Pediatric Lower Respiratory Infection Readmission Measure

Detailed Specifications

Center of Excellence for Pediatric Quality Measurement

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OVERVIEW

This report contains detailed measure specifications for calculating, using inpatient claims data, case-mix-adjusted, 30-day readmission rates following hospitalization for lower respiratory infection (LRI) in pediatric patients < 18 years old. Admissions for LRI are identified using a case definition of either a primary diagnosis of bronchiolitis, influenza, or community-acquired pneumonia or a secondary diagnosis of 1 of these LRIs plus a primary diagnosis of asthma, respiratory failure, or sepsis/bacteremia. The measure focuses on patients discharged from general acute care hospitals, including children's hospitals. The measure excludes the following: (a) specialty hospitals; (b) non-acute care institutions, such as rehabilitation and long-term care facilities; (c) admissions for obstetric conditions, mental health conditions, and birth of healthy newborns; and (d) readmissions for planned procedures and chemotherapy.

The model for this measure consists of a 2-level hierarchical logistic regression with fixed effects for patient-level characteristics and a random intercept for hospital. The first level of the model includes adjusters for hospital case-mix based on the patient-level characteristics of age, gender, and chronic disease comorbidity (identified using the Agency for Healthcare Research and Quality (AHRQ) Chronic Condition Indicator tool). The second level of the model consists of a random effect for hospital. The hierarchical modeling adjusts for differences in case-mix and sample size across hospitals.

TABLE 1– TERMINOLOGY

Term	Definition
Case-Mix	The age, gender, and chronic condition characteristics of the patients with index admissions at a given hospital. Differences in the distributions of these characteristics across hospitals may be associated with differences in readmission rates. The measure therefore adjusts readmission rates as if each hospital cared for the same patient case-mix.
Chronic Condition Indicator	A tool developed as part of the AHRQ Healthcare Cost and Utilization Project that categorizes International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) or International Classification of Diseases, Tenth Revision, Clinical Modification (ICD-10-CM) diagnosis codes into 1 of 18 "body systems" (organ systems, disease categories, or other categories) and designates them as chronic or not chronic. ICD-9-CM codes will henceforth be referred to in this document as ICD-9 codes. ICD-10-CM diagnosis codes and ICD-10 Procedure Coding System (PCS) codes will be referred to as ICD-10 diagnosis and ICD-10 procedure codes, respectively. Patients who have a primary ICD-9 or principal ICD-10 diagnosis code for an obstetric condition or any diagnosis or procedure code for delivery are excluded from the measure cohort (the rationale for this exclusion is provided below). We have found using various datasets that this exclusion leaves very few (or sometimes no) patients who have a secondary diagnosis code for a chronic condition falling into body system 11, "Complications of pregnancy, childbirth, and the puerperium," which could create model-fitting problems if Chronic Condition Indicator 11 were included in the case-mix-adjustment model. The measure therefore does not include the Chronic Condition Indicator variable for body system 11.
Discharge Disposition	The data field on each record indicating the patient's status at time of end-of-service (e.g., left against medical advice, discharged home, deceased).
Episode of Care	A patient's complete period of inpatient care. Data for a single period of inpatient care may be covered by 1 claims record or may be contained in > 1 claims record because the patient (a) received services from > 1 cost center in the same hospital and/or (b) was transferred from 1 hospital to another. Therefore, constructing an *episode of care* for analysis as an index admission or readmission may require combining patient information across multiple records.
Index Admission	An eligible admission to an acute care hospital. The index admission serves as the starting point for enumerating readmissions.
Planned Procedure	A procedure that was judged by expert reviewers to generally be scheduled at least 24 hours in advance for an expected medical need in more than 80% of cases and to be a potential reason for hospitalization (see Data Dictionary for ICD-9 or ICD-10 procedure codes).
Planned Readmission	An admission to an acute care hospital with a primary ICD-9 or principal ICD-10 procedure code for a planned procedure, occurring

	within 30 days of discharge from a prior acute care hospitalization.
Readmission	An admission to an acute care hospital within 30 days of discharge from an acute care hospital.
Readmission Rate	The percentage of index admissions with ≥ 1 readmission within 30 days. The readmission rate, unadjusted for case-mix, is calculated as follows: $\frac{\text{number of index admissions with} \geq 1 \text{ readmission within 30 days}}{\text{total number of index admissions}}$

TABLE 2 – SAS FILES FOR MEASURE IMPLEMENTATION

Measure Implementation Step	SAS Files	Description
Data preparation (See Section 1 below.)	format_file_LRI_ICD9.sas7bdat format_file_LRI_ICD10.sas7bdat	Format file containing the ICD-9 or ICD-10 diagnosis and procedure codes required for defining variables in the measure.
	LowerRespiratoryInfection_PediatricReadmission_DataPrep_AllPayer.sas	Program for preparation of all-payer data, Steps 5-8 (details below).
	LowerRespiratoryInfection_PediatricReadmission_DataPrep_SinglePayer.sas	Program for preparation of single-payer data, Steps 5-8 (details below).
Fitting of case-mix adjustment model and estimation of hospital-level readmission rates (See Sections 2 and 3 below.)	LowerRespiratoryInfection_Zerocell.sas	Macro program for dropping index admissions if all index admissions of a given case-mix variable (i.e., *cci15* = 1) have the same outcome (i.e., readmission = 1 or readmission = 0). This helps to prevent model-fitting issues.
	LowerRespiratoryInfection_PediatricReadmission_Model.sas	Program for fitting case-mix adjustment model and estimating hospital-level readmission rates.
Fitting of case-mix adjustment model and estimation of nationally comparable hospital- and state-level	LowerRespiratoryInfection_Zerocell.sas	Macro program for dropping index admissions if all index admissions of a given case-mix variable (i.e., *cci15* = 1) have the same outcome (i.e., readmission = 1 or readmission = 0). This helps to prevent model-fitting issues.

readmission rates (See Section 4 below.)	max_lri_cov.sas7bdat max_lri_sample.sas7bdat max_lri_global_model_linux.sas7bitm max_lri_global_model_win.sas7bitm LowerRespiratoryInfection_PediatricReadmission_Nationally comparable rates.sas	Program and files for fitting case-mix adjustment model and estimating nationally comparable hospital- and state-level readmission rates

SECTION I: DATA PREPARATION

This section describes the data preparation steps that should be implemented before fitting the pediatric lower respiratory infection readmission model to inpatient claims data.

PLEASE NOTE: Steps 1 through 4, below, describe how to prepare your dataset by applying certain exclusions and creating variables needed to construct the measure cohort and calculate readmission rates. We have provided a SAS data preparation program to perform the remaining data preparation steps, Steps 5 through 8.

STEP 1: IDENTIFY HOSPITALS ELIGIBLE FOR INCLUSION IN THE MEASURE

This measure focuses on calculating pediatric readmission rates for general acute care hospitalizations for LRI. Criteria for retaining only hospitals identified as general acute care facilities are specified below.

