CBE ID

5570

Title

Excess Days in Acute Care (EDAC) After Hospitalization for Chronic Obstructive Pulmonary Disease (COPD)

Project

Cost and Efficiency

Endorsement Status

New

Is Under Review

Yes

Next Maintenance Cycle

Spring 2026

Steward

Centers for Medicare & Medicaid Services

1.0 New or Maintenance

New

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 Chronic Obstructive Pulmonary Disease (COPD) (hereafter “COPD EDAC") measure assesses days spent in acute care within 30 days of discharge from an inpatient hospitalization for COPD. This measure is intended to improve care transition quality for discharged patients hospitalized for COPD 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 based on two years of data and 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 Excess Days in Acute Care (EDAC) After Hospitalization for Chronic Obstructive Pulmonary Disease (COPD) (hereafter “COPD 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 a hospitalization for COPD. The COPD EDAC measure captures excess days in acute care within 30 days of discharge from a hospitalization for COPD by accounting for the number of days a hospital’s discharged patients spent in an unplanned inpatient readmission, in an observation stay, or in the emergency department (ED).

COPD remains a high-impact disease in the United States (US). Approximately 15 million adults in the US (6.1%) were diagnosed with COPD in 2022 (National Center for Chronic Disease Prevention and Health Promotion, 2024) and medical costs attributed to COPD for Medicare beneficiaries have been estimated at over $10 billion (Mannino et al., 2024). Hospitalizations for COPD as a diagnosis (principal or any coded diagnosis) for the Medicare population 65 years and older are substantial. In 2021, 5.11 per 1000 Medicare beneficiaries aged 65 and older were hospitalized with COPD as the principal diagnosis; and 85.44 per 1000 were hospitalized with COPD as any diagnosis (National Center for Chronic Disease Prevention and Health Promotion, 2024). Healthy People 2030 currently lists “Reduce hospitalizations for COPD” as a high-priority public health issue in developmental status, which may be added in the future as a core objective (Office of Disease Prevention and Health Promotion, n.d.).

Readmission rates for COPD remain high. Roughly 1 in 5 COPD hospitalizations is followed by a readmission within 30 days, resulting in cost estimates of more than $15 billion per year (Jacobs et al., 2018). According to the Agency for Healthcare Research and Quality (AHRQ) Prevention Indicators, in 2020, COPD was among the top 20 principal diagnoses at index admission associated with a high number of readmissions that were considered potentially preventable (Jiang et al., 2024). Readmission rates following COPD discharge vary across hospitals; from July 2020 through June 2023, publicly reported 30-day risk-standardized readmission rates ranged from 14.9% to 23.7% for patients hospitalized with COPD (Yale New Haven Health Services Corporation—Center for Outcomes Research and Evaluation, 2024).

EDAC measures capture a complete picture of acute-care post-discharge utilization that informs patients and the public about care quality and incentivizes global improvement in transitional care. EDAC measures provide complementary information to CMS’s readmission measures. The features of EDAC measures include: 1) capturing all acute-care, hospital-based post-discharge outcomes that matter to patients, such as having to return to the hospital, go to the ED, or spend

time in the hospital under observation; 2) capturing utilization in days that can reflect variation in hospital quality; 3) capturing multiple events; for example, some patients have multiple visits in 30 days; and 4) addressing the impact of post-discharge mortality by accounting for time at risk of an event (that is, survival time) (Yale New Haven Health Services Corporation—Center for Outcomes Research and Evaluation, 2015). As such, EDAC measures provide a more comprehensive capture of post-discharge acute care (Wadhera et al., 2021).

The COPD EDAC measure was developed to identify hospitals whose performance is better or worse than would be expected based on their patient case mix and therefore promote hospital quality improvement and better inform stakeholders about care quality. Measuring and reporting excess days in acute care provides transparency for consumers, and informs healthcare providers about opportunities to improve care, strengthen incentives for quality improvement, and ultimately improve the quality of care (including better inpatient management, better engagement of patients in the process of self-care, and better peri-discharge care quality) received by Medicare patients (see the Logic Model and Section 6.2.1 for more details). For example, results of a Mayo clinic collaborative that had health systems work to increase use of a standardized disease severity staging tool, inhaler appropriateness evaluations during admission, a COPD treatment action plan and clinical contact at < 48 hours and 10 ± 4 days post-discharge showed significant reductions in 30 day readmissions (17.7% to 14.5%) (Morgenthaler et al., 2021). Also, real-world evidence from over 190,000 hospitalized COPD patients showed that pulmonary rehabilitation initiated within 90 days of discharge was associated with lower mortality risk and fewer rehospitalizations at one year (Lindenaur et al., 2020). If implemented, hospitals will be able to use their hospital-specific measure results to identify specific areas of improvement and implement or develop processes (supported by evidence) that are tailored to their own institution.

Testing for this measure included 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 just Medicare FFS beneficiaries.

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1.13 Data Dictionary

Attached

1.13a Attach Data Dictionary

5570-1.13a-COPD-EDAC-Data-Dictionary-Spring2026.xlsx

1.14 Numerator

The outcome for the COPD 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 emergency department (ED) visits, observation stays, and unplanned readmissions) is defined specifically below; all outcomes are captured for 30 days after discharge from the index admission:

- **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, *COPD EDAC_Data Dictionary.xlsx*, for the code definitions. 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 Excel attachment, *COPD EDAC_Data Dictionary.xlsx*, 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's Planned Readmission Algorithm version 4.0 2024 (see additional information below and Figure 1 in the Supplemental Attachment). Readmissions are counted in days and are 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 another event, 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 the readmission; if an observation stay and ED visit happen on the same day, we count 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 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.

Please see *COPD EDAC Risk Variable Complications of Care* tab in the Excel file entitled *COPD EDAC_Data Dictionary.xlsx* for the list of potential complications referred to in Step 3 of the planned readmission algorithm.

1.15 Denominator

The target population for the COPD EDAC cohort is defined as patients aged 65 years or older with a principal discharge diagnosis of COPD or a principal discharge diagnosis of acute respiratory failure and a secondary diagnosis of COPD with exacerbation, 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 COPD EDAC measure includes index admissions for patients who meet all the following criteria:

- **Principal discharge diagnosis of COPD or principal discharge diagnosis of acute respiratory failure with a secondary diagnosis of COPD with exacerbation**
  - *Rationale:* COPD is the condition targeted for measurement. Acute respiratory failure admissions with a secondary diagnosis of COPD are also included to capture the full spectrum of severity among patients hospitalized with exacerbations of COPD.
- **Enrolled in Medicare (FFS or 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 up to 12 months prior to the index admission, to augment the index admission claim itself.
- **Aged 65 or over**
  - *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**
  - *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).

