Partnership for Quality Measurement
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CBE ID

2879e

Title

Hybrid Hospital-Wide Readmission (HWR) Measure with Claims and Electronic Health Record Data

Project

Cost and Efficiency

Endorsement Status

Endorsed with Conditions

E&M Committee Rationale/Justification

After the endorsement meeting, the developer of CBE #2879e submitted an appeal due to the following rationale:

- *Misapplication of measure evaluation criteria.*

The appellant posited that:

- *Excessive weight was given to factors beyond criteria.*
- *EHR data elements are feasible and usable; endorsed in 2015. EHR data elements exist; no primary data collection needed.*
- *Empirical data support the 30-day readmission capture. Measure provides actionable information for quality improvement. Data shows improvement in readmission rates over time.*

The Appeals Committee voted to uphold the appeal. Therefore, the measures' s endorsement decision was overturned to Endorsed with Conditions. When the measure returns for maintenance (5 years), the measure developer should have:

- *Explored actionability of the measure with reporting entities (e.g., qualitative assessments, empirical analyses).*
- *Explored analyses to justify the 30-day time window (e.g., baseline rate, related diagnosis).*

Is Under Review

No

Next Maintenance Cycle

Fall 2029

Previous Endorsement Cycle

Fall 2024

Initial Endorsement

Fri, 12/09/2016 - 18:36

Steward

Centers for Medicare & Medicaid Services

1.0 New or Maintenance

Maintenance

1.1 Measure Structure

Single Measure

1.3 Electronic Clinical Quality Measure (eCQM)

Yes

1.6 Measure Description

Hybrid Hospital-Wide Readmission (HWR) Measure with Claims and Electronic Health Record Data measures facility-level risk-standardized rate of readmission (RSRR) within 30 days of discharge from an inpatient admission, among Medicare Fee-For-Service (FFS) and Medicare Advantage (MA) patients aged 65 years and older.

Index admissions are divided into five groups based on their reason for hospitalization (e.g., surgery/gynecology, general medicine, cardiorespiratory, cardiovascular, and neurology); the final measure score (a single risk-standardized readmission rate) is calculated from the results of these five different groups, modeled separately. Variables from administrative claims and electronic health records are used for risk adjustment.

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

Hospital readmission, for any reason, is disruptive to patients and caregivers, costly to the healthcare system, and puts patients at additional risk of hospital-acquired infections and complications. Readmissions are also a major source of patient and family stress and may contribute substantially to loss of functional ability, particularly in older patients.

Some readmissions are unavoidable and result from inevitable progression of disease or worsening of chronic conditions. However, readmissions may also result from poor quality of care or inadequate transitional care. Transitional care includes effective discharge planning, transfer of information at the time of discharge, patient assessment and education, and coordination of care and monitoring in the post-discharge period. Numerous studies have found an association between quality of inpatient or transitional care and early (typically 30-day) readmission rates for a wide range of conditions.[1-8]

Randomized controlled trials have shown that improvement in the following areas can directly reduce readmission rates: quality of care during the initial admission; improvement in communication with patients, their caregivers and their clinicians; patient education; predischarge assessment; and coordination of care after discharge.[9-24] Successful randomized trials have reduced 30-day readmission rates by 20-40%. Widespread application of these clinical trial interventions to general practice has also been encouraging. Since 2008,[32] Medicare Quality Improvement Organizations have been funded to focus on care transitions, applying lessons learned from clinical trials. Several have been notably successful in reducing readmissions within 30 days.[31] Evidence that hospitals have been able to reduce readmission rates through these quality-of-care initiatives illustrates the degree to which hospital practices can affect readmission rates.

Despite these isolated successful interventions, the overall national readmission rate remains high, with a 30-day readmission following nearly one fifth of discharges. Furthermore, readmission rates vary widely across institutions.[25-27] Both the high baseline rate and the variability across institutions speak to the need for a quality measure to prompt more concerted and widespread action.

Given that studies have shown readmissions within 30 days to be related to quality of care, that interventions have been able to reduce 30-day readmission rates for a variety of specific conditions, and that high and variable readmission rates indicate opportunity for improvement, it is reasonable to consider an all-condition 30-day readmission rate as a quality measure.

Core Clinical Data Elements (CCDE) are included in the Hybrid HWR measure to improve upon case-mix risk-adjustment, using only claims-based comorbidity information, by adding laboratory values and vital signs to reflect patients' clinical status at the start of inpatient encounter.

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1.11 Measure Webpage

https://qualitynet.cms.gov/inpatient/measures/hybrid/methodology

1.13 Data Dictionary

Not attached. I attest that all information will be provided where codes and/or value sets are needed (1.14a - 1.15c).

1.13a Attach Data Dictionary

2024_HWR_Final_Data Dictionary.xlsx

1.14 Numerator

The outcome for this measure is 30-day readmission. We define readmission as an inpatient admission for any cause, with the exception of certain planned readmissions, within 30 days from the date of discharge from an eligible index admission. If a patient has more than one unplanned admission (for any reason) within 30 days after discharge from the index admission, only one is counted as a readmission for calculating the measure.

1.14a Numerator Details

The outcome for this measure is 30-day readmission. We define readmission as an inpatient admission for any cause, with the exception of certain planned readmissions, within 30 days from the date of discharge from an eligible index admission. If a patient has more than one unplanned admission (for any reason) within 30 days after discharge from the index admission, only one is counted as a readmission for calculating the measure. The outcome is a dichotomous yes or no indicating if each admitted patient has an unplanned readmission within 30 days. However, if the first readmission after discharge is considered planned, any subsequent unplanned readmission is not counted as an outcome for that index admission because the unplanned readmission could be related to care provided during the intervening planned readmission rather than during the index admission.

The measure counts readmissions to an acute care hospital for any cause within 30 days of the date of discharge from the index admission, excluding planned readmissions as defined below.

<u>Planned Readmission Algorithm (Version 4.0)</u>

The planned readmission algorithm is a set of criteria for classifying readmissions as planned using Medicare claims and administrative data. The algorithm identifies admissions that are typically planned and may occur within 30 days of discharge from the hospital.

The planned readmission algorithm has three fundamental principles:

1. A few specific, limited types of care are always considered planned (transplant surgery, maintenance chemotherapy/immunotherapy, rehabilitation);

2. Otherwise, a planned readmission is defined as a non-acute readmission for a scheduled procedure; and,

3. Admissions for acute illness or for complications of care are never planned.

The algorithm was developed in 2011 during the development of this measure. The measure uses version 4.0 of the algorithm (released in 2015 and updated annually); the algorithm is reviewed yearly to address coding changes.

The planned readmission algorithm and associated code tables are attached (Data Dictionary). More details on the Planned Readmission Algorithm can be found in the Hybrid HWR Comprehensive Methodology Report, also attached.

1.15 Denominator

Admissions are included if all of the following criteria are met: Enrolled in Medicare fee-for-service (FFS) Part A or Medicare Advantage for the 12 months prior to the date of admission and during the index admission.Rationale: The 12-month prior enrollment criterion ensures that the comorbidity data used in risk adjustment can be captured from inpatient claims data in the 12 months prior to the index admission. Enrollment during the index admission is needed to qualify for the cohort and to ensure availability of data from the index admission for risk adjustment.Aged 65 or over.Rationale: Medicare beneficiaries younger than 65 are not included in the measure because they are considered to be too clinically distinct from Medicare beneficiaries who are 65 or older.Discharged alive from a non-federal short-term acute care hospital.Rationale: It is only possible for patients to be readmitted if discharged alive.Not transferred to another acute care facility.Rationale: Hospitalizations that result in a transfer to another acute care facility are not included in the measure because the measure’s focus is on admissions that result in discharge to a non-acute care setting (for example, to home or a skilled nursing facility).The measure aggregates the ICD-10 principal diagnosis and all procedure codes of the index admission into clinically coherent groups of conditions and procedures (condition categories or procedure categories) based on the v2019.1 Agency for Healthcare Research and Quality (AHRQ) Clinical Classification Software (CCS) beta maps. There are 285 mutually exclusive AHRQ condition categories, most of which are single, homogenous diseases such as pneumonia or acute myocardial infarction. Some are aggregates of conditions, such as “other bacterial infections.” There are also 231 mutually exclusive procedure categories.Using the AHRQ CCS procedure and condition categories, the measure assigns each index hospitalization to one of five mutually exclusive specialty cohorts: surgery/gynecology, cardiorespiratory, cardiovascular, neurology, and medicine. The rationale behind this organization is that conditions typically cared for by the same team of clinicians are expected to experience similar levels of readmission risk. Please see attached figure HWR Flow Diagram of Inclusion and Exclusion Criteria and Specialty Cohort Assignment for the Index Admission.

1.15a Denominator Details

Please see Figure 1 (in the attachment "HHWR Cohort Flow Chart") and Section 1.15b for an overview of cohort inclusions, and the attached data dictionary for further details that define the cohort.

Defining the Specialty Cohorts

The measure aggregates the ICD-10 principal diagnosis and all procedure codes of the index admission into clinically coherent groups of conditions and procedures (condition categories or procedure categories) based on the v2019.1 Agency for Healthcare Research and Quality (AHRQ) Clinical Classification Software (CCS) beta maps. There are about 300 mutually exclusive AHRQ condition categories, most of which are single, homogenous diseases such as pneumonia or acute myocardial infarction. Some are aggregates of conditions, such as “other bacterial infections.” There are also about 230 mutually exclusive procedure categories.

Please see Figure 1 for a flow chart that shows how admissions are assigned to specialty cohorts. Using the AHRQ CCS procedure and condition categories, the measure assigns each index hospitalization to one of five mutually exclusive specialty cohorts: surgery/gynecology, cardiorespiratory, cardiovascular, neurology, and medicine. The rationale behind this organization is that conditions typically cared for by the same team of clinicians are expected to experience similar levels of readmission risk.

The measure first assigns admissions with qualifying AHRQ procedure categories to the Surgical/Gynecological Cohort. This cohort includes admissions likely cared for by surgical or gynecological teams.

The measure then sorts admissions into one of the four remaining specialty cohorts based on the AHRQ diagnosis category of the principal discharge diagnosis:

The Cardiorespiratory Cohort includes several condition categories with very high readmission rates such as pneumonia, chronic obstructive pulmonary disease, and heart failure. These admissions are combined into a single cohort because they are often clinically indistinguishable, and patients are often simultaneously treated for several of these diagnoses.

The Cardiovascular Cohort includes condition categories such as acute myocardial infarction that in large hospitals might be cared for by a separate cardiac or cardiovascular team.

The Neurology Cohort includes neurologic condition categories such as stroke that in large hospitals might be cared for by a separate neurology team.

The Medicine Cohort includes all non-surgical patients who were not assigned to any of the other cohorts.

The full list of the specific diagnosis and procedure AHRQ CCS categories and ICD-10 codes used to define the specialty cohorts are attached in the Data Dictionary.

