Potential Impact of Initial Clinical Data on Adjustment of Pediatric Readmission Rates

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The authors have no conflicts of interest to disclose.
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Received for publication March 6, 2018; accepted September 17, 2018.

ABSTRACT

OBJECTIVE: Comparison of readmission rates requires adjustment for case-mix (ie, differences in patient populations), but previously only claims data were available for this purpose. We examined whether incorporation of relatively readily available clinical data improves prediction of pediatric readmissions and thus might enhance case-mix adjustment.

METHODS: We examined 30-day readmissions using claims and electronic health record data for patients ≤18 years and 29 days of age who were admitted to 3 children's hospitals from February 2011 to February 2014. Using the Pediatric All-Condition Readmission Measure and starting with a model including age, gender, chronic conditions, and primary diagnosis, we examined whether the addition of initial vital sign and laboratory data improved model performance. We employed machine learning to evaluate the same variables, using the L2-regularized logistic regression with cost-sensitive learning and convolutional neural network.

RESULTS: Controlling for the core model variables, low red blood cell count and mean corpuscular hemoglobin concentration and high red cell distribution width were associated with greater readmission risk, as were certain interactions between laboratory and chronic condition variables. However, the C-statistic (0.722 vs 0.713) and McFadden's pseudo R^2 (0.085 vs 0.076) for this and the core model were similar, suggesting minimal improvement in performance. In machine learning analyses, the F-measure (harmonic mean of sensitivity and positive predictive value) was similar for the best-performing model (containing all variables) and core model (0.250 vs 0.243).

CONCLUSIONS: Readily available clinical variables do not meaningfully improve the prediction of pediatric readmissions and would be unlikely to enhance case-mix adjustment unless their distributions varied widely across hospitals.

KEYWORDS: patient readmission; quality improvement; risk adjustment

ACADEMIC PEDIATRICS 2018;19:589−598

WHAT'S NEW

Previously, only claims data were available for adjustment of readmission rates. We found that incorporation of initial vital sign measurements and common laboratory results minimally enhanced the prediction of pediatric readmissions and thus might have limited impact on case-mix adjustment.

DESPITE THE FOCUS by hospitals, health systems, and payers on reducing readmissions, the use of readmission rates as a measure of health care quality remains controversial. Stakeholders disagree about which factors should be included in readmission rate case-mix adjustment (defined as adjustment for differences in hospital patient populations to distinguish quality of care from effects of patient characteristics that are not under clinicians' control).[1−3] In addition, to date, readmission measures have used hospital claims as the primary data source, yet these data have substantial limitations. Because their purpose is billing, they lack clinical granularity, including details such as disease severity and timing of complications.[4−6]

With greater use of electronic health records (EHRs), certain clinical data are now somewhat more available.

This information has the potential to improve readmission rate adjustment by better controlling for health-related factors that affect readmission risk but are inadequately represented in claims data. In particular, we postulate that these data could better reflect severity of illness and the resulting likelihood of persistent illness or sequelae that might lead to readmission. However, it remains to be determined whether EHR data can improve the accuracy of adjustments enough to justify the cost of extraction and analysis and, if so, which variables offer the most incremental value.

As part of the Pediatric Quality Measures Program under the Agency for Healthcare Research and Quality and the Centers for Medicare and Medicaid Services (CMS), we developed the Pediatric All-Condition Readmission Measure, which is publicly available and endorsed by the National Quality Forum, to assess readmissions after hospitalization for almost all pediatric conditions.[7,8] As is standard in the field, our measure relies on hospital claims for both readmission identification and case-mix adjustment. We investigated incorporating clinical variables commonly collected in EHRs into the measure's case-mix adjustment model, evaluating their association with readmission and impact on model performance. The potential impact of these variables on readmission rate adjustment depends on both their patient-level relationship with readmission risk and their extent of variation across hospitals. We examined the former—the ability of the clinical variables to improve prediction of readmissions compared with standard case-mix variables alone—as a first step in assessing whether such clinical data might be valuable for case-mix adjustment.

METHODS

DATA SOURCES, STUDY POPULATION, AND READMISSION DEFINITION

We used claims and EHR data of patients ≤18 years and 29 days of age who were admitted to Boston Children's Hospital, Children's Hospital Colorado, and Lucile Packard Children's Hospital Stanford from February 1, 2011, to February 28, 2014. Our readmission measure excludes admissions for healthy newborn births (not hospitalized for disease management), obstetric conditions (generally not within the purview of pediatrics), and mental health disorders (typically cared for in psychiatric centers that are not comparable to short-term acute care hospitals) (Figure). The measure evaluates the first readmission occurring ≤30 days from the discharge date for

