
CBE ID

2414

Title

Pediatric Lower Respiratory Infection Readmission Measure

Project

Cost and Efficiency

Endorsement Status

Endorsement Removed

E&M Committee Rationale/Justification

Prior to the Cost and Efficiency endorsement meeting, the measure developer withdrew this measure due to data access concerns. This measure was last endorsed in 2016 and used data from 2008 for endorsement. After the measure was submitted to the Fall 2023 cycle, Battelle drew attention to the lack of more recent data, which limits the committee's ability to assess whether a performance gap remains, whether scientific acceptability (i.e., reliability and validity) of the measure is still established, and whether improvement on this measure has occurred due to its use. The developer withdrew the measure from the Fall 2023 cycle prior to the endorsement meeting and endorsement was removed at the conclusion of the Fall 2023 cycle.

Is Under Review

No

Previous Endorsement Cycle

Fall 2023

Removal Date

Tue, 03/26/2024 - 09:48

Initial Endorsement

Fri, 12/09/2016 - 00:00

Steward

Center of Excellence for Pediatric Quality Measurement

1.0 New or Maintenance

Maintenance

1.3 Electronic Clinical Quality Measure (eCQM)

No

1.6 Measure Description

This measure calculates case-mix-adjusted readmission rates, defined as the percentage of admissions followed by 1 or more readmissions within 30 days, following hospitalization for lower respiratory infection (LRI) in patients less than 18 years old. The measure covers patients discharged from general acute care hospitals, including children's hospitals.

1.7 Composite Measure

No

1.7 Measure Type

Outcome

1.8 Level of Analysis

Facility

1.9 Care Setting

Hospital: Inpatient

1.10 Measure Rationale

Not applicable.

1.11 Measure Webpage

<https://www.ahrq.gov/sites/default/files/wysiwyg/pqmp/measures/acute/chipra-131...>

1.13 Data Dictionary

Attached

1.13a Attach Data Dictionary

[Pediatric Lower Respiratory Infection Readmission Measure ICD-10 Data Dictionary.xlsx_.zip](#)

1.14 Numerator

The numerator consists of hospitalizations at general acute care hospitals for LRI in patients less than 18 years old that are followed by 1 or more readmissions to general acute care hospitals within 30 days. Readmissions are excluded from the numerator if the readmission was for a planned procedure or for chemotherapy. The measure outcome is a readmission rate, defined as the percentage of index admissions with 1 or more readmissions within 30 days. The readmission rate, unadjusted for case-mix, is calculated as follows: number of index admissions with 1 or more readmissions within 30 days/total number of index admissions

1.14a Numerator Details

A readmission is operationalized as the first unplanned admission to any acute care hospital within 30 days of discharge from a prior hospitalization 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.

Readmissions are excluded if they are for a planned procedure or for chemotherapy. 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. 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 admissions.

We identify planned procedures using an algorithm based on primary procedure codes. Expert pediatric clinicians in 15 different procedure-oriented specialties reviewed procedures typically performed by their specialty. The reviewers indicated which procedures (1) are usually planned (defined as planned in more than 80% of cases) and (2) could require hospitalization. Admissions for which the principal International Classification of Diseases, Tenth Revision, Procedure Coding System (ICD-10-PCS) procedure code for a planned procedure coded was 1 of these procedures are excluded from readmissions. 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.

EXCLUSIONS FROM THE NUMERATOR (READMISSIONS):

- Hospitalizations with a principal ICD-10 code for a planned procedure (i.e., planned = 1).
- Hospitalizations with a principal ICD-10 diagnosis or procedure code for chemotherapy (i.e., chemo = 1).

These exclusions are applied without deleting the records from the dataset as these hospitalizations may still meet criteria for index admissions, detailed in Section S.10.

Variable definitions and ICD-10 codes for identifying readmissions for planned procedures and for chemotherapy are provided in the Data Dictionary.

If a planned 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.

1.15 Denominator

Hospitalizations at general acute care hospitals for LRI in patients less than 18 years old.

1.15a Denominator Details

Index hospitalizations are identified by applying a case definition for LRI and the exclusion criteria detailed in Sections S.10 and S.11. The LRI case definition requires either a principal ICD-10 diagnosis code for bronchiolitis, influenza, or community-acquired pneumonia (CAP) or an additional ICD-10 diagnosis code for one of these LRIs plus an additional ICD-10 diagnosis code for asthma, respiratory failure, or sepsis/bacteremia. The variable definition and ICD-10 codes for the case definition are provided in the ICD-10 Data Dictionary.

1.15b Denominator Exclusions

EXCLUSIONS FROM THE NUMERATOR (READMISSIONS) AND DENOMINATOR (INDEX HOSPITALIZATIONS)

We exclude certain hospitalizations from the measure entirely (i.e., from the numerator and denominator) based on clinical criteria or for issues of data completeness or quality that could prevent assessment of eligibility for the measure cohort or compromise the accuracy of readmission rates. Hospitalizations are excluded from the measure if they meet any of the following criteria:

1. The hospitalization was at a specialty or non-acute care hospital.

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.

2. Records for the hospitalization contain incomplete data for variables needed to assess eligibility

for the measure or calculate readmission rates, including hospital type, patient identifier, admission date, discharge date, disposition status, date of birth, principal ICD-10 diagnosis codes, and gender.

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. 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.

3. Records for the hospitalization contain data of questionable quality for calculating readmission rates, including

- a. Inconsistent date of birth across records for a patient.
- b. Discharge date prior to admission date.
- c. Admission or discharge date prior to date of birth.
- d. Admission date after a disposition status of death during a prior hospitalization.

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. A valid 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.

4. Codes other than ICD-10 codes are used for the primary procedure.

Rationale: ICD-10 procedure codes are necessary for applying clinical exclusions.

5. The patient was older than 18 years, 29 days at the time of admission.

Rationale: This 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, a patient's hospitalization is ineligible for inclusion in the measure as an index admission if the patient was 18 years old or greater at the time of discharge. Because the subsequent observation period for readmissions is 30 days, a patient's hospitalization is ineligible for inclusion in the measure as a readmission if the patient was older than 18 years, 29 days at the start of the readmission.

6. The hospitalization was for obstetric care, including labor and delivery.

Rationale: Hospitalizations for obstetric conditions are excluded because care related to pregnancy does not generally fall within the purview of pediatric providers.

7. The principal ICD-10 diagnosis code was for a mental health condition.

Rationale: Hospitalizations for mental health conditions are excluded because we found that hospitals with high readmission rates for mental health hospitalizations tend to have low readmission rates for hospitalizations for other conditions, and vice versa. We describe this analysis in detail in Section 2b.3 of the Measure Testing Submission Form.

8. The hospitalization was for birth of a healthy newborn.

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

EXCLUSIONS FROM THE DENOMINATOR ONLY (INDEX HOSPITALIZATIONS ONLY)

We also apply further exclusions to the denominator only (i.e., these hospitalizations are excluded from index hospitalizations but could still meet criteria for readmissions). Hospitalizations are excluded from the denominator only if they meet any of the following criteria:

9. The patient was 18 years old or greater at the time of discharge.

Rationale: Age eligibility for inclusion in the measure is based on age at the time of discharge from the index admission. Because the measure covers pediatric patients, a patient's hospitalization is ineligible for inclusion in the measure as an index admission if the patient was 18 years old or greater at the time of discharge.

10. The discharge disposition was death.

Rationale: 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.

11. The discharge disposition was leaving the hospital against medical advice.

Rationale: 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.

12. The hospital has less than 80% of records with complete patient identifier, admission date, and discharge date or less than 80% of records with complete principal ICD-10 diagnosis codes. (Records for these hospitals are still assessed as possible readmissions, but readmission rates are not calculated for these hospitals due to their lack of complete data.)

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 apply measure cohort exclusions 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.

