one, this suggests that our models are not unreasonably overfit.

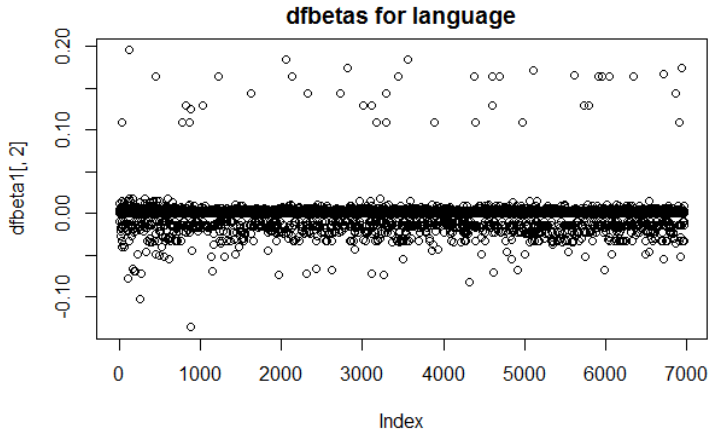
Table 4.8. Internal validation utilizing bootstrap samples

Model	**Original c-statistic**	**Mean c-statistic from 500 bootstrapped samples**	**Slope**
General pediatric model at admission	0.68	0.67	0.94
General pediatric model at discharge	0.69	0.68	0.94
CMC model at admission	0.65	0.63	0.87
CMC model at discharge	0.67	0.65	0.89

4.2.2. Model Diagnostics

To assess for potential influence points in our final models, we utilized dfbetas and deviance residuals. Dfbetas quantify how much each of the model coefficients changes if each observation were omitted from the data set. Deviance residuals compare the observed outcome to the predicted probability for a given patient, and large residuals indicate outliers that could potentially represent influence points. The following are 2 representative examples of the techniques we utilized.

Figure 4.1. Df betas for non-English language, for the general pediatric model at admission



We removed patients with dfbetas greater than 0.19 and with dfbetas less than -0.1, and then re-ran the model to determine whether β-coefficients were significantly affected, which would suggest significant influence points:

```
genpedsindex2<-genpedsindex1[dfbeta1[,2]<0.19,]
genpedsindex3<-genpedsindex2[dfbeta1[,2]>-0.1,]
```

Here is the original regression:

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-3.47514	0.10196	-34.082	< 2e-16	***
primlang_catv21	0.28696	0.17565	1.634	0.102328	
Admit_tot_cat1	0.46767	0.17848	2.620	0.008783	**
EDVst_cat1	0.60743	0.17193	3.533	0.000411	***
meds_catv31	-0.03367	0.20389	-0.165	0.868822	
meds_catv32	0.53425	0.22827	2.340	0.019263	*
cmc_any.f1	0.88721	0.13107	6.769	1.3e-11	***
tech.f1	0.32249	0.18675	1.727	0.084200	.
svcteam_cat1	-0.48391	0.13193	-3.668	0.000245	***

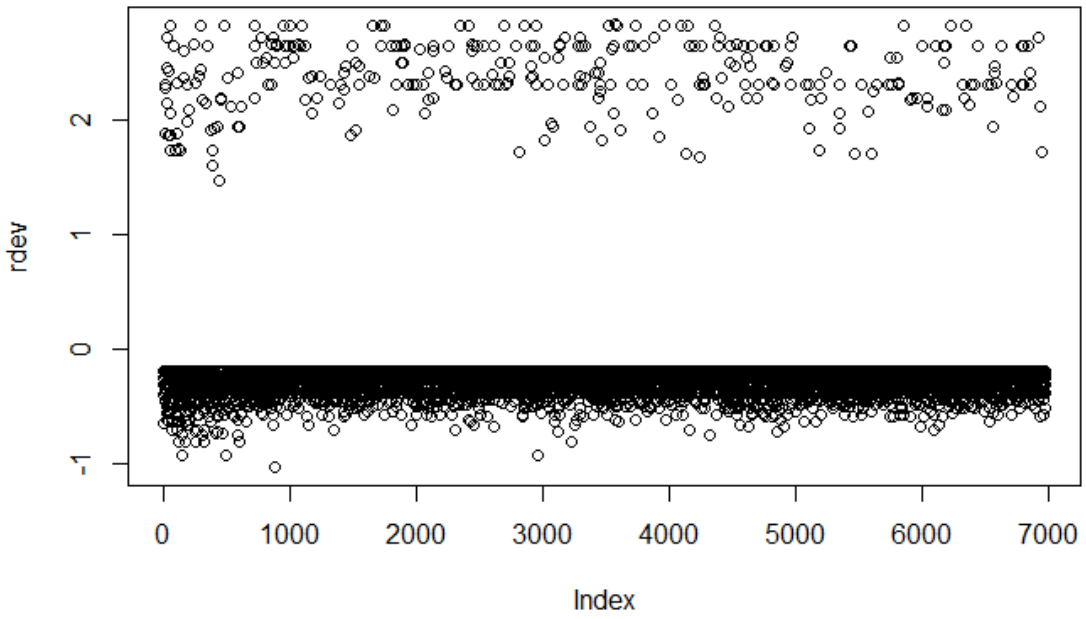
And the new regression with genpedsindex3 (data set with outliers removed):