Figure 2 (in the Supplemental Attachment) shows the final COPD cohort with the inclusions and exclusions applied.

1.15b Denominator Exclusions

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

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

1.15c Denominator Exclusions Details

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**
  - *Rationale*: 30-day outcomes cannot be assessed in this group since claims/encounter data are used to determine whether a patient experienced post-discharge acute care.
- **Discharged against medical advice (AMA)**
  - *Rationale*: Providers did not have the opportunity to deliver full care and prepare the patient for discharge.
- **COPD admissions within 30 days of discharge from a prior COPD index admission**
  - *Rationale*: Additional COPD admissions within 30 days are excluded as index admissions because they are part of the outcome. CMS does not want to count the additional admission as both an index admission and an unplanned readmission outcome for the first 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 steps in measure calculation are as follows:

- **Define the cohort** (the index admissions that will be counted in the measure)
  - **Apply inclusion criteria (see Section 1.15a for details)**
  - **Apply exclusion criteria (see Section 1.15b and 1.15c for details)**
- **Apply the predictive model** and calculate the “predicted” and “expected” values for each hospital.

- **Apply planned readmission algorithm (see Section 1.14a for details).**
- **Sum the predicted days for each patient at each hospital**

  Using the predictive model including the model's risk variables (see Excel attachment *COPD EDAC_Data Dictionary.xlsx*), sum the predicted days in acute care within 30-days after discharge for each admission at the hospital level.
  The risk-adjustment model is a hierarchical generalized linear model. 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. Please see the Measure Score Calculation EDAC Attachment for details.

- **Calculate the expected days for an average-performing hospital with the same case mix.**

  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.

- **Calculate the hospital measure score ("excess" days per 100 discharges)**

  For each hospital, subtract the summed expected days from the predicted days. Then to make the results comparable across hospitals, divide by the total number of qualifying admissions (the cohort) for that hospital, and multiply by 100 (to ease in interpretability). A negative score indicates fewer days in acute care than expected (better performance), while a positive score indicates more days in acute care than expected.

1.18a Attach measure score calculation diagram

5570-1.18a.-Measure-Score-Calculation-EDAC-Spring2026.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.

MA claims data quality has improved, and it is increasingly being used for quality measurement. Its addition to quality measures captures a broader group of patients, increases the precision of measurement, and increases the number of hospitals that can be included in measurement (Kyanko et al., 2024). MA data has recently been included within three quality measures related to the COPD EDAC measure that were recently newly endorsed or re-endorsed by the Consensus-Based Entity (CBE) Cost & Efficiency Recommendation Group, after considering the addition of MA admissions. Those measures include: hybrid Hospital-Wide Readmission [hHWR] (CBE 2879e) re-endorsed in Fall 2024, AMI EDAC (CBE 2881) re-endorsed in Spring 2025, and Sepsis Readmission (CBE 5275) newly endorsed in Fall 2025. The details of how MA claims are identified for this measure are described in more detail below.

The hospital inpatient claims, outpatient claims, professional claims, and durable medical equipment (DME) claims can be identified using the claim types in the table below. Notably, most MA beneficiary inpatient admissions have two claim submission sources: hospital-submitted claims and Medicare Advantage Organization (MAO)-submitted encounter claims. Both types of claims are information-only (i.e., not billing) that include items and services provided. CMS requires MAOs and hospitals that receive disproportionate-share hospital or medical education payments from Medicare to submit information-only claims for inpatient stays for MA beneficiaries. We use both sources for cohort and outcome derivation.

Medicare FFS and Advantage Claim Type Codes

Type of Claim	FFS	Hospital-submitted MA	MAO-submitted (Encounter) MA
Inpatient	60	62, 63, 64	4011, 4041
Outpatient Facility	40	-	4012 – 4014, 4022, 4023, 4034, 4043, 4071 – 4077, 4079, 4083, 4085, 4089
Professional	71, 72	-	4700
DME	81, 82	-	4800

There are benefits to using both inpatient claims sources for MA beneficiaries for the broadest and most timely capture of MA claims. First, not all hospitals are required to submit claims for MA beneficiaries (i.e., hospitals that do not receive disproportionate-share hospital or medical education payments from Medicare), and using only hospital-submitted data would miss capture of these claims. All hospitals submit inpatient claims for MA beneficiaries to MAO, and therefore MAO-submitted claims capture these additional admissions not found in the hospital-submitted claims. However, relying solely on MAO-submitted claims poses three challenges: 1) MAO-submitted claims are not as timely as hospital-submitted claims, which is disadvantageous for reporting deadlines for CMS hospital outcome measures; 2) in measure testing, a small proportion of MA admissions were only found in the hospital-submitted claims; and 3) MAO-submitted claims identify hospitals using a National Provider Identifier (NPI), whereas hospital-submitted claims are already associated with a CMS Certification Number (CCN) used to identify hospitals in the CMS outcome measures.

As a result, if an MA admission was found in both datasets, we used the claim found in the hospital-submitted data. For the small portion of MA admissions with only MAO-submitted claims, we obtained the CCN with Integrated Data Repository provider history data, using the NPI, claim discharge date, provider history begin (effective) date, and provider history end (obsolete) date.

Because it is expected that this COPD EDAC measure would be implemented by CMS for public reporting in the Hospital Inpatient Quality Reporting (IQR) program, which is limited to short-term acute care hospitals and critical access hospitals, we used the CCN taxonomy to further restrict the claims to those filed by acute care hospitals (3rd and 4th digit as '01') and critical access hospitals (3rd and 4th digit as '13').

References

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1.26 Minimum Sample Size

The measure does not have a minimum sample size.