13. The hospital is in a state not being analyzed.

Rationale: A claims database used for readmission analysis may contain records for hospitals located in states that are not included in the database (because covered patients may sometimes be admitted to out-of-state hospitals). Records for these 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.

14. Thirty days of follow-up data are not available for assessing readmissions.

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

15. The hospitalization does not have a principal ICD-10 LRI diagnosis or does not have an additional ICD-10 LRI diagnosis plus a principal ICD-10 diagnosis of asthma, respiratory failure, or sepsis/bacteremia.

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.

1.15c Denominator Exclusions Details

DATA PREPARATION AND APPLICATION OF EXCLUSIONS TO THE MEASURE COHORT (NUMERATOR AND DENOMINATOR) AND TO THE DENOMINATOR ONLY

Steps 1 through 8, below, describe the data preparation steps to implement and the exclusions to apply to the measure cohort (numerator and denominator) and to the denominator only before fitting the pediatric all-condition readmission model to inpatient claims data.

STEP 1: IDENTIFY HOSPITALS ELIGIBLE FOR INCLUSION IN THE MEASURE

This measure focuses on calculating pediatric readmission rates for general acute care hospitalizations. 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: 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, see the Data Dictionary submitted in Section S.2b. 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.

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 less than 80% of records with complete unique patient identifier, admission date, and end-of-service date
- Hospitals with less than 80% of records with complete principal ICD-10 diagnosis codes
- 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. 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.

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-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.

STEP 4: SPECIFY VARIABLES DEFINED AT THE RECORD LEVEL

The variables listed in the Data Dictionary (provided in Section S.2b) are used to construct the measure cohort and/or to calculate readmission rates. These variables must be named and coded as specified in the Data Dictionary and should be created prior to identifying episodes of care and applying further exclusions to the data.

STEP 5: DEFINE EPISODES OF CARE

Data for a single period of inpatient care may be contained in more than 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.

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 the Data Dictionary (provided in Section S.2b) 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 in that 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)

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`, and `newborn`. 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 chronic condition

indicator and clinical exclusion variables across records captures the presence of a chronic condition or clinical exclusion for the entire episode of care. For example, if 1 record contains a 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, 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 in the Data Dictionary provided in Section S.2b, prior to applying further exclusion criteria to the data.

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

The exclusions listed below are applied 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 principal ICD-10 diagnosis code is missing (i.e., hasprimary = 0) for ANY episode of care for that patient.

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.

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

- Drop episodes of care for patients greater than 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 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 principal ICD-10 mental health diagnosis (i.e., mh = 1).

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 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)

- Episodes of care that either do not have a principal ICD-10 LRI diagnosis or do not have an additional ICD-10 LRI diagnosis plus a principal ICD-10 diagnosis of asthma, respiratory failure, or sepsis/bacteremia (i.e., `lri` = 0)

The above exclusions are applied without deleting the records from the dataset as these episodes of care may still meet criteria for readmissions.

Exclusions at the Hospital Level for Defining Index Admissions:

- Hospitals with less than 80% of records with complete unique patient identifier, admission date, and end-of-service date
- Hospitals with less than 80% of records with complete 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.

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.

1.16 Type of Score

Rate/proportion

1.17 Measure Score Interpretation

Better performance = Lower score

1.18 Calculation of Measure Score

PREPARATION OF DATA AND IDENTIFICATION OF MEASURE COHORT

Identify Hospitals Eligible for Inclusion in the Measure

1. Starting with the complete set of claims from the time period being analyzed, exclude

hospitalizations that occurred at specialty or non-acute care hospitals or at hospitals for which hospital type is missing.

Identify Hospitals for which Readmission Rates Should Not Be Calculated

2. Identify and flag out-of-state hospitals and hospitals with incomplete data for key variables for more than 20% of records.

Exclude Patients Who Have Missing or Invalid Data for Analyzing Readmissions

3. Exclude patients whose records use procedure codes other than ICD-10 codes or have missing or invalid data for 1 or more of the following variables: patient identifier, hospital identifier, admission date, end-of-service date, disposition status, date of birth, and gender.

Specify Variables Defined at the Record Level

4. Define variables for measure cohort exclusions and readmission analysis that should be created at the record level.

Define Episodes of Care

5. For hospitalizations with data contained in more than 1 claim, combine the multiple claims into a single record for each hospitalization.

Specify Variables Defined at the Episode of Care Level

6. Define variables for measure cohort exclusions and readmission analysis that should be created at the episode of care level.

Define Episodes of Care Eligible for Inclusion in Measure Cohort

7. Exclude hospitalizations with a missing principal ICD-10 diagnosis code.

8. Exclude hospitalizations with an admission date occurring after a previous hospitalization with a disposition status of death.

9. Exclude hospitalizations for patients older than 18 years, 29 days at the time of admission.

10. Exclude hospitalizations for obstetric conditions, mental health conditions, and birth of healthy newborns.

DEFINE INDEX HOSPITALIZATIONS

11. Exclude hospitalizations for patients 18 years, 0 days old or older at the time of discharge.

12. Exclude hospitalizations with a discharge disposition of death.

13. Exclude hospitalizations with a discharge disposition of leaving against medical advice.

14. Exclude hospitalizations for which 30 days of follow-up data are not available for assessing readmissions.

15. Exclude hospitalizations that do not have a principal ICD-10 diagnosis code for an LRI or an additional ICD-10 diagnosis code for an LRI plus a principal ICD-10 diagnosis code for asthma, respiratory failure, or sepsis/bacteremia.

16. Exclude hospitalizations that occurred at hospitals that (a) have less than 80% of records with complete patient identifier, admission date, and end-of-service date; (b) have less than 80% of records with principal ICD-10 diagnosis codes; or (c) are located in a state not being analyzed.

DEFINE READMISSIONS

17. Identify index hospitalizations followed by one or more readmissions within 30 days.

18. When identifying readmissions, exclude hospitalizations with (a) a principal ICD-10 procedure code for a planned procedure or (b) a principal ICD-10 diagnosis code or procedure code for

chemotherapy.

CASE-MIX ADJUSTMENT MODEL FITTING AND DIRECT STANDARDIZATION

19. Fit the case-mix adjustment model to the prepared dataset to estimate coefficients for the case-mix variables (age, gender, presence of chronic conditions in each of 17 body systems, and number of body systems affected by chronic conditions) and a hospital random intercept for each hospital.

20. Perform direct standardization by fitting the model again for each hospital. Use the hospital's random intercept, adjusted for its own case-mix, from Step 19, but instead of using the hospital's own case-mix data, use 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. 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.

21. 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.

22. 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.

23. The resulting hospital-specific standardized readmission rate can be interpreted as the readmission rate the hospital would have if it treated a patient cohort with the case-mix composition of all eligible index admissions within 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 we have prepared for the measure.

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 in the original dataset for all hospitals.
2. Set the outcome (readmission) 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 that 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 case-mix adjustment model to the dataset created in the previous step. 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.

1.19 Measure Stratification Details

Not applicable.

1.20 Types of Data Sources

Claims Data

1.25 Data Source Details

The measure could be used with state Medicaid or all-payer databases. There are several options for calculating rates that could be compared nationally. CMS could analyze Medicaid claims from multiple states. A private payer with data from multiple states could compare hospitals from across state lines. Multiple states with all-payer databases could combine them to enable cross-state comparisons. Individual states could calculate nationally comparable rates using a method we have developed by which readmission rates can be estimated for Medicaid-insured patients and standardized using a MAX reference dataset. Please see the Detailed Measure Specifications (provided in the Appendix) for instructions on implementing this method.

1.26 Minimum Sample Size

N/A.

2.1 Attach Logic Model

[logic model.docx](#)

2.2 Evidence of Measure Importance

Evidence suggests that readmission rates provide a useful measure of health care quality. Use of effective, evidence-based approaches to diagnosis, treatment, and monitoring of disease leads to fewer complications and decreased exacerbations, which can, in turn, result in a decreased frequency of hospitalizations. Readmission rates therefore in part reflect the quality of clinical care and resulting disease outcomes.