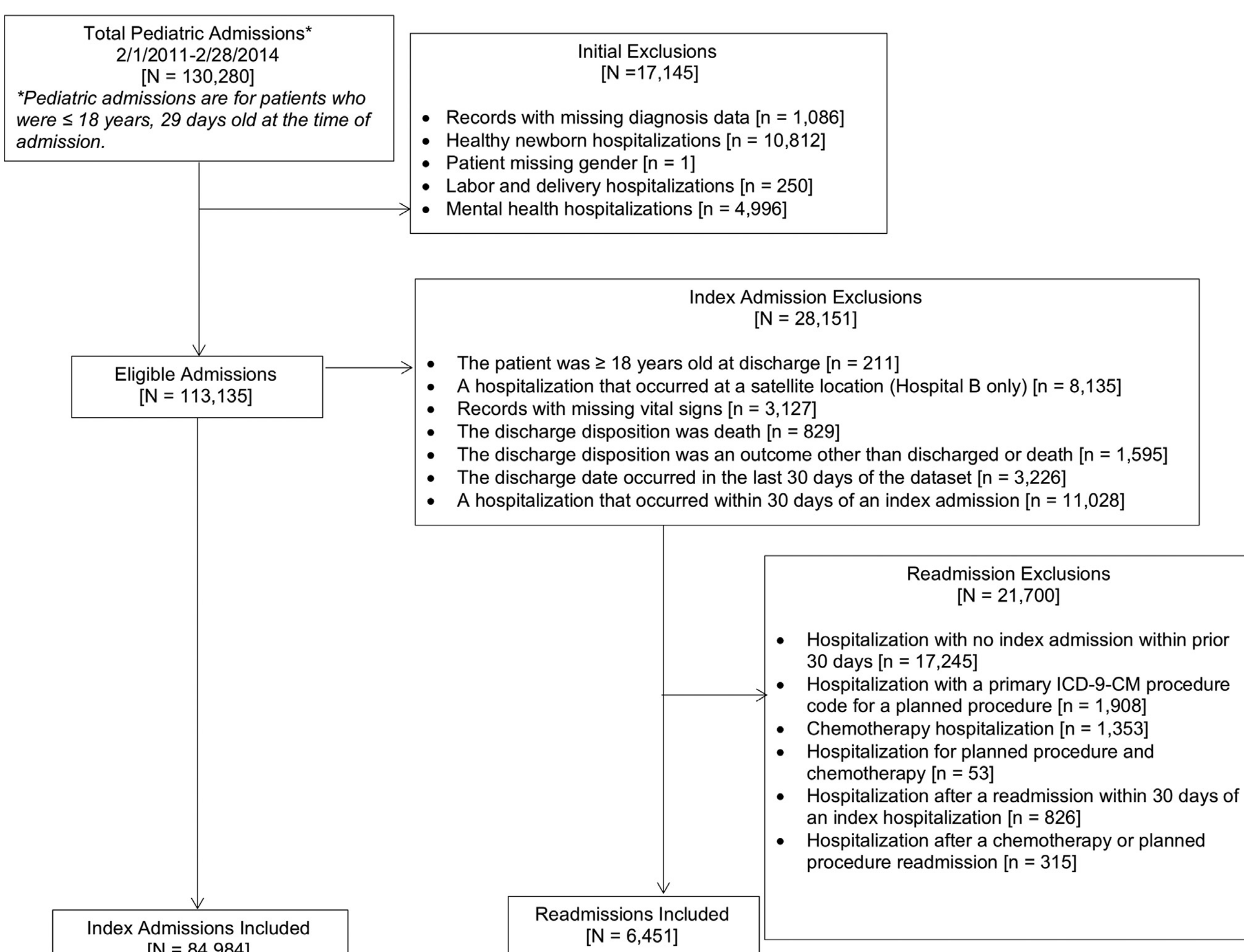

Figure. *Cohort flowchart for all hospitals.*

an index admission, excluding readmissions for planned procedures or chemotherapy. For details of index admission and readmission definitions and exclusions, please refer to Figure and the Supplementary Appendix. The Boston Children's Hospital and Stanford University School of Medicine institutional review boards approved the study with a waiver of informed consent. The Colorado Multiple Institutional Review Board determined that the study was not human subjects research.

CASE-MIX ADJUSTMENT MODELS

To explore the use of clinical EHR data for case-mix adjustment, we began with a core model containing age, gender, and chronic conditions (previously developed for case-mix adjustment of our Pediatric All-Condition Readmission Measure)[7] and incorporated primary diagnosis. (Because the purpose of the readmission measure is assessment of health care quality, it does not adjust for factors that could be related to both readmission risk and quality of care, such as length of stay or regional variation in readmission rates.) We then examined whether adding clinical EHR variables to the model improved model performance.

CORE CASE-MIX MODEL

In the core model, age was categorized into 5 groups (Table 1). Chronic conditions were included using dichotomous variables to indicate presence of a chronic condition in a particular Agency for Healthcare Research and Quality Chronic Condition Indicator (CCI) body system (organ system, disease category, or other category).[9] The CCI system places International Classification of Diseases, Ninth Revision, Clinical Modification diagnosis codes into 18 mutually exclusive categories and classifies them as chronic or not chronic. We excluded CCI 11, "Complications of pregnancy, childbirth, and the puerperium," due to the exclusion of obstetric admissions, leaving 17 chronic condition variables. In addition, the total number of CCI categories in which a patient had ≥ 1 chronic condition (capped at 4+) was included as a measure of medical complexity. We also included 16 body system variables to indicate the primary diagnosis category for the index admission (mental health and obstetrics conditions were not included due to exclusion criteria). Henceforth, we refer to the age, gender, chronic condition, and primary diagnosis variables as "administrative case-mix variables."