Exclusions at the Hospital Level:

- Drop records for specialty and non-acute care hospitals: See Data Dictionary for the list of American Hospital Association (AHA) hospital codes and Centers for Medicare & Medicaid Services (CMS) taxonomy codes for general acute care hospitals eligible for inclusion in the measure. Drop records for a hospital if the records contain only an AHA code or only a CMS code and the code is NOT for a general acute care hospital. If a hospital's records include both an AHA and a CMS code, drop the records for the hospital if either code is NOT for a general acute care hospital.
- Drop records for which hospital type is missing.

Rationale: The focus of the measure is admissions to hospitals that provide general pediatric acute care. Records for admissions to specialty and non-acute care hospitals are therefore omitted from the dataset. Because hospital type cannot be determined for records with missing data in the hospital type variable, these records are also removed from the dataset.

STEP 2: IDENTIFY HOSPITALS FOR WHICH READMISSION RATES SHOULD NOT BE CALCULATED

Hospitals with very incomplete data may lack adequate information to calculate accurate readmission rates. Readmission rates should therefore not be evaluated for these hospitals (i.e., their admissions should not be included in the measure as index admissions). To provide an accurate assessment based on the full dataset, data completeness at the hospital level should be assessed *before* excluding individual records for data quality or clinical criteria. Criteria for identifying hospitals for which readmission rates should not be calculated are listed below.

Exclusions at the Hospital Level for Calculating Readmission Rates:

- Hospitals with < 80% of records with complete unique patient identifier, admission date, and end-of-service date
- Hospitals with < 80% of records with complete primary ICD-9 or principal ICD-10 diagnosis code
- Out-of-state hospitals

Create a dichotomous variable named "*hosp_noindex*," coded 1 for hospitals meeting the above exclusion criteria (this variable will be used to exclude these hospitals' admissions from being evaluated as index admissions) and 0 for all other hospitals.

PLEASE NOTE: Although readmission rates should not be calculated for these hospitals, these hospitals' records should *remain in the dataset* so that their admissions can be evaluated as potential readmissions for other hospitals.

Rationale: Readmission rates are not calculated for hospitals missing large amounts of data for the above variables because these hospitals have limited data to accurately define the measure cohort and calculate case-mix-adjusted readmission rates. Assessing eligibility for the measure cohort and performing case-mix adjustment requires information on admission dates, end-of-service dates, and diagnosis codes. Identifying readmissions requires information on admission dates and end-of-service dates and the ability to link unique patient identifiers across inpatient claims records.

Regarding out-of-state hospital admissions, it is possible that a state inpatient claims database may contain records for admissions to out-of-state hospitals. Records for out-of-state hospital admissions are not excluded from the measure dataset because these records may meet criteria for being counted as readmissions as part of an in-state hospital's readmission rate. However, readmission rates are not calculated for out-of-state hospitals due to the lack of complete data for these hospitals.

STEP 3: EXCLUDE PATIENTS WHO HAVE MISSING OR INVALID DATA FOR ANALYZING READMISSIONS

Exclusions at the Patient Level:

- Drop all records for a patient if ANY record is missing patient identifier, hospital identifier, admission date, end-of-service date, or disposition status.
- Drop all records for a patient if date of birth is missing in ALL records.
- Drop all records for a patient if date of birth is not consistent across records.
- Drop all records for a patient if ANY record has an end-of-service date prior to the admission date.
- Drop all records for a patient if ANY record has an admission date or end-of-service date prior to the date of birth.
- Drop all records for a patient if ANY record uses codes other than ICD-9 or ICD-10 codes for the primary procedure.
- Drop all records for a patient if gender is missing in ALL records.
- Drop all records for a patient if gender is not consistent across records.

Rationale: Complete and valid information for the variables listed above is needed to define the measure cohort and calculate case-mix-adjusted readmission rates. Identifying readmissions within 30 days requires information on dates of admission and end-of-service dates and the ability to link unique patient identifiers across inpatient claims records. Hospital identifiers are needed to determine the hospital at which index admissions occurred. The disposition status is needed to determine whether a patient was discharged or experienced some other outcome (e.g., was transferred to another acute care hospital, left against medical advice, died). Establishing a patient's eligibility for membership in the pediatric cohort and performing case-mix adjustment requires an accurate date of birth and end-of-service date. ICD-9 or ICD-10 procedure codes are necessary for applying clinical exclusions (described below). Because gender is 1 of the variables used for case-mix adjustment, episodes of care with missing or inconsistent gender cannot be evaluated in the measure.

PLEASE NOTE: If working with a large dataset containing records for children and adults, the exclusion of records for patients >18 years, 29 days old, as described in Step 7, may be applied at this point to make the dataset more manageable.

STEP 4: SPECIFY VARIABLES DEFINED AT THE RECORD LEVEL

The variables listed in the table below are used to construct the measure cohort and/or to calculate readmission rates. These variables must be named and coded as specified below and should be created prior to identifying episodes of care and applying further exclusions to the data. All variables should be numeric unless otherwise specified. All dates should be Julian dates without times. Please see the Data Dictionary for all ICD-9 or ICD-10 code sets for the measure.

Table 3 – Variables Defined at the Record Level

Variable Name	Description
patientid	unique patient identifier Note: *patientid* will have no missing values due to the exclusion applied in Step 3.
dob	patient date of birth Note: If date of birth is missing in some records for a patient but present and consistent in others, then apply the date of birth from the records in which it is present to the records in which it is missing. This approach, together with the exclusion in Step 3 of patients with date of birth missing in all records, will result in no missing values for *dob*.
hospitalid	unique hospital identifier Note: *hospitalid* will have no missing values due to the exclusion applied in Step 3. *hospitalid* must be a character variable.
admit_dt	admission date Note: *admit_dt* will have no missing values due to the exclusion applied in Step 3.
end_service_dt	end-of-service date Note: *end_service_dt* will have no missing values due to the exclusion applied in Step 3.
hasprimary	dichotomous variable indicating whether the primary ICD-9 or principal ICD-10 diagnosis code is complete 1 = primary or principal diagnosis code is present 0 = primary or principal diagnosis code is missing Note: *hasprimary* will have no missing values.
ccix (where *x* represents the number of the AHRQ CCI body system, e.g., *cci1, cci2, cci3*)	17 dichotomous variables indicating the presence of a chronic condition in a particular body system (organ system, disease category, or other category) classified using the AHRQ CCI tool 1 = present 0 = otherwise Patients who have a primary ICD-9 or principal ICD-10 diagnosis