Studies have shown that hospitals that provide care in accordance with clinical practice guidelines have lower readmission rates than those that do not.¹⁻⁴ Several retrospective cohort analyses and case-control studies and a prospective pre-post observational study have demonstrated that adherence to evidence-based processes of care results in improved clinical outcomes.^{1,2,5-11} For example, improved adherence to the Joint Commission's recommended 3 Children's Asthma Care (CAC 1-3) measures was associated with improved chronic asthma symptoms and fewer exacerbations, as well as longer periods out of the hospital with fewer readmissions.⁹ Similarly, Get With the Guidelines (GWTG) programs have been associated with significant improvements in processes of cardiovascular care strongly linked to improved outcomes.⁴ Lower quality of inpatient care is associated with a higher risk of unplanned readmission.⁵

Readmission rates also reflect the quality of key health care processes. Several studies, largely in adults, have demonstrated that interventions focused on improving the quality of the discharge process, the transition from the hospital to ambulatory or long-term care, and the provision of timely follow-up care have been associated with reduced hospital readmission rates, suggesting that the quality of these processes is associated with readmission risk.¹²⁻³¹ For example, hospitals that provide patient-focused, individualized pre-discharge education as well as post-discharge

support have fewer readmissions than those that do not provide such services.^{13-15,17-25,28,31-39}

Project RED and the Care Transition Measure are 2 examples of initiatives that have improved the quality of discharge and care transition processes for adult patients by incorporating such interventions as a transition coach who provides assistance with medication self-management, makes home visits and telephone calls to patients after discharge, and sets up timely follow-up appointments with primary or specialty care providers. Such interventions that emphasize the importance of teaching patients about their diagnoses and reviewing their treatment and discharge plan with them throughout their hospital stay are associated with a subsequent reduction in 30-day readmission rates.^{19,32}

Studies identify care coordination, discharge planning, and hospital-to-home care transition as key processes that influence pediatric readmission rates.⁴⁰⁻⁴² Indeed, parental perception that a child is not healthy enough for discharge is associated with a greater risk of subsequent, unplanned 30-day readmission.²⁹ Responding to parental concerns about a child's health prior to hospital discharge may help mitigate readmission risk. In another study of both pediatric and adult patients with sickle cell disease, patients who had post-discharge follow-up within 30 days of hospital discharge were readmitted less often than those who did not have post-discharge follow-up.²⁴ Improving consensus among families and providers, improved communication among care team members and between care teams and families, and clear definitions of care team member roles may be valuable areas for future efforts to reduce readmission.^{41,42}

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Table 1. Performance Scores by Decile

	Performance Gap												
	Overall	Minimum	Decile_1	Decile_2	Decile_3	Decile_4	Decile_5	Decile_6	Decile_7	Decile_8	Decile_9	Decile_10	Maximum
Mean Performance Score	0.053	0.038	0.045	0.047	0.049	0.050	0.052	0.053	0.055	0.059	0.065	N/A	0.105
N of Entities	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
N of Persons / Encounters / Episodes	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

2.6 Meaningfulness to Target Population

Previous (2015) Submission:

Hospitalization of a child is disruptive to families. It can affect parent/caregiver work and sibling school or daycare arrangements and expose families to various psychosocial stressors.^{1,2} In addition, readmission exposes patients to additional hospital days and thus increased potential for infections and medical errors that can occur during hospitalization.^{3,4}

Frequent hospitalization may have negative developmental effects, including anxiety and feelings of isolation, particularly for children who are chronically ill and return to school after prolonged hospitalizations.⁵ Frequently hospitalized adolescents are more likely to drop out of school than their healthy peers.^{6,7} School reintegration can be complicated by side effects caused by treatment or the illness itself or by increased social, emotional, and behavioral problems.⁸

Current Submission:

New evidence affirms that hospitalizations, including readmissions, impact the psychological well-being of patient families.^{9,10} Furthermore, children frequently miss school, and their parents may miss work, for multiple weeks after hospital discharge.¹¹ School absenteeism may lower educational achievement, cause economic strain, and lead to poor health in adulthood.

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3.1 Contributions Towards Closing Care Gaps

Prior (2015) Submission:

We evaluated disparities using 2008 MAX data for 26 states, which include Medicaid claims from 67,191 index hospitalizations at 1,743 children's and non-children's hospitals. We also used 2005-2009 AHRQ Revisit data for New York and Nebraska, which include claims for all payers from 87,877 index hospitalizations at 241 children's and non-children's hospitals, to evaluate disparities in readmission risk associated with race/ethnicity and insurance status. We chose which states' data to use based on assessment of data quality and completeness. Both datasets can be used to evaluate readmissions back to the same hospital or to different hospitals.

DISPARITIES ASSOCIATED WITH RACE/ETHNICITY

We assessed disparities in readmission risk associated with race/ethnicity using both 2005-2009 AHRQ Revisit data for New York (all-payer) and the MAX dataset (Medicaid only). AHRQ Revisit data for Nebraska do not include a race/ethnicity variable and so could not be used in the analysis.

Race/ethnicity is recorded in AHRQ Revisit data using the categories Asian or Pacific Islander, Black, Hispanic, Native American, Other, or White. For our analysis, we combined the Asian or Pacific Islander, Native American, and Other categories into a single "Other" category because each category contained a very small number of observations. We found that compared with White patients, Black patients (odds ratio [OR] 1.25, 95% CI 1.13-1.38; $p < .001$) and Hispanic patients (OR 1.33, 95% CI 1.20-1.48; $p < .001$) had higher odds of readmission, independent of case-mix (age, gender, and chronic conditions) and index admission hospital.

Race/ethnicity is recorded in MAX data using the categories Asian/Pacific Islander, Black, Latino, Mixed race, Native American, or White. When we assessed the relationship between readmission risk and each race/ethnicity category using White patients as the reference group, controlling for case-mix (age, gender, and chronic conditions) and index admission hospital, we found significant differences in the odds of readmission for patients of Mixed race (OR 1.53, 95% CI 1.10-2.13; $p = .01$) and Native American patients (OR 1.27, 95% CI 1.07-1.51; $p = .01$) but not Black or Latino patients.

The finding of a higher likelihood of readmission for Black and Hispanic patients as compared to White patients in our all-payer dataset but not our Medicaid-only dataset suggests that socioeconomic status, as reflected by insurance status, might explain at least some of the apparent difference in readmission risk. To test this hypothesis, we repeated the race/ethnicity analysis in the AHRQ Revisit New York dataset and also controlled for insurance status. We found that the differences in readmission risk between Black and White patients (OR 1.18, 95% CI 1.06-1.32; $p < .001$) and between Hispanic and White patients (OR 1.25, 95% CI 1.12-1.40; $p < .001$) were attenuated but not eliminated, indicating, at least for this particular patient sample, some association of race/ethnicity with higher readmission risk, independent of insurance status.

DISPARITIES ASSOCIATED WITH INSURANCE STATUS

We assessed disparities in readmission risk associated with insurance status using 2005-2009 AHRQ Revisit New York and Nebraska data. We found that compared with Medicaid-insured patients, the odds of readmission were significantly lower for those who had private insurance (OR 0.79, 95% CI 0.73-0.85; $p < .001$), other types of insurance (such as Medicare or other government-sponsored insurance)(OR 0.71, 95% CI 0.53-0.94; $p < .001$), or self-pay status (OR 0.75, 95% CI 0.64-0.88; $p < .001$), independent of case-mix (age, gender, and chronic conditions) and index admission hospital.