CLINICAL VARIABLES FROM ELECTRONIC HEALTH RECORD DATA

EHR data were obtained for the first 24 hours of admission and included vital sign measurements and results of laboratory tests, including basic metabolic panel (BMP), complete blood count (CBC), and automated differential. We chose these parameters because we hypothesized that they reflect severity of illness and because they are commonly evaluated in hospitalized patients, thus providing information for a large proportion of patients.

Normal ranges for all EHR parameters were defined using published data (Supplementary Appendix).[10–17] Four variables were created for each EHR parameter: 1) an indicator variable coded positive if above the normal range and negative otherwise, 2) an indicator variable coded positive if below the normal range and negative otherwise, 3) a continuous variable equal to the distance above the high threshold of the normal range (or 0 if below this threshold), and 4) a continuous variable equal to the distance below the low threshold of the normal range (or 0 if above this threshold). For example, a subject with a respiratory rate of 72 breaths/min and reference range of 40 to 60 breaths/min would have values of positive for the first variable, negative for the second variable, 12 for the third variable, and 0 for the fourth variable. If an EHR parameter was not collected in the first 24 hours of an index admission, it was coded as within the normal range based on the assumption that it would have been evaluated had there been clinical concern for an abnormal value.[18] However, to assess potential differences between subjects for whom laboratory studies were or were not evaluated, we included 3 variables indicating whether a BMP, CBC, or automated differential was obtained.

STATISTICAL ANALYSIS

Including index admissions from all 3 hospitals, logistic regression was used to test the association of 30-day readmission and each of the 121 EHR variables (4 variables per EHR parameter, as described above). For this analysis, we used the first values during an admission to better represent disease severity at the time of presentation and limit the influence of hospital quality of care. Each model included the administrative case-mix variables and a categorical hospital variable. The Holm-Bonferroni method was used to control the family-wise error rate (to adjust for multiple comparisons) for these 121 tests.[19,20] EHR variables found to be significantly related to readmission were included in a stepwise backward-selection logistic regression predicting readmission, with administrative case-mix variables and hospital forced into the model. The largest Holm-Bonferroni-adjusted alpha level that yielded a significant result was used as the alpha level for the stepwise model. A second-stage Holm-Bonferroni procedure and stepwise logistic regression were conducted for possible inclusion of interaction effects. To limit comparisons, we considered interactions between core case-mix variables that were significant at $P < .05$ and EHR variables that were selected for the model in the previous step. This final multivariable model was compared to a model with only administrative case-mix variables to assess the contribution of the retained EHR variables; specifically, we examined differences in C-statistic and McFadden's pseudo R^2.

MACHINE LEARNING ANALYSIS

We evaluated the administrative case-mix and clinical EHR variables using machine learning, an analytical approach in which computational models are devised and

Table 1. Patient Characteristics

	Percentage (%) of Index Hospitalizations			
	Hospital A (n = 33,953)	Hospital B (n = 35,298)	Hospital C (n = 15,733)	All Hospitals (N = 84,984)
Age				
<1 y	21.2	21.6	37.5	24.4
1 to <5 y	26.9	30.0	20.8	27.0
5 to <8 y	12.2	12.9	10.0	12.1
8 to <12 y	13.8	13.9	11.8	13.5
12 to <18 y	26.0	21.5	19.8	23.0
Gender				
Female	46.1	44.7	46.4	45.6
Primary diagnosis system				
1. Infectious and parasitic disease	3.5	2.7	5.3	3.5
2. Neoplasms	3.5	2.5	6.5	3.6
3. Endocrine, nutritional, and metabolic diseases and immunity disorders	6.4	3.5	27.9	9.2
4. Diseases of blood and blood-forming organs	2.7	1.9	5.7	2.9
6. Diseases of the nervous system and sense organs	7.9	9.3	6.6	8.2
7. Diseases of the circulatory system	3.5	2.2	4.0	3.1
8. Diseases of the respiratory system	17.1	26.8	5.4	18.9
9. Diseases of the digestive system	9.4	9.3	4.9	8.5
10. Diseases of the genitourinary system	4.4	2.2	1.2	2.9
12. Diseases of the skin and subcutaneous tissue	2.6	1.8	0.8	1.9
13. Diseases of the musculoskeletal system	4.2	4.0	0.7	3.5
14. Congenital anomalies	15.1	10.6	3.1	11.0
15. Certain conditions originating in the perinatal period	2.1	4.6	6.7	4.0
16. Symptoms, signs, and ill-defined conditions	6.2	6.6	0.7	5.3
17. Injury and poisoning	10.8	9.4	1.0	8.4
18. Factors influencing health status and contact with health services	2.2	2.7	0.2	2.0
Chronic Condition Indicator				
1. Infectious and parasitic disease	0.1	0.2	0.1	0.1
2. Neoplasms	5.8	5.0	6.8	5.7
3. Endocrine, nutritional, and metabolic diseases and immunity disorders	14.0	13.8	22.6	15.5
4. Diseases of blood and blood-forming organs	7.8	6.7	11.9	8.1
5. Mental disorders	17.5	15.3	10.4	15.3
6. Diseases of the nervous system and sense organs	20.6	25.3	16.5	21.8
7. Diseases of the circulatory system	14.5	10.8	21.2	14.2
8. Diseases of the respiratory system	16.6	24.4	10.0	18.6
9. Diseases of the digestive system	13.8	12.3	15.6	13.5
10. Diseases of the genitourinary system	3.3	2.7	5.2	3.4
12. Diseases of the skin and subcutaneous tissue	1.0	1.0	1.0	1.0
13. Diseases of the musculoskeletal system	5.8	5.6	2.8	5.1
14. Congenital anomalies	31.0	26.5	28.9	28.7
15. Certain conditions originating in the perinatal period	0.1	0.2	0.3	0.2
16. Symptoms, signs, and ill-defined conditions	0.9	2.6	1.0	1.6
17. Injury and poisoning	0.3	0.2	0.7	0.3
18. Factors influencing health status and contact with health services	14.4	15.7	16.6	15.3
Chronic Condition Indicator count				
0 or 1 body system	56.4	55.2	54.5	55.5
2 body systems	20.5	20.5	18.4	20.1
3 body systems	10.4	11.7	12.8	11.4
4+ body systems	12.7	12.6	14.3	13.0
Race/ethnicity				
Asian/Pacific Islander	3.4	2.3	21.8	6.4
Black	9.3	6.6	3.3	7.0
Latino/Hispanic	7.5	30.2	36.9	22.4
Mixed/other	12.0	5.4	1.2	7.2
Native American	0.2	0.7	0.1	0.4
White	61.4	52.2	36.9	53.0
Missing	6.3	2.7	0.0	3.6