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-3.47505	0.10196	-34.083	< 2e-16	***
primlang_catv21	0.28682	0.17565	1.633	0.102493	
Admit_tot_cat1	0.46858	0.17850	2.625	0.008664	**
EDVst_cat1	0.60720	0.17194	3.532	0.000413	***
meds_catv31	-0.03376	0.20389	-0.166	0.868475	
meds_catv32	0.53416	0.22827	2.340	0.019282	*
cmc_any.f1	0.88696	0.13107	6.767	1.31e-11	***
tech.f1	0.32239	0.18675	1.726	0.084301	.
svcteam_cat1	-0.48354	0.13193	-3.665	0.000247	***

Noted very small change in β-coefficients, suggesting no influential points for the non-English language variable.

Figure 4.2. Deviance residuals for the general pediatric model at admission



No data points with large deviance residuals were found. Due to our large sample size, a few influential points will not cause significant change in model estimates.

4.2.3. Identification of Children with Medical Complexity

To identify children with medical complexity within our data set, I utilized Feudtner's complex chronic conditions taxonomy.[39] I followed Feudtner's table of ICD-9 and ICD-10 codes, indicating a complex chronic condition. Where there were global codes such as E75.2, inclusive of, for example, E75.23 or E75.29 contained in our data set, I clarified the code by adding .X (for example E75.2X) to indicate that all codes with

the prefix E75.2 should be included. These clarifications are highlighted in the table to aid in reproducibility.

Table 4.9. Sample from Feudtner's table of complex chronic conditions' ICD-9 and ICD-10 codes with clarifications

Categories	Subcategories	ICD-9	ICD-10
Neurologic and Neuromuscular	Brain and spinal cord malformations	740.0-742.9	Q00-Q07, G90.1
	Mental retardation	318.0-318.2	F71-F73
	CNS degeneration and diseases	330.0-330.9, 334, 335.0-335.9, 331.1, 331.11, 331.19, 331.4, 331.8, 331.89, 331.9, 333.2, 336.1, 336.8, 337.9, 759.5	E75.0, E75.1, E75.2X, E75.4, F84.2, G11.1-G11.4, G11.8, G11.9, G12.0- G12.2X, G12.8, G12.9, G31.01, G31.09, G31.8X, G31.89, G32.89, G93.8X, G93.9, G94, G91.1, G31.9, G25.3, G95.19, G95.89, G90.9, Q85.1
	Infantile cerebral palsy	343.0-343.9	G80.X
	Epilepsy	345.01, 345.11, 345.3, 345.41, 345.61, 345.71, 345.81, 345.91	G40.311, G40.301, G40.211, G40.219, G40.411, G40.419, G40.111, G40.119, G40.804, G40.911, G40.919
	Other disorders of CNS	341.8, 342.90, 344.0, 344.81, 344.9, 348.1, 348.4, 780.03, 01.52, 01.53	G37.1, G37.2, G37.8, G81.9X, G82.90, G82.50-G82.54, G83.5, G83.9, G93.1, G93.5, R40.3, 0016070, 0016071, 0016072, 0016073, 0016074, 0016075, 0016076, 0016077, 0016078, 001607B, 0016370, 0016371, 0016372, 0016373, 0016374, 0016375, 0016376, 0016377, 0016378, 001637B, 001U074, 001U076, 001U077, 001U079, 001U374, 001U376, 001U377, 001U379, 00B70ZZ, 00B73ZZ, 00B74ZZ, 00T70ZZ, 00T73ZZ, 00T74ZZ
	Occlusion of cerebral arteries	434.01, 434.91	I63.30, I63.50
	Muscular dystrophies and myopathies	359.0-359.3	G71.X, G72.X
	Movement diseases	332.0, 332.1, 333.0, 333.2,33.4, 333.5, 333.7X, 333.9X	G10, G20, G21.0, G21.11, G21.19, G21.8, G23.0-G23.2, G23.8, G24.02, G24.8, G25.3-G25.5, G25.81-G25.83, G25.89, G25.9, G80.3
	Devices	996.2, 996.63, V45.2, V53.01, V53.02, 02.2, 02.21, 02.22, 02.3, 02.31, 02.32, 02.33, 02.34, 02.35, 02.39, 02.4, 02.41, 02.42, 02.93, 03.7, 03.71, 03.72. 03.79, 03.93, 03.97, 04.92	T85.09XA, T85.190A, T85.192A, T85.199A, T85.79XA, Z98.2, Z45.41, Z45.42, 00160J0, 00160J1, 00160J2, 00160J3, 00160J4, 00160J5, 00160J6, 00160J7, 00160J8, 00160JB, 00160K0, 00160K1, 00160K2, 00160K3, 00160K4, 00160K5, 00160K6, 00160K7, 00160K8, 00160KB, 00163J0, 00163J1, 00163J2, 00163J3, 00163J4, 00163J5, 00163J6, 00163J7, 00163J8, 00163JB, 00163K0, 00163K1, 00163K2, 00163K3, 00163K4, 00163K5, 00163K6, 00163K7, 00163K8, 00163KB,