We also evaluated whether a given hospital's readmission performance tends to correlate among patients with different insurance statuses. We fitted the measure model to 2005-2009 AHRQ Revisit New York and Nebraska data, adding a random slope indicator variable for each insurance status. We found that the regression coefficients were highly correlated for Medicaid and private insurance (correlation = 0.91) and for Medicaid and other insurance types (correlation = 0.85); for self-pay and private insurance (correlation = 0.82) and for self-pay and other insurance types (correlation = 0.88); and for private insurance and other types of insurance (correlation = 0.99). However, the regression coefficients were only moderately correlated for Medicaid and self-pay (correlation = 0.51), suggesting that readmission performance for patients with these two insurance statuses tends to be disparate within hospitals.

DISPARITIES ASSOCIATED WITH RURALITY/URBANICITY

Using our MAX dataset, we assessed disparities in readmission risk associated with residence in rural versus urban areas. We used patients' 5-digit zip codes to assign rural-urban commuting area (RUCA) codes, which are a Census tract-based classification system that uses Bureau of Census Urbanized Area and Urban Cluster definitions together with work commuting information to characterize Census tracts regarding their rural and urban status.¹ We then used the RUCA codes to assign the area of each patient's residence to 1 of 5 levels of a rurality/urbanicity classification scheme created by the Dartmouth Atlas Working Group: urban core, suburban, large town, small town, or isolated rural.²

Controlling for case-mix (age, gender, and chronic conditions) and index admission hospital, we found that readmission risk did not vary significantly among the 5 levels of rurality/urbanicity ($p = .32$ for chi-square test).

Current Submission:

New evidence affirms disparities in the rate of readmissions between children insured by

Medicaid and children with private insurance. In particular, despite an overall decline in readmission rates for publicly- and privately-insured children from 2010 to 2017, readmission rates remained higher among Medicaid beneficiaries than for their counterparts. Mean hospital 30-day risk-adjusted readmission rates increased for Medicaid beneficiaries, from 6.5% (SD 2.1%) in 2010 to 6.9% (SD 1.8%) in 2017 ($P = .017$), but remained stable for privately insured patients, from 5.9% (SD 2.0%) in 2010 to 6.0% (SD 1.1%) in 2017 ($P = .14$).³

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4.1 Feasibility Assessment

This submission was drafted prior to this field being created. Not Applicable.

4.3 Feasibility Informed Final Measure

The measure uses pediatric inpatient claims data. These data are readily available to hospitals and payers, including State Medicaid programs and private insurers. In addition, several States maintain or are implementing all-payer claims databases.

To address potential issues with data quality or completeness, we have provided in the measure specifications guidelines for assessing records and excluding them from the measure if they contain indicators of poor data quality (e.g., an inconsistent date of birth for the same patient across records) or have missing values for key variables.

4.4 Proprietary Information

Not a proprietary measure and no proprietary components

4.4a Fees, Licensing, or Other Requirements

No fees or licensures apply to the measure.

5.1.1 Data Used for Testing

We developed and tested the measure using Medicaid Analytic eXtract (MAX) data for 26 states, which include Medicaid claims from children's and non-children's hospitals. We used MAX data for hospitalizations with discharge dates from 12-01-2007 - 12-31-2008.

5.1.2 Differences in Data

To evaluate the criterion validity of the measure—its ability to identify correctly the outcome of interest, readmission—we assessed performance of the measure against the gold standard of chart reviews. To perform this analysis, we used administrative data and electronic health records for patients admitted to Boston Children's Hospital between March 1, 2012 and February 28, 2013. The table below describes the characteristics of patients with index hospitalizations during this time period (for patients for whom these data were available).

Table 7 □ Boston Children's Hospital Cohort Patient Characteristics (Total N = 8,387)

Patient Characteristic

*

Number (%) of Index Hospitalizations

Age

< 1 year

2,113 (25.2)

*

1 to < 5 years

2,041 (24.3)

*

5 to < 8 years

978 (11.7)

*

8 to <12 years

1,123 (13.4)

*

12 to < 18 years

2,132 (25.4)

Gender

Female

3,956 (47.2)

CCIs

CCI 1 - Infectious and parasitic disease

11 (0.1)

*

CCI 2 - Neoplasms

272 (3.2)

*

CCI 3 - Endocrine, nutritional, and metabolic diseases and immunity disorders

873 (10.4)

*

CCI 4 - Diseases of blood and blood-forming organs

471 (5.6)

*

CCI 5 - Mental disorders

805 (9.6)

*

CCI 6 - Diseases of the nervous system and sense organs

1,234 (14.7)

*

CCI 7 - Diseases of the circulatory system

878 (10.5)

*

CCI 8 - Diseases of the respiratory system

1,042 (12.4)

*

CCI 9 - Diseases of the digestive system

557 (6.6)

*

CCI 10 - Diseases of the genitourinary system

157 (1.9)

*

CCI 12 - Diseases of the skin and subcutaneous tissue

69 (0.8)

*

CCI 13 - Diseases of the musculoskeletal system

337 (4.0)

*

CCI 14 - Congenital anomalies

2,212 (26.4)

*

CCI 15 - Certain conditions originating in the perinatal period

6 (0.1)

*

CCI 16 - Symptoms, signs, and ill-defined conditions

44 (0.5)

*

CCI 17 - Injury and poisoning

16 (0.2)

*

CCI 18 - Factors influencing health status and contact with health services

420 (5.0)

CCI count

0 or 1 body system

5,858 (69.8)

*

2 body systems

1,793 (21.4)

*

3 body systems

602 (7.2)

*

4+ body systems

134 (1.6)

Race/ethnicity

Asian/Pacific Islander

290 (3.4)

*

Black

852 (10.2)

*

Latino

826 (9.8)

*

Mixed

15 (0.2)

*

Native American

731 (8.7)

*

White

5,054 (60.3)

*

Missing

618 (7.4)

This table displays Boston Children's Hospital cohort patient characteristics, including the number and frequency of index hospitalizations by age, gender, CCI category, CCI count, and race/ethnicity.

*Cell intentionally left empty

5.1.3 Characteristics of Measured Entities

The MAX dataset includes 1,743 hospitals with ≥ 1 pediatric hospitalization for LRI. The median hospital volume of annual pediatric LRI index hospitalizations for these hospitals was 58 (IQR 18-189). Characteristics of these hospitals are detailed below.

Table 5 □ MAX Cohort Hospital Characteristics (Total N = 1,743)

Hospital Characteristics

Hospitals

Index Hospitalizations

Children's hospital [Number (%) of hospitals]

78 (4.5%)

14,734 (21.9%)

Teaching hospital [Number (%) of hospitals]

114 (6.6%)

15,769 (23.5%)

Rural/urban location [Number (%) of hospitals]

*

*

Urban

608 (34.9%)

44,561 (66.4%)

Suburban

88 (5.1%)

992 (1.5%)

Large town

390 (22.4%)

13,198 (19.7%)

Small town

455 (26.1%)

6,522 (9.7%)

Rural

200 (11.5%)

1,865 (2.8%)

This table displays MAX cohort hospital characteristics, including the number and frequency of children's hospitals, teaching hospitals, and a breakdown by location.

