CBE ID

2881

Title

Excess days in acute care (EDAC) after hospitalization for acute myocardial infarction (AMI)

Project

Cost and Efficiency

Endorsement Status

Endorsed with Conditions

E&M Committee Rationale/Justification

When the measure returns in 5 years for maintenance endorsement, the developer would have empirically explored the differences with outpatient visits and post-hospitalizations for MA patients compared to fee-for-service patients

Is Under Review

No

Next Maintenance Cycle

Spring 2030

Previous Endorsement Cycle

Spring 2025

Initial Endorsement

Fri, 12/09/2016 - 08:41

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)

No

1.6 Measure Description

The Excess Days in Acute Care (EDAC) after Hospitalization for Acute Myocardial Infarction (AMI) (hereafter “AMI EDAC") measure assesses days spent in acute care within 30 days of discharge

from an inpatient hospitalization for AMI. This measure is intended to improve the quality of care transitions provided to discharged patients hospitalized for AMI by collectively measuring a set of adverse acute care outcomes that can occur post-discharge: emergency department (ED) visits, observation stays, and unplanned readmissions at any time during the 30 days post-discharge. To aggregate all three events, each event is measured in terms of days. The outcome is adjusted to account for age and comorbidities and incorporates exposure time to account for survival times shorter than 30 days (for patients who die within 30 days of discharge). The measure cohort includes admissions for patients who are 65 years or older, are enrolled in Medicare Fee-For-Service (FFS) or Medicare Advantage (MA) and are hospitalized in non-federal short-term acute care hospitals. The final risk-adjusted measure score is calculated as the difference ("excess") between a hospital's "predicted days" and "expected days," per 100 discharges.

1.7 Measure Type

Outcome

1.8 Level of Analysis

Facility

1.9 Care Setting

Hospital: Inpatient

1.10 Measure Rationale

The goal of the AMI EDAC measure is to improve patient outcomes by providing patients, physicians, hospitals, and policymakers with information about hospital-level, risk-standardized all-cause excess days in acute care after discharge from a hospitalization for AMI. The AMI EDAC measure captures the outcome of all-cause days in acute care within 30 days of discharge for hospitalization for AMI by counting the number of days a hospital's discharged patient spends as an inpatient (unplanned readmission), in observation, or in the emergency department (ED). The measure score (excess days in acute care) is derived by subtracting each hospital's expected days in acute care from its predicted days in acute care (described in more detail in Section 1.18) and then standardizing the result by hospital volume.

Coronary artery disease (CAD), the main underlying cause of AMI, affects more than 18 million adults in the United States; according to the American Heart Association, about 800,000 experience an AMI each year (Dimala et al., 2024; Tsao et al., 2023). Nearly one in five older adults (over 65) hospitalized for AMI is readmitted within 30 days of discharge resulting in a significant burden for the healthcare system and patients (Dodson, 2019). Between 2012 and 2018, AMI amounted to about $18.3 billion per year of the nation's medical expenses (Tajeu et al.,2024).

EDAC measures capture a complete picture of post-discharge hospital-based acute-care utilization that informs patients and the public about care quality and incentivizes global improvement in transitional care. EDAC measures provide information complementary to readmission measures; the features of EDAC measures include: 1) the capture of all post-discharge, hospital-based acute care that matter to patients, such as having to return to the hospital, go to the ED, or spend time in the hospital under observation after an initial inpatient admission; (2) the capture of the full

length of stay in days, that can reflect variation in hospital quality; (3) the capture of multiple events such as multiple visits in 30 days; and (4) accounting for time at risk of an event (that is, survival time).

The AMI EDAC measure was developed to identify institutions whose performance is better or worse than would be expected based on their patient case mix. Measuring and reporting excess days in acute care provides transparency for consumers, informs healthcare providers about opportunities to improve care, strengthens incentives for quality improvement, and ultimately improves the quality of care (including better inpatient management, as well as better peri-discharge care quality) received by Medicare patients. The AMI EDAC measure has been re-specified to include both Medicare Advantage (MA) and Fee-for-Service (FFS) beneficiaries; including MA beneficiaries in CMS hospital outcome measures helps ensure that hospital quality is measured across all Medicare beneficiaries and not limited to the FFS population.

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1.13 Data Dictionary

Attached

1.13a Attach Data Dictionary

AMI_EDAC_Data Dictionary.xlsx

1.14 Numerator

This is an outcome measure and does not have a traditional numerator. We use this section to define the outcome. The outcome for the AMI EDAC measure is defined as the number of days a patient spends in acute care (ED treat-and-release visits, observation stays, and unplanned readmissions) for any cause, within 30 days after the date of discharge from an index admission.

1.14a Numerator Details

The outcome for this measure (captured in days, for ED visits, observation stays, and unplanned readmissions) is defined below; all outcomes are captured for 30 days after discharge from the index hospitalization:

- **ED visits:** An ED visit is defined as a visit with revenue center codes '0450', '0451', '0452', '0456', '0459', or '0981'. See the Excel attachment, AMI EDAC_Data Dictionary.xlsx, for the code definitions (Tab 6). Each ED visit is counted as one day (1.0 day).
- **Observation stays:** An observation stay is defined as a visit with revenue center code '0762' and a Healthcare Common Procedure Coding System (HCPCS) code 'G0378' (in the hospital outpatient data files) or when a facility claim is not available, Current Procedural Terminology (CPT) codes '99217' to '99220' or '99234' to '99236' (in the professional data files). This broad definition captures all post-discharge observation stays in the facility and professional data files. See the data dictionary ("AMI_EDAC_Data Dictionary"), Tab 6, for the code definitions. Observation stays are recorded in terms of hours and rounded up to the nearest integer of days.
- **Readmission:** A readmission is defined as any unplanned admission to an acute care hospital within 30 days of the discharge date for the index hospitalization. "Planned" readmissions, not included in the outcome, are those planned by providers for anticipated medical treatment or procedures that must be provided in the inpatient setting. To exclude planned readmissions, we use CMS' Planned Readmission Algorithm version 4.0 2024 (see Figure 1. Planned Readmission Algorithm Version 4.0 2024 Flowchart in the Figures and Tables Supplemental Attachment, and additional information below). Readmissions are counted in days. Each rehospitalization is counted according to the length of stay, calculated as the discharge date minus the admission date, plus one day. Admissions that extend beyond the 30-day follow-up period are truncated on day 30. If a patient is readmitted to the same hospital on the same day of discharge for the same diagnosis as the index admission, the measure considers the patient to have had one single continuous admission. However, if the diagnosis of the readmission is different from the index admission, this is considered a readmission in the measure.
- **Overlapping outcomes:** When an ED visit, observation stay, or readmission overlaps with each other, we count only the most severe of the overlapping events. For example, in the case of an overlapping readmission and observation or ED visit, we count only the readmission; if an observation stay and ED visit happen on the same day, we count only the observation stay.
- **Multiple events:** We count all eligible outcomes occurring in the 30-day period, even if they are repeat occurrences. For example, if a patient returns to the ED three times on three different days, we count each ED visit as one day. Similarly, if a patient has two hospitalizations within 30 days, the days spent in each are counted. We take this approach in order to capture the full post-discharge utilization.

Planned Readmission Algorithm (Version 4.0)

The planned readmission algorithm (see Figure 1. Planned Readmission Algorithm Version 4.0 2024 Flowchart in the Figures and Tables Supplemental Attachment) is a set of criteria for classifying readmissions as planned using Medicare claims and encounters. 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 complications of care are never planned.

The algorithm was developed in 2011 as part of the Hospital-Wide Readmission measure. In 2013, CMS applied the algorithm to its other readmission measures.

In applying the algorithm to condition- and procedure-specific measures, teams of clinical experts reviewed the algorithm in the context of each measure-specific patient cohort and, where clinically indicated, adapted the content of the algorithm to better reflect the likely clinical experience of each measure's patient cohort. The planned readmission algorithm is applied to the AMI EDAC measure without modifications.

1.15 Denominator

The target population for the AMI EDAC cohort is defined as patients aged 65 or older with a principal discharge diagnosis of AMI, who were enrolled in Medicare Fee-for-Service (FFS) or Medicare Advantage (MA) for the 12 months prior to and during the index admission, discharged alive from a non-federal short-term acute care hospital, and not transferred to another acute care facility.