The following is a representative example of the SAS coding I then wrote to classify patients with a neurological complex chronic condition utilizing all of the diagnostic and procedural ICD-9 and ICD-10 codes in our data set and Feudtner's table of ICD-9 and ICD-10 codes (sample shown above). I repeated this technique for the additional 10 complex chronic condition categories, to identify patients with medical complexity in our data set.

```
data neuro0; set jana;
if code in (
/*brain and spinal cord*/ /*no 740s*/ "741" "740.03"
"741.9" "741.93" "742" "'742.1'" "742.2" "742.3" "742.4"
```

```
"742.53" "742.59" "742.9" "Q02" "Q03.0" "Q03.1" "Q03.8"
"Q03.9" "Q04.0" "Q04.2" "Q04.3" "Q04.6" "Q04.8" "Q05.7"
"Q06.8" "Q07.00" "Q07.02" "G90.1"
/*mental retardation*/ "318" "318.1" "318.2" /*no Fs*/
/*CNS degeneration and diseases*/ "330" "330.1" "330.3"
"330.8" "334.1" "334.3" "334.4" "335" "335.1" "335.11"
"335.19" "335.21" /*no 331.1-331.19*/ "331.4" /*no 331.8,
331.89, or 331.9*/ "333.2" "336.1" /*no 336.8*/ "337.9"
"759.5" /*no E75.0, E75.1*/ "E75.2" "E75.23" "E75.29" /*no
E75.4*/ "F84.2" "G11.4" /*no G11.8*/ "G11.9" "G12.0"
"G12.21" /*no G12.8-G12.9, no G31.01, no G31.09*/ "G31.82"
"G31.84" /*no G31.89, no G32.89*/ "G93.82" "G93.89" /*no
G93.9*/ "G94" "G91.1" /*no G31.9*/ "G25.3" "G95.19" /*no
G95.89*/ "G90.9" "Q85.1"
/*infantile cerebral palsy*/ "343" "343.1" "343.2" "343.4"
"343.8" "343.9" "G80.0" "G80.1" "G80.2" "G80.8" "G80.9"
/*Epilepsy*/ "345.01" "345.11" "345.3" "345.41" /*no 345.61
or 345.71*/ "345.81" "345.91" /*no G40.311*/ "G40.301" /*no
G40.211*/ "G40.219" "G40.411" "G40.419" /*no G40.111*/
"G40.119" "G40.804" "G40.911" "G40.919"
/*Other disorders of CNS*/ "341.8" "342.9" "344" "344.81"
"344.9" "348.1" "348.4" /*no 780.03 or 01.52 or 01.53*/
/*no G37s*/ "G81.94" /*no G82.9*/ "G82.50" "G82.54" /*no
G83.5 or G83.9*/ "G93.1" "G93.5" "R40.3" /*no 0016070-
00T74ZZ*/
/*Occlusion of cerebral arteries*/ "434.01" "434.91" /*no
I63.3 or I63.5*/
/*Muscular dystrophies and myopathies*/ "359" "359.1"
"359.21" "359.22" "G71.0" "G71.13" "G72.81"
/*Movement diseases*/ "332" /*no 332.1*/ "333" "333.2" /*no
33.4*/ "333.5" "333.72" "333.9" "333.94" "333.99" /*no G10s
or G20s or G21s or G23s, no G24.02 or G24.8*/ "G25.3" /*no
G25.8s or G25.9s, no G80.3*/
/*Devices*/ "996.2" "996.63" "V45.2" /*no V53.01 or
V53.02*/ "02.2" "02.21" "02.22" /*no 02.31-02.32*/ "02.33"
"02.34" /*no 02.35-39*/ "02.41" "02.42" /*no 02.93*/
"03.71" /*no 03.72-79, no 03.93*/ "03.97" "04.92" /*no
T85.09s or T85.19s*/ "T85.79XA" "Z98.2" /*no Z45.41 or
Z45.42, no 160J0-J5s*/ "00160J6" /*no 00160J7-JB or 160Ks,
no 00163J0-J5*/ "00163J6" /*no 00163J7-JBs or 163Ks, no
1Us*/ "009600Z" "009630Z" "009640Z" /*no H00Ms, no H03Ms or
H04Ms or H60-64Ms, no HEs, no HU0Ms, no HU3MZs, no HU4MZs,