*Cell intentionally left empty

5.1.4 Characteristics of Units of the Eligible Population

Table 6 □ MAX Cohort Patient Characteristics (Total N = 67,191)

Patient Characteristic

*

Number (%) of Index Hospitalizations

Age

< 1 year

33,175 (49.4)

*

1 to < 5 years

24,715 (36.8)

*

5 to < 8 years

4,501 (6.7)

*

8 to <12 years

2,544 (3.8)

*

12 to < 18 years

2,257 (3.4)

Gender

Female

29,008 (43.2)

Chronic Condition Indicators (CCIs)

CCI 1 - Infectious and parasitic disease

27 (0.04)

*

CCI 2 - Neoplasms

224 (0.3)

*

CCI 3 - Endocrine, nutritional, and metabolic diseases and immunity disorders

1,762 (2.6)

*

CCI 4 - Diseases of blood and blood-forming organs

2,464 (3.7)

*

CCI 5 - Mental disorders

1,620 (2.4)

*

CCI 6 - Diseases of the nervous system and sense organs

2,586 (3.8)

*

CCI 7 - Diseases of the circulatory system

1,115 (1.7)

*

CCI 8 - Diseases of the respiratory system

18,377 (27.4)

*

CCI 9 - Diseases of the digestive system

2,756 (4.1)

*

CCI 10 - Diseases of the genitourinary system

123 (0.2)

*

CCI 12 - Diseases of the skin and subcutaneous tissue

213 (0.3)

*

CCI 13 - Diseases of the musculoskeletal system

246 (0.4)

*

CCI 14 - Congenital anomalies

3,798 (5.6)

*

CCI 15 - Certain conditions originating in the perinatal period

27 (0.04)

*

CCI 16 - Symptoms, signs, and ill-defined conditions

114 (0.2)

*

CCI 17 - Injury and poisoning

6 (0.01)

*

CCI 18 - Factors influencing health status and contact with health services

1,924 (2.9)

CCI count

0 or 1 body system

60,576 (90.1)

*

2 body systems

4,204 (6.3)

*

3 body systems

1,567 (2.3)

*

4+ body systems

844 (1.3)

Race/ethnicity

Asian/Pacific Islander

861 (1.4)

*

Black

14,051 (22.6)

*

Latino

19,444 (31.2)

*

Mixed

520 (0.8)

*

Native American

3,403 (5.5)

*

White
24,010 (38.6)
Rural/urban residence
Urban
37,235 (55.6)
*
Suburban
4,839 (7.2)
*
Large town
11,867 (17.7)
*
Small town
7,899 (11.8)
*
Rural
5,109 (7.6)

This table displays MAX cohort patient characteristics, including the number and frequency of index hospitalizations by age, gender, CCI category, CCI count, race/ethnicity, and rural/urban residence.

*Cell intentionally left empty

5.2.1 Level(s) of Reliability Testing Conducted

Accountable entity level (i.e., measure score) (e.g., signal-to-noise analysis)

5.2.2 Method(s) of Reliability Testing

We evaluated the reliability of hospital-level readmission rates using the following formula:

$$\text{Reliability} = \sigma^2 / (\sigma^2 + V)$$

where σ^2 is the systematic variance among hospitals and V is the sampling variance of the sample estimate of a hospital's rate (both on the probability scale):

- $\sigma^2 = \sigma_L^2 * p^2 * (1-p)^2$

where σ_L^2 = variance component from model output in logit scale

- $V = p * (1-p) / N$,

where p = the overall readmission rate across all hospitals and N = the hospital's volume

5.2.3 Reliability Testing Results

Using the MAX dataset, we found that among the 1,743 total hospitals, 229 hospitals had a readmission rate reliability ≥ 0.5 ; these hospitals accounted for 62% of total LRI index hospitalizations. The readmission rate reliability was ≥ 0.7 for 70 hospitals, accounting for 35% of total LRI index hospitalizations.

Because hospitals with few pediatric patients would be less likely to participate in measuring pediatric readmissions, we evaluated readmission rate reliability for hospitals meeting selected minimum thresholds of pediatric all-condition and LRI index hospitalizations per year. We determined that among the 539 hospitals with ≥ 100 annual index hospitalizations for any condition and ≥ 25 annual LRI index hospitalizations, readmission rate reliability was ≥ 0.5 for 229 hospitals, accounting for 74% of the LRI index hospitalizations at hospitals in this volume category. Readmission rate reliability was ≥ 0.7 for 70 hospitals, accounting for 42% of LRI index hospitalizations at hospitals in this volume category.

We found that among the 179 hospitals with ≥ 500 annual index hospitalizations and ≥ 25 annual LRI index hospitalizations, readmission rate reliability was ≥ 0.5 for 146 hospitals, accounting for 95% of the LRI index hospitalizations at hospitals in this volume category. Readmission rate reliability was ≥ 0.7 for 69 hospitals, accounting for 67% of LRI index hospitalizations at hospitals

in this volume category.

5.2.4 Interpretation of Reliability Results

Reliability values range from 0 to 1. If perfect information from a very large sample were available for a hospital, so the hospital's random effect could be determined with perfect precision, then the reliability of that hospital's readmission rate would approach 1. If no information were available for a hospital, then the reliability of that hospital's readmission rate would be 0.

We found that among the 179 hospitals with ≥ 500 annual index hospitalizations and ≥ 25 annual LRI index hospitalizations, readmission rate reliability was ≥ 0.5 for 146 hospitals, accounting for 95% of the LRI index hospitalizations at hospitals in this volume category. Readmission rate reliability was ≥ 0.7 for 69 hospitals, accounting for 67% of LRI index hospitalizations at hospitals in this volume category.

Table 2. Accountable Entity Level Reliability Testing Results by Denominator, Target Population Size

	Accountable Entity-Level Reliability Testing Results			
	Overall	Minimum	Decile_1	Decile_2
Reliability	N/A	N/A	N/A	N/A
Mean Performance Score	N/A	N/A	N/A	N/A
N of Entities	N/A	N/A	N/A	N/A

5.3.1 Level(s) of Validity Testing Conducted

Accountable entity level (i.e., measure score) (e.g., criterion validity)

5.3.3 Method(s) of Validity Testing

CONSTRUCT VALIDITY

As detailed in Section 1a.2.1 of the Evidence form, many studies have provided evidence that readmission rates serve as a measure of healthcare quality. Use of approaches to diagnosis, treatment, and monitoring of disease that adhere to clinical practice guidelines has been correlated with lower readmission rates.¹⁻³ Likewise, improvements in the quality of clinical management have been associated with reductions in readmissions.⁴⁻⁶ Readmission rates have also been found to reflect the quality of discharge and care transition processes. Several studies, mostly in adults, have demonstrated that interventions focused on improving these processes have been linked with decreased readmissions, suggesting that the quality of these processes is associated with readmission risk.^[1-20]

Although the medical literature provides ample evidence for the relationship between quality of care and pediatric and adult readmission risk, assessing the construct validity of pediatric readmission rates directly by examining the correlation of rates with other pediatric measures of quality does not appear to be currently feasible. To perform this analysis, pediatric inpatient

claims-based quality measures or large, multi-hospital datasets of scores from pediatric quality measures would be required. However, to our knowledge, no other publicly available claims based pediatric inpatient quality measures exist, including among the Healthcare Effectiveness Data and Information Set (HEDIS) measures, the CHIPRA Initial Core Set of Children's Health Care Quality Measures, and other measure collections that we examined. There also do not appear to be large datasets with scores from pediatric inpatient quality measures.

CRITERION VALIDITY

We evaluated the ability of our measure to identify the outcome of interest, readmission, from administrative data by comparing the measure's performance against the gold standard of chart reviews. We performed this analysis using administrative data and electronic health records for patients admitted to Boston Children's Hospital over a 1-year period (see Section 1.7 above for a summary of patient characteristics). We determined from the administrative data that 8,833 index hospitalizations occurred during this time period. We then identified hospitalizations that met measure criteria for readmissions (i.e., the readmissions were not for a planned procedure or chemotherapy) in 2 ways: (1) analysis of the administrative data using the measure program and (2) review of electronic health records. We assessed the health records by first examining whether each index hospitalization was followed by a readmission within 30 days based on presence of inpatient admission orders (such an order is entered for every hospitalization). We then reviewed clinical documentation, including admission notes, discharge summaries, and procedure notes, for 500 randomly selected readmissions to determine whether the readmission had been for a planned procedure or chemotherapy. The results of our analysis of criterion validity are provided in response to item 2b.03.