	code for an obstetric condition or any diagnosis or procedure code for labor and delivery are excluded from the measure cohort (the rationale for this exclusion is provided below). We have found using various datasets that this exclusion leaves very few (or sometimes no) patients who have a secondary diagnosis code for a chronic condition falling into body system 11, "Complications of pregnancy, childbirth, and the puerperium," which could create model-fitting problems if Chronic Condition Indicator 11 were included in the case-mix-adjustment model. The measure therefore does not include the Chronic Condition Indicator variable for body system 11. See Table 4 below. Code a Chronic Condition Indicator as present if a diagnosis code for that body system is present as either a primary or secondary ICD-9 diagnosis or a principal or additional ICD-10 diagnosis. Note: *ccix* should have no missing values.
planned	dichotomous variable indicating the presence of a planned primary ICD-9 or principal ICD-10 procedure 1 = present 0 = otherwise Note: *planned* should have no missing values.
chemo	dichotomous variable indicating the presence of a primary ICD-9 or principal ICD-10 diagnosis code or procedure code for chemotherapy 1 = present 0 = otherwise Note: *chemo* should have no missing values.
mh	dichotomous variable indicating the presence of a primary ICD-9 or principal ICD-10 diagnosis code for a mental health condition 1 = present 0 = otherwise Note: *mh* should have no missing values.
obstetric	dichotomous variable indicating the presence of a non-delivery obstetric primary ICD-9 or principal ICD-10 diagnosis code or any labor and delivery diagnosis or procedure 1 = present 0 = otherwise Note: *obstetric* should have no missing values.
newborn	dichotomous variable indicating an admission for birth of a healthy newborn 1 = present 0 = otherwise For births by Cesarean section: Code a record as the birth admission for a healthy newborn if the birth diagnosis code is the primary ICD-9 or principal ICD-10 diagnosis and length of stay is <5 days. For births by vaginal or unspecified delivery: Code a record as the birth admission for a healthy newborn if the birth diagnosis code is the

	primary ICD-9 or principal ICD-10 diagnosis and length of stay is <3 days. Note: *newborn* should have no missing values.
disp_status	categorical variable indicating disposition status 0 = other (any disposition status not accounted for below) 1 = discharge 2 = transfer to an acute care hospital 3 = left against medical advice 4 = died Note: *disp_status* will have no missing values due to the exclusion applied in Step 3.
male	categorical variable indicating patient gender 0 = female 1 = male Note: Female serves as the reference group. If gender is missing in some records for a patient but present and consistent in other records, then apply the value of gender from the records in which it is present to the records in which it is missing. This approach, together with the exclusion in Step 3 of patients with gender missing in all records, will result in no missing values for *male*.
ins_end	variable containing the end date of the period of insurance coverage that includes the record's end-of-service date For example: If a patient was insured from 1/1 to 1/31 and from 4/15 to 12/31: • For a record with an end-of-service date of 1/29, the value of *ins_end* would be 1/31. • For a record with an end-of-service date of 7/23, the value of *ins_end* would be 12/31. Note: This variable should only be included in single-payer analyses. It will be used to determine whether a patient has insurance coverage for at least 30 days after discharge from an index hospitalization and thus has 30 days of follow-up data to evaluate readmissions. It will have no missing values because it is calculated using the end-of-service date, which should never be missing due to the exclusion applied in Step 3.
lri	dichotomous variable indicating the presence of either (1) a primary ICD-9 or principal ICD-10 diagnosis code for LRI or (2) a secondary ICD-9 or additional ICD-10 diagnosis code for LRI plus a primary ICD-9 or principal ICD-10 diagnosis code for asthma, respiratory failure, or sepsis/bacteremia 1 = present 0 = otherwise Note: *lri* should have no missing values.

Table 4 – Chronic Condition Indicator Body Systems

Body System Indicator	Body System
1	Infectious and parasitic disease
2	Neoplasms
3	Endocrine, nutritional, and metabolic diseases and immunity disorders
4	Diseases of blood and blood-forming organs
5	Mental disorders
6	Diseases of the nervous system and sense organs
7	Diseases of the circulatory system
8	Diseases of the respiratory system
9	Diseases of the digestive system
10	Diseases of the genitourinary system
11	Complications of pregnancy, childbirth, and the puerperium – The Chronic Condition Indicator for this body system is not included in the measure.
12	Diseases of the skin and subcutaneous tissue
13	Diseases of the musculoskeletal system
14	Congenital anomalies
15	Certain conditions originating in the perinatal period
16	Symptoms, signs, and ill-defined conditions
17	Injury and poisoning
18	Factors influencing health status and contact with health services

For convenience, we have provided SAS format files containing all of the ICD-9 or ICD-10 diagnosis and procedure codes required to define variables for the measure.

Instructions for Using the SAS Format File to Define Variables Based on ICD-9 or ICD-10 Codes

1. Define a libname where you can save the SAS format file, "format_file_LRI_ICD9.sas7bdat" or "format_file_LRI_ICD10.sas7bdat" (i.e., libname format "c:\Format Files";).
2. Save the format file in the location you designated in step 1.
3. Bring the format file into the SAS work drive by using the procedure format. For example:

```
proc format library=work cntlin=format. format_file_LRI_ICD9;
run;
```

or

```
proc format library=work cntlin=format. format_file_LRI_ICD10;
run;
```

4. Table 5 lists the SAS format names and labels in the format file.

Table 5 – SAS Format Names and Labels

Variable	Type of ICD-9 Code	Type of ICD-10 Code	Format Name	Label
cci1-cci10, cci12-cci18	primary or secondary diagnosis	principal or additional diagnosis	**$CHRONF**	chronic
	primary or secondary diagnosis	principal or additional diagnosis	**$SYSTEMF**	cci1, cci2, cci3, cci4, cci5, cci6, cci7, cci8, cci9, cci10, cci11, cci12, cci13, cci14, cci15, cci16, cci17, cci18 Note: The variable *cci11* is not used in the measure, but the label cci11 is included in the format file so that as the CCI variables are created, the program must run through the records only once. (If instead the variables *cci1-cci10* were created in

				1 step and *cci12-cci18* were created in a second step, the program would have to run through the records twice.) However, even though *cci11* is created as a variable, it is then dropped using the SAS code below.
planned	primary procedure	principal procedure	**$PLANNEDF**	planned
chemo	primary diagnosis	principal diagnosis	**$CHEMODX1F**	chemo
	primary procedure	principal procedure	**$CHEMOPR1F**	chemo
mh	primary diagnosis	principal diagnosis	**$MHDX1F**	mh
obstetric	primary diagnosis	principal diagnosis	**$OBSTETRICDX1F**	obstetric
	primary or secondary diagnosis	principal or additional diagnosis	**$OBSTETRICDXF**	obstetric
	primary or secondary procedure	principal or additional procedure	**$OBSTETRICPRF**	obstetric
newborn	primary diagnosis	principal diagnosis	**$NEWBORNCF**	newborn
	primary diagnosis	principal diagnosis	**$NEWBORNNOCF**	newborn
lri	primary or secondary diagnosis	principal or additional diagnosis	**$LRIDXF**	lri
	primary diagnosis	primary diagnosis	**$OTHERLRIDXSECF**	lri

Use the *put* function with the SAS formats to define the variables *cc1-cci10* and *cci12-cci18*, *planned*, *chemo*, *mh*, *obstetric*, *newborn, and lri*. We have provided examples of the SAS code to define each variable in Table 6.