2.1 Attach Logic Model

5570-SupplementalAttachment-Spring2026.pdf

2.2 Evidence of Measure Importance

Chronic Obstructive Pulmonary Disease (COPD) is a major cause of hospitalization in older individuals, with serious clinical, economic, and quality-of-life implications. Khamooshi et al. (2021) found that in 2018, there were 342,314 patients hospitalized in the U.S. for an index admission of COPD; about 20% were readmitted within 30 days, with the most common reason for readmission being a diagnosis of COPD with exacerbation (29%). In another study, the substantial proportion of hospital visits for patients with COPD were shown to be readmissions through the ED (82% as noted by Rezaee et al., 2017), with most seen as potentially preventable with higher quality care transitions and outpatient monitoring (Rezaee et al., 2017; Shah et al., 2015). The COPD Excess Days in Acute Care (EDAC) measure meets this need to capture excess days spent in acute care by assessing the full spectrum and length of post-discharge acute care use after a COPD hospitalization, including ED visits, observation stays, and unplanned readmissions. This composite outcome, therefore, provides a more patient-centered and complete measure of the effectiveness of hospital discharge procedures and continuity of care.

As shown by the COPD EDAC Logic Model (see the Supplemental Attachment), there is compelling evidence that a combination of structural factors—multidisciplinary care teams, data systems, patient engagement tools, and clinical guidelines [identified in the logic model as inputs]—can improve transitional care for COPD patients. The 2026 GOLD Global Strategy provides evidence-based recommendations for hospital-based COPD therapy, emphasizing the need for structured

discharge planning and post-discharge monitoring to minimize exacerbations and rehospitalizations (Global Initiative for Chronic Obstructive Lung Disease, 2026). Hospitals that use skilled multidisciplinary teams, which include pulmonologists, respiratory therapists, pharmacists, case managers, and discharge planners, are better able to provide and coordinate treatment across settings (Chew & Mahadeva, 2018). Analytic tools, such as machine learning algorithms that predict readmission risk and identify high risk patients to allow for targeted interventions (Bonomo et al., 2022), and EHR and claims-based tracking systems, aid in identifying opportunities in post-discharge care to improve outcomes (Shah et al., 2015). Follow-up systems, such as in-person visits or telemonitoring, promote preventive care and reduce the need for ED services (Mínguez Clemente et al., 2021). Self-management technologies and remote monitoring of their use, such as inhaler adherence applications, pulse oximeters, and exacerbation action plans, also help by enabling patients to identify early symptoms and treat their disease at home, lowering the need for acute care (Abraham et al., 2025; Lenferink et al., 2017). Patient self-management interventions are linked to enhanced confidence, improved inhaler use, higher satisfaction with care and lower risk of hospital readmission (Schrijver et al., 2022).

These inputs support a variety of standardized actions that have been extensively demonstrated in the literature as effective strategies for reducing post-discharge use. Early initiation of triple therapy [(inhaled corticosteroid (ICS), a long-acting β_2-agonist (LABA) and a long-acting muscarinic antagonist (LAMA)] during or following hospitalization is associated with significant reductions in readmissions. Observational studies demonstrate that starting triple therapy within 0-30 days after a first COPD exacerbation reduces the risk of subsequent moderate or severe exacerbations by 20-30% and decreases rehospitalizations (Bogart et al., 2018; Evans et al., 2022). However, a large real-world study found that only 17.5% of patients receive appropriate triple therapy at discharge, with over one-quarter prescribed only short-acting beta-agonists or no inhaled medication at all (Bhutani et al., 2025). Furthermore, implementing evidence-based discharge bundles, such as those described by Miravitlles et al. (2023), ensures that patients are educated on inhaler technique, symptom monitoring, medication management, and follow-up care scheduling before discharge. Education on proper inhaler technique is crucial since inappropriate use has been related to poor disease control and decreased quality of life (Amini et al., 2020). Medication reconciliation coordinated by a pharmacist helps to ensure accurate prescriptions and reduces medication errors, which are significant causes of readmission (Mekonnen et al., 2016). Early follow-ups have been consistently linked to lower readmission rates and better symptom management (Health Quality Ontario, 2017). Additionally, The American Thoracic Society recommends pulmonary rehabilitation for adults with COPD after hospitalization for exacerbation, as it reduces both mortality (relative risk 0.58) and hospital readmissions (relative risk 0.47) (American Thoracic Society, 2024; Jenkins et al., 2024). Telehealth platforms have also proven effective for early discharge follow-up and patient engagement (Mínguez Clemente et al., 2021). Referrals to pulmonary rehabilitation, smoking cessation support, and community-based programs are essential components of sustained COPD management (Early et al., 2020).

These initiatives shared through peer-reviewed research and guidelines of care for COPD patients can produce tangible results that are directly related to improved care and fewer excess days in acute care. For example, in a large Medicare cohort of over 197,000 patients, those who initiated pulmonary rehabilitation within 90 days experienced fewer rehospitalizations over one year (mean 0.95 vs 1.15 rehospitalizations, hazard ratio 0.83) (Lindenauer et al., 2020). In addition, interprofessional COPD care bundles that integrate multiple interventions significantly reduce

readmissions (Criner et al., 2015; Global Initiative for Chronic Obstructive Lung Disease, 2026). As shown by the use of The Global Initiative for Chronic Obstructive Lung Disease, discharge bundles that include patient education, medication optimization, inhaler technique assessment and correction, adherence reinforcement, comorbidity management, pulmonary rehabilitation referral, self-management support, early specialist follow-up, and telemonitoring improve post-discharge outcomes. One study of one such interprofessional care bundle demonstrated reductions in 30-day (21.7% vs 11.8%), 60-day (18% vs 8.7%), and 90-day (19.6% vs 4.7%) all-cause readmissions (Kendra et al., 2023). These bundles often include pharmacist involvement in medication access and therapy escalation (Kendra et al., 2023).

In parallel, facilities that hold regular quality improvement (QI) meetings and do root cause analysis on readmissions can continuously enhance discharge practices and system-level interventions (Rohde et al., 2021). According to the literature, hospitals that use standardized COPD discharge protocols have better patient education and safer transfers (Miravitlles et al., 2023). Dashboards and performance data, when used correctly, assist hospitals in identifying variations in care and benchmarking their outcomes (Shah et al., 2015). Staff training on COPD transitions of care has demonstrated improvement in implementation fidelity while decreasing care variance (Portillo et al., 2023; Sibbald et al., 2022).

As the structures and procedures described above become integrated into routine care, they produce significant intermediate and long-term results. Improved discharge communication and coordination between inpatient and outpatient teams result in fewer gaps in care (Miravitlles et al., 2023), and enhanced follow-up adherence promotes patient stability (Health Quality Ontario, 2017). Structured reconciliation processes increase medication adherence while lowering the risk of adverse events (Mekonnen et al., 2016). Participation in pulmonary rehabilitation has been linked to lowering exacerbation risk, increased functional ability, and long-term disease control (Early et al., 2020).