1.15b Denominator Exclusions

The measure excludes index admissions for patients who meet any of the following criteria:

1. Admitted to Prospective Payment System (PPS)-exempt cancer hospitals;

2. Without at least 30 days post-discharge enrollment in Medicare FFS or Medicare Advantage;

3. Discharged against medical advice (AMA);

4. Admitted for primary psychiatric diagnoses;

5. Admitted for rehabilitation;

6. Admitted for medical treatment of cancer; or,

7. Admitted with a principal or secondary diagnosis of COVID-19.

8. With less than 7 of 13 CCDE reported.

1.15c Denominator Exclusions Details

This measure excludes index admissions for patients:

1. Admitted to a Prospective Payment System (PPS)-exempt cancer hospital, identified by the Medicare provider ID.

Rationale: These hospitals care for a unique population of patients that cannot reasonably be compared to the patients admitted to other hospitals.

2. Without at least 30 days post-discharge enrollment in Medicare FFS, which is identified with enrollment data from the Medicare Enrollment Database (EDB).

Rationale: The 30-day readmission outcome cannot be assessed in this group since claims data are used to determine whether a patient was readmitted.

3. Discharged against medical advice (AMA) (identified using the discharge disposition indicator in claims data).

Rationale: Providers did not have the opportunity to deliver full care and prepare the patient for discharge.

4. Admitted for primary psychiatric disease, identified by a principal diagnosis in one of the specific AHRQ CCS categories listed in the attached data dictionary.

Rationale: Patients admitted for psychiatric treatment are typically cared for in separate psychiatric or rehabilitation centers which are not comparable to acute care hospitals.

5. Admitted for rehabilitation care, identified by the specific ICD-10 diagnosis codes included in CCS 254 (Rehabilitation care; fitting of prostheses; and adjustment of devices).

Rationale: These admissions are not typically admitted to an acute care hospital and are not for acute care.

6. Admitted for medical treatment of cancer, identified by the specific AHRQ CCS categories listed in the attached data dictionary.

Rationale: These admissions have a very different readmission profile than the rest of the Medicare population, and outcomes for these admissions do not correlate well with outcomes for other admissions.

7. With a principal or secondary diagnosis of COVID-19.

Rationale: Patients with a primary or secondary diagnosis of COVID-19 are excluded from the measure cohort in response to the COVID-19 Public Health Emergency.

8. Patients for whom less than 7 of 13 CCDE are reported.

Rationale: Patients for whom a large portion of CCDE is missing are excluded from the measure as their status upon hospital arrival would not be complete.

1.15d Age Group

Older Adults (65 years and older)

1.16 Type of Score

Rate/proportion

1.17 Measure Score Interpretation

Better performance = Lower score

1.18 Calculation of Measure Score

Below we provide the individual steps to calculate the measure score:

Define Cohort

1._Create five mutually exclusive specialty cohort using groups of related conditions or procedures. See Tab 1, "HWR Specialty Cohort Inclusions – Procedure and Diagnosis CCS Groups" of the data dictionary; and the inclusion/exclusion indicators.

2. Apply the inclusions/exclusions criteria to construct the measure cohort:

- Identify discharges meeting the inclusion criteria described in the denominator section above and assign to one of five specialty cohorts. Eligible discharges are from July 1-June 30 for any respective year.
- Exclude admissions meeting any of the exclusion criteria described in the exclusion section above, and patients for whom less than 7 of 13 CCDE are reported.

Define outcome

3. Derive the measure outcome of 30-day readmission, by identifying a binary flag for an unplanned hospital visit within 30 days of index admission as described above.

Define risk variables

4. Use patients' historical and index admission claims data, as well as CCDE values to create risk-adjustment variables. (Note: Risk variables from claims are based on secondary diagnoses with POA from index claims and all diagnosis codes from inpatient claims within one year prior to the index admission.)

Measure score calculation

5. For each specialty cohort group, estimate a separate hierarchical logistic regression model (HGLM) to produce a standardized risk ratio (SRR), calculated as the ratio of the number of "predicted" readmissions to the number of "expected" readmissions at a given hospital. The

HGLM is adjusted for age, selected clinical covariates, and a hospital-specific effect. Details about the risk-adjustment model can be found in the original measure development methodology report: https://www.qualitynet.org/inpatient/measures/readmission/methodology.

6. Pool each specialty cohort SRRs for each hospital using a volume-weighted geometric mean to create a hospital-wide SRR (or RSRR). Calculations can be found attached and posted at: https://www.qualitynet.org/inpatient/measures/readmission/methodology.

7. Use statistical bootstrapping to construct a 95% confidence interval estimate for each facility's RSRR. For more information about the measure methodology, please see the most recent Hybrid HWR Comprehensive Methodology Report attached and posted here: https://www.qualitynet.org/inpatient/measures/readmission/methodology.

1.18a Attach measure score calculation diagram

Measure Calculation Formulas.pdf

1.19 Measure Stratification Details

While the current measure is not yet stratified, the related claims-based measure has been stratified by dual eligibility, Area Deprivation Index, and race/ethnicity. For details on how the claims-based measure has been stratified, please see this report: https://qualitynet.cms.gov/files/663cf02ecc07c26dc84863bf?filename=2024….

We note that while not currently stratified by social risk factors, testing for future potential stratification by social risk factors is ongoing.

1.20 Types of Data Sources

Administrative Data, Claims Data, Electronic Health Records

1.25 Data Source Details

The components of this HWR measure, as specified in this CBE submission, are comprised of data from the following sources:

Cohort: Medicare fee-for-service claims and Medicare Advantage encounters; Medicare enrollment data.

Outcome: Medicare enrollment data

Risk adjustment: Medicare fee-for-service claims, Medicare Advantage encounters, supplemented with EHR data (core clinical data elements, or CCDE).

Feasibility of data collection is addressed in Section 3.1, "Feasibility".

Additional information on the data sources for this CBE submission can be found in Section 4.1 "Data and Samples" and in Table 7 of the Tables and Figures attachment.

1.26 Minimum Sample Size

There is no minimum sample size for the calculation of this measure.

2.1 Attach Logic Model

Hybrid HWR Logic Model.pdf

2.2 Evidence of Measure Importance

The hospital-wide risk-standardized readmission rate (RSRR) measure is intended to inform quality-of-care improvement efforts, as individual process-based performance measures cannot encompass all the complex and critical aspects of care within a hospital that contribute to patient outcomes. As a result, many stakeholders, including patient organizations, are interested in outcomes measures that allow patients and providers to assess relative outcomes performance for hospitals.

A hospital-wide readmission measure captures a large cohort of patients admitted for a wide range of diagnoses, and also illuminates a broad range of performance among hospitals. According to internal analyses, from July 1, 2018 to June 30, 2019, there were about 11 million inpatient admissions nationally among Medicare FFS and Medicare Advantage beneficiaries aged 65 and older at about 4,800 US hospitals. This comprehensive cohort is inclusive of patients not currently captured by existing condition-specific mortality measures and provides stakeholders with a broad quality signal (in addition to more granular data to support quality improvement). In addition to capturing an expansive cohort of patients, variation in hospital-level readmission rates demonstrates a quality gap: hospital-level readmission rates ranged widely, from 10.4% to 47.2% (using data from July 1, 2018-June 30, 2019). The average hospital-level, risk standardized 30-day readmission rate was 15.5%. Overall, studies have estimated the rate of preventable readmissions to be as low as 12% and as high as 76%.[18,19]

Randomized controlled trials demonstrate reduced readmission rates through the following: improvement of quality of care during the initial admission improvement in communication with patients, their caregivers, and their clinicians; patient education; pre-discharge assessment; and coordination of care after discharge. Evidence that hospitals have been able to reduce readmission rates through these quality-of-care initiatives illustrates the degree to which hospital practices can affect readmission rates. Successful randomized trials have reduced 30-day readmission rates by 20-40%.[1-13, 21-24] Since 2008, 14 Medicare Quality Improvement Organizations have been funded to focus on care transitions, applying lessons learned from clinical trials. Several have been notably successful in reducing readmissions. Hospital processes that reflect the quality of inpatient and outpatient care such as discharge planning, medication reconciliation, and coordination of outpatient care have also been shown to reduce readmission rates.[14.] Although readmission rates are also influenced by hospital system characteristics, such as the bed capacity or hospitalist and nurse staffing levels, these hospital characteristics should not influence quality of care.[15-17] Therefore, this measure does not risk adjust for such hospital characteristics.

While the cost of a readmission varies widely, a recent study estimated an average cost of about $16,000 USD per readmission. There were more than 11 million admissions captured by the (claims-based) HWR measure (using data from July 1, 2018 through June 30, 2019) and the mean readmission rate was about 15.4%, representing a conservative estimate of about $27 billion US dollars in expenditures for the unplanned readmissions captured by this measure alone.

The quality gap described above, together with evidence that readmissions are related to quality of care, and that interventions have been able to reduce 30-day readmission rates, supports an all-cause unplanned hospital-wide readmission measure for quality measurement.[19,20]

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2.4 Performance Gap

We refer readers to Section 1.18 for information on how performance scores are calculated.

As described in section 4.1.2, we provide results using a nationally representative dataset that includes both FFS and MA admissions and claims-based risk adjustment (but without the EHR-based data elements [CCDE] for enhanced case-mix risk adjustment), and separately, results from 2024 Voluntary Reporting (representing the measure as currently implemented, without Medicare Advantage (MA) admissions but with both the claims-based and clinical data elements from the EHR [CCDE] to enhance risk adjustment).

We characterize the degree of variation by reporting the distribution of RSRRs.

Measure Score Distribution

The distribution of measure scores from the Claims-Only HWR (Medicare FFS + MA) dataset and Hybrid HWR 2024 Voluntary Reporting dataset is shown below in Tables 2 and 3, and Figures 3 and 4 (please see "Hybrid HWR All Tables and Figures" attachment).

There is wide variation in measure scores in the national dataset (Claims Only HWR [Medicare FFS + MA]): RSRRs for the 4,782 hospitals in the dataset range from 10.37% to 47.22% with a mean of 15.48% (standard deviation, 1.28%); the 25th percentile is 14.79% and the 75th percentile is 16.06% (Table 2). There is meaningful variation in performance across hospitals: the worst performing facility (RSMR 11.60%) is performing about 89% worse than the median (6.11%), while the best performing facility (RSMR 1.52%) is performing 75% better than the median.

As expected, we see less variation in the 1,162 hospitals within the Hybrid HWR 2024 Voluntary Reporting dataset. We see less variation in this dataset due to the voluntary nature of public reporting, where we expect that better performers may be more likely to choose to report. As shown in Table 3, RSRRs ranged from 10.21% to 16.90%, with a mean of 14.29% (standard deviation, 0.59%). The 25th percentile was 13.97% and the 75th percentile was 14.58%.