Table 6 – Examples of Using SAS Formats to Define Variables

Variable	**Formats Used to Define Variable**	**SAS Code Example** In the examples below, diagnosis variable names start with DX and procedure variable names start with PR. For the variables *cci1-cci10* and *cci12-cci18*, *obstetric,* and *lri*, 25 diagnosis and procedure fields are used in the example, but more than 25 codes may be used to define the variable.

cci1-cci10, cci12-cci18	$CHRONF
	$SYSTEMF
		`/*creates cci1-cci10 and cci12-cci18*/`
		`array cci_systems [18] cci1-cci18;`
		`array DXS[*] $ DX1-DX25;`
		`array PRS[*] $ PR1-PR25;`

		do i=1 to 18;
		cci_systems[i]=0;
		end;
		
		do i=1 to 25;
		if put(dxs[i],$CHRONF.)='chronic' then do j=1 to 18;
		if input(substr(put(dxs[i],$SYSTEMF.),4,2),2.0)=j
		then cci_systems[j]=1;
		end;
		end;
		drop cci11;

planned	$PLANNEDF	/*creates planned*/
		planned=0;
		if put(pr1,$PLANNEDF.)='planned' then planned=1;

chemo	$CHEMODX1F
	$CHEMOPR1F
		/*creates chemo*/
		chemo=0;
		if put(DX1,$CHEMODX1F.)='chemo' or put(PR1,$CHEMOPR1F.)='chemo'
		then chemo=1;

mh	$MHDX1F	/*creates mh*/
		mh=0;
		if put(dx1,$MHDX1F.)='mh' then mh=1;

obstetric	$OBSTETRICDX1F
	$OBSTETRICDXF
	$OBSTETRICPRF
		/*creates obstetric */
		obstetric=0;
		if put(dx1,$OBSTETRICDX1F.)='obstetric' then obstetric=1;
		
		do i=1 to 25;
		if put(dxs{i},$OBSTETRICDXF.)='obstetric' then
		obstetric=1;
		end;
		
		do i=1 to 25;
		if put(prs{i},$OBSTETRICPRF.)='obstetric' then

		obstetric=1; end;

newborn	$NEWBORNCF
	(C-section)
	$NEWBORNNOCF
	(No C-section)
		/*creates newborn*/
		newborn=0;
		if (put(dx1,$NEWBORNNOCF.)='newborn'
		and 0=<(end_service_dt-admit_dt)<3)
		
		or (put(dx1,$NEWBORNCF.)='newborn'
		and 0=<(end_service_dt-admit_dt)<5)
		then newborn=1;

lri	$LRIDXF
	$OTHERLRIDXSECF
		/*creates lri*/
		lri=0;
		if put(dx1,$LRIDXF.)='lri' then lri=1;
		
		do i=2 to 25;
		if put(dxs{i},$LRIDXF.)='lri' and
		put(dx1,$OTHERLRIDXSECF.)='lri' then lri=1;
		end;

PLEASE NOTE: Steps 1 through 4, above, describe how to prepare your dataset by applying certain exclusions and creating variables needed to construct the measure cohort and calculate readmission rates. We have provided a SAS data preparation program to perform the remaining data preparation steps, Steps 5 through 8.

STEP 5: DEFINE EPISODES OF CARE

Data for a single period of inpatient care may be contained in > 1 claims record. It therefore may be necessary to collapse instances of multiple claims for the same hospitalization into a single episode of care prior to applying some exclusion criteria and evaluating readmissions. This allows all data relevant to a given hospitalization to be appropriately evaluated for measure cohort exclusion. The process for defining episodes of care is detailed below.

Process for Defining Episodes of Care:

1. IDENTIFY TRUE DUPLICATES AND DROP ALL BUT 1.
   - True duplicates are records that have identical values for all key variables needed to assess cohort eligibility and calculate case-mix-adjusted readmission rates, where these key variables include all variables listed in Table 3 except *hasprimary*. Combine true duplicates, using the MAXIMUM value of *hasprimary*.

2. IDENTIFY AND COMBINE MULTIPLE VALID RECORDS FROM THE SAME HOSPITAL FOR THE SAME HOSPITALIZATION.
   - Sort records by the following variables, in the specified order: *patientid*, *hospitalid*, *admit_dt*, *end_service_dt*, and *disp_status*.
   - Define records to be part of the same hospitalization at the same hospital if (a) *patientid* and *hospitalid* are equal to those in the previous record and (b) admission dates and end-of-service dates indicate consecutive time periods or nesting of 1 time period within another because any of the following is true:
     - admission date is before the previous record's end-of-service date
     - admission date is equal to the previous record's end-of-service date AND the previous record's disposition status is other (i.e., *disp_status* = 0) or transfer to an acute care hospital (i.e., *disp_status* = 2)
     - admission date is 1 day after the previous record's end-of-service date AND the previous record's disposition status is other (i.e., *disp_status* = 0) or transfer to an acute care hospital (i.e., *disp_status* = 2)
     - admission and end-of-service dates are both the same as those of the previous record, and admission date is equal to end-of-service date (i.e., the records are for a same-day discharge)

     Example:

hospitalid	admit_dt	end_service_dt
1700181814	18427	18427
1700181814	18427	18427

     If the above criteria for multiple valid records from the same hospital for the same hospitalization are met, combine all of the records. Retain the variables *patientid*, *dob*, *hospitalid*, *male*, and *hosp_noindex*, which will be the same across records by this step. Use the MINIMUM value for *admit_dt*. Use the MAXIMUM value for *end_service_dt, hasprimary, cci1-cci10* and *cci12-cci18, planned*, *chemo*, *mh*, *obstetric*, *newborn*, and *lri*. Use the value of *disp_status* and *ins_end* (this variable is only used in single-payer analyses) from the record with the

MAXIMUM end-of-service date. If multiple records have the same maximum end-of-service date but inconsistent values for *disp_status,* use the MAXIMUM value of *disp_status* within those records. Using the maximum value for *end_service_dt* captures the discharge date that serves as the starting point for the 30-day follow-up period for evaluating readmissions. Using the maximum value for the case definition, chronic condition indicator, and clinical exclusion variables across records captures the presence of a condition or clinical exclusion for the entire episode of care. For example, if 1 record contains a primary ICD-9 or principal ICD-10 mental health diagnosis, this diagnosis will be applied to the entire episode of care, and the entire episode of care will be excluded.

3. IDENTIFY AND COMBINE MULTIPLE VALID RECORDS FROM MULTIPLE HOSPITALS FOR HOSPITALIZATIONS THAT INCLUDED TRANSFERS.
   - Sort records by the following variables, in the specified order: *patientid*, *admit_dt*, *end_service_dt*, and *disp_status*.
   - Define records to be in the same episode of care if (a) *patientid* is equal to *patientid* in the previous record, (b) the previous record's disposition status is transfer to an acute care hospital (i.e., *disp_status* = 2), and (c) the admission date is equal to or is 1 day after the previous record's end-of-service date.
     If the above criteria for connected hospitalizations are met, combine all of the records. Retain the variables *patientid*, *dob*, and *male*, which will be the same across records by this step. Use the MINIMUM value for *admit_dt.* Use the MAXIMUM value for *end_service_dt, hasprimary*, *cci1-cci10* and *cci12-cci18*, *planned*, *chemo*, *mh*, *obstetric*, and *newborn*. Use the value of *hospitalid, disp_status, ins_end, lri,* and *hosp_noindex* from the last record.
4. IDENTIFY AND EXCLUDE INVALID EPISODES OF CARE
   There may be episodes of care that are temporally overlapping, (i.e., in which it appears that a patient was in 2 different hospitals at the same time). These episodes should be dropped.
   - Drop all episodes of care that share the same patient identifier, admission date, and end-of-service date but have different hospital identifiers.
   - For each patient identifier, drop all temporally adjacent episodes of care if there are overlapping dates (i.e., admission date is before the end-of-service date for the preceding episode of care) but different hospital identifiers.