These adjustments reduce ED visits, observation stays, and unexpected readmissions, which are key components of the EDAC measure score. At the health-care system level, widespread adoption of these strategies helps hospitals perform better on publicly reported quality indicators, improves patient experience, and reduces overall expenditures associated with needless acute care usage (Press et al., 2021). The COPD EDAC measure provides an actionable and meaningful outcome that is consistent with value-based care models and CMS accountability programs (Press et al., 2019). The COPD EDAC measure not only covers an important quality area, but it also encourages real system improvement. 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 timeliness of post-discharge follow-up and referral to pulmonary rehabilitation, while others may have gaps in such processes, resulting in higher EDAC. Each hospital must identify the root cause of poor performance.

The measure’s importance is underscored by the outcome window, which assesses eligible outcomes within a 30-day period from the date of discharge from an index hospitalization. We considered 30 days as a clinically reasonable timeframe because (1) within a 30-day timeframe, ED visits, observation stays, and readmissions are more likely attributable to the care received during the index admission and during hospital discharge than outcomes occurring later post-discharge, and (2) the 30-day timeframe is consistent with CMS’s existing, publicly reported,

Consensus-Based Entity-endorsed 30-day readmission measures. Empirical evidence from this measure submission supports attributing the 30-day outcome to the discharging hospital, both in terms of the timing and volume of post-discharge acute care use relative to the index admission, and the clinical relatedness of the readmission, as the most common principal discharge diagnoses are clinically associated with the index hospitalization.

There is both a quality gap and a measurement gap for post-discharge outcomes for patients hospitalized for COPD. The quality gap is illustrated by variation at the hospital level in risk standardized post-discharge acute care utilization for patients hospitalized for COPD (see section 2.4, Performance Gap); a hospital at the 10th percentile (better performance) has -48.5 excess days in acute care per 100 discharges, whereas a hospital at the 90th percentile (worse performance) has 70.2 excess days in acute care per 100 discharges. In terms of a measurement gap, while there is a COPD readmission measure in CMS's Hospital Readmission Reduction Program (HRRP), there are no outcome measures in any federal programs that comprehensively address all post-discharge acute care utilization for patients hospitalized for COPD (that is, include the outcomes of ED visits and observation stays, in addition to inpatient admissions). Therefore, this COPD EDAC measure provides information and transparency to consumers, policy makers, and hospitals, to allow them to better understand and care for this population of Medicare beneficiaries.

The evidence above, including the burden of COPD, variation in hospital performance, and the existence of effective interventions, demonstrate the importance and value of the hospital-level quality measure for post-discharge acute care. Hospitals taking these steps, informed by their results on the COPD EDAC measure can provide safer, more efficient, and patient-centered care by incorporating evidence-based structural and procedural improvements.

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2.3 Anticipated Impact

As noted above in Section 2.2, COPD is a common and costly condition, associated with high healthcare utilization, including post-discharge acute care. Because there are existing evidence-based standards of care designed for patients hospitalized with COPD, and because there is variation in care and outcomes, we anticipate that a COPD EDAC measure will support hospital efforts to optimize the quality of care for patients hospitalized for COPD, with a concomitant reduction in post-discharge, hospital-based acute care (please see the COPD EDAC Logic Model in the Supplemental Attachment). Because this measure identifies a comprehensive picture of post-discharge acute care (including unplanned readmission, ED visits, and observation stays), and if implemented, supplementary reports provide hospitals with patient-level details including the reason (principal discharge diagnosis) for the hospital visit, this measure can help hospitals identify areas of focus for their quality improvement efforts. The measure will also provide information to consumers about hospital-level variation in a more comprehensive capture of post-discharge acute care utilization after discharge. Please see the COPD EDAC Logic Model in the Supplemental Attachment for details on activities, outputs, outcomes, and impact expected as a result of the implementation of the COPD EDAC quality measure.

As described in the logic model, anticipated short- and long-term outcomes impacted by this measure include improvements in clinical, patient-experience-related, and economic outcomes. For example, health system staff trained on how to guide patients with COPD self-management (e.g., medications, exacerbation triggers) and transitions of care will increase adherence to maintenance medications and improve self-management in response to environmental triggers of COPD. These in-turn will improve patient quality of life and functional status and lower overall healthcare costs by preventing rehospitalizations from COPD and other conditions.

For hospitals, there is no associated cost for reporting the measure, because it is calculated by CMS directly from claims. The costs of interventions to improve outcomes will vary by hospital based on their existing infrastructure, and the specific structure/process gaps that underlie their performance on the COPD EDAC measure. Implementing an evidence-based quality improvement effort has many benefits, including short and long-term clinical benefits (that may have spill-over effects to other conditions), direct and indirect impact on patients (impacting physical and mental

health, finances, employment, and larger impacts on the family), as well as short- and long-term financial impacts on the hospital itself.

While a formal economic analysis is outside the scope of a developer's resources, we estimate that if all patients hospitalized for COPD in the cohort were seen at a hospital that performed at the mean of the best performing (1st) decile of performance on the COPD EDAC measure (see Table 1), this would avoid about 475,464 days in acute care (estimate based on unadjusted data). Taking into account an estimated average cost of post-discharge hospital stay per day of roughly $3,000 (Kaiser Family Foundation, 2024), and an estimated average intervention cost of about $500 per admission (Hirschman et al. 2015; Transitional Care Model, 2018), we estimate that across all admissions there would be substantial net economic direct short-term savings (more than $1 billion per performance period). While this cost savings scenario assumes that all hospitals could meet measure performance at the mean for hospitals in the best-performing (1st) decile, and is based on rough cost estimates, the magnitude of potential savings suggests a true net economic benefit even if a smaller proportion of hospitals can shift to a better-performing decile (reduce post-discharge acute care utilization). In addition, this estimate does not include any long-term or indirect costs, nor does it reflect post-discharge short- and long-term clinical benefits of improved care spill-over effects to other patients, and economic benefits to the patients themselves (see the COPD EDAC Logic Model for more details). It also, however, does not account for the likely shifting of services to the outpatient setting (which is the desired outcome).

No actual unintended consequences have been identified because this measure has not yet been implemented. Potential unintended consequences are discussed in Section 6.2.5a.

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2.4 Performance Gap

Table 1 and Figure 3 (in the 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 admissions at any one hospital) and expected days (what would be expected for the average hospital with the same patient case mix), 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.