no 00HVs*/ "00W60JZ" "00W63JZ" /*no 00W64JZ, no WUs, no
01Hs, no 0DH60MZ-64MZ, no W11s, no 3E1Qs*/
);
neuro=1;
keep neuro patientaccountid;
```

```
run;

data neuro1; set main;
if proccd in (
/*brain and spinal cord*/ /*no 740s*/ "741" "740.03"
"741.9" "741.93" "742" "'742.1'" "742.2" "742.3" "742.4"
"742.53" "742.59" "742.9" "Q02" "Q03.0" "Q03.1" "Q03.8"
"Q03.9" "Q04.0" "Q04.2" "Q04.3" "Q04.6" "Q04.8" "Q05.7"
"Q06.8" "Q07.00" "Q07.02" "G90.1"
/*mental retardation*/ "318" "318.1" "318.2" /*no Fs*/
/*CNS degeneration and diseases*/ "330" "330.1" "330.3"
"330.8" "334.1" "334.3" "334.4" "335" "335.1" "335.11"
"335.19" "335.21" /*no 331.1-331.19*/ "331.4" /*no 331.8,
331.89, or 331.9*/ "333.2" "336.1" /*no 336.8*/ "337.9"
"759.5" /*no E75.0, E75.1*/ "E75.2" "E75.23" "E75.29" /*no
E75.4*/ "F84.2" "G11.4" /*no G11.8*/ "G11.9" "G12.0"
"G12.21" /*no G12.8-G12.9, no G31.01, no G31.09*/ "G31.82"
"G31.84" /*no G31.89, no G32.89*/ "G93.82" "G93.89" /*no
G93.9*/ "G94" "G91.1" /*no G31.9*/ "G25.3" "G95.19" /*no
G95.89*/ "G90.9" "Q85.1"
/*infantile cerebral palsy*/ "343" "343.1" "343.2" "343.4"
"343.8" "343.9" "G80.0" "G80.1" "G80.2" "G80.8" "G80.9"
/*Epilepsy*/ "345.01" "345.11" "345.3" "345.41" /*no 345.61
or 345.71*/ "345.81" "345.91" /*no G40.311*/ "G40.301" /*no
G40.211*/ "G40.219" "G40.411" "G40.419" /*no G40.111*/
"G40.119" "G40.804" "G40.911" "G40.919"
/*Other disorders of CNS*/ "341.8" "342.9" "344" "344.81"
"344.9" "348.1" "348.4" /*no 780.03 or 01.52 or 01.53*/
/*no G37s*/ "G81.94" /*no G82.9*/ "G82.50" "G82.54" /*no
G83.5 or G83.9*/ "G93.1" "G93.5" "R40.3" /*no 0016070-
00T74ZZ*/
/*Occlusion of cerebral arteries*/ "434.01" "434.91" /*no
I63.3 or I63.5*/
/*Muscular dystrophies and myopathies*/ "359" "359.1"
"359.21" "359.22" "G71.0" "G71.13" "G72.81"
/*Movement diseases*/ "332" /*no 332.1*/ "333" "333.2" /*no
33.4*/ "333.5" "333.72" "333.9" "333.94" "333.99" /*no G10s
or G20s or G21s or G23s, no G24.02 or G24.8*/ "G25.3" /*no
G25.8s or G25.9s, no G80.3*/
/*Devices*/ "996.2" "996.63" "V45.2" /*no V53.01 or
V53.02*/ "02.2" "02.21" "02.22" /*no 02.31-02.32*/ "02.33"
"02.34" /*no 02.35-39*/ "02.41" "02.42" /*no 02.93*/
"03.71" /*no 03.72-79, no 03.93*/ "03.97" "04.92" /*no
T85.09s or T85.19s*/ "T85.79XA" "Z98.2" /*no Z45.41 or
Z45.42, no 160J0-J5s*/ "00160J6" /*no 00160J7-JB or 160Ks,
no 00163J0-J5*/ "00163J6" /*no 00163J7-JBs or 163Ks, no
1Us*/ "009600Z" "009630Z" "009640Z" /*no H00Ms, no H03Ms or
```

```
H04Ms or H60-64Ms, no HEs, no HU0Ms, no HU3MZs, no HU4MZs,
no 00HVs*/ "00W60JZ" "00W63JZ" /*no 00W64JZ, no WUs, no
01Hs, no 0DH60MZ-64MZ, no W11s, no 3E1Qs*/
);
neuro=1;
keep neuro patientaccountid;
run;

data neuro; set neuro0 neuro1;
run;

proc sort data=neuro out=neuronodup nodupkey; by
patientaccountid;
run;
```