In summary, the variation in rates, especially in the Claims-Only (Medicare FFS + MA) dataset, which is nationally representative suggests there are differences in the quality of care received across hospitals. This evidence supports continued measurement to reduce the variation.

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	15.48	10.37	13.53	14.40	14.78	15.05	15.29	15.49	15.74	16.08	16.57	17.92	47.22
N of Entities	4,782	1	478	478	478	479	478	478	479	478	478	478	1
N of Persons / Encounters / Episodes	11,029,470	3,802	1,321,954	1,160,299	899,771	701,058	735,186	681,808	969,925	1,256,604	1,445,531	1,857,334	1,416

2.6 Meaningfulness to Target Population

Hospital readmission, for any reason, is disruptive to patients and caregivers, costly to the healthcare system and policy holders, and puts patients at additional risk of hospital-acquired infections and complications. Readmissions are also a major source of patient and family stress and may contribute substantially to loss of functional ability and independence, particularly in older patients.[1] CORE interviewed patients and caregivers for a Technical Expert Panel (TEP) related to readmissions; patients and caregivers shared their stories of frustration, confusion, and suffering, as they or their loved ones faced unexpected returns to the hospital after discharge. In our interviews they cited experiences such as return to the hospital following exacerbation of a condition caused by changes in medication after discharge, returns to the hospital due to infection after an inpatient procedure, and other signs of poor coordination of care including insufficient communication from providers and hospital staff.

While some readmissions are unavoidable and result from inevitable progression of disease or worsening of chronic conditions, many readmissions may also result from poor quality of care or inadequate transitional care. Transitional care includes effective discharge planning, transfer of information at the time of discharge, patient assessment and education, and coordination of care and monitoring in the post-discharge period. Numerous studies have found an association between quality of inpatient or transitional care and early (typically 30-day) readmission rates for a wide range of conditions. [2-5] A study examined perspectives of patients, compared with registered nurses (RNs) and physicians, on the preventability of readmissions. Interestingly, the study found that compared with physicians, patients were more likely to identify a readmission as preventable, and patients were more likely than physicians to identify system issues as an underlying reason for their readmission (58% of cases vs 2%, respectively). Furthermore, RNs and patients had similar assessments as to the preventability of their readmission.[6]

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3.1 Contributions Towards Closing Care Gaps

Please see Social Risk Factors attachment.

Social Risk Factors

We weigh social risk factor adjustment using a comprehensive approach that evaluates the following:

• Well-supported conceptual model for influence of social risk factors on measure outcome (detailed below);

- Feasibility of testing meaningful social risk factors in available data: and
- Empiric testing of social risk factors.

Below, we summarize the findings of the literature review and conceptual pathways by which social risk factors may influence risk of the outcome, as well as the statistical methods for social risk factor empiric testing. Our conceptualization of the pathways by which patients' social risk factors affect the outcome is informed by the literature cited below and IMPACT Act–funded work by the National Academy of Science, Engineering and Medicine (NASEM) and the Department of Health and Human Services Assistant Secretary for Policy and Evaluation (ASPE 2016; ASPE 2020).

Causal Pathways for Social Risk Variable Selection

Although some recent literature evaluates the relationship between patient social risk factors and the readmission outcome, few studies directly address causal pathways or examine the role of the hospital in these pathways.[1, 2, 4, 7, 8, 11, 14, 17]Moreover, the current literature examines a wide range of conditions and risk variables with no clear consensus on which risk factors demonstrate the strongest relationship with readmission.

The social risk factors that have been examined in the literature can be categorized into three domains: (1) patient-level variables, (2) neighborhood/community-level variables, and (3) hospital-level variables.

Patient-level variables describe characteristics of individual patients and include the patient's income or education level.[8] Neighborhood/community-level variables use information from sources such as the ACS as either a proxy for individual patient-level data or to measure environmental factors. Studies using these variables use one dimensional measures such as median household income or composite measures such as the Area Deprivation Index (ADI).[12, 15, 16] Some of these variables may include the local availability of clinical providers.[5-6] Hospital-level variables measure attributes of the hospital which may be related to patient risk. Examples of hospital-level variables used in studies are ZIP code characteristics aggregated to the hospital level or the proportion of Medicaid patients served in the hospital.[3, 9-10]

The conceptual relationship, or potential causal pathways by which these possible social risk factors influence the risk of readmission following an acute illness or major surgery, like the factors themselves, are varied and complex. There are at least four potential pathways that are important to consider:

1. **Patients with social risk factors may have worse health at the time of hospital admission**. Patients who have lower income/education/literacy or unstable housing may have a worse general health status and may present for their hospitalization or procedure with a greater severity of underlying illness. These social risk factors, which are characterized by patient-level or neighborhood/community-level (as proxy for patient-level) variables, may contribute to worse health status at admission due to competing priorities (restrictions based on job), lack of access to care (geographic, cultural, or financial), or lack

of health insurance. Given that these risk factors all lead to worse general health status, this causal pathway should be largely accounted for by current clinical risk-adjustment.

2. **Patients with social risk factors often receive care at lower quality hospitals**. Patients of lower income, lower education, or unstable housing have inequitable access to high quality facilities, in part, because such facilities are less likely to be found in geographic areas with large populations of poor patients. Thus, patients with low income are more likely to be seen in lower quality hospitals, which can explain increased risk of readmission following hospitalization.
3. **Patients with social risk factors may receive differential care within a hospital**. The third major pathway by which social risk factors may contribute to readmission risk is that patients may not receive equivalent care within a facility. For example, patients with social risk factors such as lower education may require differentiated care (e.g. provision of lower literacy information – that they do not receive).
4. **Patients with social risk factors may experience worse health outcomes beyond the control of the health care system.** Some social risk factors, such as income or wealth, may affect the likelihood of readmissions without directly affecting health status at admission or the quality of care received during the hospital stay. For instance, while a hospital may make appropriate care decisions and provide tailored care and education, a lower-income patient may have a worse outcome post-discharge due to competing financial priorities which don't allow for adequate recuperation or access to needed treatments, or a lack of access to care outside of the hospital.

Although we analytically aim to separate these pathways to the extent possible, we acknowledge that risk factors often act on multiple pathways, and as such, individual pathways can be complex to distinguish analytically. Further, some social risk factors, despite having a strong conceptual relationship with worse outcomes, may not have statistically meaningful effects on the risk model. They also have different implications on the decision to risk adjust or not.

Based on this model and that the Area Deprivation Index (ADI) and dual-eligibility variables aim to capture the social risk factors that are likely to influence these pathways (income, education, housing, and community factors) - the following social risk variables were considered for risk-adjustment:

- Dual-eligible status: Dual eligibility for Medicare and Medicaid is available at the patient level in the Medicare Master Beneficiary Summary File. The eligibility threshold for over 65-year-old Medicare patients considers both income and assets. For the dual-eligible (DE) indicator, there is a body of literature demonstrating differential health care and health outcomes among beneficiaries.[18]
- High Area Deprivation Index (ADI): The ADI, initially developed by Health Resources & Services Administration (HRSA), is based on 17 measures across four domains: income, education, employment, and housing quality.[12, 16]

The 17 components are listed below:

- Population aged ≥ 25 y with < 9 y of education, %
- Population aged ≥ 25 y with at least a high school diploma, %
- Employed persons aged ≥ 16 y in white collar occupations, %
- Median family income, $

- Income disparity
- Median home value, $
- Median gross rent, $
- Median monthly mortgage, $
- Owner occupied housing units, % (home ownership rate)
- Civilian labor force population aged ≥16 y unemployed, % (unemployment rate)
- Families below poverty level, %
- Population below 150% of the poverty threshold, %
- Single parent households with children aged < 18 y, %
- Households without a motor vehicle, %
- Households without a telephone, %
- Occupied housing units without complete plumbing, % (log)
- Households with more than 1 person per room, % (crowding)

ADI scores were derived using beneficiary's 9-digit ZIP Code of residence, which is obtained from the Medicare Enrollment Database, and is linked to 2017-2021 US Census/American Community Survey (ACS) data. In accordance with the ADI developers' methodology, an ADI score is calculated for the census block group corresponding to the beneficiary's 9-digit ZIP Code using 17 weighted Census indicators. Raw ADI scores were then transformed into a national percentile ranking ranging from 1 to 100, with lower scores indicating lower levels of disadvantage and higher scores indicating higher levels of disadvantage. Percentile thresholds established by the ADI developers were then applied to ADI percentile to dichotomize neighborhoods into more disadvantaged (high ADI areas=ranking equal to or greater than 85) or less disadvantaged areas (Low ADI areas= ranking of less than 85).

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Social Risk Factors Summary

While our testing results (see below, and in the attachment of figures and tables) show that patients with social risk factors (DE or high ADI) have higher unadjusted rates of the outcome, we find that that the impact of each social risk factor on measure scores is minimal: measure scores calculated with and without each social risk factor are highly correlated, and differences between measure scores calculated with and without each social risk factor are small. These empiric results, together with the measure's use in a pay-for reporting (not pay for performance) program and CMS's desire to not mask disparities, support the decision to not adjust the measure for social risk factors. To better understand disparities related to readmission, CMS instead reports readmission measures stratified by social risk factors (DE, high ADI) and by race/ethnicity. For more information on the stratification approach, please see Section 1.19.

We note that the existing FFS-only, claims-only HWR measure has been stratified by DE, high ADI, and that while the current hybrid MA+FFS HWR measure is not currently stratified by social risk factors, testing for future potential stratification by social risk factors is ongoing.

Analysis #1: Variation in prevalence of the factor across measured entities in the Claims Only HWR (Medicare FFS and MA) dataset

The prevalence of social risk factors at hospital-level in the HWR cohort varies widely across hospitals (Table 16, "Hybrid HWR All Tables and Figures" attachment). In the Claims Only HWR (Medicare FFS and MA) dataset, the median percentage of dual-eligible patients was 15.8% (Interquartile Range [IQR]: 10.8%-23.3%) and the median percentage of patients with high ADI variable [score equal to or above 85] was 12.4% (IQR: 2.4%-30.8%).

Analysis #2: Observed outcome rates in patients with social risk factors

In the Claims Only HWR (Medicare FFS and MA) dataset, patient-level observed readmission rates were higher for dual-eligible patients (19.6%) compared with non-dual-eligible patients (14.7%) (Table 17, "Hybrid HWR All Tables and Figures" attachment). Similarly, the observed readmission rate for patients with the high ADI variable are higher (17.2%) compared to patients without the social risk factor (15.2%).