VALIDITY OF PLANNED PROCEDURE ALGORITHM

We also verified the face validity of the planned procedure algorithm used to identify hospitalizations for planned procedures. We sought public comments on the algorithm in a Federal Register Notice.^[21] No comments were submitted to suggest that procedures be removed from the list of planned procedures because they are not typically planned or are not a reason for hospitalization. Twenty-four procedures were submitted with the suggestion that they be added to the list of planned procedures. Of these, 7 were already included on the planned procedure list; our expert clinicians in 3 relevant specialties reviewed the remaining 17 procedures. Most of the remaining codes were for procedures for which patients are not hospitalized. Based on the experts' review, however, 2 procedures, both organ transplantation procedures, were added to the planned procedure list. These transplantation procedures originally had been excluded because they did not meet our operational definition of "planned" (i.e., scheduled at least 24 hours in advance), but it was agreed that they should be added as a special case of procedures for which the need is typically known in advance, even though the actual operation occurs urgently once an organ becomes available. For the same reason, 9 other transplantation procedures were also added to the planned procedure list.

IDENTIFICATION OF INTERNATIONAL CLASSIFICATION OF DISEASES, 10TH REVISION (ICD-10) CODES

To identify ICD-10 codes for chronic conditions, mental health conditions, and obstetric conditions, we used AHRQ's ICD-10 version of its Chronic Condition Indicator tool. For all other codes used in the measure, we obtained ICD-10 codes by performing conversions from the ICD-9 codes we had selected during measure development. Our goal for the conversions was to compile an ICD-10 code set that was fully consistent with the intent of the original ICD-9 set. We carried out the conversions using the 3M™ Code Translation Tool and reviewed all conversions to ensure that the resulting ICD-10 codes captured the intended concepts, removing ICD-10 codes from the code set as appropriate. This ICD-10 code set has been updated periodically, most recently in 2022.

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5.3.4 Validity Testing Results

We evaluated the validity of the measure's case-mix adjustment model by assessing the

discriminative ability of the model using the concordance (c-) statistic. Discrimination refers to how well the model distinguishes between subjects with and without the outcome (in this case, readmission). The c-statistic is a unitless measure of the probability that a randomly selected subject who experienced readmission will have a higher predicted probability of having been readmitted than a randomly selected subject who did not experience readmission. The c-statistic for our case-mix adjustment model, when applied to our 26-state MAX dataset, was 0.71, which is very much in range with results for other 30-day readmission models.

5.3.5 Interpretation of Validity Results

The measure is able to identify eligible readmissions from administrative data with high sensitivity and specificity.[1-4] We found face validity for our planned procedure algorithm.

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5.4.1 Methods Used to Address Risk Factors

Statistical risk adjustment model with risk factors

5.4.2 Conceptual Model Rationale

Readmissions signal how well disease is managed in hospital and home settings. Care management at home is influenced by health-related social needs. The conceptual model presented (adapted from Zumbrunn et al¹) identifies patient risk factors (e.g., age, chronic condition) and social risk factors (e.g., child and family health literacy, neighborhood and community resources) that influence possibility of readmission.

References

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5.4.2a Attach Conceptual Model

[conceptual_model.docx_.zip](#)

5.4.3 Variable Distribution Across Measured Entities

There were 1,738,043 records for pediatric patients (those ≤ 18 years, 29 days old on admission) in the MAX dataset with discharge dates from December 1, 2007 to December 31, 2008. We provide below the number and percentage of records for pediatric patients excluded because they met the indicated exclusion criteria for the measure (i.e., these records were excluded *from both index hospitalizations and readmissions*):

1. The hospital was a specialty or non-acute care hospital: 212,593 (12.2%)
2. Records for the hospitalization contain incomplete data for variables needed to assess eligibility for the measure or calculate readmission rates, including hospital type, patient identifier, admission date, discharge date, disposition status, date of birth, primary diagnosis code, or gender: 174,724 (10.0%)
3. The hospitalization was for birth of a healthy newborn: 599,419 (34.5%)
4. The hospitalization was for obstetric care, including labor and delivery: 56,281 (3.2%)
5. The primary diagnosis code was for a mental health condition: 25,459 (1.5%)
6. Information for some hospitalizations is contained in multiple records. These records were combined into a single record for each hospitalization, reducing the total number of records: 142,720 (8.2%)

We indicate below the number and percentage of records excluded from *index hospitalizations only* because they met the indicated exclusion criteria for index hospitalizations:

1. The patient was 18 years old or greater at the time of discharge: 984 (0.1%)
2. The discharge disposition was death: 11 (0.001%)
3. The discharge disposition was an outcome other than discharged or death (e.g., left against medical advice): 7,976 (0.5%)
4. The hospital had incomplete data or was located in a state not being analyzed: 15,038 (0.9%)
5. Thirty days of follow-up data are not available for assessing readmissions because the discharge date of the hospitalization occurred in the last month of the dataset: 18,614 (1.1%)
6. Thirty days of follow-up data are not available for assessing readmissions because the patient was enrolled in Medicaid for < 30 days after discharge from the index

hospitalization: 60,220 (3.5%)

7. A hospitalization that occurs within 30 days of an index hospitalization was not counted as a new index hospitalization: 2,128 (0.1%)

8. The hospitalization does not have a primary LRI diagnosis or does not have a

secondary LRI diagnosis plus a primary diagnosis of asthma, respiratory failure, or

sepsis/bacteremia: 354,685 (20.4%)

After applying all of the above exclusions, 67,191 index hospitalizations remained for patients whose characteristics are described in the table below.

Table 2 □ MAX Cohort Patient Characteristics (Total N = 67,191)

Patient Characteristic

Number (%) of Index Hospitalizations

Age

< 1 year

33,175 (49.4)

1 to < 5 years

24,715 (36.8)

5 to < 8 years

4,501 (6.7)

8 to <12 years

2,544 (3.8)

12 to < 18 years

2,257 (3.4)

Gender

Female

29,008 (43.2)

Chronic Condition Indicators (CCIs)

CCI 1 - Infectious and parasitic disease

27 (0.04)

CCI 2 - Neoplasms

224 (0.3)

CCI 3 - Endocrine, nutritional, and metabolic diseases and immunity disorders

1,762 (2.6)

CCI 4 - Diseases of blood and blood-forming organs

2,464 (3.7)

CCI 5 - Mental disorders

1,620 (2.4)

CCI 6 - Diseases of the nervous system and sense organs

2,586 (3.8)

CCI 7 - Diseases of the circulatory system

1,115 (1.7)

CCI 8 - Diseases of the respiratory system

18,377 (27.4)

CCI 9 - Diseases of the digestive system

2,756 (4.1)

CCI 10 - Diseases of the genitourinary system

123 (0.2)

CCI 12 - Diseases of the skin and subcutaneous tissue

213 (0.3)

CCI 13 - Diseases of the musculoskeletal system

246 (0.4)

CCI 14 - Congenital anomalies

3,798 (5.6)

CCI 15 - Certain conditions originating in the perinatal period

27 (0.04)

CCI 16 - Symptoms, signs, and ill-defined conditions

114 (0.2)

CCI 17 - Injury and poisoning

6 (0.01)

CCI 18 - Factors influencing health status and contact with health services

1,924 (2.9)

CCI count

0 or 1 body system

60,576 (90.1)

2 body systems

4,204 (6.3)

3 body systems

1,567 (2.3)

4+ body systems

844 (1.3)

Race/ethnicity

Asian/Pacific Islander

861 (1.4)

Black

14,051 (22.6)

Latino

19,444 (31.2)

Mixed

520	(0.8)
Native American	
3,403	(5.5)
White	
24,010	(38.6)
Rural/urban residence	
Urban	
37,235	(55.6)
Suburban	
4,839	(7.2)
Large town	
11,867	(17.7)
Small town	
7,899	(11.8)
Rural	
5,109	(7.6)

The distribution by state of the LRI index hospitalizations is shown in the table below.