1.15a Denominator Details

The AMI EDAC measure includes index admissions for patients who meet all the following criteria:

- **Principal discharge diagnosis of AMI;**
  - *Rationale:* Hospitalization for AMI is the target for measurement.
  - ICD-10 codes used to define the AMI EDAC cohort inclusion criteria are shown in Tab 1 ("AMI EDAC Cohort Inclus") of the Excel file entitled *AMI EDAC_Data Dictonary.xlsx*
- **Enrolled in Medicare Fee-For Service (FFS) or Medicare Advantage (MA) 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, outpatient, and physician claims data for the 12 months prior to the index admission, to augment the index admission claim itself.
- **Aged 65 or older;**
  - *Rationale*: Patients younger than 65 are not included in the measure because they are considered clinically distinct from patients 65 or over.
- **Discharged alive from a non-federal short-term acute care hospital; and,**
  - *Rationale*: It is only possible for patients to experience the outcome if they are 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 (e.g., to home or a skilled nursing facility).

1.15b Denominator Exclusions

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

- Without at least 30 days of post-discharge enrollment in Medicare FFS or MA
- Discharged against medical advice (AMA)
- AMI admissions within 30 days of discharge from a prior AMI index admission

1.15c Denominator Exclusions Details

The measure excludes index hospitalizations that meet any of the following exclusion criteria (see Figure 2 in the Figures and Tables Supplemental Attachment).

- **Without at least 30 days of post-discharge enrollment in Medicare FFS or MA;**
  - *Rationale:* The 30-day outcome cannot be assessed in this group since claims data are used to determine whether a patient visited the ED, was placed under observation, or was readmitted.
- **Discharged against medical advice;**
  - *Rationale:* Providers did not have the opportunity to deliver full care and prepare the patient for discharge.
- **Same-day discharges; and,**
  - *Rationale:* Patients admitted and then discharged on the same day are not included as an index admission because it is unlikely that these admissions are for clinically significant AMIs.
- **AMI admissions within 30 days of discharge from a prior AMI index admission.**
  - *Rationale:* Additional AMI admissions within 30 days are excluded as index admissions because they are part of the outcome. A single admission is not considered both an index admission and a readmission for another index admission.

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

The risk-adjustment model is a hierarchical generalized linear model (HGLM). This consists of a

binomial model specified for days in acute care as a proportion of the number of exposure days (alive days up to 30 days post-discharge) and includes random effects for hospitals. This accounts for the within-hospital correlation of the observed outcome and accommodates the assumption that underlying differences in quality across hospitals lead to systematic differences in outcomes.

Specifically, CMS calculates EDAC, for each hospital, as the difference ("excess") between a hospital's predicted days and expected days per 100 discharges. "Predicted days" is the sum across all patients of the model-predicted number of days spent in acute care, based on the hospital's performance and adjusting for patient-level risk factors (described in Tabs 2 and 3 of the file *AMI EDAC_Data Dictionary.xlsx*). "Expected days" is the sum across all patients of the model-predicted number of days that would have been expected if the patients were discharged from an average-performing hospital, after adjusting for patient case mix. We risk adjust the day count to account for age, and comorbidities The difference (predicted days minus expected days) is then divided by hospital volume and multiplied by 100 so the final EDAC measure is EDAC per 100 discharges. The model used is appropriate for count data, and we incorporate exposure time to account for survival times shorter than 30 days.

1.18a Attach measure score calculation diagram

Measure Score Calculation EDAC.pdf

1.19 Measure Stratification Details

This measure is not stratified.

1.20 Types of Data Sources

Administrative Data, Claims Data

1.21a Data Collection Tool URL(s)

http://example.com

1.25 Data Source Details

Medicare Fee-for-Service (FFS) claims and Medicare Advantage (MA) encounters, in addition to Medicare administrative data, are used to derive all components of the measure.

1.26 Minimum Sample Size

The measure does not have a minimum sample size.

2.1 Attach Logic Model

AMI_EDAC_Logic_Model_Supplemental_Attachment.pdf

2.2 Evidence of Measure Importance

Acute myocardial infarction (AMI) is a serious condition with significant health and cost

implications. Between 2012 and 2018, there were over 620,000 AMI hospitalizations annually in the United States, with a mean cost of $29,500 per case. These resulted in an estimated annual expenditure of $18.3 billion (Tajeu et al., 2024).

Post-acute care utilization following AMI discharge such as emergency department (ED) visits, observation stays, or readmissions is common. While there have been improvements in clinical treatment, readmission and mortality rates remain high. In fact, after years of decline, cardiovascular disease mortality is once again increasing (Virani et al., 2020; Birger et al., 2021). For patients recovering from AMI, the post-discharge period often involves ongoing challenges. A study of nearly one million Medicare beneficiaries found that patients spent a median of only 24 of the first 30 days after discharge at home (Pandey et al., 2020). This suggests that many patients experience complications, poor care transitions, or unmet recovery needs which contribute to higher rates of acute care use after discharge.

The AMI EDAC measure captures the number of days spent in the ED, in observation, or in inpatient settings within 30 days of discharge. Unlike traditional readmission measures that only focus on readmission, EDAC captures all hospital-based unplanned acute care, likely resulting from post-discharge complications and/or inadequate care transitions. The AMI EDAC measure can, therefore, indicate how well hospitals and systems coordinate post-AMI care and follow-up. From an underlying process perspective, the EDAC measure can reflect the quality of discharge planning, medication reconciliation, and coordination with outpatient care, which have a direct impact on intermediate outcomes, such as an increase in ED visits and repeat hospitalizations; failures in these processes can also contribute to longer-term poor outcomes, such as delayed long-term recovery, increased mortality, and reduced quality of life (Donzé et al., 2023; Fernandes et al., 2023; Gonçalves-Bradley et al., 2022).

We know there is variation in hospital performance on the AMI EDAC measure (see Section 2.4, Performance Gap); a hospital at the 10th percentile has -37.7 excess days in acute care per 100 discharges whereas a hospital at the 90th percentile (worse performance) has 58.1 excess days in acute care per 100 discharges.

As an outcome measure, the measure itself does not identify the specific underlying cause of better or worse performance, nor does it proscribe a specific intervention to address poor performance. For example, some hospitals may excel in coordinating specific aspects of post-discharge care, such as post-discharge follow-up, while others may have gaps in such processes, resulting in higher EDAC. Each hospital must identify the root cause of poor performance. Several interventions have been shown to reduce EDAC-related utilization including transitional care programs, such as early follow-up calls and structured discharge planning, which have been effective in reducing 30-day readmissions and ED visits—particularly for frail older adults (Feltner et al., 2014; Lee et al., 2022; Tyler et al., 2023). In addition, digital health interventions have also shown evidence to reduce EDAC as shown in one study where a bundled smartphone-based intervention reduced 30-day readmissions by more than 50% among AMI patients (Marvel et al., 2021). See Section 6.2.1 for a detailed description of interventions that hospitals can implement to reduce post-discharge hospital-based acute care utilization.

The evidence above including the burden of AMI, variation in hospital performance, and the existence of effective interventions demonstrates the importance and value of a hospital-level quality measure for post-discharge acute care. The AMI EDAC measure, as an outcome measure,

alerts hospitals to identify where care transitions may be failing and where improvements in post-discharge care coordination can make a meaningful difference in patient outcomes.

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2.4 Performance Gap

Table 1, Table 2, and Figure 3 (see the Figures and Tables Supplemental Attachment) show that there is meaningful variation in the distribution of measure scores (Excess Days in Acute Care per 100 discharges) using the most recent testing data (January 1, 2022 - December 31, 2023).

Because the measure score (see Section 1.18) is calculated as the difference between the predicted days (sum, across all patients at any one hospital) and expected days (what would be expected for the average hospital), a hospital performing better than expected will have a negative measure score, a hospital performing as expected will have a measure score of zero, and a hospital performing worse than expected will have a positive measure score.

As shown in Table 1 in the Figures and Tables Supplemental Attachment, AMI EDAC measure scores range from -172.1 to 709.3; the median is -1.3; the 10th percentile is -37.7, and the 90th percentile is 58.1. A hospital at the 10th percentile (-37.7 excess days per 100 discharges) has 95 fewer excess days per 100 discharges compared with a hospital performing at the 90th percentile (58.1 excess days per 100 discharges). The distribution of performance is skewed to the right, with greater excess days between the median and the 90th percentile (about 60 excess days per 100 discharges) compared to the 10th and the median (about 36 excess days per 100 discharges). If all hospitals performed at the 10th percentile, on average, Medicare patients would be spared about 280,000 days in post-discharge hospital-based acute care, with an estimated savings of more than $600 million.