4.2.4. Determination of Planned Admissions

Similarly, I wrote the following SAS coding to determine which admissions were for chemotherapy or planned procedures, so that we could exclude planned readmissions. The ICD-9 and ICD-10 codes corresponding to chemotherapy and planned procedures are made publically available on request by the group who developed and determined what constitutes a planned pediatric procedure.[6,40] I followed their ICD-9 and ICD-10 code dictionaries to write SAS code, ultimately allowing us to code planned readmissions as non-readmissions in terms of our primary outcome. Below, I present a representative example of the coding I utilized to determine admissions for planned pediatric procedures. Similar coding was written to determine admissions for chemotherapy.

```
data planadmit0; set main;
if proccd in (
/*planproc ICD9*/ /*no 0.14-0.94, no 1.02*/ "1.11" "1.13"
"1.14" "1.15" "1.23" /*no 01.24, 01.25, 01.31, 01.39*/
"01.41" "01.51" "01.59" "01.6" "02.01" /*no 02.02*/ "02.06"
/*no 02.12, 02.2, 02.21, 02.22*/ "02.33" "02.34" /*no
02.41, 02.42, 02.43, 02.92*/ "3.09" /*no 03.31*/ "03.32"
"03.4" /*no 03.51, 03.53*/ "03.59" "03.6" "03.71" /*no
03.90, 03.92*/ "03.95" /*no 03.97, 03.98, 04.07, 04.3,
04.6, 04.74, 04.81*/ "04.92" "05.29" /*no 06.01*/ "06.2"
```