Table 3 □ LRI Index Hospitalizations by State (Total N=67,191)

State**Index Admissions****Percentage**

Alabama

1,337

2.0%

Arizona

4,837

7.2%

Connecticut

119

0.2%

Iowa

1,283

1.9%

Idaho

719

1.1%

Indiana

1,931

2.9%

Kansas

1,662

2.5%

Kentucky

2,184

3.2%

Louisiana

4,776

7.1%

Minnesota

1,332

2.0%

Missouri

3,207

4.8%

Mississippi

4,201

6.2%

Montana

404

0.6%

North Carolina

4,465

6.6%

North Dakota

248

0.4%

New Jersey

2,283

3.4%

New Mexico

1,486

2.2%

New York

7,369

11.0%

Oklahoma

3,733

5.6%

Oregon

841

1.2%

South Dakota

642

1.0%

Texas

14,376

21.4%

Virginia

1,643

2.4%

Vermont

126

0.2%

Wisconsin

1,533

2.3%

Wyoming

454

0.7%

5.4.4 Risk/Case-Mix Adjustment Modeling and/or Stratification Results

Age

We found that age had a non-linear statistically significant relationship with 30-day readmission in both bivariate and multivariate analysis (see Table 5). The final specification for age is detailed below. We chose the specification because (a) the categorical variable captures the non-linear relationship of age with the outcome of readmission, (b) the specification has a high likelihood ratio chi-square relative to other less parsimonious specifications, and (c) the age group categories are clinically and developmentally meaningful.

Table 8 □ Bivariate and Multivariate Results for Age

Age (*agegroup*)

Bivariate Analysis

Multivariate Analysis

Likelihood ratio 139.70

OR

p-value

OR

p-value

1 = 0 ≤ age < 1

reference

*

reference

*	
2 = 1 ≤ age < 5	
0.70	
< .001	
0.62	
< .001	
3 = 5 ≤ age < 8	
0.55	
< .001	
0.42	
< .001	
4 = 8 ≤ age < 12	
0.74	
.001	
0.45	
< .001	
5 = 12 ≤ age < 18	
1.10	
.26	
0.59	
< .001	

This table displays the bivariate and multivariate results in terms of odds-ratios by age group.

*Cell intentionally left empty

Gender

We found that male gender was significantly associated with increased odds of readmission in

bivariate and multivariate analysis (see Table 6) and therefore retained the variable in our model.

Table 9 □ Bivariate and Multivariate Results for Gender

Gender (*male*)

Bivariate Analysis

Multivariate Analysis

Likelihood ratio 19.72

OR

p-value

OR

p-value

0 = female

reference

*

reference

*

1 = male

1.15

< .001

1.14

< .001

This table displays the bivariate and multivariate results in terms of odds-ratios by gender.

*Cell intentionally left empty

Chronic Conditions

To account for chronic disease comorbidity, we used the AHRQ CCI tool to classify ICD-9-CM diagnosis codes for chronic conditions into 18 body systems (organ systems, disease categories, or other categories). We created a dichotomous variable for each body system, with a value of 1 if ≥ 1 chronic condition was present (coded as a primary or secondary diagnosis for an index hospitalization) in that body system or 0 if no chronic condition was present in that body system. We examined each of the 18 CCI variables in relation to the outcome of readmission in bivariate and multivariate analysis, using absence of a chronic condition in the body system in question as the reference.

We found that 12 of the 18 dichotomous variables were significantly related to readmission in bivariate analysis and 11 of the 18 were significantly related in multivariate analysis.

We chose to retain all but the CCI for body system 11, “Complications of pregnancy, childbirth, and the puerperium,” in the final model (a) to maintain, to the extent possible, the coherence of the complete AHRQ CCI tool, (b) because most of the CCI variables had a statistically significant relationship with the outcome of readmission, and (c) for harmonization with our Pediatric All-Condition Readmission Measure. Patients who have a primary diagnosis code for an obstetric condition or any diagnosis or procedure code for delivery are excluded from the measure cohort. 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 within body system 11, which could create model-fitting problems if CCI 11 were included in the case-mix-adjustment model.

Table 10 ■ Bivariate and Multivariate Results for CCIs

CCI (*cci*)

Bivariate

Multivariate

Likelihood ratio range: 0.19 (*cci1*) to 340.07 (*cci14*)

OR

p-value

OR

p-value

1

Infectious and parasitic disease

1.41

.64

1.19

0.82

2

Neoplasms

2.26

< .001

2.75

< .001

3

Endocrine, nutritional, and metabolic diseases and immunity disorders

2.34

< .001

2.19

< .001

4

Diseases of blood and blood-forming organs

1.40

< .001

1.66

< .001

5

Mental disorders

1.95

< .001

1.51

< .001

6

Diseases of the nervous system and sense organs

3.00

< .001

2.49

< .001

7

Diseases of the circulatory system

2.49

< .001

1.79

< .001

8

Diseases of the respiratory system

0.92

.03

1.18

< .001

9

Diseases of the digestive system

2.55

< .001

2.05

< .001

10

Diseases of the genitourinary system

3.79

< .001

2.43

< .001

11

Complications of pregnancy, childbirth, and the puerperium

No cases

No cases

No cases

No cases

12

Diseases of the skin and subcutaneous tissue

1.53

.09

1.44

.17

13

Diseases of the musculoskeletal system

1.69

.01

1.08

.76

14

Congenital anomalies

2.82

< .001

2.23

< .001

15

Certain conditions originating in the perinatal period

1.72

.38

1.24

.73

16

Symptoms, signs, and ill-defined conditions

0.43

.15

0.34

.07

17

Injury and poisoning

3.61

.25

1.70

.67

18

Factors influencing health status and contact with health services

3.50

< .001

2.51

< .001

This table displays the bivariate and multivariate results in terms of odds-ratios by CCI category.

Number of body systems affected by chronic conditions

We also evaluated a count variable of the number of body systems in which a chronic condition was present for each index hospitalization. To avoid problems with model estimation, we top-coded the variable at ≥ 4 systems affected by a chronic disease because there were few index admissions with diagnoses in ≥ 5 systems.

The CCI count variable had a statistically significant relationship with readmission in bivariate and multivariate analysis. In multivariate analysis, an increasing count was associated with decreasing odds of readmission. This finding indicates that the presence of chronic conditions in multiple body systems confers a readmission risk that is lower than the sum of the risk of chronic conditions in each of the individual body systems, such that the CCI count variable serves to prevent overestimation of the risk associated with having chronic conditions in multiple body systems. We chose to retain *cci count* as an ordinal variable based on (a) its statistically significant relationship with the outcome of readmission and (b) because it adjusts the readmission risk associated with having chronic conditions in multiple body systems.

Table 11 ■ Bivariate and Multivariate Results for CCI Count

CCI Count (*cci count*)

Bivariate

Multivariate

Likelihood ratio 547.89

OR

p-value

OR

p-value

1 = 0 to 1

reference

*

reference

*

2 = 2

2.46

< .001

0.93

< .001

3 = 3

3.65

< .001

0.74

< .001

4 = 4 or more

4.45

< .001

0.40

< .001

This table displays the bivariate and multivariate results in terms of odds-ratios by CCI count.

*Cell intentionally left empty

5.4.4a Attach Risk/Case-mix Adjustment Modeling and/or Stratification Specifications

[Pediatric Lower Respiratory Infection Readmission Measure ICD-10 Data Dictionary.xlsx](#)

5.4.5 Calibration and Discrimination

We assessed the discriminative ability of the model using the c-statistic.[1,2] Discrimination refers to how well the model distinguishes between subjects with and without the outcome (in this case, readmission).[1] The c-statistic is a unitless measure of the probability that a randomly selected subject who experienced readmission will have a higher predicted probability of having been readmitted than a randomly selected subject who did not experience readmission.[1] The c-statistic for our case-mix adjustment model, when applied to the MAX dataset, was 0.71.