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	7.2	-172.1	-54.6	-30.8	-19.5	-11.8	-5.1	2.2	11.2	22.5	42.8	115.3	709.3
N of Entities	3,623	1	362	362	363	362	362	363	362	363	362	362	1
N of Persons / Encounters / Episodes	474,196	1	9,573	29,479	41,181	52,014	59,782	75,281	81,446	64,348	46,916	14,176	1

2.6 Meaningfulness to Target Population

Acute care utilization after discharge such as return to the emergency department, observation unit, or hospital readmission is disruptive to patients and caregivers, costly to the healthcare system, and can expose patients to additional risks such as hospital-acquired infections or complications (Dhaliwal & Dang, 2024). Patients and families frequently described the period after AMI discharge as one of the most difficult parts of the recovery process (Eriksson, Asplund & Svedlund, 2009). During this time, they are adjusting to new medications and learning to manage their condition outside of the hospital. Rather than a time of healing, this period can feel unstable and emotionally exhausting.

Many of these challenges are reflected in how often patients return to acute care. According to Pandey et al. (2020), patients spent a median of only 24 out of the first 30 days after AMI discharge alive and at home. The rest of that time was spent in hospitals, skilled nursing facilities, or lost to early mortality. While attempting to prevent complications leading to patient hospitalizations, they are also adapting to new medications, routines, and symptoms throughout this period (Eriksson, Asplund & Svedlund, 2009). To patients, the recovery period is about regaining stability, confidence, and the ability to resume daily life. Because of this, outcome measures like AMI EDAC are significant as they calculate the number of extra days a patient spends in ERs, observation units, or readmitted to the hospital within 30 days after being discharged. These days are a disruption to recovery and often reflect pain, fear, or complications for the patient—whether related to their heart condition or other emerging health issues.

These experiences are often tied to real, tangible issues. Patients have described returning to the hospital due to symptoms triggered by medication changes made during their initial admission, infections from procedures, or a lack of communication that left them unsure of how to manage symptoms at home. When CORE interviewed patients and caregivers for an EDAC Technical Expert Panel (TEP), 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 shared experiences such as returning to the hospital following exacerbation of a condition caused by changes in medication after discharge, returning 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. These experiences take a toll—emotionally, physically, and financially—on both patients and caregivers.

These concerns are especially pressing given the broader context. AMI remains a leading cause of hospitalization and spending in the United States, with an average of 620,986 hospitalizations per year between 2012 and 2018 and a mean cost of $29,500 per case, totaling $18.3 billion annually (Tajeu et al., 2024). These trends mean that more families are likely to experience financial burdens, compounding their already existing emotional and physical health toll.

Fortunately, some interventions have helped reduce these burdens. Transitional care interventions, such as early follow-up, structured discharge planning, and caregiver support, have been shown to reduce hospital readmissions, especially for frail or older adults (Feltner et al., 2014; Lee et al., 2022; Tyler et al., 2023). Digital tools have also helped patients manage their care more effectively. In one study, a smartphone-based program significantly reduced 30-day readmissions, lowering the rate from 16.8% to 6.5% among AMI patients (Marvel et al., 2021; see Section 6.2.1 for more about evidence-based interventions). These findings show that patient

experiences after AMI discharge are not only common and difficult—they are also changeable. With the right support and care coordination, patients can spend more time healing at home and less time in hospital settings. Patients have made it clear that what matters most to them during recovery is stability, clarity, and the ability to return to daily life without disruption.

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3.1 Contributions Towards Closing Care Gaps

This domain is optional for Spring 2025.

4.1a Data Structure and Availability

This is a claims-based measure and there are no difficulties in testing or operational use of the measure regarding data collection, availability of data, missing data, or time and frequency of data collection. CMS can calculate this measure using data submitted by hospitals for payment; there are no patient confidentiality concerns or other feasibility or implementation issues. The measure is not based on a sample.

4.1b Implementation Costs and Burden

No data are collected by facilities; therefore, this measure imposes no burden on measured entities and no implementation effort. CMS monitors feedback from the public and measured entities through CMS's Question and Answer (Q&A) portal on *QualityNet*; there have been no concerns about burden related to this measure.

4.1c Confidentiality

There are no concerns about patient confidentiality because the measure is based on claims data submitted by facilities to CMS, and CMS then uses that data for the calculation of the measure score.

4.3 Feasibility Informed Final Measure

As this is a claims-based measure, there are no feasibility concerns and no burden on the facility; the measure is calculated by CMS using claims data submitted by facilities for payment.

There are no missing data concerns for the measure because it uses final action claims submitted by facilities for payment. To ensure complete claims, we allow at least 3 months of time between accessing the data and the end of the performance period.

4.4 Proprietary Information

Not a proprietary measure and no proprietary components

5.1.1 Data Used for Testing

For most of the testing in this submission, we used two years of Medicare (Fee-for-Service (FFS) and Medicare Advantage (MA)) data (January 1, 2022-December 31, 2023). Descriptions of the data used for testing are outlined in Table 3 in the attachment.

5.1.1a Dates of Testing Data

Field not required for Spring 2025.

5.1.2 Differences in Data

Please see Section 5.1.4 for details. Differences in data used for testing are outlined in Table 3 (Data Descriptions) in the Figures and Tables Supplemental Attachment.

5.1.3 Characteristics of Measured Entities

The datasets, dates, number of measured hospitals, and number of admissions used in each type of testing are in Table 3 in the Figures and Tables Supplemental Attachment. For most measure testing, we used two years of Medicare data from January 1, 2022 to December 30, 2023. These datasets also include data on each patient for the 12 months prior to the index admission and contain facility inpatient and Medicare Enrollment Database (EDB) data.

5.1.4 Characteristics of Units of the Eligible Population

Please see Section 5.1.4 for details. Characteristics of units of eligible population are outlined in Table 3 (Data Descriptions) in the Figures and Tables Supplemental Attachment.

5.2.1 Level(s) of Reliability Testing Conducted

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

5.2.2 Method(s) of Reliability Testing

To ascertain measure score reliability, we calculated the intra-class correlation coefficient (ICC) using a split-sample (also known as the split-half) method using two years of data (CY2022/2023). We calculated the ICC as the average over 100 iterations of resampling without replacement, described in more detail below.

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 (within hospitals) 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 (Rousson et al., 2002). 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. Recent research by Nieser and Harris (2024) shows that averaging multiple split-sample reliability estimates yields a more stable result (referred to as permutation split sample reliability), so we adopted this approach to the reliability testing for this measure.

Specifically, for the testing of the AMI EDAC measure, using two years of data (CY2022/2023) we randomly sampled half of the patients within each hospital, calculated the measure score 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. We repeated this process, randomly sampling the data 100 times without replacement, and, as a metric of agreement, we calculated the average intra-class correlation coefficient across all 100 samples (Shrout and Fleiss, 1979; Nieser and Harris, 2024). The agreement of the two measure scores was quantified for hospitals in each sample using the intra-class correlation as defined by ICC (2,1) (Shrout and Fleiss, 1979), and a correction using the Spearman-Brown prophecy formula was performed. We calculated split-half reliability for all hospitals with at least one admission and for hospitals with at least 50 admissions.

References

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5.2.3 Reliability Testing Results

For hospitals with at least one admission, the average ICC for the AMI EDAC measure using split-half reliability testing across 100 random samples was 0.392.

For hospitals with at least 50 admissions, the average ICC for the AMI EDAC measure using split-half reliability testing across 100 random samples was 0.816.

5.2.3a Attach Additional Reliability Testing Results

AMI_EDAC_Figures_and_Tables_Supplemental_Attachment.pdf

5.2.4 Interpretation of Reliability Results

Two years of performance data, split-half reliability, using 100 random samples, resulted in an average ICC of 0.816 for hospitals with at least 50 admissions. This result meets the consensus-based entity (CBE) endorsement threshold (minimum >=0.6) and shows that the AMI EDAC measure is sufficiently reliable for public reporting for hospitals with at least 50 admissions.

5.3.1 Level(s) of Validity Testing Conducted

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

5.3.2 Type of Accountable Entity Level Validity Testing Conducted

Empirical validity testing at the accountable entity-level (e.g., criterion validity, construct validity, known groups analysis), Systematic assessment of face validity of the measure’s performance

score as an indicator of quality or resource use

5.3.3 Method(s) of Validity Testing

Face Validity

During the original measure development of the Fee-for-Service (FFS)-only measure, we asked our TEP, made up of 16 members including patient representatives, expert clinicians, methodologists, researchers, and providers, to formally assess the face validity of the AMI EDAC measure that is currently implemented (FFS-only patients). We provided the TEP with background information on the previous consensus-based entity's (National Quality Forum) measure evaluation criteria and presented the measure specifications and testing and performance results for their evaluation.

We systematically assessed the face validity of the measure score as an indicator of quality by soliciting the TEP members' agreement with the following statement: "The risk-standardized acute care days obtained from the measures as specified can be used to distinguish between better and worse quality hospitals." We measured agreement using a six-point scale (strongly agree, agree, somewhat agree, somewhat disagree, disagree, strongly disagree).