adapted iteratively to produce automatic predictions based on insights gained from the data. Machine learning methods explore the feature space effectively and efficiently with automatic feature engineering and capabilities of weighting multiple variables at the same time (unlike rule-based approaches, which rely exclusively on insights from humans). For many tasks, machine learning performs at least on par with humans.[21] Given the existing data and variables and the suite of state-of-the-art machine learning methods, we assessed the performance that can be achieved when predicting readmissions. We used the L2-regularized logistic regression with

Table 2. Frequency of Index Admissions with Abnormally Low or High Values for Vital Signs and Laboratory Studies

		Percentage (%) of Index Hospitalizations			
Vital Signs		Hospital A (n = 33,953)	Hospital B (n = 35,298)	Hospital C (n = 15,733)	All Hospitals (N = 84,984)
Temperature	Low	15.0	17.4	6.2	14.4
	High	8.6	9.2	3.6	7.9
Heart rate	Low	1.9	2.6	2.6	2.3
	High	38.7	40.5	28.6	37.6
Respiratory rate	Low	26.9	22.9	25.8	25.0
	High	41.9	45.8	22.5	39.9
Systolic blood pressure	Low	13.6	11.1	12.1	12.3
	High	39.1	42.1	30.9	38.8
Diastolic blood pressure	Low	13.5	14.8	13.4	14.0
	High	35.1	31.6	21.5	31.1
Oxygen	Low	16.0	37.2	12.5	24.2
Basic metabolic panel					
Test performed		57.6	36.3	46.5	46.7
Creatinine	Low	8.2	5.2	3.8	6.1
	High	1.7	1.5	3.5	2.0
Sodium	Low	8.8	2.4	5.0	5.4
	High	1.7	3.3	3.0	2.6
Potassium	Low	5.1	2.5	2.9	3.6
	High	8.6	4.8	3.3	6.0
Chloride	Low	4.6	0.8	1.4	2.4
	High	2.4	5.3	3.4	3.8
Carbon dioxide	Low	7.8	6.6	3.7	6.5
	High	1.4	0.9	1.4	1.2
Blood urea nitrogen	Low	1.1	0.7	0.1	0.8
	High	10.6	7.9	9.5	9.3
Glucose	Low	0.9	0.8	0.4	0.8
	High	28.8	16.8	27.3	23.5
Complete blood count					
Test performed		61.2	40.0	54.6	51.1
WBC	Low	10.4	7.2	10.1	9.0
	High	24.8	17.5	19.4	20.8
Hemoglobin	Low	15.9	8.5	13.9	12.5
	High	14.4	14.4	12.0	13.9
Hematocrit	Low	12.5	7.3	14.3	10.7
	High	20.6	17.3	14.9	18.2
Platelet count	Low	12.0	8.6	12.5	10.7
	High	18.8	9.1	7.9	12.7
RBC	Low	12.8	9.4	19.1	12.6
	High	15.6	10.9	8.0	12.3
MCV	Low	11.1	3.4	4.9	6.8
	High	23.7	22.9	29.3	24.4
MCH	Low	20.9	6.5	7.2	12.4
	High	11.0	15.0	24.4	15.2
MCHC	Low	41.8	20.8	22.4	29.5
	High	2.2	0.7	5.3	2.2
RDW	Low	20.4	9.6	19.8	15.8
	High	15.1	11.9	14.1	13.6
Differential (automated)					
Test performed		33.8	39.3	29.3	35.3
Neutrophil count	Low	2.9	6.9	5.9	5.1
	High	16.1	15.3	9.0	14.4
Lymphocyte count	Low	9.2	10.9	7.2	9.5
	High	7.1	11.5	5.6	8.6
Eosinophil count	Low	5.7	7.3	5.1	6.2
	High	9.1	8.6	5.0	8.1
Neutrophil %	Low	1.1	4.0	2.5	2.6
	High	12.0	12.9	6.3	11.3
Lymphocyte %	Low	4.1	6.7	2.7	4.9
	High	1.4	4.7	3.0	3.0