“06.4” “06.7” “06.89” /*no 06.98*/ “07.21” “07.29” “07.61” “07.62” “07.65” “07.82” “08.09” /*no 08.81, 08.85*/ “09.42” “09.43” /*no 10.6, 11.51*/ “12.14” “13.19” “13.69” /*no 14.24*/ “14.74” “15.11” /*no 15.7*/ “16.09” “16.42” /*no 16.82*/ “16.92” “17.33” /*no 17.7*/ “18.09” “18.21” “18.29” /*no 18.4*/ “18.6” /*no 18.72, 18.79*/ “19.4” “19.53” “19.6” “20.01” “20.1” “20.23” “20.41” “20.42” “20.49” “20.51” “20.92” “20.96” “20.97” “20.99” /*no 21.01, 21.03, 21.1, 21.21*/ “21.62” /*no 21.81*/ “21.86” “21.88” “21.89” “22.19” “22.39” “22.41” “22.42” “22.52” “22.60” “22.62” “22.63” “23.01” “23.09” “23.19” “24.0” /*no 24.5*/ “25.02” “25.1” “25.2” /*no 25.51, 25.59*/ “25.91” “26.0” “26.11” “26.29” “26.30” “26.32” /*no 27.0*/ “27.23” /*no 27.51, 27.52*/ “27.54” /*no 27.57*/ “27.62” “27.63” “27.69” “27.92” /*no 28.0*/ “28.2” “28.3” “28.6” /*no 28.7, 28.91*/ “28.92” “29.11” “29.2” “29.39” /*no 29.4*/ “29.52” /*no 30.01, 30.09, 30.1, 30.21, 30.29, 31.0, 31.1, 31.29, 31.41, 31.42*/ “31.73” /*no 31.74, 31.75, 31.79, 31.92, 31.98, 31.99, 32.01*/ “32.20” “32.30” “32.39” “32.41” “32.49” “33.20” /*no 33.21, 33.22, 33.23, 33.24, 33.26, 34.04, 34.06, 34.09, 34.25*/ “34.26” “34.3” 34.4” /*no 34.52*/ “34.59” “34.6” “34.74” /*no 34.91*/ “35.11” “35.12” “35.13” “35.21” “35.25” “35.26” “35.34” “35.51” “33.52” “33.53” “33.55” “35.61” “35.62” “35.63” “35.71” “35.72” “35.81” /*no 35.82*/ “35.91” “35.94” /*no 35.96*/ “36.12” “36.99” “37.0” /*no 37.21, 37.22, 37.23, 37.26*/ “37.33” “37.34” /*no 37.71, 37.72, 37.74, 37.83*/ “37.87” “37.94” /*no 38.23*/ “38.34” “38.45” “38.62” /*no 38.78*/ “38.82” “38.85” “38.86” /*no 38.91, 38.93, 38.95*/ “38.97” “39.21” /*no 39.29*/ “39.49” /*no 39.50*/ “39.56” /*no 39.65, 39.71*/ “39.72” /*no 39.73*/ “39.75” /*no 39.79, 39.95*/ “39.99” “40.11” “40.29” “40.3” “40.41” “41.00” “41.03” “41.04” “41.05” “41.06” “41.07” “41.31” “41.42” “41.5” “41.91” “41.99” /*no 42.23*/ “42.33” “42.7” “42.92” “43.0” “43.11” “43.19” “43.41” “43.82” /*no 44.13, 44.29*/ “44.38” /*no 44.41, 44.42*/ “44.43” “44.62” “44.63” “44.67” “44.69” “44.99” “45.01” /*no 45.12, 45.13, 45.14, 45.16, 45.19, 45.23, 45.24, 45.25*/ “45.33” “45.61” “45.62” “45.72” “45.73” “45.76” “45.79” “45.81” “45.82” “45.83” “45.90” “45.91” “45.93” “45.95” “46.01” “46.10” “46.11” “46.13” “46.21” “46.23” /*no 46.32*/ “46.39” “46.41” “46.51” “46.52” “46.62” /*no 46.73*/ “46.76” /*no 46.79, 46.80, 46.81, 46.82*/ “46.99” /*no 47.01, 47.09, 47.2*/ “47.91” /*no 48.23, 48.24, 48.29*/ “48.41” “48.43” “48.71” “48.81” “48.93” “49.01” “49.21” /*no 49.71*/ “50.0” /*no 50.11*/ “50.12” “50.22” “50.3” /*no 51.10*/ “51.22” “51.23” “51.69” /*no 51.85*/ “51.88” “52.52” “53.00” “53.02” “53.10”