Table 1. Performance Scores by Decile

	Overall	Min	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10	Max
Mean Performance Score	**11.2**	**-161.9**	**-66.0**	**-39.0**	**-23.7**	**-11.8**	**-0.8**	**10.0**	**22.3**	**36.0**	**56.1**	**128.9**	**1889.8**
N of Entities	**4397**	**1**	**439**	**440**	**440**	**440**	**439**	**440**	**440**	**440**	**440**	**439**	**1**
N of Persons / Encounters / Episodes	**453,692**	**5**	**11,445**	**17,326**	**29,802**	**38,631**	**55,708**	**65,491**	**73,761**	**66,802**	**62,490**	**32,236**	**2**

As shown in Table 1a, COPD EDAC measure scores (excess days per 100 discharges) range from -161.9 to 1,889.8; the median is 4.5; the 10th percentile is -48.5 and the 90th percentile is 70.2. A hospital at the 10th percentile has about 119 fewer excess days per 100 discharges compared with a hospital performing at the 90th percentile.

Table 1a. COPD EDAC: Hospital Distribution of Risk-Adjusted Measure Scores per 100 Discharges, January 1, 2022 – December 31, 2023 (N = 4,397)

Category	Value
Number of Hospitals	4,397
Mean (SD)	11.2 (66.0)
Range (min. to max.)	-161.9 to 1,889.8
10th Percentile	-48.5
25th Percentile	-23.8
50th Percentile	4.5
75th Percentile	36.0
90th Percentile	70.2

2.5 Health Care Quality Landscape

The COPD EDAC measure joins a group of EDAC measures that address specific conditions and procedures. The COPD EDAC measure is unique in the following aspects:

- The COPD EDAC measure addresses a target population that is not captured by other implemented or new EDAC measures. This measure captures the full spectrum of post-discharge utilization (readmission/ED visit/observation stay) for this specific population of people hospitalized for COPD.
- While overlapping in cohort and part of the outcome with the existing COPD readmission measure, and overlapping with part of the cohort and part of the outcome for the hybrid Hospital Wide Readmission (hHWR) measure, the COPD EDAC measure:
    - Has a more comprehensive outcome (it includes ED visits and observation stays, in

addition to readmission) and accounts for the total length of stay
- Accounts for post-discharge time at risk for the outcome
- Allows for assessment of risk-adjusted post-discharge hospital visits specifically for COPD

By capturing a range of utilization outcomes that are important to patients, this measure can produce a complete picture of post-discharge outcomes that inform the public about care quality and incentivize global improvement in transitional care.

2.6 Meaningfulness to Target Population

Acute care utilization after discharge (that is, return to the ED, observation stay, and readmission) for any reason, is disruptive to patients and caregivers, costly to the healthcare system, and puts patients at additional risk of hospital-acquired infections and complications. Although some hospital returns are unavoidable, others may result from poor quality of care or inadequate transitional care.

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 return to the hospital following exacerbation of a condition caused by changes in medication after discharge, returns to the hospital due to infection after an inpatient procedure, and other signs of poor coordination of care including insufficient communication from providers and hospital staff. As part of assessing face validity (discussed further in sections 5.3.3 and 5.3.4), four patient and caregiver TEP members participated in the face validity vote on the COPD EDAC measure, with all agreeing that the measure as specified is meaningful and produces information that is valuable in making care decisions. The strong agreement among members indicates that the measure is meaningful and valued.

3.1 Contributions Towards Closing Care Gaps

This domain is optional for the Spring 2026 cycle.

4.1a Data Structure and Availability

This is a claims-based measure, and all data elements are in structured fields that are available in electronic sources.

CMS monitors feedback from the public and measured entities and there have been no concerns about feasibility or burden related to the currently implemented related measures and hence, we expect no new concerns regarding this new measure.

We did not perform an analysis of missing data for the measure because it is based on a 100% sample of paid, final action claims submitted by facilities for payment.

4.1b Implementation Costs and Burden

If implemented, there will be no costs or other burdens for this measure (for any component, including the calculation of the score) because the measure score would be calculated (by CMS) automatically from claims data which are routinely generated during the delivery of care.

Because the measure's data are automatically generated during patient care, and because CMS would calculate and report the data, there is no impact on clinician workflow (e.g., modifications), diagnostic thought processes, or patient-physician interaction. There are no barriers to implementing measure specifications, including data collection and measure calculation, and no barriers to performance reporting.

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 uses that data for both reimbursement and calculation of the measure score.

4.3 Feasibility Informed Final Measure

Because this is a claims-based measure, there is no burden on the facility or its clinicians and no feasibility concerns; rates are automatically calculated by CMS based on claims data submitted by facilities for payment.

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 national Medicare [Fee-for-Service (FFS)] and Medicare Advantage (MA)) claims and administrative data (January 1, 2022-December 31, 2023). Descriptions of the data used for testing are outlined in the table below.

COPD EDAC: Dataset Descriptions

Dataset	Applicable Testing	Description of Dataset

CY2022/CY2023: 2-year Medicare FFS and Medicare Advantage dataset (January 1, 2022-December 31, 2023)	Reliability testing Empirical validity Measure score distribution Risk variable frequencies and odds ratios Model performance testing (discrimination and calibration) Social risk factor testing	Dates of Data: January 1, 2022-December 31, 2023 Total number of hospitals (with at least 1 admission): 4,397 Total number of admissions: 453,692 Male (n=180,841), 39.9% Female (n=272,851), 60.1% Dual eligible (DE) (n=116,726), 25.7% Total number of hospitals with at least 25 admissions: 2,960 (67.3% of total) Number of admissions within facilities with at least 25 admissions: 438,469 (96.6% of total)
CY2022: 1-year Medicare FFS and Medicare Advantage Dataset (January 1, 2022-December 30, 2022)	Cohort definition Risk variable selection Face validity	Dates of Data: January 1, 2022-December 30, 2022 Total number of hospitals (with at least 1 admission): 4,269 Total number of admissions: 214,005

5.1.1a Dates of Testing Data

January 1, 2022-December 31, 2023

5.1.2 Differences in Data

Please see Section 5.1.4 for details. Differences in data used for testing are outlined in the table in Section 5.1.1.

5.1.3 Characteristics of Measured Entities

Characteristics of measured entities differ depending on the dataset. Please see the table in Section 5.1.1.