(continued)

Table 2 (*Continued*)

Vital Signs		Hospital A (n = 33,953)	Hospital B (n = 35,298)	Hospital C (n = 15,733)	All Hospitals (N = 84,984)
		Percentage (%) of Index Hospitalizations			
Monocyte %	Low	5.5	7.3	2.8	5.8
	High	2.9	12.0	9.7	7.9
Eosinophil %	Low	11.3	15.4	9.7	12.7
	High	3.2	4.0	2.8	3.5
Basophil %	Low	6.6	7.5	0.0	5.7
	High	0.6	2.1	0.9	1.3

WBC indicates white blood cell count; RBC, red blood cell count; MCV, mean corpuscular volume; MCH, mean corpuscular hemoglobin; MCHC, mean corpuscular hemoglobin concentration; and RDW, red cell distribution width.

cost-sensitive learning,[22] assessing all values from the first 24 hours of admission. L2-regularized logistic regression weights all variables according to their contribution in decision-making. In addition, we experimented with convolutional neural networks (CNNs),[23] a cutting-edge machine learning method. A CNN employs one or more convolutional layers (often with a subsampling step) for achieving efficient training and transformation-invariant classification. CNNs are hierarchical feature-learning neural networks that reason over the set of case-mix and clinical variables and identify a combination of features optimized for the task through automatic filtering and pooling operations. Filters of size *f* evaluate a group of *f* features. A pooling mechanism finds the best features across groups. The filter and pooling steps are repeated in a hierarchical fashion to learn automatically the best unique combination of features.

Results

Patient Characteristics

Just over half of index admissions (55.5%) were for patients with no chronic conditions or chronic conditions in only a single body system (Table 1). The most common types of chronic conditions were congenital anomalies, diseases of the nervous system and sense organs, and diseases of the respiratory system (28.7%, 21.8%, and 18.6% of index admissions, respectively). These results were similar for the individual hospitals.

Frequency of Abnormal Initial Vital Signs and Laboratory Results

The most common initial vital sign abnormalities were high respiratory rate, systolic blood pressure, and heart rate (39.9%, 38.8%, and 37.6% of index admissions, respectively) (Table 2). Vital sign trends were similar for the individual hospitals except that the percentage of index admissions with abnormally low oxygen saturations was greater at 1 hospital (37.2%) than the other 2 (16.0% and 12.5%), and the percentage of index admissions with abnormally high respiratory rates was lower at 1 hospital (22.5%) than the other 2 (41.9% and 45.8%). The most frequent initial abnormal chemistry results were high glucose, high blood urea nitrogen, and low carbon dioxide (23.5%, 9.3%, and 6.5% of index admissions, respectively). The most common initial CBC abnormalities were low mean corpuscular hemoglobin concentration (MCHC), high mean corpuscular volume, and high white blood cell count (29.5%, 24.4%, and 20.8% of index admissions, respectively). Trends for laboratory results were similar for the individual hospitals except that the percentage of index admissions with abnormally low mean corpuscular hemoglobin results was higher at 1 hospital (20.9%) than the other 2 (6.5% and 7.2%).

Readmission Rates

Among the 84,984 index admissions across the 3 hospitals, 6451 were followed by ≥1 readmissions within 30 days (Figure), resulting in a readmission rate of 7.6%. The unadjusted readmission rates for the individual hospitals were 6.6%, 8.0%, and 8.8%, respectively.

Case-Mix Adjustment Using Core Model

In our multivariable model using administrative case-mix variables only, we found a nonlinear statistically significant relationship between age and readmission risk (Table 3). Having ≥1 chronic condition in a CCI category was also associated with increased readmission risk for most categories. The highest odds of readmission were associated with "Neoplasms" (odds ratio [OR], 2.44; 95% confidence interval [CI], 2.16−2.75); "Factors influencing health status and contact with health services," such as technology dependence (OR, 1.89; 95% CI, 1.75−2.04); and "Diseases of blood and blood-forming organs" (OR, 1.51; 95% CI, 1.38−1.66). In addition, compared with having chronic conditions in 0 or 1 body system, having chronic conditions in 2 (OR, 1.60; 95% CI, 1.46−1.76), 3 (OR, 1.56; 95% CI, 1.37−1.77), or ≥4 (OR, 1.53; 95% CI, 1.26−1.85) body systems was associated with increased readmission risk, suggesting that the effect of chronic conditions in multiple body systems is greater than simply the sum of the effects of chronic conditions in single body systems. The risk of readmission was significantly lower at 2 hospitals (OR, 0.83; 95% CI, 0.78−0.88 and OR, 0.86; 95% CI; 0.79−0.94) compared with the third.