Analysis #4: Impact of social risk factor on hospital-level measure scores

To determine the impact of adding social risk factors on measure scores, we compared correlation coefficients of measures scores calculated with and without the social risk factors in the models (Table 19, and Figures 11 and 12, "Hybrid HWR All Tables and Figures" attachment), and we compared differences in measure scores (Table 19). Hospitals' risk-standardized readmission rates (RSRRs) are highly correlated: the correlation coefficient of RSRRs between hospitals using the Claims-Based HWR (Medicare FFS and MA) dataset, calculated with and without the high ADI variable is 0.999 (Figure 11) and correlation coefficient between measure scores calculated with and without the dual-eligible variable is 0.995 (Figure 12). The median difference in hospitals' RSRRs when adding either social risk factor is small (0.001% for high ADI and 0.000% for dual-eligibility for the Claims-Only HWR (Medicare FFS and MA) dataset (Table 19).

4.1 Feasibility Assessment

As part of broader measure development, we originally tested the feasibility of electronic extraction of the EHR-based data elements used to enhance risk adjustment (the core clinical data elements or CCDEs). The CCDE are a set of data elements that are captured on most adults admitted to acute care hospitals, are easily extracted from EHRs, and can be used to risk adjust hospital outcome measures for a variety of conditions and procedures. Feasibility testing included: 1) identification of potentially feasible clinical data through qualitative assessment, 2) empirical feasibility testing of several clinical data elements electronically extracted from two large multifacility health systems, and 3) validity testing of the CCDE at an additional health system. Results from these analyses show conceptual feasibility by a Technical Expert Panel (TEP), while empiric feasibility demonstrates consistent capture and match rate of CCDE from the EHRs. For more information on our initial feasibility testing conducted during measure development, please see the Hybrid HWM methodology report and 2013 Core Clinical Data Elements Technical Report attached to this form.

Prior to measure implementation, CMS received feedback through the FY2022 Inpatient Prospective Payment System Final Rule[1] indicating concerns about reporting burden, in terms of variation in readiness and eCQM reporting capabilities across hospitals. This concern was addressed by delaying implementation for several years after rule finalization by adding one rounds of Confidential Reporting (and two rounds of Confidential Reporting for Hybrid Hospital-Wide Readmission, which shares similar data elements and submission/ collection processes) to allow hospitals and their vendors additional time to upgrade IT systems, improve data mapping and other capabilities, and increase staff training for measure reporting. This eCQM reporting cycle was delayed in comparison to reporting requirements for other Hospital IQR Program measures.

Also as described in Section 6.2.3, hospitals also provided feedback about challenges in meeting the IQR reporting threshold for submission of CCDE (within 24 hours before/after inpatient admission for 90% of discharges, and linking variable [used to merge EHR to claims data] for 95% of discharges) that are required to receive their Annual Payment Update. CMS was responsive to these comments and has proposed that the submission of CCDE remain voluntary for 2025 reporting.[2] Additionally, CORE (the measure developer) is updating the data collection approach (effective with the 2025 Annual Update Cycle) to expand the CCDE lookback period beyond the 24 hours prior to/after inpatient admission, to the first result captured during the hospital encounter. By increasing the window from which CCDE can be extracted, hospitals are likely to report CCDE for a higher percentage of discharges, improving their ability to meet the IQR submission percentage.

Finally, we also note that after initial feasibility testing of the CCDE during measure development we identified potential for barriers related to data collection for some data elements. For example, we found a lower capture rate for the “Bicarbonate” variable. Because of this low capture rate, we expanded the Bicarbonate Lab Test value set to include carbon dioxide lab codes, which are often performed in lieu of bicarbonate lab tests. We refer readers to section 4.3.4 Validity Testing Results (Missing Data), where results show missingness for bicarbonate lab tests for 2024 Voluntary Reporting ranged from 5.70% to 13.09%, showing improvement for this data element from initial development testing.

Analyses around missing data are presented in Section 4.3.4.

The estimated costs of data collection are minimal, as this measure utilizes information from EHR systems already within the hospital. We estimate 12 hours for one employee to extract and submit patient files through the Quality Reporting Document Architecture (QRDA) Submission Portal, consistent with all eCQMs. This measure is not intended to influence clinical workflow, as CCDE were selected by a Technical Expert Panel (TEP) because they are routinely captured on all adult inpatients, and data are submitted electronically (CCDE); other measure components, including other risk adjustment variables, numerator and denominator inclusion and exclusion are captured using Medicare inpatient claims.

References

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4.2 Attach Feasibility Scorecard

eCQM-Feasibility-Scorecard_Hybrid HWR.xlsx

4.3 Feasibility Informed Final Measure

Based on results from testing shown below, the CCDE were selecting for the final specifications to be feasible to extract, and routinely collected for all adult inpatient EHRs.

To address CBE's requirement for feasibility in relation to data elements and measure logic, we reevaluated this measure against the feasibility domains (see attached Feasibility Scorecard). The results of feasibility assessment for the 15 data elements are below:

- The data elements are in a structured format within the EHR systems (scoring 1 for Availability),
- Some data elements were transmitted directly from other electronic systems into the EHR or resulted from clinician assessment or interpretation (scoring 1 for accuracy)
- This measure's data elements are coded using either RXNORM or SNOMED (scoring 1 for data standards)
- The data elements required for this measure (lab values, vital signs, referral orders, problem list entries) are captured during the course of care and do not impact workflow (scoring 1 for workflow)

4.4 Proprietary Information

Not a proprietary measure and no proprietary components

5.1.1 Data Used for Testing

Please see Table 4 in the attachment entitled "Hybrid HWR All Tables and Figures."

5.1.2 Differences in Data

For the updated testing in this CBE endorsement submission, we provide results from two datasets. Each dataset is described in detail in Table 4 in the attachment entitled "Hybrid HWR All Tables and Figures."

1. **HWR Claims-Only Dataset.** This dataset includes both FFS and MA admissions and was used to provide a national dataset that includes all Medicare beneficiaries. While this dataset includes all claims-based variables used for risk adjustment, it does not include the CCDE EHR elements; the addition of the EHR data elements in the CCDE provides risk adjustment supplemental to claims-based risk adjustment, therefore results derived from the HWR claims-only dataset provides a close approximation for nationally representative results. Measure scores calculated with and without the CCDE are highly correlated. See Table 3 of Hybrid HWR Comprehensive Methodology Report.
2. **2024 Hybrid HWR Voluntary Reporting Dataset**: This dataset was used to provide information on the integration of EHR data elements (CCDE) for case-mix risk-adjustment that supplements the claims-based variables; this dataset includes both claims-based risk adjustment variables and EHR-based data elements (CCDE). This dataset, however, does not include MA admissions, as MA were not part of the measure specifications at the time of data collection; MA admissions will be added to the measure in 2026 Reporting per the Fiscal Year 2024 Inpatient Prospective Payment System Final Rule.

See dataset descriptions in Table 4 (in the attachment entitled "Hybrid HWR All Tables and Figures") for further details on each dataset. We note that we also include results derived from datasets from original measure development as this is the data that was used for risk variable selection.

5.1.3 Characteristics of Measured Entities

For this measure, hospitals are the measured entities. All non-federal, short-term acute care inpatient US hospitals (including territories) with Medicare fee-for-service (FFS) and Medicare Advantage (MA) beneficiaries aged 65 years or over are included. In addition, where we present testing results for the claims-only measure, the testing data presented includes data from patients 65 and older who were enrolled in Medicare FFS and Medicare Advantage. For Data Element Reliability and Validity testing, we present testing from the original development of this measure, using a historical dataset—21 Kaiser Permanente hospitals, that includes all-payer and all adults aged 18+. The number of measured entities varies by testing type: see Table 4 in the attachment entitled "Hybrid HWR All Tables and Figures."

5.1.4 Characteristics of Units of the Eligible Population

Please see Table 4 in the attachment entitled "Hybrid HWR All Tables and Figures."

5.2.1 Level(s) of Reliability Testing Conducted

Person or encounter level (i.e., data element) (e.g., inter–abstractor reliability), Accountable entity level (i.e., measure score) (e.g., signal-to-noise analysis)

5.2.2 Method(s) of Reliability Testing

Data Element Reliability (Patient/Encounter Level)

Data element reliability for the EHR-based variables (CCDE) used in this measure were established during development. In this testing we used the capture rate to establish reliability. We refer readers to the attached 2013 Core Clinical Data Elements Technical Report (Version 1.1) for methodologic details.

Measure Score Reliability: Split-Sample

To ascertain measure score reliability we calculated the intra-class correlation coefficient (ICC) using a split-sample (also known as the split-half) method in both the Claims-Only HWR (Medicare FFS + MA) (discharges July 1, 2022-June 30, 2023), and the Hybrid HWR 2024 Voluntary Reporting (July 1, 2022-June 30, 2023) datasets. We did not calculate signal-to-noise reliability for the overall measure score because the signal-to-noise calculation should be based on a statistical model;[1] the measure score (risk-standardized readmission rate or RSRR) for the HWR measure is a combined score that is not calculated from a single statistical model.

The reliability of a measurement is the degree to which repeated measurements of the same entity agree with each other. For measures of hospital performance, the measured entity is the hospital, and reliability is the extent to which repeated measurements of the same hospital give similar results. Accordingly, our approach to assessing reliability is to consider the extent to which assessments of a hospital using different but randomly selected subsets of patients produce similar measures of hospital performance. Hospital performance is measured once using a random subset of patients from a defined dataset from a measurement period, and then measured again using a second random subset exclusive of the first from the same measurement period, and the agreement of the two resulting performance measures compared across hospitals.[2]

For split-sample reliability of the measure, we randomly sampled half of patients within each hospital from a one-year measurement period, calculated the measure for each hospital, and repeated the calculation using the second half of patients. Thus, each hospital is measured twice, but each measurement is made using an entirely distinct set of patients. To the extent that the calculated measures of these two subsets agree, we have evidence that the measure is assessing an attribute of the hospital, not of the patients. As a metric of agreement, we calculated the intra-class correlation coefficient.[3] Specifically, we used the Claims-Only Hospital Wide Readmission (Medicare FFS + MA) and 2024 Hybrid Hospital-Wide Readmission Voluntary Reporting datasets, randomly split each into two approximately equal subsets of patients, and then calculated the RSRR for each hospital for each sample. The agreement of the two RSRRs was quantified for hospitals in each sample using the intra-class correlation as defined by ICC (2,1).[3]

Using two non-overlapping random samples provides a conservative estimate of the measure's reliability, compared with using two random, but potentially overlapping samples which would exaggerate the agreement. Moreover, because our final measure is derived using hierarchical logistic regression, and a known property of hierarchical logistic regression models is that smaller volume hospitals contribute less 'signal', a split sample using a single measurement period would introduce extra noise. This leads to an underestimate in the actual split-sample reliability that would be achieved if the measure were reported using the full measurement period, as evidenced by the Spearman Brown prophecy formula.[4] We used this formula to estimate the reliability of the measure if the whole cohort were used, based on an estimate from half the cohort.