5.1.4 Characteristics of Units of the Eligible Population

The datasets, dates, number of measured hospitals, and number of admissions used in each type of testing are in the table in Section 5.1.1. For most measure testing, we used two years of Medicare data from January 1, 2022, to December 31, 2023. These datasets also include claims data on each patient for the 12 months prior to the index admission and contain facility inpatient

and Medicare Enrollment Database (EDB) data.

5.2.1 Level(s) of Reliability Testing Conducted

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

5.2.2 Method(s) of Reliability Testing

Data Element Reliability

For data element reliability, we provide information from literature, related measures that use the same ICD-10 code list, and from CMS coding guidance.

Entity-Level Reliability (Signal-to-Noise)

The EDAC statistical model uses hierarchical logistic regression to estimate the predicted and expected proportions of acute care days post discharge (please see the attachment in Section 1.18a). The rationale for calculating signal-to-noise reliability is stated in CBE guidance materials (PQM 2025, p.14) cited below:

“Logistic regression is a commonly used method for estimating reliability, especially for risk-adjusted measures with binomial data. In this approach, a hierarchical (multi-level) logistic regression model is fit, with the entity (e.g., hospital, provider) included as a random effect. This allows for estimation of both between-entity variance (signal) and within-entity variance (noise). The reliability estimate is then calculated as the ratio of between-entity variance to total variance, similar to the IUR.”

Specifically, we tested facility-level measure score reliability with the above-mentioned variant of the signal-to-noise method, using the formula presented in Figure 4 in the Supplemental Attachment (Adams et al., 2010; Yu et al., 2013). Specifically, for each facility, we calculate reliability using the hospital intercept estimated through the random intercept of the hierarchical logistic regression model, which is the quality signal, as follows:

Reliability=(σ_(facility-to-facility)^2)/(σ_(facility-to-facility)^2+ (σ_(facility error variance)^2)/n)

Where facility-to-facility variance is estimated from the hierarchical logistic regression model, n is equal to each facility’s observed case size, and the facility error variance is estimated using the variance of the logistic distribution (pi^2/3).

If implemented in a national quality program, public reporting will be limited to hospitals with a minimum index admission volume of at least 25. The volume restriction will mitigate concerns related to the “shrinkage” effect.

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5.2.3 Reliability Testing Results

Data Element Reliability

CMS claims data, used for reimbursement, are routinely used for quality measurement, and represent electronic data from structured fields; according to Battelle guidance, reliability is assumed for electronic data from structured fields (PQM, 2026).

CMS has in place multiple hospital auditing programs used to assess and improve claims coding reliability and validity, to ensure appropriate billing, and for overpayment recoupment (for example, CMS's Comprehensive Error Rate Testing Program and Fee-for-Service Recovery Audit Program) (Centers for Medicare & Medicaid Services, n.d.-a; Centers for Medicare & Medicaid Services, n.d.-b). CMS routinely conducts data analysis to identify potential problem areas and detect fraud, and audits important data fields used in our measures, including diagnosis and procedure codes as well as other elements that are consequential to reimbursement. In addition, CMS codes are updated annually effectively on October 1st of every year. Updates are jointly managed by CMS and the National Center for Health Statistics (NCHS) (Centers for Medicare & Medicaid Services, 2026).

The ICD-10 codes used to capture the cohort are aligned with common code sets that have been established in the literature (Kwok et al., 2025). In addition, the data elements used to capture the clinical cohort (ICD-10 codes that define the COPD-diagnosed population) are the same that are used in the CBE endorsed COPD mortality measure (CBE 1893). Finally, the developer annually tracks the volume of admissions for each of the ICD-10 codes used to define the cohort and has not detected large code-level changes or coding anomalies.

Other elements of the measure that are not specific to the COPD clinical cohort (for example, those that are used to define the outcome) are currently in use in other valid and recently CBE-endorsed measures (e.g. the AMI EDAC measure [CBE 2881].)

Entity-Level Reliability (Signal-to-Noise)

Table 2a provides the Battelle-required table of reliability within deciles of entity volume. Table 2b provides the distribution of entity-level signal-to-noise reliability.

As shown in Table 2b, for hospitals with at least 25 admissions for COPD, median signal-to-noise reliability was 0.869. Signal-to-noise reliability ranged from a minimum of 0.593 to a maximum of 0.989; the 25th and 75th percentiles were 0.759 and 0.921, respectively.

Using two years of data (the performance period) and a minimum public reporting threshold of 25,

reliability meets Battelle's threshold (at least 70% of entities >=0.6).

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5.2.3a Attach Additional Reliability Testing Results

5570-SupplementalAttachment-Spring2026.pdf

5.2.4 Interpretation of Reliability Results

Data Element Reliability

Because the fields used for all aspects of this measure are derived from electronic data from structured claims, and because data elements from Medicare claims that are used for reimbursement are collected using standardized coding and billing procedures and are routinely audited, they are considered sufficiently reliable. Data from literature further supports their reliability.

Entity-Level Reliability (Signal-to-Noise)

Using two years of data (the performance period) and a minimum public reporting threshold of 25 index admissions, reliability meets Battelle's threshold (at least 70% of entities >=0.6).

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

	Overall	Min	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10	Max

Reliability	0.835	0.593	0.627	0.694	0.758	0.814	0.853	0.883	0.903	0.920	0.937	0.959	0.989
Mean Performance Score	14.96	-7.19	1.46	6.61	11.74	8.16	16.70	18.21	19.99	20.40	22.39	23.89	16.33
Number of Entities	2960	25	284	311	288	303	298	290	298	297	295	296	1
Number of Persons / Encounters / Episodes	438,469	625	8,245	12,214	15,625	22,961	29,792	37,681	47,767	59,153	76,451	128,580	1,505

Table 2b. Accountable Entity Level Reliability Testing Results by Reliability Score

Minimum Case Volume	Number of Hospitals (%)	Mean (SD)	Min-Max	25th Percentile	Median	75th Percentile
>=1	4397 (100)	0.674 (0.263)	0.055-0.989	0.482	0.762	0.899
>=25	2960 (67)	0.835 (0.105)	0.593-0.989	0.759	0.869	0.921

5.3.1 Level(s) of Validity Testing Conducted

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

5.3.2 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

Data Element Validity

For data element validity we provide evidence from literature, and related measures.