STEP 6: SPECIFY VARIABLES DEFINED AT THE EPISODE-OF-CARE LEVEL

Because multiple records may be combined to create an episode of care, some variables used for measure cohort exclusions and readmission analysis should be defined only *after* defining valid episodes of care. This sequencing assures that the variable values accurately represent information for the entire hospitalization, rather than capturing only a subset of information for the hospitalization. These variables should be created as specified below, prior to applying further exclusion criteria to the data.

Table 7 – Variables Defined at the Episode-of-Care Level

Variable Name	Description
cci_count	ordinal variable that consists of the total number of body systems affected by a chronic condition Constructed using the AHRQ CCI tool and top-coded (has an upper limit defined) at 4 or more body systems. 1 = 0 or 1 body system 2 = 2 body systems 3 = 3 body systems 4 = 4+ body systems Note: For analysis, 0 or 1 body system serves as the reference group.
dob18	date of the patient's 18th birthday, expressed as a Julian date
ageyrs_disch	continuous variable containing age in years at discharge
agegroup	ordinal variable that consists of age in years at discharge with 5 groupings of age 1 = 0 ≤ age < 1 2 = 1 ≤ age < 5 3 = 5 ≤ age < 8 4 = 8 ≤ age < 12 5 = 12 ≤ age < 18 Note: For analysis, age 0 to < 1 serves as the reference group.

STEP 7: DEFINE EPISODES OF CARE ELIGIBLE FOR INCLUSION IN MEASURE COHORT

PLEASE NOTE: If working with a large dataset containing records for children and adults, records for patients >18 years, 29 days old may be excluded after Step 3, above, to make the dataset more manageable. Apply all other exclusions listed below only after defining episodes of care (in Step 5) and defining variables at the episode-of-care level (in Step 6).

Exclusions at the Patient Level Based on Data Completeness Criteria:

- Drop all episodes of care for a patient if the primary ICD-9 or principal ICD-10 diagnosis code is missing (i.e., *hasprimary* = 0) for ANY episode of care for that patient.

Rationale: Primary ICD-9 or principal ICD-10 diagnosis codes are needed to determine whether an index admission meets the LRI case definition, to assess chronic conditions for case-mix adjustment, and to evaluate for clinical exclusions.

Exclusions at the Episode-of-Care Level Based on Data Quality Criteria:

- Drop episodes of care with admission dates that occur after a discharge status of death during a prior episode of care.

Rationale: Episodes of care with admission dates that occur after a prior hospitalization ending in death suggest poor data quality that could result in inaccurate readmission rates.

Exclusions at the Episode-of-Care Level Based on Clinical Criteria:

- Drop episodes of care for patients > 18 years, 29 days old at the time of admission.
- Drop episodes of care for birth of healthy newborns (i.e., *newborn* = 1).

- Drop episodes of care with a primary ICD-9 or principal ICD-10 non-delivery obstetrics diagnosis or any labor and delivery diagnosis or procedure (i.e., *obstetric* = 1).
- Drop episodes of care with a primary ICD-9 or principal ICD-10 mental health diagnosis (i.e., *mh* = 1).

Rationale*:* Applying the above exclusions increases the fidelity of fitting the model to the intended population of interest. The age exclusion limits the population to pediatric patients and prevents inclusion of records that overlap with adult readmission measures. (Age eligibility for inclusion in the measure is based on age at the time of discharge from the index admission. Because the focus of the measure is pediatric patients, patients' hospitalizations are ineligible for inclusion in the measure as *index admissions* if the patients are ≥ 18 years old at the time of discharge. Because the subsequent observation period for readmissions is 30 days, patients' hospitalizations are ineligible for inclusion in the measure as *readmissions* if the patients are > 18 years, 29 days old at the start of the readmission.)

Hospitalizations for birth of healthy newborns are excluded because these hospitalizations, unlike all others, are not for evaluation and management of disease.

Hospitalizations for obstetric conditions are excluded because care related to pregnancy does not generally fall within the purview of pediatric providers. We have found using various datasets that this exclusion leaves very few (or sometimes no) patients who have a secondary ICD-9 or additional ICD-10 diagnosis code for a chronic condition falling into body system 11, "Complications of pregnancy, childbirth, and the puerperium," which could create model-fitting problems if Chronic Condition Indicator 11 were included in the case-mix-adjustment model. We therefore do not include the Chronic Condition Indicator variable for body system 11 in the measure because model-fitting problems could result.

Hospitalizations for mental health conditions are excluded because patients admitted for psychiatric treatment are typically cared for in separate psychiatric centers that are not comparable to short-term acute care hospitals.

Although hospitalizations with a primary ICD-9 or principal ICD-10 mental health diagnosis are excluded from the measure, the Chronic Condition Indicator for body system 5, "Mental disorders," is still used in the measure. We have found using various datasets that even after exclusion of hospitalizations with a primary mental health diagnosis, several hospitalizations remain with secondary diagnoses that fall into body system 5 (i.e., patients are commonly admitted with secondary diagnoses of mental health conditions and primary diagnoses in other body systems). Using Chronic Condition Indicator 5 in the case-mix-adjustment model therefore does not pose the same potential model-fitting problems as using Chronic Condition Indicator 11.

STEP 8: DEFINE INDEX ADMISSIONS AND READMISSIONS

A clean dataset containing only *eligible admissions* must be prepared before defining index admissions and readmissions. This dataset should consist of all admissions that are eligible for inclusion in the measure cohort based on the criteria detailed in data preparation steps 1 through 7, above.

Exclusions at the Episode-of-Care Level for Defining Index Admissions:

- Episodes of care that either do not have a primary ICD-9 or principal ICD-10 LRI diagnosis or do not have a secondary ICD-9 or additional ICD-10 LRI diagnosis plus a primary ICD-9 or principal ICD-10 diagnosis of asthma, respiratory failure, or sepsis/bacteremia (i.e., *lri* = 0)
- Episodes of care for patients ≥ 18 years, 0 days old at the time of discharge
- Episodes of care with a discharge disposition of death
- Episodes of care with a discharge disposition of leaving the hospital against medical advice
- Episodes of care for which 30 days of follow-up data are unavailable, either (a) because the dataset's time range for claims does not include the full 30 days, or (b) because, for single-payer analyses, the patient was not enrolled with the payer for the full 30 days (i.e., the difference between *ins_end* and *end_service_dt* is less than 30 days).

PLEASE NOTE: When applying the above exclusions, it is important to do so *without deleting the records from the dataset* as these episodes of care may still meet criteria for readmissions, outlined below.

Rationale: This measure focuses on readmissions following hospitalization for LRI. Episodes of care that do not meet the case definition for an LRI hospitalization are therefore excluded from index admissions.

Age eligibility for inclusion in the measure is based on age at the time of discharge from the index admission. Because the focus of the measure is pediatric patients, patients' hospitalizations are ineligible for inclusion in the measure *as index admissions* if the patients are ≥ 18 years old at the time of discharge.

A patient must be discharged alive from an index admission in order to be readmitted. Therefore, any record with a discharge disposition of death cannot serve as an index admission.