References

1. Adams J, Mehrota, A, Thoman J, McGlynn, E. (2010). Physician cost profiling – reliability and risk of misclassification. NEJM, 362(11): 1014-1021.
2. Rousson V, Gasser T, Seifert B. "Assessing intrarater, interrater and test–retest reliability of continuous measurements," Statistics in Medicine, 2002, 21:3431-3446.
3. Shrout P, Fleiss J. Intraclass correlations: uses in assessing rater reliability. Psychological Bulletin, 1979, 86, 420-3428.
4. Spearman, Charles, C. (1910). Correlation calculated from faulty data. British Journal of Psychology, 3, 271–295.

5.2.3 Reliability Testing Results

Measure Score Reliability Results

In the Claims-Only HWR [Medicare FFS and Medicare Advantage] dataset (Dataset 2), there were 4,401 hospitals in the development sample and 4,402 hospitals in the validation sample. The intraclass correlation between the two RSRRs for each sample was 0.780, which meets current CBE thresholds for reliability (0.6).

In the Hybrid HWR 2024 Voluntary Reporting dataset (Dataset 3), there were 1,058 hospitals in the development sample and 1,055 hospitals in the validation sample. The intraclass correlation between the two RSRRs for each sample was 0.645, which also meets current CBE thresholds for reliability (0.6).

We note that we did not complete Table 5 in this CBE submission because the split-sample reliability calculation results in a single statistic, not a distribution.

5.2.4 Interpretation of Reliability Results

Data Element Reliability

Based on prior testing of the CCDE for a related measure, data element reliability shows rate of clinical capture of each CCDE within each of the five cohorts to be well over 90%, with the exception of laboratory results in the Surgical/Gynecological cohort, which are not used in the measure.

Measure Score Reliability Results

The split-sample reliability score (using the Claims-Only HWR [Medicare FFS and Medicare Advantage] and Hybrid HWR 2024 Voluntary Reporting datasets) of 0.780 and 0.645, respectively, meet the current CBE threshold for split-sample reliability (0.6).[1]

Reference:

1. Batelle (2023). Endorsement & Maintenance (E&M) Guidebook. Partnership for Quality Measurement. October 2023.

5.3.1 Level(s) of Validity Testing Conducted

Person or encounter level (i.e., data element) (e.g., sensitivity and specificity), Accountable entity level (i.e., measure score) (e.g., criterion validity)

5.3.3 Method(s) of Validity Testing

Data Element Validity Testing (CCDE)

Chart Abstraction:

We developed electronic specifications (e-specifications) using the Measure Authoring Tool (MAT) and analyzed extracted data from EHRs. We assessed the ability of hospitals to use the e-specifications to query and electronically extract CCDEs from the EHR, within 24 hours before or up to 24 hours after inpatient admission for labs; within 24 hours before or up to 2 hours after inpatient admission for vital signs, for all adult inpatient admissions occurring over the course of one year. Validity testing assessed the accuracy of the electronically extracted CCDEs compared to the same CCDEs gathered through manual abstraction (from the EHR) in a subset of 368 charts identified in the data query in 3 hospitals that used Cerner as their EHR Vendor (Dataset 4), and 391 charts identified in the data query in data extracted from 1 hospital with 391 admissions that used GE Centricity as their clinical EHR (Dataset 5).

We calculated the number of admissions that needed to be randomly sampled from the EHR dataset and manually abstracted to yield a statistical margin of error (MOE) of 5% and a confidence level of 95% for the match rates between the two data sources. Sites then used an Access-based manual abstraction tool provided (along with training) to manually abstract the CCDEs from the random samples of the medical records identified through the EHR data query. The manual chart abstraction data is considered the “gold standard” for the purpose of this analysis.

We conducted validity testing on the critical EHR data elements in the Hybrid HWR measure. For each continuous data element, we were only interested in the case where the electronic abstraction value exactly matched the manual abstraction value. We therefore only calculated the raw agreement rate between data from electronic and manual chart abstraction. For simple data values, we believe taking this approach, as compared to reporting statistical tests of accuracy, better reflects the concept of matching exact data values rather than calculated measure results.

Therefore, we do not report statistical testing of the accuracy of the EHR derived data value as compared with the abstracted value. Instead, we counted only exact matches in the data value as well as the time and date stamp associated with that value when we calculated the match rate. The 95% confidence level was established based on the sample size and reflects the exact match rate using these criteria.

Missing Data

For the EHR data elements used in the measure's risk models, we anticipate that there will be some missing data. We examined rates of missing data using the Hybrid HWR 2024 Voluntary Reporting dataset (discharges July 1, 2022-June 30, 2023), which includes CCDE submitted by 1,162 hospitals during Confidential Reporting, in Table 9 of the Tables and Figures attachment. Please note that not all CCDE are included in each specialty cohort, for example laboratory values are not included in the Surgical/Gynecological cohort Table 8 (see "Hybrid HWR All Tables and Figures" attachment). We characterize CCDE as "missing" when: 1) the hospital did not report any data for that value, or 2) when the reported value is unusable in risk-adjustment (e.g. missing units or data not able to be standardized [string data, or values which cannot be converted to primary Unified Code for Units of Measure (UCUM) units without additional information]). For measure calculation, where CCDE values are missing or unusable, we impute the median value reported across all hospitals for that CCDE, to profile a "typical" patient.

Measure Score Validity

Empiric Validity

To assess the construct validity of the HWR measure, we identified and assessed the measure's correlation with other measures with publicly reported data that we hypothesized would be related to readmission based on the evidence for similar or overlapping causal pathways.

Figure 2 in Section 2.1 (see "Hybrid HWR All Tables and Figures attachment, page 2) shows the logic model (causal pathway) for the HWR measure, where underlying processes, such as the delivery of timely care, ensuring proper communication during transitions of care including at discharge result in better downstream patient support and management (including patient education to support self-care), resulting in a decreased risk of readmission.

We reviewed measures with publicly available data on Medicare.gov and identified several outcome (readmission) and patient experience measures that fall within the same causal pathway (see Figure 2) including measures that summarize overall hospital quality (Overall Hospital Quality Star Rating). Outcome or patient experience measures in the same causal pathway are hypothesized to be correlated with the HWR measure because the same underlying processes of care are expected to impact both the HWR measure and the comparator outcome/patient experience measure.

CMS is the steward for the readmission measures published on Medicare.gov as well as the steward of the Overall Hospital Quality Star Ratings, which includes a Summary Score for the readmission measures (Readmission Group Score) and a summary score that encompasses all of the measures (organized into five Groups: Readmission, Mortality, Safety, Patient Experience, and Timely & Effective Care) within the Overall Hospital Quality Star Ratings. The readmission measures are, by definition, within the same causal pathway as the HWR measure, and as an overall hospital-wide measure of quality, the Star Ratings Summary Score (which includes measure related to patient safety and prevention of infection, for example) is also within the causal pathway (see Figure 2). (More information about the Star Ratings-related measures can be found below under the heading "About the comparator measures.") We note that prior to running these analyses, we removed the claims-based HWR measure currently implemented (FFS-only) from the Star Ratings comparators, because it is one of the measures included in Overall Hospital Quality Star Rating.[1]

We also identified a sub-set of the patient experience measures within the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) as candidate measures. There are measures within HCAHPS related to care transitions, which are within the causal pathway for the HWR measure (Figure 2). For example, the Care Transition Measure (CTM3) is a three-question measure that includes questions about patient understanding of managing their health after discharge, and about patient understanding of their medications.[2] In addition, HCAHPS contains survey questions related to communication, and the discharge process; both of these domains are in the same causal pathway as HWR (Figure 2). (More information about the Star Ratings-related measures can be found below under the heading "About the comparator measures.")

We then hypothesized the strength and the direction of the relationship for each measure (Table 6, "Hybrid HWR All Tables and Figures" attachment). For the HWR measure, a lower measures score means better performance, therefore for comparator measures where better performance is hypothesized to be related to be better performance on HWR (such as care transition, and communication), the direction of the association is shown as "negative."

We then examined the relationship of performance of the HWR measure scores (RSRRs) with each of these external measures of hospital quality as measured by Pearson correlation coefficients (Table 4 of the Tables and Figures attachment). We also compared hospital performance on the HWR measure within quartiles of the comparator measures (Figures 5-8). For purposes of this testing, we used the Claims-Based HWR (Medicare FFS and MA) dataset (discharges July 1, 2018, through June 30, 2019) as it is a national sample, similar to the Star Ratings.

About the comparator measures:

1. **Overall Hospital Star Rating Readmission Group Score**: CMS's Overall Hospital Star Rating assesses hospitals' overall performance (expressed on CMS' *Care Compare site,* graphically as stars) based on a weighted average of group scores from five different domains of quality (mortality, readmissions, safety, patient experience, timely & effective care)). The Readmission Group is comprised of the readmission measures that are publicly reported on *Care Compare*. The Readmission Group Score is calculated using a simple average of the scores for the individual measures and is on a higher-is-better scale. For the validity testing presented in this testing form, **we first removed the FFS-only claims-based HWR measure from the group of measures**, and then re-calculated the Star Rating readmission group scores. We used Readmission Group Scores from the 2021 release

of the Star Ratings. The full methodology for the Overall Hospital Star Rating can be found at https://www.qualitynet.org/dcs/ContentServer?c=Page&pagename=QnetPublic...

2. **Overall Hospital Star Rating Summary Score**: CMS's Overall Hospital Star Rating assesses hospitals' overall performance (shown on *Care Compare* graphically, as stars) based on a weighted average of "group scores" from five different domains of quality (mortality, readmissions, safety, patient experience, timely & effective care,). Each group is comprised of individual measures that are reported on *Care Compare*. Group scores for each individual group are derived from a simple average of the scores for the individual measures. The Summary Score is on a higher-is-better scale. For the validity testing presented in this testing form, **we first removed the FFS-only claims-based HWR measure from the group of measures** used to calculate the Readmission Group score and then re-calculated the summary scores. The measure scores include data from Medicare FFS hospitals from the 2020 and 2021 release of *Medicare.gov* .The full methodology for the Overall Hospital Star Rating can be found at https://www.qualitynet.org/inpatient/public-reporting/overall-ratings/r...
3. **HCAHPS**: The Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey is an CBE-endorsed, publicly reported survey of patients' perspectives of hospital care. Discharged patients (all patients over 18; not limited to Medicare beneficiaries) are asked 29 questions about their hospital experiences, including questions related to communication with doctors and nurses, responsiveness of staff, and communication about medications, and discharge information. Scores used for this analysis are based on response categories (for example "No" or "Yes"), the score rate (which is based on the two top box responses), or the linear mean score, which is an average of item-level responses for each question.

The Discharge Information linear mean score is a composite calculated from responses to two discharge-related questions in HCAHPS: (1) During this hospital stay, did doctors, nurses or other hospital staff talk with you about whether you would have the help you needed when you left the hospital? (2) During this hospital stay, did you get information in writing about what symptoms or health problems to look out for after you left the hospital?