Our TEP, which included 16 members, including patient representatives, expert clinicians, researchers, providers, and purchasers (please see the Figures and Tables Supplemental Attachment, Table 4).

Empiric (Construct) Validity

We also explored validation through meaningful comparisons of the AMI EDAC measure scores with those from existing quality metrics where we would expect to see a relationship.

To identify candidate measures for construct validity testing, we first reviewed the logic model (Figure 2, in the Figures and Tables Supplemental Attachment) to identify quality measures that fall within the same causal pathway. From that candidate list of measures, we determined which measures had data publicly available at the hospital level. From this candidate list, we selected the following measures: Overall Hospital Star Rating: Readmission Group Score, Summary Score, Patient Experience Group Score, and Medicare Spending per Beneficiary (each measure is described in more detail below). We then assessed the relationship between those measures and the AMI EDAC measure score, as described below.

We examined correlations between AMI EDAC measure scores and components of the Overall Hospital Star Rating, including the Readmission Group Score (with and without the related Hospital-Wide Readmission measure and the existing AMI EDAC measure), the Summary Score (with and without the entire Readmission Group), the Patient Experience Group score, and Medicare Spending per Beneficiary (MSPB). Because the AMI EDAC measure is on a lower-is-better scale while the Star Rating measures function on a higher-is-better scale, we hypothesized that the AMI EDAC measure would be negatively correlated (weakly to moderately) with Star Rating-related measures. For MSPB, higher scores indicate higher costs, so we hypothesized that the AMI EDAC measure would be positively correlated (weakly to moderately) with MSPB. We

calculated Pearson's correlation coefficients for the associations between the AMI EDAC measure and these existing quality/cost measures on the same measured entities. For these analyses, we used CY2022/2023 data for the AMI EDAC measure scores and Star Rating data from the April 2025 Star Rating preview, with measure dates ranging from 7/2020 to 06/2023. The full methodology for the Overall Hospital Star Rating can be found at: https://qualitynet.cms.gov/files/603966dda413b400224ddf50?filename=Star...;

The full methodology of the MSPB measure can be found at: https://qualitynet.cms.gov/inpatient/measures/hiqr-mspb/methodology

Validity of the Outcome

To assess the validity of the outcome, we examined the time in days until the first post-discharge hospital visit (inpatient admission, ED visit, or observation stay) for patients in the AMI EDAC cohort, using the two-year dataset (CY2022/2023). Additionally, we further validated the outcome by analyzing the reasons (principal discharge diagnoses) for post-discharge hospitalizations within 30 days. For this analysis, we mapped each principal discharge diagnosis to its associated Agency for Healthcare Research and Quality (AHRQ) Clinical Classifications Software (CCS) category; AHRQ CCS categorizes ICD-10 diagnosis codes into a smaller number of clinically meaningful groups (AHRQ, 2019). We then identified the most frequently occurring AHRQ CCS categories associated with readmission in the AMI cohort.

References

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5.3.4 Validity Testing Results

Table 5 in the Figures and Tables Supplemental Attachment shows the results of the TEP face validity vote from original measure development of the FFS-only measure, where TEP members indicated their agreement with the following statement*: "The risk-standardized acute care days obtained from the measures as specified can be used to distinguish between better and worse quality hospitals."* Twelve TEP members responded to the TEP survey; 11 out of 12 (92%) agreed (strongly agreed, agreed, or somewhat agreed) with the face validity of the measure, indicating support for the validity of the AMI EDAC measure.

Empiric Validity: Construct Validity

Selection of Comparator Measures

Below we describe the rationale behind the measures that were selected as comparator measures for construct validity testing.

In our evaluation of the logic model, we identified the following comparator measures for construct validity testing.

- **Overall Hospital Star Rating Readmission Group Score**: The Readmission Group Score is calculated as the simple average of measures within the Readmission Group, which includes hospital-level (inpatient) readmission and EDAC measures, and hospital visit measures following outpatient procedures. Because there is evidence that broad-based interventions are effective in reducing unplanned readmissions (which is part of the AMI EDAC measure's outcome), we hypothesized that hospitals with lower (better) AMI EDAC measure scores would also perform better on the composite Readmission Group Score. We note that all of the measures within the Readmission Group currently include only Medicare FFS patients and therefore we hypothesized a weak association between the AMI EDAC measure scores and the Readmission Group Score. We further hypothesized that removing the Hospital-Wide Readmission measure (whose cohort overlaps with the AMI EDAC measure) and the related [FFS-only] AMI EDAC measure from the Readmission Group Score, would result in a weaker association.
- **Patient Experience Group Score**: The Patient Experience Group Score is calculated from eight components of the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey, including important components of care coordination both during and after hospitalization, and for this reason, it was selected as a compactor measure. For example, components of HCAHPS in the Patient Experience Group Score include patients' assessments of doctor and nurse communication and whether patients understood their care when they left the hospital. The score also includes patient reports of receiving discharge instructions, and reports of staff explaining patients' medications. This measure is calculated for a sample of patients aged 18 and over; we therefore expect a weak negative association between patient experience and AMI EDAC.
- **Medicare Spending per Beneficiary** (MSPB): MSPB shows whether Medicare spends more, less, or about the same for an episode of care at a specific hospital compared to all hospitals nationally. An MSPB episode includes Medicare Part A and Part B payments for services provided by hospitals and other healthcare providers the 3 days prior to, during, and 30 days following a patient's inpatient stay. This measure evaluates hospitals' costs compared to the costs of the national median hospital and is adjusted for patient age, comorbidities, and geographic payment differences. MSPB was selected as a comparator measure as in our logic model, we hypothesize that quality improvement to lower EDAC would result in lower costs. MSPB is calculated only for Medicare FFS patients and covers all episodes of care, therefore we hypothesize a weak, positive correlation between MSPB and AMI EDAC measure scores.

Analysis of Construct Validity

Table 6 in the Figures and Tables Supplemental Attachment provides Pearson correlation coefficients that show the relationship between the AMI EDAC measure score and related measures. Pearson correlation coefficients between the AMI EDAC measure and the comparator measures (Readmission Group Score, Readmission Group Score excluding HWR and AMI EDAC [currently implemented FFS version], and the Patient Experience Group Score) were –0.335, -0.252, and –0.173, respectively (all p-values <.0001). Pearson correlation coefficients between the AMI EDAC measure scores and MSPB were 0.117, p <.0001. These results show a significant

association with the expected strength and in the expected direction with measures in the same casual pathway, which supports the validity of the AMI EDAC measure.

Analysis of Confounders of Construct Validity

We chose the comparator measures due to our hypotheses of related constructs identified in our logic model, which resulted in significant correlations between measure scores in the expected direction and strength. It is possible, however, that any such relationship could be confounded by another variable that is responsible for the association rather than the hypothesized one. The largest potential confounder is case-mix differences among patients, where hospitals with patients with fewer comorbidities would be expected to have both lower EDAC rates and lower readmission rates, better patient experience, and lower MSPB. All of the quality measures we examined, however, are risk-adjusted or adjusted for case mix, mitigating this confounder.

We note that it is not possible for developers to address all confounders directly, due to limitations in resources, including the availability of data. Furthermore, for this measure (and most measures) there is little published literature to examine the mechanisms underlying these relationships, in part due to the fragmented nature of our healthcare system resulting in fragmented and limited access to and availability of data with which to study such relationships.

Empiric Validity: Validity of the Outcome

We provide additional evidence for the validity of the 30-day, all-cause outcome through two analyses: a time course showing the time to the first hospital visit (inpatient, observation, or ED visit) after discharge, and an analysis of principal discharge diagnoses associated with the post-discharge hospital visit.

The 30-day, all-cause outcome was chosen for this and other related measures based on empiric evidence showing the time course of readmissions. We illustrate this In Figure 4 (in the Figures and Tables Supplemental Attachment), for the AMI EDAC cohort, where it is evident that post-discharge hospital visits continue beyond 30 days, and do not reach baseline until about 80 days, which is consistent with the literature and our empiric analyses for other related measures.

Table 7 (in the Figures and Tables Supplemental Attachment) provides further validation of the 30-day, all-cause outcome. In Table 7, we show that the most frequent reasons (principal discharge diagnoses) associated with readmission are associated with the initial index admission for AMI.

Validity of Claims-Based Variables

We did not provide patient/encounter validity testing for the AMI EDAC measure because this is a claims-based measure; the fields used to specify the measure are structured, used for reimbursement, and audited. Claims data are widely seen as valid and reliable for use in quality measurement.