A discharge disposition of leaving against medical advice indicates that a patient left care before the hospital determined that the patient was ready to leave.

Identifying readmissions within 30 days requires a full 30 days of follow-up data.

Exclusions at the Hospital Level for Defining Index Admissions:

- Hospitals with < 80% of records with complete unique patient identifier, admission date, and end-of-service date
- Hospitals with < 80% of records with complete primary ICD-9 or principal ICD-10 diagnosis code
- Out-of-state hospitals

Hospitals meeting the above exclusion criteria were identified in Step 2, above. The dichotomous variable *hosp_noindex* was created in Step 2 and coded 1 for hospitals meeting the above criteria and 0 for all other hospitals. Episodes of care for hospitals with *hosp_noindex* = 1 are therefore excluded from index admissions.

PLEASE NOTE: Although these hospitals' episodes of care should not be evaluated as index admissions (i.e., readmission rates should not be calculated for these hospitals), their episodes

of care should *remain in the dataset* so they can be evaluated as potential readmissions for other hospitals.

Rationale: Readmission rates are not calculated for hospitals missing large amounts of data for the above variables because these hospitals have limited data to accurately define the measure cohort and calculate case-mix-adjusted readmission rates. Assessing eligibility for the measure cohort and performing case-mix adjustment requires information on admission dates, end-of-service dates, and diagnosis codes. Identifying readmissions requires information on admission dates and end-of-service dates and the ability to link unique patient identifiers across inpatient claims records.

Regarding out-of-state hospital admissions, it is possible that a state inpatient claims database may contain records for admissions to out-of-state hospitals. Records for out-of-state hospital admissions are not excluded from the measure cohort dataset because these records may meet criteria for being counted as readmissions as part of an in-state hospital's readmission rate. However, readmission rates will not be calculated for out-of-state hospitals due to the lack of complete data for these hospitals.

Exclusions at the Episode-of-Care Level for Defining Readmissions:

- Episodes of care with a primary ICD-9 or principal ICD-10 procedure code for a planned procedure (i.e., *planned* = 1)
- Episodes of care with a primary ICD-9 or principal ICD-10 diagnosis code or procedure code for chemotherapy (i.e., *chemo* = 1)

PLEASE NOTE: When applying these exclusions, it is important to do so *without deleting the records from the dataset* as these episodes of care may still meet criteria for index admissions, outlined above.

Rationale: Readmissions for planned procedures and for chemotherapy are part of a patient's intended course of care and thus unlikely to be related to health system quality. The purpose of this measure is to identify readmissions that may be attributable to poor quality of care. This measure therefore focuses on *unplanned* readmissions because they are more likely to be related to a defect in quality of care during the index admission or during the interval between the index admission and readmission. In adult and pediatric medicine, most planned readmissions are for planned procedures or chemotherapy; therefore, these exclusions are intended to capture the majority of planned readmissions.

SECTION 2: MODEL SPECIFICATION

This section describes the detailed specifications of the regression model used to obtain estimates of 30-day LRI hospital-level readmission rates for the pediatric population aged < 18 years old. We have provided a SAS program that fits the model, as described in this section, and performs direct standardization, as described in Section 3. We have also provided a program that estimates hospital- and state-level readmission rates that can be compared at a national level, as described in Section 4.

The model consists of a 2-level logistic regression model with fixed effect variables for patient case-mix at the first level and random intercepts for hospitals at the second level.

The model estimates 3 types of parameters. First, the coefficients of patient demographic and clinical characteristics represent the influence of these characteristics on predicted probabilities of readmission for an individual patient. Second, hospital-level random intercept estimates (evaluated for each hospital) represent the greater or lesser adjusted probability of readmission not explained by patient-level fixed effects for patients discharged from each hospital within a given state. Finally, variance estimates of the hospital random effects summarize the amount of variation among the intercepts for different hospitals and hence summarize the amount of variation in adjusted readmission rates across hospitals, at least some of which may be due to variation in health system quality.

After the case-mix-adjusted coefficients and hospital-level random intercept for each record are calculated, the hospital-specific case-mix-adjusted readmission rate is estimated through direct standardization using a case-mix representative of all hospitals in the entire dataset. The resulting estimates represent the readmission rate that each hospital would have if it served the same representative case-mix and are therefore conducive to comparisons among hospitals (for details, see Section 3).

DEFINITION OF OUTCOME

The model outcome, pediatric LRI readmission, is operationalized as the first unplanned admission to any acute care hospital within 30 days of discharge from a hospitalization for LRI at an acute care hospital. This prior admission, which serves as the reference point for enumerating 30-day readmissions, is the *index admission*. Additional admissions within 30 days from discharge from an index admission are not counted as index admissions. An admission more than 30 days from discharge from an index admission is counted as a new index admission.

We chose 30 days as the follow-up period during which to evaluate readmissions for multiple reasons. Readmissions within 30 days seem likely to reflect the quality of care provided both in the hospital and following discharge, which is consistent with the measure's intended purpose of assessing quality not just for a hospital but also for its wider health system. A follow-up period of 30 days is consistent with many readmission measures already in use, including the CMS readmission measures for adults. In addition, when we used a time-to-event curve to evaluate the proportion of readmissions within 1 year that occur within timeframes from 1 day up to 365 days, we observed a smooth curve with no obvious break to suggest an alternative follow-up period.

If a planned or chemotherapy readmission occurs within 30 days of an index admission, it *does not* count as a readmission against the index admission, and no subsequent admissions

occurring within 30 days of discharge from the index admission count as readmissions against the index admission. After 30 days from discharge from the index admission, a new index admission can be counted.

CASE-MIX VARIABLES INCLUDED IN THE MODEL

The following case-mix variables, defined from the index admission, have been selected for inclusion in the model and are specified in Tables 3 and 7 in Section 1.

- Age group
- Gender
- Presence of chronic conditions in each of 17 body systems (organ systems, disease categories, or other categories)
- Number of body systems affected by chronic conditions

Detailed Model Specification

$$\ln\left(\frac{y_{ij}}{1-y_{ij}}\right) = \beta_0 + \beta_1 x_{1ij} + \cdots + \beta_n x_{nij} + u_{oj}$$

Where:

- y_{ij}
  - represents a readmission event for an index admission *i* in hospital *j*
  - $y_{ij} \sim Bernoulli(\pi_{ij})$, where π_{ij} represents the probability of readmission for the *i*th admission in the jth hospital
  - takes on the following values for each index admission:
    - 0 = non-readmission
    - 1 = readmission
- β_0 is the intercept representing the overall readmission rate
- u_{0j} represents the jth hospital's deviation from β_0 and $u_{0j} \sim iid\ N(0, \tau_{00})$
- $\beta_{1j} x_{1ij}$ to $\beta_{nj} x_{nij}$ represent the n case-mix adjustment constant values for the *i*th index admission in the jth hospital

The first level of the model, which adjusts for hospital case-mix, includes patient gender and the following patient-level characteristics identified from the index admission: age group in years at the time of discharge, presence of a chronic condition in each of 17 body systems as identified by the AHRQ CCI tool, and the number of body systems affected by chronic conditions. The second level of the model consists of an estimate of a hospital-specific random effect that represents each hospital's systematic deviation from an average intercept across all hospitals. Estimates from this 2-level model can be used to calculate the hospital-specific readmission rate after accounting for patient case-mix by taking the average of the predicted probabilities of readmission that the model produces for each record by hospital.