Face Validity

During measure development, we obtained expert and stakeholder input by convening a technical expert panel (TEP) of clinicians, patients, patient advocates, and other stakeholders (see Table 3 for a complete list). Collectively, TEP members brought expertise in clinical content, performance measurement, coding, informatics, quality improvement, hospital administration, and patient and caregiver experience. In 2023 and 2024, we held two TEP meetings, where TEP members provided input on the cohort definition and specifications, risk variable selection, and risk model assessment, and reviewed model testing results, measure score reliability and validity, and testing variables related to economic disadvantage. Following completion of measure development, we systematically assessed the face validity of the measure score as an indicator of quality by soliciting the agreement from the TEP members via a survey, with the following question: "Do you

think that the COPD EDAC measure as specified, can distinguish between better and/or worse performance across hospitals?" We measured agreement using a six-point scale (strongly agree, agree, somewhat agree, somewhat disagree, disagree, strongly disagree).

Table 3. COPD EDAC: Technical Expert Panel (TEP)

Name and Credentials	Organization (if applicable) and Role	Location
Rosie Bartel, MA	PFAnetwork, PFCCpartners; Person Family Engagement Partner	Chilton, WI
Ann Borzecki, MD, MPH	VA Bedford Healthcare; Physician-Investigator	Bedford, MA
Jean Boyer	Person Family Engagement Partner	Picayune, MS
Sophia Brasil, MPH	Stratis Health; Senior Data Analyst	Boise, ID
Matt Cheung, PhD, RPh	University of the Pacific, Thomas J Long School of Pharmacy (part-time); Adjunct Professor of Pharmacy Practice, Independent Consultant (Medical Reviewer, Patient/Stakeholder Research Partner)	Gatos, CA
Steven Coffee, MA, EM CQSL	Headquarters U.S. Cyber Command, Patients for Patient Safety, U.S., Head2HeartConnections, LLC; Colonel, USAF Director, Military Personnel, Patient Advocate/Caregiver	Dumfries, VA
Craig Davies	Person Family Engagement Partner	New Orleans, LA
Michael Duan, MS	Premier, Inc.; Principal Data Scientist	Charlotte, NC
Ryan Merkow, MD, MS	University of Chicago Medicine Comprehensive Cancer Center and Cancer Service Line, Department of Surgery; Director for Surgical Cancer Quality, Associate Director of Health Services Research, Director Hepatic Artery Infusion Pump Program	Chicago, IL
Sachin Shah, MD, MPH	Massachusetts General Hospital, Harvard University; Physician; Clinical Researcher	Boston, MA
Donté Smith	Legacy Community Health; Person Family Engagement Partner, Caregiver/Patient Navigator	Houston, TX
Brian Stein, MD, MS	Rush University Medical Center; Physician and Chief Quality Officer	Chicago, IL
Mary Vaughan-Sarrazin, PhD	University of Iowa Department of Internal Medicine, VA Medical Center; Associate Professor, Department of Internal Medicine	Iowa City, IA
Bonnie Weiner, MD, MSEC, MBA, MSCAI, FACC, FAHA, DNBPAS	Saint Vincent Hospital, Worcester Medical Center, Accreditation for Cardiovascular Excellence; Physician and Director – Interventional Cardiology; Associate Program Director of Cardiovascular Medicine Fellowship; Chief Medical Officer at Accreditation for Cardiovascular Excellence Inc.	Harvard, MA

Empiric (Construct) Validity

We also explored validation through meaningful comparisons of the COPD 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 reviewed the logic model (see the COPD EDAC Logic Model in the Supplemental Attachment) to identify quality measures that fell within the same causal pathway. From that candidate list of measures, we determined which measures had data available publicly, at the hospital level. We then assessed the relationship between those measures and the COPD EDAC measure score, as described below.

We examined correlations between COPD 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), the Summary Score (with and without the entire Readmission Group), the Patient Experience Group score, and Medicare Spending Per Beneficiary (MSPB). Because the COPD EDAC measure score is on a lower-is-better scale, and the Star Rating measures are on a higher-is-better scale, we hypothesized that the COPD EDAC measure would be negatively correlated (weakly to moderately) with Star Rating-related measures. For MSPB, higher scores are associated with higher costs, so we hypothesized that the COPD EDAC measure would be positively correlated (weakly to moderately) with MSPB. We expect, however, to see different effect sizes, based on the specific comparator construct. For example, for comparisons that compare associations with and without readmission measures, we expect to see the largest effect size for the comparisons with readmission components, and we expect to see weaker associations when they are removed. For example, we expect the association between the Star Ratings Summary Score with the Readmission Group to be stronger compared with the Summary Score without the Readmission Group.

We calculated Pearson's correlation coefficients for the association between the COPD EDAC measure and these existing quality/cost measures on the same measured entities. For these analyses, we used calendar year (CY) 2022/2023 data for COPD EDAC measure scores, and April 2025 Star Rating preview data with measure dates of data ranging from 07/2020 - 06/2023. The full methodology for the Overall Hospital Quality Star Rating can be found at: https://qualitynet.cms.gov/files/603966dda413b400224ddf50?filename=Star_Rtngs_CompMthdlgy_v4.1.pdf

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 (unplanned inpatient readmission, ED visit, or observation stay) for patients in the COPD 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. To assess the clinical reason (principal discharge diagnoses) for post-discharge hospitalization within 30 days 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 (Table 6).

References

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5.3.4 Validity Testing Results

Data Element Validity

The data elements used to calculate the COPD EDAC measure are currently used in other validated quality measures. For example, the cohort is defined by ICD-10 codes that are also used in the CBE-endorsed COPD 30-day Risk-Standardized Mortality measure (CBE 1893). The outcome is defined by clinical events that are captured by multiple data fields and used for reimbursement; it is highly unlikely that the occurrence of an emergency department visit, observation stay or readmission is captured in error.

COPD is a group of lung diseases characterized by airway obstruction. Patients hospitalized for an acute exacerbation of COPD (AECOPD) present with varying degrees of severity ranging from a worsening of baseline symptoms (dyspnea, cough, and/or sputum) to respiratory failure. To capture the full spectrum of severity of patients hospitalized for an AECOPD, we included admissions, defined by ICD-10 codes, with a principal discharge diagnosis of COPD, as well as those with a principal diagnosis of respiratory failure who had a secondary diagnosis of an AECOPD. Requiring AECOPD as a secondary code helps to identify respiratory failure due to COPD exacerbation versus another condition (e.g., heart failure).