Table 3. Core Case-Mix Adjustment Model Excluding and Including Clinical Electronic Health Record Variables

Variable	Core Case-Mix Adjustment Model		Case-Mix Adjustment Model with Clinical Electronic Health Record Variables	
	Odds Ratio (95% CI)	P Value	Odds Ratio (95% CI)	P Value
Age				
<1 y	Reference	...	Reference	...
1 to <5 y	0.73 (0.67–0.79)	<.001	0.73 (0.67–0.79)	<.001
5 to <8 y	0.60 (0.54–0.66)	<.001	0.60 (0.54–0.66)	<.001
8 to <12 y	0.70 (0.63–0.77)	<.001	0.70 (0.63–0.77)	<.001
12 to <18 y	0.69 (0.63–0.75)	<.001	0.69 (0.64–0.76)	<.001
Gender				
Female	Reference	...	Reference	...
Male	1.00 (0.94–1.05)	.879	1.01 (0.96–1.06)	.724
Primary diagnosis category				
1. Infectious and parasitic disease	0.89 (0.75–1.04)	.139	0.87 (0.74–1.02)	.088
2. Neoplasms	0.95 (0.81–1.11)	.487	0.93 (0.79–1.08)	.320
3. Endocrine, nutritional, and metabolic diseases and immunity disorders	0.78 (0.69–0.89)	<.001	0.78 (0.69–0.89)	<.001
4. Diseases of blood and blood-forming organs	1.12 (0.95–1.32)	.170	0.93 (0.79–1.09)	.347
6. Diseases of the nervous system and sense organs	0.88 (0.76–1.01)	.074	0.93 (0.81–1.07)	.320
7. Diseases of the circulatory system	0.72 (0.61–0.86)	<.001	0.73 (0.62–0.87)	<.001
8. Diseases of the respiratory system	0.80 (0.70–0.91)	.001	0.87 (0.77–0.99)	.031
9. Diseases of the digestive system	0.92 (0.80–1.06)	.251	0.94 (0.82–1.07)	.365
10. Diseases of the genitourinary system	1.05 (0.88–1.27)	.581	1.10 (0.92–1.32)	.301
12. Diseases of the skin and subcutaneous tissue	0.59 (0.44–0.79)	<.001	0.65 (0.49–0.87)	.004
13. Diseases of the musculoskeletal system	0.54 (0.43–0.68)	<.001	0.59 (0.47–0.74)	<.001
14. Congenital anomalies	0.64 (0.56–0.74)	<.001	0.67 (0.58–0.77)	<.001
15. Certain conditions originating in the perinatal period	0.70 (0.58–0.85)	<.001	0.66 (0.55–0.80)	<.001
16. Symptoms, signs, and ill-defined conditions	1.03 (0.89–1.19)	.701	1.08 (0.94–1.24)	.258
17. Injury and poisoning	0.86 (0.74–0.99)	.036	0.90 (0.78–1.03)	.128
18. Factors influencing health status and contact with health services	0.78 (0.65–0.93)	.006	0.81 (0.68–0.97)	.023
Chronic Condition Indicator[*,†]				
1. Infectious and parasitic disease	0.80 (0.42–1.52)	.493	0.78 (0.41–1.49)	.459
2. Neoplasms	2.44 (2.16–2.75)	<.001	2.65 (2.30–3.05)	<.001
3. Endocrine, nutritional, and metabolic diseases and immunity disorders	1.32 (1.21–1.43)	<.001	1.24 (1.14–1.34)	<.001
4. Diseases of blood and blood-forming organs	1.51 (1.38–1.66)	<.001	1.67 (1.44–1.94)	<.001
5. Mental disorders	1.11 (1.02–1.20)	.011	1.10 (1.01–1.19)	.026
6. Diseases of the nervous system and sense organs	1.16 (1.07–1.26)	<.001	1.23 (1.13–1.34)	<.001
7. Diseases of the circulatory system	1.38 (1.27–1.49)	<.001	1.29 (1.19–1.40)	<.001
8. Diseases of the respiratory system	0.89 (0.82–0.97)	.007	0.83 (0.75–0.91)	<.001
9. Diseases of the digestive system	1.46 (1.35–1.58)	<.001	1.42 (1.31–1.53)	<.001
10. Diseases of the genitourinary system	1.26 (1.11–1.42)	<.001	1.23 (1.08–1.39)	.001
12. Diseases of the skin and subcutaneous tissue	0.96 (0.76–1.20)	.709	0.91 (0.73–1.15)	.440
13. Diseases of the musculoskeletal system	0.96 (0.84–1.09)	.504	0.92 (0.81–1.06)	.252
14. Congenital anomalies	1.07 (0.99–1.15)	.108	1.05 (0.97–1.14)	.190
15. Certain conditions originating in the perinatal period	1.09 (0.61–1.92)	.777	1.05 (0.59–1.85)	.870
16. Symptoms, signs, and ill-defined conditions	0.92 (0.75–1.12)	.401	0.94 (0.77–1.15)	.553
17. Injury and poisoning	1.32 (0.97–1.80)	.078	1.32 (0.97–1.79)	.080
18. Factors influencing health status and contact with health services	1.89 (1.75–2.04)	<.001	1.87 (1.72–2.03)	<.001
Chronic Condition Indicator count				
0 or 1 body systems	Reference	...	Reference	...
2 body systems	1.60 (1.46–1.76)	<.001	1.53 (1.39–1.68)	<.001
3 body systems	1.56 (1.37–1.77)	<.001	1.48 (1.31–1.69)	<.001
4+ body systems	1.53 (1.26–1.85)	<.001	1.48 (1.22–1.80)	<.001
Hospital				
Hospital A	Reference	...	Reference	...
Hospital B	0.83 (0.78–0.88)	<.001	0.90 (0.85–0.96)	.002
Hospital C	0.86 (0.79–0.94)	<.001	0.96 (0.88–1.05)	.361