In summary, the model specification used in this measure accounts for hospital case-mix, the clustering of certain types of patients within hospitals, and differences in sample size across hospitals. In theory, after adjusting for patient case-mix, the hospital intercepts should be equal across all hospitals if the patient case-mix has been correctly specified and hospitals are providing comparable quality of care. Therefore, variation among the hospital intercepts is presumed to capture systematic differences in hospital readmission rates.

IDENTIFYING AND TROUBLESHOOTING MODEL-FITTING ISSUES

We found while testing the measure that model-fitting issues may occur if, for a given level of a case-mix variable (e.g., *cci15* = 1), all index admissions for which that level is present have the same outcome (e.g., all index admissions for which *cci15* = 1 are followed by a readmission, or none of the index admissions for which *cci15* = 1 are followed by a readmission). We have included a macro program to be used with the SAS model program that evaluates each variable for this condition and excludes the involved index admissions from the analysis. The program should therefore prevent the majority of model-fitting issues. As a precaution, however, we recommend reviewing the SAS log notes and output after running the model program for signs that may indicate problems with the model.

Below are indicators that a model-fitting problem may have occurred. If 1 or more of these indicators is present, we recommend reviewing the rich text file, named "lowerrespiratoryinfection_crosstabs.rtf," generated by the model program. This file shows cross-tabulations of each case-mix variable with the readmission outcome. If any variable has a level with very few index admissions having a particular outcome (readmission or no readmission), consider dropping all of those index admissions and running the model program again.

1. The Covariance Parameter Estimate is > 0 and its standard error is missing (example below).

Covariance Parameter Estimates			
Cov Parm	**Subject**	**Estimate**	**Standard Error**
Intercept	hospitalid	0.06709	.

2. The SAS output includes a coefficient with a standard error of 0 (which will also result in a t-statistic of infinity).

Effect		**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr > |t|**
male	Male	0.01700	0	18791	Infty	<.0001
male	_Female	0	.	.	.	.

3. The SAS output includes a coefficient with an extremely large standard error relative to those of the other coefficients.

Solutions for Fixed Effects					
Effect	**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr > |t|**
cci13	-11.9677	327.76	18808	-0.04	0.9709

PLEASE NOTE: As you review the SAS log notes and output, the following are not reasons for concern.

1. In the log file, the following note will appear after the Glimmix procedure because cases with missing outcomes are intentionally generated as part of the direct standardization process.

   "NOTE: Some observations are not used in the analysis because of: missing response values (n = 363909)."

2. The SAS output may include an estimate of 0 and a missing standard error for the Covariance Parameter Estimate. The SAS log may also contain the note, "NOTE: Estimated G matrix is not positive definite." This means that evidence of variation across hospitals was not found (for example, because few hospitals had readmissions) but does not indicate a problem with model fitting.

Covariance Parameter Estimates			
Cov Parm	**Subject**	**Estimate**	**Standard Error**
Intercept	hospitalid	0	.

3. The log file may include notes such as "WARNING: Attempt to delete macro variable VAR 4 failed. Variable not found." These notes result from 1 of the steps of the macro program used with the SAS model program and do not indicate a problem.

4. The log file will include the note, "NOTE: Variable madeup_var is uninitialized." This note results from 1 of the steps of the macro program used with the SAS model program and does not indicate a problem.

SECTION 3: DIRECT STANDARDIZATION

Hospital populations in the dataset have differing case-mix compositions, making meaningful interpretations of comparisons of readmission rates across hospitals challenging. The hospital estimate from the fitted equation above is an estimate of the random effects intercept $u_{0j,}$ which is not a readily interpretable quantity. We therefore use direct standardization to generate readmission rates that have a meaningful interpretation across hospitals. The interpretation that can be posited from this methodology is that the predicted readmission rate estimated for each hospital represents the readmission rate it would have if the hospital treated a patient cohort with the case-mix composition of all eligible index admissions within the entire dataset.

As described in Section 2 above, we fit a 2-level hierarchical logistic regression model to the observed data to obtain hospital-specific random intercepts that are adjusted for each hospital's case-mix. In order to implement direct standardization, we apply the estimates from the model to a hypothetical dataset in which (a) all admissions are re-coded as if they are from the hospital for which a readmission rate is being estimated and (b) the readmission outcome has been set to missing. Otherwise, the dataset is identical to the actual observed data from all hospitals in the cohort. This methodology uses the hospital's own random intercept, which is case-mix adjusted by its own specific index admission population, to determine the probability that a record in the dataset will generate a readmission.

Each hospital's predicted probabilities for all records are summed by hospital and divided by the total number of index admissions in the dataset to produce the hospital-specific standardized readmission rate. The upper confidence bound for this estimate is calculated as the mean of the

upper confidence bound for each index admission's probability of leading to a readmission. The corresponding procedure is followed to estimate the lower confidence bound.

Finally, the point estimate and bound values are multiplied by a factor that corrects for estimation error produced by transformations used during estimation. The bias correction factor is a constant value specified as the observed number of readmissions across all hospitals in the dataset divided by the predicted number of readmissions across all hospitals in the dataset. After calculating the point estimates and confidence intervals of hospital-specific readmission rates for each hospital using this methodology, hospitals are identified as outliers if the confidence bounds around their predicted readmission rates do not overlap with the overall observed readmission rate across the entire dataset.

Detailed Methods for Implementing Direct Standardization in SAS

One method to implement direct standardization in SAS involves obtaining the predicted values of every patient in the dataset in each hospital using the steps listed below. This is the method used in the SAS program provided.

1. For each hospital being standardized, create a duplicate copy of the original dataset. The duplicate dataset should contain exactly the same variables and records as the original data for all hospitals.
2. Set the outcome (readmissions) in the duplicate dataset to missing. This prevents these duplicate records from being used in model estimation.
3. For ALL records in the duplicate dataset, set the hospital identifier to the hospital identifier of the hospital being standardized. Add a variable to the dataset that indicates these records contain hypothetical data.
4. Concatenate the duplicate datasets to the original dataset. If the concatenated dataset is too large to handle, the same procedure may be conducted for subgroups of hospitals, or for 1 hospital at a time, and the results combined afterward.
5. Fit the model as specified in Section 2 of this document to the dataset created in step 4. In SAS, the model will be fitted only on the original data since the outcome is missing for the duplicate data. This process will produce a case-mix-adjusted random intercept for each hospital. However, the procedure will also produce predicted probabilities for both original and duplicate records (SAS calculates predicted probabilities for any record in which the predictors are not missing, regardless of whether the outcome is missing).
6. Calculate the mean predicted probability and lower and upper bounds for only the duplicate records (those flagged as containing hypothetical data) in order to obtain the predicted readmission rate for the hospital being standardized. This rate represents the readmission rate for this hospital if it were to treat the *entire dataset's* population mix.