“53.49” “53.51” “53.61” “53.71” “53.72” “53.81” “53.9” /*no 54.0, 54.11, 54.19, 54.21, 54.23, 54.4*/ “54.51” /*no 54.59, 54.63*/ “54.91” /*no 54.93, 54.95, 54.98*/ “54.99” /*no 55.01, 55.02, 55.03*/ “55.04” /*no 55.11*/ “55.23” “55.24” “55.31” “55.35” “55.4” “55.51” “55.69” “55.86” “55.87” /*no 55.92, no 56.0*/ “56.41” “56.74” “56.83” “56.84” /*no 56.89, no 57.08*/ “57.18” “57.19” “57.21” “57.22” “57.32” “57.49” “57.51” “57.59” “57.85” “57.87” “57.88” /*no 57.93, 57.94*/ “58.39” “58.45” “58.5” “58.93” “59.72” /*no 59.8, 61.0, 61.49*/ “62.2” “62.3” “62.5” “64.0” “64.42” “64.44” /*no 64.92, 64.98, 65.25, 65.29, 65.41, 65.49, 65.61, 65.95, 66.48*/ “66.61” /*no 66.62, 67.59, 68.49, 69.01, 69.51, 69.52*/ “70.31” “70.33” /*no 70.79, 71.09, 71.61, 71.71, 72.0, 72.71, 72.79*/ “73.09” “73.4” /*no 73.59*/ “74.0” /*no 74.1, 75.0, 75.1, 75.34, 75.51, 75.69*/ “76.09” “76.2” “76.31” “76.41” ”76.43” “76.5” “76.62” “76.63” “76.64” “76.65” “76.66” “76.68” “76.69” “76.72” “76.75” “76.76” “76.79” “76.91” “76.97” “76.99” “77.12” “77.17” “77.25” “77.27” “77.35” “77.37” “77.38” “77.39” “77.45” “77.47” “77.49” “77.51” “77.52” “77.62” “77.63” “77.65” “77.67” “77.68” “77.69” “77.79” “77.85” “77.89” “77.91” “77.99” “78.05” “78.07” /*no 78.12, 78.15, 78.17*/ “78.25” “78.27” “78.32” “78.35” “78.37” “78.38” “78.39” /*no 78.45, 78.47, 78.48, 78.49*/ “78.55” “78.57” “78.59” “78.63” “78.65” “78.67” “78.69” /*no 79.01, 79.02, 79.05, 79.06, 79.11, 79.12, 79.14, 79.15, 79.16, 79.17, 79.18*/ “79.25” “79.31” “79.32” “79.33” “79.34” “79.35” “79.36” “79.37” “79.38” “79.39” /*no 79.45, 79.46*/ “79.56” /*no 79.62, 79.64, 79.65, 79.66, 79.69, 79.71, 79.75, 79.76, 79.81, 79.85, 79.86, 79.87, 80.12, 80.14, 80.15, 80.16*/ “80.36” “80.37” “80.45” “80.46” “80.48” “80.51” “80.6” “80.76” “80.77” “80.81” “80.82” “80.84” “80.85” “80.86” “80.87” “80.95” “81.02” “81.03” “81.05” “81.06” “81.07” “81.08” “81.13” “81.35” “81.37” “81.38” “81.39” “81.40” “81.44” “81.45” “81.47” “81.51” “81.63” /*no 81.91, 81.92*/ “81.95” “82.01” “82.09” “82.11” /*no 82.12*/ “82.39” “83.02” “83.09” “83.12” “83.13” /*no 83.14*/ “83.19” “83.21” “83.32” “83.39” “83.43” “83.44” “83.45” “83.64” “83.65” “83.71” “83.72” “83.75” “83.81” “83.84” “83.85” “83.98” “84.11” “84.13” “84.17” “84.53” “84.54” “84.59” /*no 85.0*/ “85.21” “85.32” “85.36” /*no 86.01*/ “86.03” /*no 86.04*/ “86.05” ”86.06” “86.07” “86.09” “86.11” “86.21” /*no 86.22, 86.28*/ “86.3” “86.4” “86.59” “86.61” “86.69” “86.74” “86.85” “86.89” “86.93” /*no 87.03, 87.41, 87.74, 87.76, 88.01, 88.38, 88.41, 88.42, 88.44, 88.45, 88.47, 88.49, 88.66, 88.72, 88.76, 88.78, 88.79, 88.91, 88.92, 88.93, 88.94, 88.97, 89.14,

```
89.19*/ “89.26” /*no 89.31, 89.34, 89.39, 89.52, 92.04*/
“92.24” “92.29” /*no 92.32, 93.42, 93.52, 93.53, 93.54*/
“93.55” /*no 93.57, 93.59, 93.90, 93.94, 93.96, 93.99,
95.02, 95.41, 96.04, 96.07*/ “96.23” /*no 96.26, 96.29,
96.34*/ “96.38” “96.52” /*no 96.55, 96.59, 96.6, 96.71,
96.72, 97.01, 97.02*/ “97.03” “97.14” /*no 97.23, 97.37*/
“97.41” “97.49” /*no 97.51, 97.62, 97.89, 98.02, 98.03,