The Care Transition Measure (CTM3) is a three-question measure, administered within HCAHPS, that asks the following questions: (1) During this hospital stay, staff took my preferences and those of my family or caregiver into account in deciding what my healthcare needs would be when I left. (2) When I left the hospital, I had a good understanding of the things I was responsible for in managing my health. (3) When I left the hospital, I clearly understood the purpose for taking each of my medications.

For more information on HCAHPS, see: https://hcahpsonline.org/en/#AboutTheSurvey. For more information on HCAHPS scoring, see: https://hcahpsonline.org/globalassets/hcahps/star-ratings/tech-notes/20...; For more information on the CTM measure, see: https://secureservercdn.net/72.167.242.33/253.582.myftpupload.com/wp-co... analysis presented here used HCAHPS data from calendar year 2018-2019.

References:

1. Centers for Medicare & Medicaid Services (CMS). Hospitals - Overall hospital quality star

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2. Parry C, Mahoney E, Chalmers SA, Coleman EA. Assessing the quality of transitional care: further applications of the care transitions measure. Med Care. 2008;46(3):317-322. doi:10.1097/MLR.0b013e3181589bdc

5.3.4 Validity Testing Results

Summary

Our validity testing results, described below, provide strong evidence for the validity of the EHR based data elements (CCDE) (based on comparison of data elements through chart abstraction and analysis of missing data), and validity of the measure score, shown through construct validity, and face validity.

Validity of EHR Data Elements

We note that these CCDE were selected by a Technical Expert Panel to be routinely collected on all adult inpatients, in order to guide clinical decision making. See the 2013 Core Clinical Data Elements Technical Report (Version 1.1) attached for details.

Of these candidate variables, chart abstraction for validity testing was done in Dataset 4 (Electronically extracted data from 3 hospitals with Cerner as their EHR) and Dataset 5 (Data element validity dataset- from one hospital using GE Centricity as their EHR vendor). Table 7 ("Hybrid HWR All Tables and Figures" attachment) demonstrates the comparison between electronic and manual abstraction of data in the two health systems. We found that the percent agreement between the EHR-based variables and chart-abstracted values ranged from 14.66% to 97.22%.

A post-validation review of the code used by the hospital in Dataset 5 (one hospital with GE Centricity as EHR vendor), revealed that the hospital experienced a number of errors. The most significant of which was extracting data only within an incorrect two-hour window for laboratory test results (the correct window was 24 hours). Additionally, physical exam (vital signs) data were extracted based on the date/time that results were documented rather than the date/time the physical exams were performed, driving down the accuracy of these data. However, post-validation review of the code used by the hospital in Dataset 4 (three hospitals with Cerner as their EHR vendor) showed no such errors in the query executed. As a result, the match rate for Dataset 4 was much higher.

Our analysis of missing data (Table 9, "Hybrid HWR All Tables and Figures" attachment) shows that reporting of CCDE varied across cohorts, from 1.27% missing for Systolic Blood Pressure in the Neurology cohort, to 23.99% missing for White Blood Cell Count in the Cardiovascular cohort.

Measure Validity Testing Results

Empiric Measure Score Validity

Table 11 of the Tables and Figures attachment shows the results of the analyses examining associations between the HWR measure and quality metrics in the same causal pathway, as described in Section 2.1. All analyses were performed with the Medicare FFS + MA claims-only dataset.

Readmission Group Score and Star Rating Summary Score: As hypothesized, the HWR measure score was moderately, negatively correlated with both the Readmission Group Score, and the Summary Score, meaning that higher scores (better performance) on the comparator measures were associated with lower scores (better performance) on the HWR measure. This is expected because the star ratings quality measures focus on, or contain a portion of, the same domain of quality as the HWR measure (readmission).

Patient Experience: The HCAHPS measures related to transitions of care, communication about medications, doctor and nurse communication, and discharge instructions, were also correlated with HWR in the expected direction (Table 10, "Hybrid HWR All Tables and Figures" attachment). For example, the HCAHPS discharge information linear mean score had a Pearson correlation coefficient of -0.324, indicating that better performance on the discharge measure was correlated with lower measure scores (better performance) on the HWR measure. Similar relationships are shown in Table 10 below for the HCAHPS Care Transition composite score.

Box plots (whisker plots) that visualize these relationships are shown below in Figures 5-6.

Association between HWR and Quality Measures (box plots)

Figure 5 (see "Hybrid HWR All Tables and Figures" attachment, page 10) shows the box-whisker plots of the HWR measure RSRRs within each quartile of Star-Rating Readmission Group Scores. The blue diamonds represent the mean RSRRs of the HWR measure, within each quartiles of the Star Rating Readmission Group Scores. The correlation between HWR RSRRs and Star Rating Readmissions Group Score is -0.520, which suggests that hospitals with lower HWR RSRRs (better performance) are more likely to have higher Star Rating Readmission Group Scores (better performance).
Figure 6 (see "Hybrid HWR All Tables and Figures" attachment, page 11) shows the box-whisker plots of HWR measure RSRRs within each quartile of Star Rating Summary scores. The blue diamonds represent the mean RSRRs of the HWR measure within each quartile of Star Rating Summary Scores. The correlation between HWR RSRRs and Star-Rating summary score is -0.398, which suggests that hospitals with lower HWR RSRRs (better performance) are more likely to have higher Star-Rating summary scores (better performance).

Association between HWR and HCAHPS Discharge-related measures (box plots)

Figures 7-8 (see "Hybrid HWR All Tables and Figures" attachment, pages 11-12) show the box-whisker plots of the HWR measure RSRRs within each quartile of the transitions of care and discharge-related HCAHPS items. For each figure, the blue diamonds represent the mean RSRRs within quartiles of the comparator measures. The mean RSRR for the HWR measure trends in the expected direction across each quartile of the comparator measures. For example, the relationship with HWR measure scores is in the negative direction for the discharge information linear mean score; better performance, or lower scores on the HWR measure are associated with higher (better performance) on the discharge information linear mean score.

5.3.5 Interpretation of Validity Results

The combination of data element, and measure score validity testing supports the validity of the Hybrid HWR Measure. We discuss each category of testing below.

Data Element Validity

Our chart abstraction results show a high percent agreement for most variables. We note that the lower capture rate (see reliability section) and lower % agreement rate for the bicarbonate value have been addressed in measure updates that were made to the accepted value for this data element (see Section 3.1). The rate of missing values continues to be low for most data elements and not likely to introduce bias. We note that the impact of missing values for the White Blood Cell laboratory test is very low. As we employ an imputation strategy for missing data, missingness is unlikely to have a meaningful impact on measure scores. We refer readers to section 4.3.4 Testing Results (Missing data) which shows improved missingness from development testing to 2024 Voluntary Reporting. We note that for missing CCDE values, multiple imputation is used to impute a value based on the characteristics of the CCDE reported. To minimize any small potential for bias from CCDE values, we account for potential outlier values, using winsorization, as well as account for missing values in our risk models. It is expected that CCDE reporting will continue to improve in future years, when the CCDE lookback period is expanded beyond 24 hours, and as hospitals gain familiarity with the measures.

Measure Score Validity

Measure score validity testing supports the validity of the Hybrid HWR measure. Measure score validity testing between the Hybrid HWR RSRR and related HCAHPS and Star Ratings Scores show statistically significant, moderate negative agreement, as expected, validating that the measure score correlates with other metrics related to readmission.

Taken together, these results support the validity of the Hybrid HWR measure.

5.3.2 Type of Accountable Entity Level Validity Testing Conducted (derived)

Empirical validity testing at the accountable entity-level (e.g., criterion validity, construct validity, known groups analysis)

5.4.1 Methods Used to Address Risk Factors

Statistical risk adjustment model with risk factors

5.4.2 Conceptual Model Rationale

This section addresses clinical risk variables; please see Section 5.1 for a discussion of social risk factors.

Approach to Variable Selection

Our approach to risk adjustment was tailored to and appropriate for a publicly reported outcome measure, as articulated in the American Heart Association (AHA) Scientific Statement, "Standards for Statistical Models Used for Public Reporting of Health Outcomes."[1] The measure estimates hospital-level 30-day all-cause RSRRs using hierarchical logistic regression models. In brief, the approach simultaneously models data at the patient and hospital levels to account for variance in patient outcomes within and between hospitals.[2]

The approach to risk adjustment is the only component of the Hybrid HWR measure that differs from the original HWR measure methodology. The original HWR measure uses claims data to adjust for two aspects of risk: 1) case mix or how sick individual admitted patients are; and, 2) service mix or the proportion of admitted patients with various different principal discharge diagnoses. Different claims data are used to assess each of these.

To select candidate variables for the Hybrid risk model, we began with the list of all administrative claims-based risk-adjustment variables included in the claims-only HWR measure, described below. We then added EHR-based risk variables, also described below.

Claims-based Risk Variables

In order to select the comorbid risk variables during the original development of this measure, we developed a "starter" set of 30 variables drawn from previous readmission measures (AMI, heart failure, pneumonia, hip and knee arthroplasty, and stroke). Next, we reviewed all the remaining CMS-CCs and determined on a clinical basis whether they were likely to be relevant to an all-condition measure. We selected 11 additional risk variables to consider.

Using data from the index admission and any admission in the prior 12 months, we ran a standard logistic regression model for every discharge condition category with the full set of candidate risk adjustment variables. We compared odds ratios for different variables across different condition categories (excluding condition categories with fewer than 700 readmissions due to the number of events per variable constraints). We selected the final set of comorbid risk variables based on the following principles:

- We excluded risk variables that were statistically significant for very few condition categories, given that they would not contribute much to the overall models.
- We excluded risk variables that behaved in clinically incoherent ways. For example, we dropped risk variables that sometimes increased risk and sometimes decreased risk, when we could not identify a clinical rationale for the differences.
- We excluded risk variables that were predominantly protective when we felt this protective effect was not clinically reasonable but more likely reflected coding factors. For example,

drug/alcohol abuse without dependence (CC 53) and delirium and encephalopathy (CC 48) were both protective for readmission risk although clinically they should increase patients' severity of illness.
- Where possible, we grouped together risk variables that were clinically coherent and carried similar risks across condition categories. For example, we combined coronary artery disease (CCs 83-84) with cerebrovascular disease (CCs 98, 99, and 103).
- We examined risk variables that had been combined in previous CMS publicly reported measures, and in one instance separated them: for cancers, the previous measures generally pool 5 categories of cancers (CCs 8 to 12), together. In our analysis, lung cancer (CC 8) and other severe cancers (CC 9) carried higher risks, so we separated them into a distinct risk variable and grouped other major cancers (CC 10), benign cancers (CC 11), and cancers of the urinary and GI tracts (CC 12) together. Consistent with other publicly reported measures, we also left metastatic cancer/leukemia (CC 7) as a separate risk variable.

Complications occurring during hospitalization are not comorbid illnesses, may reflect hospital quality of care, and therefore should not be used for risk adjustment. Hence, conditions that may represent adverse outcomes due to care received during the index hospital stay are not included in the risk-adjusted model (see the current list in Hybrid Risk-Variable Complications of Care in the Data Dictionary). CCs on this list were not counted as a risk variable in our analyses if they appeared only on the index admission.