(continued)

Table 3 (*Continued*)

Variable	Core Case-Mix Adjustment Model		Case-Mix Adjustment Model with Clinical Electronic Health Record Variables	
	Odds Ratio (95% CI)	*P* Value	Odds Ratio (95% CI)	*P* Value
Clinical electronic health record variables				
Basic metabolic panel performed			1.30 (1.22−1.39)	<.001
Low red blood cell count (continuous)			1.54 (1.40−1.69)	<.001
Low mean corpuscular hemoglobin concentration (continuous)			1.04 (1.00−1.08)	.050
High red cell distribution width (dichotomous)			1.39 (1.29−1.51)	<.001
CCI 2 × red cell distribution width interaction			0.60 (0.51−0.71)	<.001
CCI 4 × basic metabolic panel interaction			0.70 (0.59−0.82)	<.001
CCI 8 × mean corpuscular hemoglobin concentration interaction			1.18 (1.10−1.26)	<.001
CCI 16 × red blood cell count interaction			0.71 (0.59−0.85)	<.001
CCI 18 × red blood cell count interaction			0.75 (0.64−0.88)	<.001

*The reference group for each CCI variable is no condition in the body system.

†We excluded the CCI variable for body system 11, "Complications of pregnancy, childbirth, and the puerperium," because patients who have a primary diagnosis code for an obstetric condition or any diagnosis or procedure code for delivery are excluded from the cohort.

Association of Initial Clinical Data with Readmission Risk

When we added the clinical EHR variables to the core model, none of the vital signs were associated with readmission risk, so none of the vital sign variables were retained in the final multivariable model. Collection of a BMP was associated with increased odds of readmission (OR, 1.30; 95% CI, 1.22−1.39), but no panel components were associated with readmission (Table 3). Initial abnormalities of some red cell indices were also associated with readmission: low red blood cell count (OR, 1.54; 95% CI, 1.40−1.69 for the continuous variable), low MCHC (OR, 1.04; 95% CI, 1.00−1.08 for the continuous variable), and high red cell distribution width (OR 1.39; 95% CI, 1.29−1.51 for the dichotomous variable). Five interaction effects were retained in the model (out of 92 tested): red cell distribution width with chronic neoplasms, BMP with chronic blood diseases, MCHC with chronic respiratory diseases, and red blood cell count with chronic condition body systems 16 (symptoms, signs, and ill-defined conditions) and 18 (factors influencing health status and contact with health services) (Table 3).

Model Performance with Incorporation of Clinical EHR Variables

The C-statistics for the final multivariable model (containing both administrative case-mix and clinical EHR variables) and the original core model were similar—0.722 (95% CI, 0.715−0.728) vs 0.713 (95% CI, 0.706−0.719)—suggesting minimal improvement in model discrimination with the addition of the clinical EHR data. Likewise, McFadden's pseudo R^2 values for the final and core models were similar: 0.085 vs 0.076.

Results of Machine Learning Analysis

Using regression, the F-measure (harmonic mean of sensitivity and positive predictive value) was similar for the best-performing model (containing all variables) and the core model (0.250 vs 0.243). The F-measure was similar for both regression and CNN models containing all variables (0.250 vs 0.283).

Discussion

When we evaluated the addition of commonly available initial clinical EHR variables to a case-mix adjustment model containing patient-level variables from administrative claims, we found that a few red cell indices were associated with readmission for children admitted to 3 freestanding children's hospitals. In addition, interactions between these variables and certain types of chronic conditions were also significant, suggesting differences by condition in the relationship between abnormal results and readmission risk. Although these relationships were statistically significant, the increase in odds of readmission was small. In addition, the augmented model containing clinical EHR variables performed only marginally better than the model containing only administrative variables. Our findings were similar when using machine learning analysis.

We postulated that initial clinical results might reflect severity of illness on presentation, thus enabling adjustment for the possible effect of acute clinical status on readmission risk. In the absence of an accessible measure of severity of illness, however, our study was not designed to test the relationship between this parameter and the clinical EHR variables. The variables we examined may be inadequate correlates of severity or reflect severity variably across different conditions. Alternatively, a patient's condition on presentation may influence readmission risk less strongly than his or her status closer to discharge. Although clinical values later in a patient's course might be better predictors of readmission, they are problematic for case-mix adjustment because they potentially could be influenced by the quality of care received during the hospitalization.