We assessed model calibration with a chi-square goodness-of-fit test analogous to the Hosmer-Lemeshow test.[3] We used the test, which evaluates how well observed outcomes correspond to those predicted by the fitted logistic regression model,[3] to determine how well observed and predicted numbers of readmissions matched for the levels of the 2 ordinal variables in our case-mix adjustment model, age and CCI count. The lack of a significant difference between observed and predicted values indicates good model calibration.

When we stratified records by age categories, the p-value for the chi-square goodness-of-fit test was not significant ($p = .56$). When we stratified records by categories of the number of body systems affected by chronic conditions, the p-value for the chi-square goodness-of-fit test also was not significant ($p = .32$).

The discriminative ability of the case-mix adjustment model is good, with a c-statistic that is very similar to that of other 30-day readmission measures.[4-6] The model calibration is also good, with a close match between observed and predicted numbers of readmissions.

5.4.5a Attach Calibration and Discrimination Testing Results

[LRI calibration_discrimination_0.pdf](#)

5.4.6 Interpretation of Risk/Case-mix Factor Findings

This submission was drafted prior to this field being created. Not Applicable.

5.4.7 Final Approach to Address Risk Factors

Other

5.4.7a Other Methods Used

This submission was drafted prior to this field being created. Not Applicable.

6.1.3 Current Use(s)

Public Health/Disease Surveillance, Payment Program, Quality Improvement with Benchmarking (external benchmarking to multiple organizations), Quality Improvement (Internal to the specific organization)

6.1.3 Program Details

Name of the program and sponsor

New York State Department of Health

URL of the program

<https://www.health.ny.gov/>

Purpose of the program

We partnered with the New York Office of Quality and Patient Safety to test implementation of our pediatric lower respiratory infection readmission measure on its Medicaid and all-payer inpatient claims databases.

Geographic area and percentage of accountable entities and patients included

New York State children

Applicable level of analysis and care setting

Hospital-level inpatient setting.

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Name of the program and sponsor

MassHealth

URL of the program

<https://www.mass.gov/topics/masshealth>

Purpose of the program

We partnered with MassHealth to test implementation of our pediatric lower respiratory infection readmission measure on its Medicaid claims databases.

Geographic area and percentage of accountable entities and patients included

Massachusetts children on Medicaid

Applicable level of analysis and care setting

Hospital-level inpatient setting.

6.2.1 Actions of Measured Entities to Improve Performance

Measuring readmission rates among Medicaid-insured patients is particularly important because multiple analyses have demonstrated that they are at higher risk of readmission than privately-insured patients. An analysis of the 2007 Healthcare Cost and Utilization Project State Inpatient Databases for 10 states found that the 30-day readmission rate for pediatric Medicaid

beneficiaries (ages 0 to 20 years old, including newborns but excluding obstetric patients) was 3.1%, compared with 2.0% for privately-insured children ($p < 0.05$). Readmission rates were higher for Medicaid-insured patients than for their privately-insured counterparts in every age and gender category except for the subcategory of 13- to 20-year-old females admitted for obstetric care.¹ An analysis using our candidate measure also found that compared with Medicaid-insured children, children with private insurance (odds ratio (OR) 0.76 [95% confidence interval (CI) 0.75 to 0.78], $p < 0.001$); other types of insurance, such as Medicare or other government-sponsored insurance (OR 0.85 [95% CI 0.78 to 0.92], $p < 0.001$); or self-pay status (OR 0.73 [95% CI 0.69 to 0.78], $p < 0.001$) are at lower risk of LRI readmission.

Given their higher risk of readmission, Medicaid-insured children are a vulnerable population for whom targeted interventions to reduce readmissions are especially critical. Interventions that reduce hospital readmission rates by improving hospital discharge, transition and post-discharge care as well as disease management should be beneficial to all patients, including those insured by Medicaid. Interventions that specifically address the complex needs of Medicaid-insured patients may be particularly effective in reducing readmission rates in this group.

The impact of insurance type on LRI-related readmissions has not been studied specifically, and interventions to reduce readmission rates targeted specifically for Medicaid beneficiaries with LRIs have not yet been reported. However, interventions that have effectively reduced readmission rates for other conditions in Medicaid-insured patients could also be effective in preventing readmission for LRIs.

The Care Transitions Innovation (C-TraIn) is a low-cost, multi-component transitional care intervention that has decreased readmission rates in uninsured and Medicaid-insured populations.² The intervention helps remove financial barriers to care by providing inpatient pharmacy consultation, a 30-day supply of medications for use after discharge, payment for medical homes for uninsured patients who lack access to outpatient care, and access to a transitional care nurse to bridge care between the inpatient and outpatient settings. This low-cost intervention illustrates how investing a relatively small amount of resources upfront could potentially avert the much greater cost of hospital readmission.

North Carolina has demonstrated that interventions implemented via a Medicaid program can be highly effective in reducing readmissions. Its state-wide initiative focused on comprehensive transitional care for Medicaid beneficiaries with complex chronic medical conditions, with the intensity of the intervention tailored to patients' readmission risk.³ Patients who received the intervention were 20% less likely to experience a readmission during the subsequent year than clinically similar patients who received routine care. Additionally, patients who received the transitional care were less likely than routine-care patients to experience multiple readmissions. These findings suggest that transitional care interventions targeted to address the particular

needs of Medicaid-insured patients can reduce hospital readmissions among this high-risk population. A pediatric readmission measure could be used to track the impact of similar interventions in Medicaid-insured children after hospitalization for LRI.

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6.2.2 Feedback on Measure Performance

Feedback from two states on their testing experiences indicated that the measure is straightforward and can be implemented quickly. Based on helpful suggestions from the states, we improved the clarity of the detailed measure specifications, particularly with regard to use of certain ICD-9-CM codes for applying clinical exclusions and identifying chronic conditions for case-mix adjustment.

6.2.3 Consideration of Measure Feedback

Testing the measure on the states' databases also illustrated potential model-fitting issues that may result when a variable has a very rare value. We have revised the specification of case-mix variables to help avoid these model-fitting issues and included guidance in the detailed measure specifications for evaluating and troubleshooting such issues.

6.2.4 Progress on Improvement

POTENTIAL FOR LRI QUALITY IMPROVEMENT

As mentioned above in Section 1b.03, studies have shown hospital-level variation in pediatric readmission rates for LRI, suggesting there is potential for improvement in the quality of LRI care. One study found significant variation among children's hospitals in 3-day pediatric bronchiolitis readmission rates, which ranged from 0% to 2.7% ($p < .001$).¹ Another study of children's hospitals found significant variation in risk-adjusted 30-day readmission rates for admission diagnoses of bronchiolitis and pneumonia.²

Effective interventions to reduce LRI readmissions have been demonstrated.³⁻⁵ For bronchiolitis, for example, implementation of a clinical pathway with management and discharge criteria significantly reduced 14-day readmission rates.³ For pneumonia, improvements during hospitalization in use of recommended antibiotics, communication of discharge information to patients, and use of electronic medical records have reduced readmission rates.⁶⁻⁷

Unplanned readmissions following hospitalization for LRI care are commonly for complications of the original disease. Interventions aimed at preventing these complications when possible, or better managing them when they occur, could potentially reduce readmissions. The most common complications for bronchiolitis are asthma and other chronic respiratory problems.⁸⁻⁹ Neurologic conditions are increasingly frequent complications of influenza.¹⁰⁻¹² Local complications of pneumonia, such as empyema, lung abscess, and necrotizing pneumonia, are becoming more prevalent, particularly in younger children.¹²⁻¹³

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6.2.5 Unexpected Findings

No unintended negative consequences were identified during implementation.

Measure Developer POC

United States

Measured/accountable entity (reliability and/or validity) methodology and results (if available)

Measured entity (reliability and validity) methodology and results (if available)

Responder for Survey

Patient

Specify number of risk factors

20 fixed effect variables representing 4 types of risk factors.

The measure developer is different from the measure steward

Yes

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