Our team has, however, demonstrated for a number of prior measures the validity of claims-based measures for profiling hospitals by comparing either the measure results or individual data elements against medical records. CMS validated six CBE-endorsed measures currently in public

reporting (AMI, heart failure, and pneumonia mortality and readmission) with models that used chart-abstracted data for risk adjustment. Specifically, claims model validation was conducted by building comparable models using abstracted medical chart data for risk adjustment for heart failure patients (National Heart Failure data) (Krumholz et al. 2006; Keenan et al. 2008), AMI patients (Cooperative Cardiovascular Project data) (Krumholz, Wang, et al. 2006), and pneumonia patients (National Pneumonia Project dataset) (Bratzler et al. 2011). When both models were applied to the same patient population, the hospital risk-standardized rates estimated using the claims-based risk-adjustment models had a high level of agreement with the results based on the medical record model, supporting the use of the claims-based models for public reporting.

References

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Krumholz HM, Brindis RG, Brush JE, et al. 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. January 24, 2006 2006;113(3):456-462.

Krumholz HM, Wang Y, Mattera JA, et al. An administrative claims model suitable for profiling hospital performance based on 30-day mortality rates among patients with an acute myocardial infarction. Circulation 2006;113(13):1683-1701.

5.3.4a Attach Additional Validity Testing Results

AMI_EDAC_Figures_and_Tables_Supplemental_Attachment_0.pdf

5.3.5 Interpretation of Validity Results

Both strong face validity and empiric validity testing results support the validity of the AMI EDAC measure. Ninety-two percent of TEP members voted in support of the face validity statement, and our empiric results show a significant association with the expected strength and in the expected direction with measures in the same casual pathway (see Table 6 in the Figures and Tables Supplemental Attachment, and the Logic Model Supplemental Attachment), which supports the construct validity of the AMI EDAC measure. In addition, we provide evidence for the validity of the 30-day, all-cause outcome. The interpretation of these results is discussed below.

Face validity

The validity of the measure (established during original measure development) is supported by strong face validity results, as measured by systematic feedback from the TEP. As shown in Table 5 (in the Figures and Tables Supplemental Attachment), 11 of 12 (91.7%) TEP members strongly,

moderately, or somewhat agreed with the statement: “The risk-standardized acute care days obtained from the measures as specified can be used to distinguish between better and worse quality hospitals.”

Empirical Validity Testing

The validity of the measure is further supported by the empiric validation results which demonstrate a correlation (in the expected strength and direction) between the AMI EDAC measure and other quality/cost measures in the causal pathway (see Logic Model Supplemental Attachment), such as the Star Rating readmission group score (without the AMI readmission or HWR measures), the Patient Experience Group Score, and MSPB. The largest potential confounder of these relationships, patient comorbidities or case mix, is addressed through risk/case-mix adjustment of the individual measures. Because we know that (1) there are effective strategies that hospitals can implement to reduce post-discharge hospital use, (2) hospitals have implemented quality improvement programs to improve readmission rates, which can be broad-based, and (3) readmission rates (and AMI EDAC performance) have improved over time (see Section 6.2.4), we conclude with moderate certainty that the relationships we see between the Readmission Group and the AMI EDAC performance are directly related. This is further supported by the fact that the readmission measures all share the same outcome (post-discharge hospital acute care).

Finally, when considering the three types of measures we analyzed, our results support the notion of convergent validity. Each of the measures examines a different quality domain (readmission, patient experience, and cost), with different data sources (patient experience vs. claims) and measure calculation approaches. Yet our results show a pattern consistent with our hypothesis with correlations in the expected direction and strength across all three domains.

Validity of the Outcome (30-day, all-cause)

The validity of the 30-day, all-cause outcome is supported by several pieces of empirical evidence. First, we show that the time course of hospital visits shows that the daily readmission rate does not return to baseline after 30 days after the index admission and is therefore temporally associated with the index admission. This provides evidence in support of a causal relationship (rather than random hospital visits for unrelated reasons). Second, we show that the reasons for readmission (principal discharge diagnoses) are clinically related to the index admission. In addition, through the literature, we show that there is a relationship between specific care processes and the outcome of hospital readmission, emergency room visits, or observation stays. As discussed in the evidence attachment (included with this submission), interventions during and after a hospitalization can be effective in reducing utilization rates in geriatric populations and, particularly, for older patients with AMI. There is also increasing evidence that hospitals and health plans have been able to reduce readmission rates through quality improvement initiatives (see Section 6.2.1 for details). For AMI specifically, the evidence shows that appropriate care for AMI during and after the index hospitalization can reduce the risk of subsequent readmission and emergency department (ED) visits. We also show potential improvement in measure scores for the AMI EDAC measure over time (see Section 6.2.4).

5.4.1 Methods Used to Address Risk Factors

Statistical risk adjustment model with risk factors

5.4.2 Conceptual Model Rationale

The goal of risk adjustment is to adjust for case-mix differences across hospitals. Risk adjustment supports fair and accurate comparison of outcomes across measured entities by including an adjustment for factors such as patient age, comorbid diseases, and indicators of patient frailty, which are clinically relevant and have relationships with the outcome. Risk variable selection for this measure, described below, was based largely on an empiric approach that utilized individual ICD-10 codes. The main advantage of leveraging ICD-10 codes in place of alternative methods that employ an ICD-10 grouper (such as CMS's Condition Categories, or CCs) is the ability to address the clinical heterogeneity found in the broadly defined CCs. Our previous research indicates that the model performance of the mortality measures is significantly improved by using individual codes instead of CCs (Krumholz et al., 2019).

The AMI EDAC measure adjusts for case-mix differences among hospitals based on the clinical status of the patient at the time of the index admission. Accordingly, only comorbidities that convey information about the patient at that time or in the 12 months prior, and not complications that arise during the course of the index hospitalization, are included in the risk adjustment.

The process for determining patient comorbidities present at the time of the index admission (from the index admission claim/encounter data) uses a present-on-admission (POA) algorithm. The POA algorithm applies only in the case of secondary diagnosis codes on the index admission used in the risk adjustment of a measure. In brief, an ICD-10-CM code on the index admission is used in risk adjustment if one of the following is true:

1. The POA indicator for the secondary diagnosis code = 'Y' on the index admission.
2. The secondary diagnosis code is classified as a POA-exempt code that is considered "always POA" (as designated by our clinical experts).
3. If the index claim/encounter data is void of POA coding (that is, no reported POA indicator values for any of the secondary diagnoses), then the secondary diagnosis is used in risk adjustment if it is NOT mapped to a Condition Category (CC) that is included in the potential complications list (see Tab 5, "AMI EDAC RV CoC" in the data dictionary, "AMI_EDAC_Data Dictionary").

This measure does not include an adjustment for social drivers of health because the association between social drivers of health and health outcomes can be due, in part, to differences in the quality of health care that these groups of patients receive.

The measure does not adjust for patients' admission source or their discharge disposition (for example, skilled nursing facility) because these factors are associated with the structure of the healthcare system, not solely with patients' clinical comorbidities.

Selection of Clinical Risk Variables

Risk variables were selected using a data-driven, empiric approach, followed by minor adjustments for face validity. For candidate risk variables, we used a 70% randomly selected sample of data from the CY2022 dataset and included all secondary ICD-10 codes documented as

present-on-admission (POA) during the index admission (except for the palliative care code of Z51.5, which, effective October 1, 2021, was considered POA-exempt), and both principal and secondary ICD-10 codes in the 12 months prior to admission from any inpatient, outpatient, and professional provider claims. We also considered age, frailty, and an indicator for whether the admission was Medicare Advantage (MA) vs. Fee-for-Service (FFS). We note that specific Z codes for social risk factors were removed from the candidate list to allow for the selection of clinical risk variables; we later tested the impact of adding social risk factors to the model.

The variable selection of individual ICD-10 codes mainly relied on data-driven methodologies involving three key steps: 1) identifying candidate risk variables for testing in the risk model, 2) evaluating the bivariate association with outcome, and 3) consideration of associations between other non-individual-ICD-10 code variables, including frailty, with the outcome. In the first step, we screened and included ICD-10 codes identified at the index admission (index codes) and those captured in the 12 months prior to admission (pre-index codes) if their prevalence exceeded 0.5% and 2.5%, respectively. Further, co-occurring index and pre-index codes (at the admission level) with Pearson correlation coefficients greater than 0.8 were combined into one risk variable. Finally, pairs of identical index and pre-index ICD-10 codes with similar odds ratios that acted in the same direction (where the difference in association with the outcome, measured by odds ratio [OR], was less than 0.2) were merged.