We chose the candidate clinical variables because they are widely available and stored in a structured form in EHRs, making their inclusion in a hospital readmission measure relatively straightforward. However, these data are more difficult to obtain than chronic condition data included in hospital claims, to which we found the EHR data added minimally in predicting readmissions. Scaling up to include many hospitals, rather than just 3, would still pose considerable challenges with regard to data sharing, validation, and standardization across hospitals. As EHRs and methods for accessing their data further develop, use of other types of variables that might better contribute to case-mix adjustment may become feasible. Natural language processing, the use of computational methods for deriving meaning from human language and converting it to a structured format, shows promise as an alternative to manual extraction of quality data from unstructured narrative documents.[24,25] Examples of applications that have been studied include discernment of brain tumor status from magnetic resonance imaging reports[26] and estimation of multiple sclerosis severity from free-text clinical notes and reports.[27]

Beyond clinical characteristics, other types of patient information also may be important in case-mix adjustment of readmission measures. A topic of controversy and recent investigation is adjustment for socioeconomic factors.[2,28] While participating in the National Quality Forum's trial period for risk adjustment of social risk factors, our center used New York State's all-payer data reporting system to evaluate the inclusion of insurance type, Zip Code-linked median income, and Zip Code-linked education level into the Pediatric All-Condition Readmission Measure.[29] The addition of insurance type resulted in greater model discrimination, but the magnitude of improvement was small (C-statistic 0.710 vs 0.708), as was the impact on rankings of hospitals' adjusted readmission rates. Assessing readmission rates for 47 hospitals in the Pediatric Health Information database, Sills and colleagues[30] determined that incorporation of EHR-derived socioeconomic factors (race, ethnicity, and insurance type) into the Pediatric All-Condition Readmission Measure led to only a small increase in model discrimination (0.708 vs 0.704) but resulted in a change in rank order decile for 36% of hospitals. As was observed in the National Quality Forum trial period, availability of patient-level data for only a restricted set of variables limits use of socioeconomic factors in readmission rate adjustment.[28] If the field moves toward inclusion of socioeconomic factors into readmission and other quality measures, documentation of this information in EHRs may become more common, thus providing a richer range of potential parameters for case-mix adjustment. The association we observed between abnormalities of certain red cell indices and readmission risk could reflect not just primary disease severity but also underlying nutritional status, and both could be affected by socioeconomic factors.

We are unaware of other published pediatric studies examining the use of clinical EHR data such as vital signs and laboratory results for adjusting readmission rates. Our finding of minimal improvement in model performance is consistent with studies on using such data for prediction of adult readmissions. The addition of variables such as systolic blood pressure, serum sodium and creatinine, and hemoglobin to claims-based models for predicting heart failure readmissions led to only small improvements in discrimination.[6,31] A systematic review of risk prediction models for hospital readmission concluded that physiological and laboratory variables did not improve performance over claims-only models in the CMS acute myocardial infarction, heart failure, and pneumonia readmission measures.[32]

Our study had both strengths and limitations. We assessed a large number of pediatric admissions for which we had both claims and clinical EHR data. We examined children's hospitals because they care for patients whose health conditions span a range of complexity and acuity, offering a diverse population in which to analyze relationships between clinical parameters and readmission risk. However, our focus on children's hospitals may limit the generalizability of results to other hospitals that serve pediatric patients. In addition, although we included 3 geographically diverse hospitals, our findings may not be generalizable to all children's hospitals. Another limitation is that the hospital datasets reflected only admissions to the 3 hospitals, so potential readmissions to another hospital were not captured. Furthermore, the likelihood of readmission to another hospital might vary by study hospital depending on the number and types of nearby hospitals. However, we suspect that, in many cases, a patient initially admitted to the children's hospitals in this study would likely return to the same hospital for readmission. Through close communication among the participating hospitals, we sought to overcome differences in how each hospital recorded clinical variables in its EHR, but differences in representation and accuracy may have persisted. Such heterogeneity would of course be a challenge to using clinical EHR data in real-world quality measurement. As noted above, another limitation is that we were unable to directly test the association between the EHR variables and the clinical characteristic—severity of illness—that we attempted to capture. The most important limitation was that studying only 3 hospitals precluded full examination of the impact of the EHR variables on case-mix adjustment. The small predictive gains at the patient level suggest that for the clinical variables to substantially affect readmission rate adjustment, the distribution of these variables would have to vary widely across hospitals. Without a larger sample of hospitals, however, we were unable to estimate the variation of clinical variables across a large number of hospitals.

CONCLUSIONS

Our findings suggest that inclusion of currently available clinical data leads to insufficient improvement in adjustment of pediatric all-condition readmission rates to justify the time and cost of obtaining and adding these data to readmission rate calculations. Other data that are not yet widely accessible, such as clinical information stored in non-structured formats or socioeconomic data, may be more valuable for case-mix adjustment of readmission rates.

ACKNOWLEDGMENTS

Financial disclosure: Support for this work was provided by the US Department of Health and Human Services Agency for Healthcare Research and Quality and the Centers for Medicare and Medicaid Services Children's Health Insurance Program Reauthorization Act Pediatric Quality Measures Program Centers of Excellence, under grant numbers U18 HS 020513 and U18 HS 025299 (principal investigator M.A.S.). The content is solely the responsibility of the authors and does not necessarily represent the official views of the Agency for Healthcare Research and Quality. The funding source had no involvement in the study design; collection, analysis, and interpretation of data; writing of the manuscript; or decision to submit the manuscript for publication.

SUPPLEMENTARY DATA

Supplementary data related to this article can be found online at https://doi.org/10.1016/j.acap.2018.09.006.

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