98.15, 99.04, 99.05, 99.06, 99.07, 99.09, 99.10, 99.11,
99.14, 99.15, 99.17, 99.20, 99.21, 99.23, 99.24, 99.25,
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“00BN0ZZ” /*no 00HU33Z, 00NC0ZZ, 00NG4ZZ*/ “00NW0ZZ”
“00NY0ZZ” /*no 00P60JZ, 00W60JZ, 00W63JZ, 00W6XJZ*/
“02160JQ” “021K0AR” /*no 027Q3DZ, 027Q3ZZ, 027R3ZZ,
027W3ZZ*/ “02H633Z” /*no 02HV33Z*/ “02LR3DT” “02NH0ZZ”
“02NW0ZZ” “02Q50ZZ” “02QG0ZZ” “02QM0ZZ” “02RF08Z” “02RH08Z”
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/*n0 08Q0XZZ, 08Q9XZZ*/ “08QNXZZ” “08QY0ZZ” /*no 08T43ZZ*/
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0BH17EZ, 0BH18EZ, 0BJ08ZZ, 0BQ18ZZ, 0BU107Z*/ “0C5PXZZ”
“0C5QXZZ” /*no 0C7S7ZZ, 0C7S8ZZ, 0C94XZZ*/ “0C9M00Z”
“0C9M0ZX” “0C9M0ZZ” “0C9M3ZZ” “0C9M7ZX” ” 0C9M7ZZ”
“0C9M8ZZ” “0CB80ZZ” “0CBH0ZZ” “0CBPXZZ” “0CBQ0ZZ” /*no
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/*no 0CJS8ZZ, 0CNR8ZZ, 0CNS8ZZ*/ “0CQ2XZZ” “0CQ3XZZ”
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“0CTQ0ZZ” “0CTQXZZ” “0CTX0Z1” /*no 0CUM77Z, 0CUS07Z,
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0D9670Z, 0DB28ZX, 0DB38ZX, 0DB58ZX, 0DB68ZX, 0DB98ZX*/
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0H96XZZ*/ “0H98XZX” /*no 0H98XZZ, 0H9QXZZ*/ “0HB0XZX”
“0HB4XZZ” “0HB6XZX” “0HBEXZX” /*no 0J9P3ZZ*/ “0JB40ZZ”
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“0JH638Z” “0JH63XZ” “0JH70VZ” “0JH80VZ” “0JHT0VZ” “0JHT3VZ”
“0JPT0XZ” “0JPT3WZ” “0JPT3XZ” “0JR007Z” /*no 0K9T00Z*/
“0KBQ0ZX” “0KQT0ZZ” “0KX40Z1” “0KX40Z2” “0KX40ZZ” “0L8L0ZZ”
“0L8N0ZZ” “0L8P0ZZ” “0L8P3ZZ” “0L8V0ZZ” “0LNK0ZZ” “0LNV0ZZ”
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"0MNP4ZZ" "0N8V0ZZ" "0NB00ZZ" "0NB04ZX" "0NB20ZZ" "0NB30ZZ"
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"0RGA0KJ" "0RGA0Z1" /*no 0RH00CZ, 0RW60AZ, 0S9900Z,
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3E0337Z, 3E033GC, 3E033VJ, 3E033WK, 3E033WL, 3E033XZ,
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4A023N8, 4A02XFZ, 4A10X4Z, 4A1HXCZ, 5A09357, 5A0935Z,
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B32R1ZZ B33RYZZ, B54DZZZ, BT0B1ZZ, BT41ZZZ, BT43ZZZ,
BU4CZZZ, BW21YZZ, BW28ZZZ, BW38YZZ, BW38ZZZ, BW40ZZZ,
BY4FZZZ, GZ72ZZZ*/
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/*chemo icd 10*/ /*no 3E00X05, 3E00X0M, 3E01305, 3E0130M,
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3E0F705, 3E0F70M, 3E0F805, 3E0F80M, 3E0G305, 3E0G30M,
3E0G705, 3E0G70M, 3E0G805, 3E0G80M, 3E0Hs, 3E0Js, 3E0Ks,
3E0Ls, 3E0Ms, 3E0Ns, 3E0Ps, 3E0Qs, 3E0R303*/ "3E0R305" /*no
3E0R30M, 3E0Ss, 3E0Us, 3E0Vs, 3E0Ws, 3E0Ys*/
);
planadmit=1;
keep planadmit patientaccountid;
run;

data planadmit1; set main;
if prin_dx_cd in (
/*chemo icd 9*/ "V58.11" "V58.12"
/*chemo icd 10*/ "Z51.11" /*no Z51.12*/
);
planadmit=1;
keep planadmit patientaccountid;
run;


data planadmit; set planadmit0 planadmit1;
run;

proc sort data=planadmit out=planadmitnodup nodupkey; by
patientaccountid;
run;
```

Chapter 5: Bibliography

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