In the second step, we included the remaining candidate variables (including age) in a multivariable logistic regression model that underwent variable selection through 1,000 iterations of bootstrapping. We selected variables that were statistically significantly associated with the outcome ($p<0.05$) in at least 80% of the bootstrapped samples. We determined if additional variables should be added to the multivariate model by examining if there was a resulting increase in the model c-statistic (using a threshold of at least 0.0005 increase in c-statistic for each additional variable, or an increase of at least 0.005 for including additional variables within the next 5% of bootstrapped samples [variables that were statistically significantly associated with the outcomes in at least 75% of the bootstrapped samples]).

In addition, based on evidence from the literature, expert input, guidance from the consensus-based entity for measure endorsement, the Assistant Secretary for Planning and Evaluation, input from other stakeholders, and prior testing results, we included a claims-based indicator of frailty in the final model. This indicator was developed for CMS's Multiple Chronic Conditions (MCC) measure.

For the combined MA and FFS cohort, the risk-adjustment model was updated to include an MA indicator (versus FFS) as a main effect. This was to adjust for the generally higher prevalence of comorbidities in the MA cohort, especially among the pre-index variables that were derived from services in the outpatient setting (e.g., physician visits).

Social Risk Factors

Because our risk variable selection process was based on an empirical approach using individual ICD-10 codes related to a patient's clinical status at admission and in the 12 months prior to admission, we separately considered social risk factors and the overlap between clinical and social risk factors. Although some recent literature has evaluated the relationship between social risk factors and the EDAC outcome, few studies directly address specific causal pathways or examine

the role of the hospital in these pathways (see, for example: Hamadi et al., 2019; Jacobs et al., 2018; Kaiser Permanente Washington Health Research Institute, 2022; Rogstad et al., 2022; Joynt Maddox et al., 2019). Our conceptual model (see Figure 5 in the Figures and Tables Supplemental Attachment) described below builds on published literature as well as our empirical analyses and identifies several overlapping pathways whereby patients may experience worse outcomes.

Conceptual Model for Clinical and Social Risk Factors

Our conceptual model described below builds on published literature as well as our empirical analyses and identifies several overlapping pathways whereby patients may experience worse outcomes. These pathways are not mutually exclusive.

1. **Comorbidities and social risk:** Patients with social risk factors may have worse health at the time of hospital admission and patient comorbidities are known risk factors for post-discharge acute care use in patients hospitalized for AMI (Rashidi, Whitehead, & Glass, 2021). Patients who have lower income/education/literacy or unstable housing may have a worse general health status and may present for their hospitalization with a greater severity of underlying illness (Owens et al., 2022). 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 childcare, etc.), 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**.** We note that patient comorbidities and social risk factors overlap in their contribution to a higher risk of the outcome, as shown by our empirical evidence (see Section 5.3) demonstrating the attenuating impact of model variables on the odds ratios for each social risk factor (ADI; DE).
2. **Differential care:** A second pathway by which social risk factors may contribute to post-discharge acute care risk is that patients may not receive equivalent care within a facility (Downing et al., 2018). For AMI specifically, we know from empirical evidence that across almost all hospitals (99% of hospitals with sufficient data for assessment), patients with dual eligibility have higher rates of post-discharge hospital-based care (readmission) when compared with non-dual eligible patients in the same hospital (within-hospital disparities), after accounting for comorbidities, and area-level variables (Silvestri et al., 2022).
3. **Low-quality hospitals:** Patients with social risk factors may receive care at lower-quality hospitals. Patients of lower income, lower education, or unstable housing may not have the same access to high-quality facilities, in part, because such facilities may be less likely to be found in geographic areas with large populations of patients with social risk factors (Fahrenbach et. al., 2020). Thus, patients with low income may be more likely to be treated in lower-quality hospitals, which can contribute to an increased risk of readmission. In addition, or alternatively, low-quality hospitals may not implement evidence-based interventions to reduce the risk of readmission, such as post-discharge follow-up; patients with social risk factors are known to have lower rates of follow-up after discharge and higher rates of post-discharge acute care (Anderson et al., 2022).
4. **Residual risk:** Patients with social risk factors may experience worse health outcomes only partially under the control of the healthcare system. Some social risk factors, such as income or wealth, may affect the likelihood of readmission 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 still have a worse outcome post-discharge due to competing economic priorities or a lack of access to care outside of the hospital (Downing et al., 2018). However, for AMI, it has been shown that in older patients, income is less of a predictor of the outcome of readmission compared with younger patients (Khera et al., 2018).

These proposed pathways overlap and are complex to distinguish analytically. They also have different implications on the decision to risk adjust or not depending on the degree to which hospitals can mitigate the increased risk. Furthermore, the ongoing consolidation of the healthcare market puts more control, resources, and accountability on hospitals (that are now increasingly part of large muti-hospital systems) to invest in mitigating these risks (Levinson, Godwin, Hulver, & Neuman, 2024). However, in some markets, hospital systems choose to close facilities or limit access to care, based on financial decisions, rather than assessments of resource needs (Levins, 2023), including assessment of, and investment in programs that mitigate social needs.

Social Risk Factor Variables Used in Testing

Based on the available literature, and given the limited availability of valid and reliable variables for social risk that can be tested in claims data, we selected the following variables for testing:

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 aged 65 or older 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 (ASPE, 2020).

Area Deprivation Index (ADI)

While we previously used the Agency for Healthcare Research and Quality (AHRQ) socioeconomic status (SES) variable in these types of analyses, we now use the validated ADI (Forefront Group, 2023). We made this change to align with other CMS work on social risk factors that now use the ADI. We describe the ADI variable below.

The ADI, initially developed by the Health Resources & Services Administration, is based on 17 measures across four domains: income, education, employment, and housing quality (Kind et al., 2018; Singh, 2003).

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, % (homeownership rate)
- Civilian labor force population aged ≥16 y unemployed, % (unemployment rate)
- Families below the 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 one person per room, % (crowding)

ADI scores were derived using the beneficiary's 9-digit ZIP Code of residence, which is obtained from the Master Beneficiary Summary File and is linked to 2017-2021 US Census/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 the 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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5.4.2a Attach Conceptual Model

AMI_EDAC_Conceptual Model_Supplemental_Attachment.pdf

5.4.3 Variable Distribution Across Measured Entities

Table 8 (see Figures and Tables Supplemental Attachment) shows the risk variable frequencies and odds ratios for the final risk variables selected by the process described in Section 5.4.2. Risk variables are also provided within the attached data dictionary.

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

Table 8 (see Figures and Tables Supplemental Attachment) shows the prevalence of risk variables for the final risk variables selected by the process described in Section 5.4.2. Risk variables are also provided within the attached data dictionary (see Tab 2).

Social Risk Factor Testing

Because our risk variable selection process (see Section 5.4.2) was based on an empirical approach based on individual ICD-10 codes related to a patient's clinical status at admission and in the 12 months prior to admission, we separately considered social risk factors and the relationships between clinical and social risk factors.

To understand the incremental impact of social risk factors on the AMI EDAC measure, we assessed the following: prevalence of each social risk factor (DE, high ADI) among hospitals, association with the unadjusted outcome, odds ratios in a bivariate and multivariable model, model calibration for patients with each social risk factor, and impact on measure scores. Each analysis is described in more detail below. All analyses used the CY2022/2023 dataset (two years of Medicare Advantage (MA)+Fee-for-Service (FFS) data, January 1, 2022-December 31, 2023).

At the patient level, 13.1% of patients have the DE variable, and 15.3% have the high ADI variable. At the hospital level, the median proportion of patients was 10.5% for the DE variable and 8.3% for the high ADI variable (see Table 9 in the Figures and Tables Supplemental Attachment).

As shown in Table 10 (see Figures and Tables Supplemental Attachment), unadjusted days in acute care for patients with DE or high ADI were higher than for patients without either social risk factor (mean unadjusted days for DE vs non-DE, 169 vs 111; high ADI vs. low ADI, 134 vs 116).

Similarly, odds ratios for patients with and without either variable (when only adjusting for the social risk variable) show higher odds of EDAC (1.46 [95% CI: 1.43-1.48] for DE, 1.17 [95% CI: 1.16-1.18] for high ADI), however, some of the risks is attenuated after the addition of the other risk variables in the model (1.22 [95% CI: 1.21-1.23] for DE, 1.07 [95% CI: 1.07-1.08] for high ADI), demonstrating the overlap between these social risk factors and the clinical risk variables in the final model.

We also examined model calibration for each social risk factor to determine if the risk model (without including either social risk factor) performs well for patients with each social risk factor (see Figures 5A and 5B and Figures 6A and 6B in the Figures and Tables Supplemental Attachment). The results show that the model is well calibrated for ADI patients, however, for dual eligible patients, the model underpredicts risk.