This resulted in a final risk-adjustment model that included 32 CC-based variables. Additional variables related to service line adjustment are described below.

Service mix adjustment:

The measure includes many different discharge condition categories that differ in their baseline readmission risks. In addition, hospitals differ in their relative distribution of these condition categories (service mix). To adjust for service mix, the measure uses an indicator variable for the discharge condition category in addition to risk variables for comorbid conditions. The models include a condition-specific indicator for all condition categories with sufficient volume (defined as those with more than 1,000 admissions nationally in a given year for Medicare FFS data) as well as a single indicator for conditions with insufficient volume in each model.

EHR-based risk variables

The CCDE specific to the risk adjustment for the HWR measure consists of patients' age, weight, the first set of vital signs captured within 2 hours of the start of the episode of care, and the results of the first complete blood count and basic chemistry panel drawn within 24 hours of the start of the episode of care. If the patient has values captured prior to admission, for example from the emergency department, pre-operative, or other outpatient area within the hospital, the logic also supports extraction of the first resulted vital signs and laboratory tests within 24 hours prior to the start of the inpatient admission. Preliminary work had established that the CCDE could be used to risk adjust measures of 30-day readmission across a variety of common and costly medical conditions. Application of these same data elements to the original HWR measure allows us to examine the use of the CCDE in a broader cohort of hospitalized medical and surgical patients as well as to examine its utility in predicting hospital readmission. Therefore, CORE specifically sought to determine whether the use of clinical data for risk adjustment in place of, or in combination with, comorbidity data from Medicare claims would improve the discrimination of the HWR models or the reliability of the measure.

As described in the original methodology report, to determine if adding the CCDE improved risk adjustment, we compared four risk-adjustment strategies: the original HWR approach that used claims-only data; and three new approaches that used the CCDE in various combinations with claims data. One model applied the CCDE to the full HWR risk-adjustment model, which include the Principal Diagnosis CCSs. We assumed that this model would out-perform models that used only clinical or only claims data because it is the most comprehensive model. A second model used only the CCDE for risk adjustment. A third model used the CCDE in addition to the principal discharge diagnoses CCS from the original HWR risk-adjustment model. We selected the best-performing alternative model based on discrimination in terms of the C-statistic. Based on superior model discrimination (see Table 11 of the Tables and Figures attachment), the CCDE with Original HWR model was identified as the best-performing model of those evaluated and this model was carried forward for measure development and testing using hierarchical logistic regression. The other two approaches that included the CCDE were discarded.

Although the 5 risk models use a common set of claims variables, the CCDE variables and principal discharge diagnoses CCSs are not the same across specialty cohort models. Only those data elements that are statistically significant in each individual model are included. We estimate a hierarchical logistic regression model for each specialty cohort separately, and the coefficients associated with each variable may vary across specialty cohorts.

The final set of risk-adjustment variables with their frequencies for each specialty cohort, including service-line adjustments, can be found in the Data Dictionary.

References:

1. Krumholz HM, Brindis RG, Brush JE, et al. 2006. Standards for Statistical Models Used for Public Reporting of Health Outcomes: An American Heart Association Scientific Statement From the Quality of Care and Outcomes Research Interdisciplinary Writing Group: Cosponsored by the Council on Epidemiology and Prevention and the Stroke Council Endorsed by the American College of Cardiology Foundation. Circulation 113: 456-462
2. Normand S-LT, Shahian DM. 2007. Statistical and Clinical Aspects of Hospital Outcomes Profiling. Stat Sci 22 (2): 206-226.

5.4.2a Attach Conceptual Model

4.4.2 Conceptual Model Rationale_Hybrid HWR.pdf

5.4.3 Variable Distribution Across Measured Entities

We refer the reader to risk variable frequencies in the attached data dictionary.

We provide results from both the claims-only HWR dataset (MA + FFS cohort, claims-based risk adjustment), and the 2024 Voluntary Reporting dataset (FFS cohort plus CCDE enhanced risk adjustment) to demonstrate results using a national sample, and to include the CCDE variable.

CORE's Approach to Annual Model Validation

CORE’s measures undergo an annual measure reevaluation process, which ensures that the risk-standardized models are continually assessed and remain valid, given possible changes in clinical practice and coding standards over time. Modifications made to measure cohorts, risk models, and outcomes are informed by review of the most recent literature related to measure conditions or outcomes, feedback from various stakeholders, and empirical analyses, including assessment of coding trends that reveal shifts in clinical practice or billing patterns. Input is solicited from a workgroup composed of up to 20 clinical and measure experts, inclusive of internal and external consultants and subcontractors.

We provide a link to the 2024 measure re-evaluation report for the Hybrid HWR measure. The report describes what CORE did for 2024 Voluntary Reporting; we:

- Updated the ICD-10 code-based specifications used in the measures. Specifically, we:
  - Incorporated the code changes that occurred in the FY 2019 version of the ICD-10-CM/PCS (effective with October 1, 2018+ discharges) into the cohort definitions and risk models; and,
  - Applied a modified version of the FY 2019 V22 CMS-Hierarchical Condition Category (HCC) crosswalk that is maintained by RTI International to the risk models.
  - Monitored code frequencies to identify any warranted specification changes due to possible changes in coding practices and patterns;
- Evaluated the stability of the risk-adjustment model over the three-year measurement period by examining the model variable frequencies, model coefficients, and the performance of the risk-adjustment model in each year.
- For each of the conditions, we assessed logistic regression model performance in terms of discriminant ability for each year of data and for the three-year combined period. We computed two summary statistics to assess model performance: the predictive ability and the area under the receiver operating characteristic (ROC) curve (c-statistic).

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

Please see attached data dictionary the final variables for each of the 15 risk models with associated odds ratios.

The data dictionary details the risk variables assessed for the Claims-Only HWM [Medicare FFS and MA], which is a national sample. However, the Hybrid HWM 2024 Voluntary Reporting results detail including an assessment of the CCDE. We provide results from both samples to demonstrate results using a national sample, and to include the CCDE variable (however results only include hospitals that participated in voluntary reporting n=~1,600).

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

4.4.4a Risk Adjustment Modeling and_or Stratification Specifications.pdf

5.4.5 Calibration and Discrimination

Model Testing Methods

To assess model performance, we assessed model discrimination, calibration, and overfitting. To assess discrimination, we computed two discrimination statistics, the c-statistic and predictive ability. For all analyses, we provide results from both the claims-only (Medicare FFS and MA) and hybrid 2024 VR datasets.

The **c-statistic** is the probability that predicting the outcome is better than chance, which is a measure of how accurately a statistical model can distinguish between a patient with and without an outcome.

Predictive ability measures the ability to distinguish high-risk subjects from low-risk subjects; therefore, for a model with good predictive ability, we would expect to see a wide range in observed outcomes between the lowest and highest deciles of predicted outcomes. To calculate the predictive ability, we calculated the range of mean observed outcomes between the lowest and highest predicted deciles of outcome probabilities.

For assessments of **model calibration**, we provide calibration plots, with mean predicted and mean observed outcomes plotted against deciles of predicted outcomes. The closer the predicted outcomes are to the observed outcomes, the better calibrated the model is.

In addition, we provide an analysis of **overfitting**. Overfitting refers to the phenomenon in which a model accurately describes the relationship between predictive variables and outcome in the development dataset but fails to provide valid predictions in new patients. Estimated calibration values of $\gamma 0$ close to 0 and estimated values of $\gamma 1$ close 1 provide evidence of good calibration of the model.

Please see the attachment "Hybrid HWR All Tables and Figures" for the model testing results which are described below.

Model Performance Results

Discrimination and Calibration

As shown in Table 12 and 13 (see attachment “Hybrid HWR All Tables and Figures”, pages 12-13), across specialty cohorts, c-statistics range from 0.600 to 0.695, and 0.642 to 0.680 in the Claims-Only HWR (Medicare FFS + MA) (discharges July 1, 2018-June 30, 2019) dataset and Hybrid HWR 2024 Voluntary Reporting (discharges July 1, 2022-June 30, 2023) dataset, respectively.

Model testing shows a wide range of predictive ability (Table 12 and 13), and risk decile plots

(Figures 9 and 10 in the attachment "Hybrid HWR All Tables and Figures") show that higher deciles of the predicted outcomes are associated with higher observed outcomes, demonstrating good calibration of the models across both datasets (Claims only, and HWR 2024 Voluntary Reporting).

Overfitting

Table 14 and 15 (see attachment "Hybrid HWR All Tables and Figures", page 13), show overfitting results, demonstrating that $\gamma 0$ in the validation samples is close to zero, and $\gamma 1$ is close to one across specialty cohorts, for both datasets (Claims only, and HWR 2024 Voluntary Reporting).

5.4.6 Interpretation of Risk/Case-mix Factor Findings

Our model testing results provide evidence for adequate discrimination across specialty cohorts. The c-statistic should be interpreted in the context of this particular measure (a readmission measure). If an outcome is more strongly related to quality of care rather than patient characteristics, patient factors are less predictive of the outcome. The results from our variable selection suggest that for some cohorts within this measure, patient comorbidities have a relatively limited relationship to the occurrence of the outcome; the outcome is also predicted by other factors, such as the quality of care delivered by the facility.

Our calibration plots show that higher deciles of predicted outcomes are associated with higher observed outcomes, which show good calibration of the models. The models also show a wide range of predictive ability. The overfitting values close to 0 at one end and close to 1 to the other end indicate good calibration of each of the models. The overfitting statistics are satisfactory across specialty cohorts.

Interpreted together, our diagnostic results demonstrate the risk-adjustment model adequately controls for differences in patient characteristics.

5.4.7 Final Approach to Address Risk Factors

Statistical risk adjustment model with risk factors, Stratification by risk factor category

6.1.1 Current Status

In use

6.1.3 Current Use(s)

Public Reporting, Quality Improvement with Benchmarking (external benchmarking to multiple organizations), Quality Improvement (Internal to the specific organization), Other

6.1.3 Program Details

Name of the program and sponsor
Hospital inpatient quality reporting program (IQR), CMS

URL of the program
https://qualitynet.cms.gov/inpatient
Purpose of the program
The measure has been implemented as part of CMS's Hospital Inpatient Quality Reporting (IQR) Program, which is a national pay-for-quality-data-reporting program for inpatient, acute care hospitals.
Geographic area and percentage of accountable entities and patients included
The Hospital IQR program includes acute care hospitals across the nation with nearly 4,500 hospitals and 70 million Medicare Beneficiaries
Applicable level of analysis and care setting

The level of measurement is the facility; the setting is the Hospital Inpatient.

6.1.3a Other Current Use

While this re-specified measure with MA and FFS admissions is currently not in use, the prior hybrid HWR measure (with FFS admissions only) is in use for public reporting and for quality improvement.