SECTION 4: CALCULATION OF NATIONALLY COMPARABLE HOSPITAL- AND STATE-LEVEL RATES

Pediatric inpatient claims data are widely available, but the data are presently aggregated at the hospital, payer, or state (e.g., for Medicaid or all-payer databases) level but not at the federal level. Although Medicaid claims are compiled into Medicaid Analytic eXtract (MAX) files for research use, MAX is nevertheless comprised of 51 separate state-specific datasets, with variability in completeness of data elements and inconsistencies in provider identifiers and coding practices across states.[1,2] In addition, MAX data availability lags by about 3 years, preventing assessment of quality for more recent time periods.[1] Thus, while Medicare data serve as a national database for quality measurement in adult patients, no analogous national database of pediatric claims from all states and all types of hospitals currently exists.

In order for hospital, payer, or state outcome measures to be comparable at the national level, they must be case-mix adjusted with a model derived from data from all states. Comparisons of readmission rates calculated and standardized with data from 1 state with those calculated and standardized with data from another state are not fully valid because the case-mix coefficients may differ in health systems in 1 state versus another state. Without a unified dataset, an individual state can calculate, case-mix adjust, and compare readmission rates among its own health systems, but it cannot compare its rates with those of other states.

In the absence of a national pediatric claims database, we have developed a method for calculating hospital- or state-level readmission rates for Medicaid-insured patients that can be compared across states. We have provided a SAS program to implement this method. Readmission rates are standardized using a reference dataset, consisting of MAX data for 26 states (Alabama, Arizona, Connecticut, Idaho, Indiana, Iowa, Kansas, Kentucky, Louisiana, Minnesota, Mississippi, Missouri, Montana, New Jersey, New Mexico, New York, North Carolina, North Dakota, Oklahoma, Oregon, South Dakota, Texas, Vermont, Virginia, Wisconsin, and Wyoming). The 26 states, which are diverse in size and represent each geographic region (Northeast, Midwest, South, West), were chosen based on quality and completeness of their data for readmission analyses; to our knowledge, the combined data for these states comprise the most nationally representative dataset available to standardize readmission rates for Medicaid-insured children.

The case-mix adjustment model used in our method consists of a 2-level logistic regression model with fixed effect variables for patient case-mix at the first level and random intercepts for hospitals at the second level. Our analyses showed no state-level variation in LRI readmission rates, so we do not include random intercepts for states in the model.

The model estimates 3 types of parameters. First, the coefficients of patient demographic and clinical characteristics represent the influence of these characteristics on predicted probabilities of readmission for an individual patient. Second, hospital-level random intercept estimates (evaluated for each hospital) represent the greater or lesser adjusted probability of readmission, not explained by patient-level fixed effects, for patients discharged from each hospital. Finally, variance estimates of the hospital random effects summarize the amount of variation among the intercepts for different hospitals and hence summarize the amount of variation in adjusted readmission rates across hospitals, at least some of which may be due to variation in health system quality.

Detailed Methods for Calculating Nationally Comparable Hospital-Level Readmission Rates for Medicaid-Insured Patients

After the case-mix-adjusted coefficients and hospital-level random intercepts for each record are calculated, the hospital-specific case-mix-adjusted readmission rate is estimated through direct standardization using a case-mix representative of all hospitals in the entire 26-state MAX reference dataset. The resulting estimates represent the readmission rate that each hospital would have if it served the same representative case-mix and are therefore conducive to rate comparisons.

The following describes a method to use SAS procedures to approximate the posterior predictive distribution of hospital-level rates.

1. Fit the case-mix adjustment model to the *26-state MAX reference dataset* and retain estimates for:

    a. hospital-level random intercept variance: $\sigma^2_{hospital}$
    b. fixed effect coefficients: $\boldsymbol{\beta}_{reference}$
2. Refit a hierarchical logistic regression model using the dataset for which nationally comparable readmission rates are to be calculated, hereafter referred to as the *analysis dataset*, as follows:
    a. Fix hospital-level variance and fixed effect coefficients to estimates from Step 1.
    b. Output hospital-level estimates for units in the *analysis dataset.* (It is acceptable for the *analysis dataset* to contain only 1 state*.)*
3. Next, perform direct standardization using the reference dataset. Note that patient case-mix enters the regression through the fixed effects portion of the linear predictor. Rather than requiring the actual reference dataset to perform direct standardization, one can use a representative subset of $\boldsymbol{\beta X}_i$, $i \in$ reference from the reference dataset. To obtain the representative subset, calculate the fixed effects $\boldsymbol{\beta X}_i$ for all records in the reference dataset, sort records by this value, and sample 1,000 equally spaced values, where "equally spaced" refers to rank order (e.g., if sampling 1,000 values from 100,000 ranked values, the 100th smallest, 200th smallest, 300th smallest, etc., value would be selected).
4. Perform direct standardization as described in Section 3, applying each hospital's random effect estimate 1 at a time to the subset of 1,000 $\boldsymbol{\beta X}_i$ values (retained from Step 3) to obtain an average probability for 1 hospital as if its case-mix were that of the entire dataset. For each of the 1,000 $\boldsymbol{\beta X}_i$ values, a new predicted value, $P_{analysis}$, will be generated that is a combination of $\boldsymbol{\beta X}_i$ and the random effect for the hospital of interest (this process would be repeated for each hospital). Upper and lower confidence bounds for $P_{analysis}$ will also be calculated.
5. Transform the values of $P_{analysis}$ from the logit to the probability scale, and then take the mean of those probabilities to get the nationally comparable adjusted readmission rate for that hospital. Take the means of those upper and lower bounds to get the upper and lower bounds for the hospital-level rate.

Detailed Methods for Calculating Nationally Comparable State-Level Readmission Rates for Medicaid-Insured Patients

State-level readmission rates are calculated by taking the mean of the nationally comparable readmission rates of all hospitals within a state, weighted by hospital volume. To calculate confidence bounds for the state-level readmission rate, the method below is used.

1. Fit the case-mix adjustment model as in Step 3 above, to the *analysis dataset,* as follows, which will provide estimates and standard errors for each hospital's effect.
    a. Specify hospital effect using the hospital variance estimate from the reference dataset.
    b. The model contains no intercept and no fixed effects.
    c. Specify an "offset" – essentially, an intercept that is different for each record – where the offset = $Y_{analysis}$ and

    $$Y_{analysis} = intercept_{analysis} + (\beta_{reference} * X_{analysis})$$

2. For each hospital, generate a random draw from the distribution defined by the estimate and standard error from step 2. Add this random value to $Y_{analysis}$ from step 1c, then perform direct standardization as described in Section 3, using the *subset of 1,000 $Y_{reference}$ values*. For each of the 1,000 $Y_{reference}$ values, a new predicted value, $P_{analysis}$, will be generated that is a combination of $Y_{reference}$ and the random effect for the hospital of

interest (this process would be repeated for each hospital). Upper and lower confidence bounds for $P_{analysis}$ will also be calculated.

3. Inverse-logit transform the values of $P_{analysis}$ to obtain probabilities, and then take the mean of those probabilities to get the nationally comparable adjusted readmission rate for that hospital.
4. Generate the state-level adjusted readmission rate by calculating the mean rate across hospitals, weighted by hospital volume.
5. Repeat steps 2 through 4 1,000 times, then calculate a confidence interval from the distribution of the rates generated in step 4.

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