Impact on Measure Scores

While patient-level, unadjusted days in acute care for patients with social risk factors are higher than for patients without social risk factors, we also know that the patient-level risk conferred by social and clinical risk variables overlap. Therefore, we wanted to additionally understand the impact of each variable at the hospital level on the risk-adjusted AMI EDAC measure score. For these analyses, we calculated measure scores with and without each social risk factor and then calculated the differences in measure scores and the correlation between measure scores (Table 11, and Figures 7 and 8 in the attachment). We also analyzed measure scores stratified by the proportion of patients with each social risk factor, within hospitals (see Figures 9, and 10).

Our measure score testing results show minimal impacts of social risk factors on measure scores. Measure scores calculated with and without social risk factors are highly correlated (Pearson correlation coefficients near 1) and differences between measure scores are very small. Furthermore, the distribution of measures scores for hospitals in the highest proportion of patients with social risk (fifth quintile) overlaps with the distribution of measure scores within the other quintiles.

Social Risk Factor Testing: Conclusion

Overall, our results show that patients with social risk factors have a higher risk of the EDAC outcome, but that there is little impact at the hospital level on measure scores. Patients with social risk factors (DE or high ADI) have higher unadjusted rates of the outcome, and even after adjusting for the clinical risk variables in the model, odds ratios remain greater than 1, and significant. However, we find 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 (near 1), and differences between measure scores calculated with and without each social risk factor are small. In addition, the distribution of measure scores across quintiles of the hospital proportion of patients with each social risk factor overlaps.

Because performance on AMI EDAC measures scores do not affect hospitals' payment (AMI EDAC is in a pay-for-reporting and not a pay-for-performance program), and the impact of the DE and high ADI variables on measure scores is small, CMS has decided to not adjust this measure for social risk factors.

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

AMI_EDAC_Figures_and_Tables_Supplemental_Attachment_1.pdf

5.4.5 Calibration and Discrimination

To assess model performance, we assessed model discrimination and calibration, as well as overfitting.

To assess discrimination, we computed two discrimination statistics, **the c-statistic** and **predictive ability**. The c-statistic is the probability that predicting the outcome is better than chance, which is a measure of how accurately a statistical model is able to distinguish between a patient with and without the 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 acute care days between the lowest and highest predicted deciles of hospital visit probabilities.

For **model calibration**, we assessed calibration plots, with mean predicted and mean observed days in acute care plotted against deciles of predicted days in acute care. The closer the predicted days are to the observed days, 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 outcomes in the development dataset but fails to provide valid predictions in new patients. Estimated calibration values of γ0 close to 0 and estimated values of γ1 close to 1 provide evidence of good calibration of the model.

5.4.5a Attach Calibration and Discrimination Testing Results

AMI_EDAC_Figures_and_Tables_Supplemental_Attachment_3.pdf

5.4.6 Interpretation of Risk/Case-mix Factor Findings

Discrimination

The c-statistic of 0.659 (Table 12 in the Figures and Tables Supplemental Attachment) indicates good model discrimination for a readmission-type measure.

Calibration

Higher deciles of the predicted outcomes are associated with higher observed outcomes, which show a good calibration of the model. The predictive ability of the model shows a wide range between the lowest decile and highest decile, indicating the ability to distinguish high-risk subjects from low-risk subjects. As seen in the calibration plot, higher deciles of the predicted outcomes are associated with higher observed outcomes, which show good calibration of the model (Figure 11 in the Figures and Tables Supplemental Attachment).

Over-fitting (γ0, γ1)

If γ0 is substantially far from zero and γ1 is far from one, there is potential evidence of over-fitting. Our testing results show calibration values of almost 0 at one end and almost one on the other end indicating good calibration of the model.

Overall Interpretation

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

5.4.7 Final Approach to Address Risk Factors

Statistical risk adjustment model with risk factors

6.1.1 Current Status

In use

6.1.3 Current Use(s)

Public Reporting, Quality Improvement with Benchmarking (external benchmarking to multiple organizations), Other

6.1.3 Program Details

Name of the program and sponsor
Hospital Inpatient Quality Reporting
URL of the program
https://qualitynet.cms.gov/inpatient/iqr
Purpose of the program
The Hospital IQR Program is a quality reporting program that aims to drive quality improvement through measurement and transparency. Hospitals participate by submitting data to CMS on measures of inpatient quality of care. It allows CMS to monitor and inc
Geographic area and percentage of accountable entities and patients included
Nation-wide (excepting Maryland); includes >4,000 hospitals, including hospitals paid through the Inpatient Prospective Payment System (IPPS) and voluntarily, Critical Access Hospitals (CAHs).
Applicable level of analysis and care setting

The level of analysis is at the facility (hospital) level. The care setting is inpatient, within short-term acute care hospitals.

6.1.3a Other Current Use

This re-specified measure is currently not in use, but the prior version of the measure (that includes only Medicare FFS admissions) is currently in use in the Inpatient Quality Reporting (IQR) Program.

6.2.1 Actions of Measured Entities to Improve Performance

Hospitals seeking to improve their performance on the EDAC AMI measure must implement comprehensive strategies that enhance discharge planning, strengthen post-discharge care coordination, and reduce unnecessary acute care utilization. Since this measure captures emergency department visits, observation stays, and unplanned readmissions within thirty days post-discharge, improving performance requires a patient-centered approach that focuses on proactive management of care transitions and early intervention.

One of the important actions hospitals can take to reduce excess acute care utilization following AMI is improving the quality of hospital discharge planning and transitional care management. Poor discharge planning frequently leads to preventable acute care utilization (National Institute for Health and Care Excellence, 2018). Gaps in discharge processes tied to outcomes that may be targeted for improvement include medication reconciliation, clarity of post-discharge instructions, and ensuring prompt follow-up. Research has shown that readmission and ED visit rates are lower in hospitals with structured discharge procedures, such as early follow-up scheduling (within 7 days after discharge) (Anderson et al., 2022) and effective patient education (Becker et al., 2021). Examples of effective communication interventions hospitals can implement include educating patients at discharge on their medication, diagnosis, or therapeutic regimen. To reduce complications and avoidable acute care visits, hospitals can equip patients with all the necessary information for post-discharge care so that each patient leaves the hospital knowing their medication schedule, follow-up appointments, and self-care instructions. In addition, successful transitions can be further supported by designating nurse navigators to supervise post-discharge rehabilitation and promote communication between patients and providers. Nurse navigators are part of patient navigation programs where a designated patient navigator can help the patient understand their treatment plan (Kokorelias et al., 2021).

Care coordination fragmentation is one of the main causes of high EDAC rates (Snow et., 2020). Communication gaps between inpatient and outpatient care teams may result in patients requiring post-discharge acute care rather than care in an ambulatory setting. To address care coordination issues and minimize information gaps, hospitals can use standardized care transition plans and implement electronic health record notifications for pending follow-ups (Dalal et al., 2018).

Additionally, multiple systematic reviews have demonstrated that transitional care interventions, especially those targeting older or frail adults discharged from hospital to home, can reduce unplanned acute care utilization, including ED visits and hospital readmissions. For instance, a systematic review and meta-analysis by Lee et al. (2021) found that transitional care interventions significantly reduced hospital readmissions at six months post-discharge among frail older patients. Similarly, Tyler et al. (2023) conducted a large-scale network meta-analysis of 126 randomized controlled trials (n = 97,408) and found that both low- and medium-complexity transitional care interventions were linked to significant decreases in hospital readmissions when compared to usual care at 30 days and 180 days. Moreover, these interventions have a broader

impact on acute care utilization and are associated with decreased ED visits. Although the effectiveness of transitional care varied by intensity and timing of implementation, the evidence supports its value in reducing avoidable health service use, particularly among high-risk older populations (Feltner et al., 2014; Le Berre et al., 2017; Li et al., 2021).

Outside of clinical trials, health systems have successfully implemented large-scale quality improvement initiatives aimed at reducing acute care utilization following AMI hospitalization. One example is the use of digital health interventions (DHIs), like the Corrie Health platform, which integrates smartwatches, smartphone apps, and wireless blood pressure monitors to improve patient self-management and adherence to care recommendations. Marvel et al. (2021) discovered that patients who used the DHI had a considerably lower risk of unplanned 30-day all-cause readmissions (6.5%) than the historical control group (16.8%) in multicenter research that involved 1,064 patients across four U.S. hospitals. The intervention group had a 52% decreased risk of readmission after controlling for numerous variables using a propensity score and hospital site. These results highlight the importance of including patient-centered tools in routine AMI care that address immediate requirements, like medication reminders, health education, and outpatient follow-up support. A systematic analysis of hospital-based quality improvement initiatives for AMI and other acute coronary syndromes by Bahiru et al. (2019) also supports these findings. The review identified less consistent effects on clinical outcomes like mortality, but modest improvements in in-hospital AMI care processes, including improved use of guideline-recommended medications and reperfusion treatment. This emphasizes how important it is to combine digital tools with more extensive institutional reforms. Observational studies also emphasize how readmission risk following AMI is closely linked to hospital-level and system-level characteristics that can be changed, such as prompt post-discharge follow-up and access to cardiac rehabilitation (Wasfy et al., 2020). More importantly, patient feedback consistently calls for smoother care transitions and the need for proactive, personalized discharge planning (Patel & Bechmann, 2025).