6.2.1 Actions of Measured Entities to Improve Performance

The outcome of unplanned hospital visits following discharge from an inpatient admission is a widely accepted measure of care quality. The HWR measure provides the opportunity to improve the quality of care and to lower rates of adverse events that result in unplanned readmission after an inpatient stay.

There are evidence-based interventions that can reduce readmission rates. These interventions often address inadequate transitions of care, including patient education at discharge and coordination of outpatient care. For example, a 2021 systematic review that analyzed 60 trials, including 19 randomized controlled trials, concluded, in agreement with prior systematic reviews, that interventions that focus on communication at discharge were statistically significantly associated with lower rates of hospital readmissions (Becker et al., 2021). Within the 19 trials,10 focused on medication counselling, and six focused on patient education about their condition: the other three focused on other specific communication strategies. A 2022 systematic review found that post-discharge care including home care, telephone, and/or clinic visits resulted in lower rates of readmission compared with “usual care” for cardiac patients (Chauhan & McAlister, 2022). A systematic review published in 2023 pooled the results from 73 different studies to compare transitional care interventions with different levels of complexity and their impact on improving outcomes and found that low- and medium-complexity interventions were the most effective at reducing 30-day readmissions (Tyler et al., 2023). Study authors found that compared with usual care, readmission rates were reduced by 18 percent to 55 percent for these types of interventions. Complexity was categorized by the number of components of the intervention, and the number of stages of the hospitalization that the intervention was implemented. Finally, CMS has published a guide for hospitals, aimed at leadership, staff, and clinicians, which outlines effective strategies for reducing readmissions and reducing disparities. Strategies covered in the guide include: ensuring that patients understand discharge instructions and have appropriate follow-up visits, improving accessibility (transportation) for post-discharge care, ensuring patients have a primary care provider, starting post-discharge visit planning early in the discharge process, ensuring transfer of information to the post-discharge provider, and strategies to address language barriers and low health literacy (CMS Office of Minority Health, 2024).

References

1. Becker, C., Zumbrunn, S., Beck, K., Vincent, A., Loretz, N., Müller, J., Amacher, S. A., Schaefert, R., & Hunziker, S. (2021). Interventions to Improve Communication at Hospital Discharge and Rates of Readmission: A Systematic Review and Meta-analysis. JAMA network open, 4(8), e2119346. https://doi.org/10.1001/jamanetworkopen.2021.19346
2. Chauhan, U., & McAlister, F. A. (2022). Comparison of Mortality and Hospital Readmissions Among Patients Receiving Virtual Ward Transitional Care vs Usual Post discharge Care: A Systematic Review and Meta-analysis. JAMA network open, 5(6), e2219113. https://doi.org/10.1001/jamanetworkopen.2022.19113
3. CMS Office of Minority Health (2024). Guide for Reducing Disparities in Readmissions. Accessed April 23, 2024; https://www.cms.gov/about-cms/agency-information/omh/downloads/omh_read...
4. Tyler, N., Hodkinson, A., Planner, C., Angelakis, I., Keyworth, C., Hall, A., Jones, P. P., Wright, O. G., Keers, R., Blakeman, T., & Panagioti, M. (2023). Transitional Care Interventions From Hospital to Community to Reduce Health Care Use and Improve Patient Outcomes: A Systematic Review and Network Meta-Analysis. JAMA network open, 6(11), e2344825. https://doi.org/10.1001/jamanetworkopen.2023.44825

6.2.2 Feedback on Measure Performance

CMS receives feedback on all its measures through the publicly available Q&A tool on Quality Net. Through this tool, we have received, since the last submission, only basic questions about the measure, including the cohort definition, the outcome definition, and specific questions about a facility’s data. We did not receive any suggestions for changes to the claims-based portion of this measure.

Additionally, the EHR portion of this measure goes through the Annual Updates Process (required for all eCQMs), which includes coding and logic review. Since 2023 Voluntary Reporting of the measure, we have also received suggestions from stakeholders regarding logic and coding updates through this process, as well as through JIRA.

6.2.3 Consideration of Measure Feedback

Major changes to the Hybrid HWR measure since it was last endorsed in 2019 include the addition of Medicare Advantage patients, which was finalized in the 2024 Inpatient Prospective Payment System (IPPS) Rule [1] to be incorporated in the measure for discharges June 30, 2024-July 1-2025, for 2026 Reporting (FY 2027 payment determination). Details regarding the impact of this change are in Appendix E of the Hybrid HWR comprehensive Methodology Report.

Minor measure updates to the EHR portion of the measure include:

- Annual digital quality measure maintenance, including coding, value set, and logic updates.
- Excluding patients with a primary or secondary diagnosis of COVID-19 from the measure cohort.
- Risk-adjustment for patients with history of COVID-19.

Measure developers carry out annual cycles of measure reevaluation, aiming to make continuous improvement on the measure, and to be responsive to stakeholder input. Through stakeholder Q&A, developers have been made aware of implementation challenges faced by hospitals from 2024 Voluntary Reporting:

Hospitals provided feedback regarding the topic of acceptable CCDE units for submission:

- Hospitals provided feedback in having difficulty determining which units for CCDE are acceptable for submission and ultimately used for measure calculation. We note the current strategy for missing or unusable data is to substitute the median value reported for that CCDE, assuming a somewhat typical patient. Developers review units submitted by hospitals for data pre-processing each year, with the goal of including as many units as possible for measure calculation. We note limitations with units unable to be standardized to a common unit without additional lab values, and unusable data such as text/string data (e.g. "high- see Dr. John"), an ongoing challenge in the eCQM community.

Hospitals provided feedback regarding submission of linking variables used to merge claims to EHR data, as well as IQR threshold requirements (which are not used towards measure calculation):

- Hospitals expressed concern reaching IQR program requirements, in which hospitals must submit CCDE (within 24 hours before or up to 24 hours after inpatient admission for labs; within 24 hours before or up to 2 hours after inpatient admission for vital signs) for 90% of discharges, and linking variable (used to merge EHR to claims data) for 95% of discharges in order to receive their Annual Payment Update. These comments were heard by CMS and the measure developer, and the proposal for the submission of CCDE to remain voluntary for 2025 reporting was included as a rider to the Outpatient Prospective Payment System Proposed Rule.[2] Additionally, an update to expand the CCDE lookback period beyond the 24 hours prior to/after inpatient admission is being finalized through the 2025 Annual Updates Cycle.
- Additionally, through stakeholder Q&A, hospitals voiced difficulty submitting a linking variable, Medicare Beneficiary Identifier (MBI), for Medicare Advantage patients. While MBI is available for patients for the claims portion of this measure, hospitals note its collection is not fully integrated into hospitals EHR programs. CMS and the measure developer are aware of this limitation for hospitals beginning with Reporting Year 2026, and have been in contact with multiple hospitals to address this issue for future reporting.

Reference

1. Medicare Program; Hospital Inpatient Prospective Payment Systems for Acute Care Hospitals and the Long- Term Care Hospital Prospective Payment System and Policy

Changes and Fiscal Year 2024 Rates; Quality Programs and Medicare Promoting Interoperability Program Requirements for Eligible Hospitals and Critical Access Hospitals; Rural Emergency Hospital and Physician-Owned Hospital Requirements; and Provider and Supplier Disclosure of Ownership; and Medicare Disproportionate Share Hospital (DSH) Payments: Counting Certain Days Associated with Section 1115 Demonstrations in the Medicaid Fraction. https://www.govinfo.gov/content/pkg/FR-2023-08-28/pdf/2023-16252.pdf
2. Medicare and Medicaid Programs: Hospital Outpatient Prospective Payment and Ambulatory Surgical Center Payment Systems; Quality Reporting Programs, Including the Hospital Inpatient Quality Reporting Program; Health and Safety Standards for Obstetrical Services in Hospitals and Critical Access Hospitals; Prior Authorization; Requests for Information; Medicaid and CHIP Continuous Eligibility; Medicaid Clinic Services Four Walls Exceptions; Individuals Currently or Formerly in Custody of Penal Authorities; Revision to Medicare Special Enrollment Period for Formerly Incarcerated Individuals; and All-Inclusive Rate Add-On Payment for High-Cost Drugs Provided by Indian Health Service and Tribal Facilities. Proposed on July 22, 2024. https://www.federalregister.gov/documents/2024/07/22/2024-15087/medicar...

6.2.4 Progress on Improvement

The Hybrid HWR measure, although slated for 2025 Reporting in IQR, has undergone two rounds of Voluntary Reporting, in which a small subset of hospitals participated (n=724 [2023], n= 1,162 [2024]). As such, progress on improvements cannot be generalized due to limited sample, years for comparison, and the self-selecting nature of hospitals that participate in voluntary reporting (in which they typically score better on the readmission outcome).

However, we note that there has been improvement in outcomes for Medicare FFS patients based on data from the related claims-only HWR measure that is currently in use and has been publicly reported in IQR since 2013. We compared national unadjusted outcomes for the claims-only HWR measure (that differs from the hybrid version only in that it does not include the CCDE for risk adjustment) and found that observed outcomes have improved both at the patient level across all cohorts and the overall measure (Figure 13, "Hybrid HWR All Tables and Figures" attachment), and at the hospital level across the distribution (Figure 14, "Hybrid HWR All Tables and Figures" attachment). For example, during the 2018 reporting period (discharges July 1, 2016—June 30, 2017), average patient-level observed (unadjusted) readmission rates across all cohorts (HWR) were 15.3%, compared with 14.6% in the 2024 reporting period (discharges July 1, 2022—June 30, 2023) (Table 20, "Hybrid HWR All Tables and Figures" attachment). Patient-level observed readmission rates also decreased in all five cohorts in this same timeframe (2024 compared with 2018). In addition, hospital-level observed outcomes were lower in 2024 compared with 2018 (Table 21) with a median of 13.1% [IQR 10.5%-15.2%] and 14.6%, [IQR 12.0%-16.8%] respectively.

6.2.5 Unexpected Findings

There were no unintended impacts during implementation of this measure on patients or in care delivered by hospitals. However, there were some challenges with respect to EHR data (CCDE), and IQR threshold requirements (not used for measure calculation) as described in the Section

6.2.3.

7.1 Supplemental Attachment

HHWR CBE Fall Cycle Supplemental Documents (1).zip

Developer POC email

Lisa.Suter@yale.edu

Measure Developer POC

Lisa Suter
Yale/YNHH Center for Outcomes Research and Evaluation (CORE)
New Haven, CT
United States

The measure developer is different from the measure steward

Yes

Steward Address

Raquel Myers
Windsor Mill, MD
United States

Steward Organization

Centers for Medicare & Medicaid Services

Steward Organization URL

https://www.cms.gov/medicare/quality/initiatives/hospital-quality-initiative/in...

Steward POC email

raquel.myers@cms.hhs.gov