Timely outpatient follow-up is another factor in reducing EDAC following hospitalization of AMI. Research shows that patients who schedule a follow-up appointment seven to fourteen days after being discharged are much less likely to need to return to the hospital or the emergency room (Batten et al., 2018; Tung et al., 2017). However, securing early follow-up can be difficult due to financial limitations, transportation issues, and the availability of specialist appointments. To overcome these challenges, hospitals can use telehealth check-ins for high-risk patients which may reduce readmissions (Dawson et al., 2021), and collaborate with community providers to increase access to prompt outpatient care (Obi et al., 2024). Another way to promote improved patient outcomes is to set up hospital-led, multidisciplinary AMI transition clinics (Dmitriew et al., 2024) or provide priority access to cardiology consultations within the first two weeks following discharge (Khan et al., 2024).

Finally, hospitals can use resources provided by CMS to help improve the drivers of hospital visits. To support quality improvement, CMS shares reports with measured entities that include measure results benchmarked against the state and nation (hospital-specific reports [HSRs]). These reports include, among other details, the principal diagnosis code associated with the hospitalization, which allows hospitals to tie their quality improvement efforts to the specific reasons for rehospitalization that are occurring. Hospitals can use these reports, in addition to other available data, to analyze trends in excess acute care utilization, identify areas for improvement and refine

their strategies to reduce ED visits, observation stays, and unplanned readmissions.

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6.2.2 Feedback on Measure Performance

There are several sources of feedback for the AMI EDAC measure: feedback from measure users (hospitals) as part of the ongoing stakeholder question and answer (Q&A) process for implemented measures, feedback from the TEP that was convened for measure re-specification, and feedback from other stakeholders, including through public comment and prior CBE review cycles for this and related measures. We also consider feedback from the results of regular scans of the published literature.

Feedback from Q&A and literature:

Each year we review and consider issues raised through Q&A or in the literature related to this measure, and those issues are considered by measure and clinical experts. Any issues that warrant additional analytic work due to potential changes in the measure specifications are addressed as a part of the annual measure reevaluation. If small changes are indicated after additional analytic work is complete, those changes are usually incorporated into the measure in the next measurement period. If the changes are substantial CMS may propose the changes through rulemaking and adopt the changes only after CMS receives public comment on the changes and finalizes those changes in rulemaking.

Over the past three years, we received 139 questions about the EDAC measures overall, and 15 specifically for the AMI EDAC measure. Feedback from stakeholders has included the following: questions clarifying measure specifications including risk adjustment, requests for the measure calculation software package, and specific questions about admissions pertaining to their hospital.

Feedback from the Technical Expert Panel (TEP):

The TEP provided feedback on the use of individual ICD-10 codes, including frailty and assessing social risk in the risk model. TEP members were supportive of including Do No Resuscitate (DNR) codes if it was POA in the model. The TEP was conflicted in the decision to adjust for frailty and did not wish to adjust for social risk factors within the risk model due to concerns about the quality of available data. TEP members felt the framework for assessing individual codes was clear and allowed for an understanding of clinical risk factors.

Feedback from other stakeholders:

Feedback from others, outside of the Q&A process, comes from sources such as the PRMR pre-rulemaking process, CBE review committees, and public comment.

Feedback has included the following:

- To include both Medicare Advantage and Medicare FFS admissions in claims-based measures.
- To consider patient-centered factors such as palliative care, do-not-resuscitate status, and frailty, that may impact the outcome.
- To improve the currency of reporting (shorten the lag time between the generation of data and the release of measure scores).

6.2.3 Consideration of Measure Feedback

The developer and CMS, in response to stakeholder feedback described above, extensively updated the AMI EDAC measure, including cohort expansion (adding in admissions for Medicare Advantage (MA) patients), risk variable re-selection, and shortening the reporting periods from three years to two years. We discuss each of these improvements in more detail below.

Addition of Medicare Advantage admissions

As noted, the addition of admissions for the Medicare Advantage (MA) population was an important update to the AMI EDAC measure cohort. MA beneficiary enrollment has been rapidly expanding; in 2024, about 54% of the eligible Medicare beneficiaries were covered by MA plans (Freed, Biniek, Damico & Neuman, 2024). The Congressional Budget Office projects that by 2030, 62% of beneficiaries will be covered by MA plans (Congressional Budget Office, 2022).

The inclusion of MA beneficiaries has several important benefits for the reliability and validity of the AMI EDAC measure. Increasing the size of the measure's cohort enhances the reliability of measure scores, resulting in more hospitals receiving results, which potentially increases the chance of identifying meaningful differences in quality for some low-volume hospitals (Kyanko et al., 2024). Including Medicare Advantage admissions adds to the measure's validity by providing a complete picture of quality for all Medicare patients age 65 and older.

Consideration of palliative care and DNR

A patient or their healthcare family/proxy may choose to opt for palliative care or DNR status; this choice impacts a hospital's ability to improve the outcome of EDAC. Studies have shown that models that account for DNR status can have an impact on the rank order of hospital performance for readmission (albeit less than the impact on rank order performance for mortality) (Bruckel et al., 2019; Pollock, Herrin & Neville, 2020). The connection between these variables and the outcome is empirical, in that the data-driven risk-variable selection process described in Section 5.4.2 identified both palliative care and DNR as significant risk variables, which were retained in the final model.

Consideration of frailty

Frailty is a complex syndrome that includes a decline in physiological reserves and decreased resilience to stressors and is associated with an increased risk of poor outcomes (Wang, Hu & Wu, 2022). As noted above in Section 5.4.2, based on evidence from the literature, expert input, guidance from the consensus-based entity for measure endorsement, the Assistant Secretary for Planning and Evaluation, input from other stakeholders, and prior testing results, we included a claims-based indicator of frailty in the final model. This indicator was initially developed for CMS's Multiple Chronic Conditions (MCC) measure.

More actionable results

Stakeholders, in particular patients, have asked for a shorter lag time between the performance period and the public reporting of data. CMS's claims-based measures had typically been based on a three-year performance period. To improve the currency of the measure scores and related data shared with the public and hospitals, the measure score performance period has been shortened to two years.

Routine maintenance

Each year we also review and consider changes to codes that are then incorporated into the measure. Those code set files are made available to the public on *QualityNet.*

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6.2.4 Progress on Improvement

The AMI EDAC measure described in this CBE submission has been extensively updated, including cohort expansion (adding in Medicare Advantage (MA) patients) and risk variable re-selection. In addition, the performance period has been changed from three years to two years. Because of these changes, we are unable to compare the performance of this re-specified measure with the performance of the previous (currently implemented) measure.

We provide, however, a comparison of the distribution of measure scores from the currently implemented Fee-for-Service (FFS)-only measure, comparing two non-overlapping time periods. We found that unadjusted (average days in acute care per 100 discharges) and adjusted hospital-level measure scores (excess days per 100 discharges) improved slightly across these two non-overlapping periods (July 1, 2016-June 30, 2019, and July 1, 2020-June 30, 2023). We are only able to compare two non-overlapping periods due to changes in the measure prior to the 2016-2019 period when VA hospitals were added to the measure calculation. Mean observed (unadjusted) hospital-level AMI EDAC declined from 104.13 days in acute care per 100 discharges, to 100.22; mean AMI EDAC risk-adjusted measure scores declined from a mean of 3.55 in 2016-2019, to 2.12 in 2020-2023. These results, however, could be impacted by SARS-COV2, although the measure did have adaptations to its measure specifications to mitigate the impact of COVID (excluding COVID admissions, and readmissions, and adjusting for history of COVID). We note that these results align with published literature showing a statistically significant decrease in 30- and 90-day readmission rates for patients hospitalized with AMI between 2010 and 2019 (Sana et al., 2023).

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6.2.5 Unexpected Findings

There have been no unexpected findings, negative or positive, during the implementation of this measure, including unintended impacts on patients.

7.1 Supplemental Attachment

AMI_EDAC_Supplemental Files.zip

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The measure developer is different from the measure steward

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