Literature supports the validity of discharge diagnosis codes in claims to identify COPD admissions. An older study (Stein et al., 2012) comparing coding algorithms found low sensitivity (about 24%) but high specificity (99.7%), good positive predictive value (85.4%) and high negative predictive value (93.9%) for an algorithm based on primary COPD or respiratory failure codes, which align with the COPD cohort. We support that these performance characteristics are appropriate for a quality measure use for public reporting, where it is important to capture a clinical sensical cohort with specificity and where any potentially missed cases are likely to be captured by related measures, such as the Pneumonia EDAC measure. Low sensitivity reflects what is seen in the clinical setting, where COPD is underdiagnosed, but high specificity and PPV mean that the codes identify true hospitalizations for COPD.

In addition, as discussed in the "Data element reliability" section, CMS has several audit programs in place to assess the accuracy of codes used for reimbursement.

Face Validity

Table 4 shows the results of the TEP face validity vote, where TEP members indicated their agreement with the following question*: "Do you think that the COPD EDAC measure as specified, can distinguish between better and/or worse performance across 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

COPD EDAC measure. In responding to questions about the measure, one member who disagreed stated that they did not think that the outcome could be captured in claims data, nor did they think that the outcome reflects the quality of care that a patient received.

Table 4. COPD EDAC: Technical Expert Panel (TEP) Face Validity Voting Results

Response Category	Number	Frequency
Strongly Agree	2	16.7%
Moderately Agree	6	50.0%
Somewhat Agree	3	25.0%
Somewhat Disagree	1	8.3%
Moderately Disagree	0	0.0%
Strongly Disagree	0	0.0%

Empiric Validity

Selection of Comparator Measures

Below we describe 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:

- **Star Rating Summary Score**: The Star Rating Summary score is calculated using a weighted average of Group Scores derived from quality measures assigned to five domains: Mortality (7 measures), Readmission (11), Safety of Care (8), Patient Experience (8) and Timely and Effective Care (14). Because the Summary Score contains the Readmission and Patient Experience Group Scores (see below), we hypothesized that the Summary Score would be weakly, negatively associated with the COPD EDAC measure score. Furthermore, we hypothesized that if we removed the Readmission Group from the Summary Score, that there would be a weaker, yet significant remaining association due to the presence of the Patient Experience score.
- **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 for other conditions (such as heart failure and pneumonia), and hospital visit measures following outpatient procedures (Centers for Medicaid & Medicare Services, 2025). Therefore, these measures overlap in their outcome, and because there is evidence of effectiveness of broad-based interventions to reduce unplanned readmissions (Kripalani et al., 2014), we hypothesized that hospitals with lower (better) COPD EDAC measure scores would also perform better on the composite Readmission Group Score. We note that all of the claims-based comparator measures include only Medicare Fee-For-Service (FFS) admissions and therefore we hypothesized a weak to moderate association between the COPD EDAC measure scores and the Readmission Group Score. We further hypothesized that removing the HWR measure (whose cohort and outcome partially overlap with the COPD 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 (Centers for Medicaid & Medicare Services, 2025) of the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey (Centers for Medicaid & Medicare Services, 2024), including important components of care coordination both during and after hospitalization, and for this reason it was selected as a comparator measure. For example, components of HCAHPS in the Patient Experience Group Score include patients' assessments of doctor and nurse communication, and if patients understood their care when they left the hospital. The Patient Experience Group Score also includes patient reports of receiving discharge instructions, and reports of staff explaining patients' medications. Therefore, the Patient Experience Group Score is on the same causal pathway as the COPD EDAC measure. HCAHPS is calculated for a sample of patients aged 18 and over, and only some of the patient experience subdomains overlap with EDAC (for example, questions about cleanliness and quiet do not); we therefore expect a weak negative association (and a smaller effect size compared with the Readmission Group Score) between the Patient Experience Group Score and COPD 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 COPD EDAC measure scores.

Analysis of Construct Validity

Table 5 provides Pearson correlation coefficients that show the relationship between the COPD EDAC measure score and related measures. Pearson correlation coefficients between the COPD EDAC measure and the comparator measures (Readmission Group Score, Readmission Group Score excluding HWR, and the Patient Experience Group Score) were -0.320, -0.302, and -0.222, respectively (all p-values <.0001). Pearson correlation coefficients between the COPD EDAC measure and the Summary Score, with and without the Readmission Group, were -0.269 and -0.153, respectively (p<.0001). The Pearson correlation coefficient between the COPD EDAC measure scores and MSPB was 0.152, p<.0001. These results show a significant association with the expected strength and in the expected direction with measures in the same causal pathway, which supports the validity of the COPD EDAC measure.

Table 5. COPD EDAC: Association (Pearson Correlation Coefficients) between Measure Scores and Comparator Measures for Hospitals with >=25 eligible admissions (COPD EDAC dates: January 1, 2022-December 31, 2023)

Comparison Measure	Number of Hospitals	Pearson Correlation Coefficient	p-value
Star Rating Standardized Readmission Group Scores	**2,641**	**-0.320**	**<.0001**
Star Rating Standardized Readmission Group Scores Excluding Hospital-Wide Readmission	**2,620**	**-0.302**	**<.0001**
Star Rating Standardized Summary Scores	**2,641**	**-0.269**	**<.0001**
Star Rating Standardized Summary Scores Excluding Readmission Group Score	**2,641**	**-0.153**	**<.0001**
Star Ratings Standardized Patient Experience Group Score	**2,562**	**-0.222**	**<.0001**
Medicare Spending Per Beneficiary	**2,527**	**0.152**	**<.0001**

Star Rating preview data from the April 2025 release on Hospital Care Compare with measure dates of data ranging from 07/2020 - 06/2023

Empiric Validity: Validity of the Outcome

Time to post-discharge event

The EDAC measures use a 30-day time frame that captures a clinically vulnerable post-discharge period, which is particularly relevant for older adult patients (Dharmarajan et al., 2015). Acute care in the post-discharge period can be influenced by hospital care and the early transition to the non-acute care setting. The 30-day time frame is a clinically meaningful period for hospitals to collaborate with patients and their communities to reduce acute care events (see Section 2.1, Logic Model, and Sections 2.2 and 6.2.1).

Furthermore, the 30-day, all-cause outcome is supported by empiric evidence showing the time course of post-discharge acute care visits. We illustrate this in Figure 5 (in the Supplemental Attachment), for the COPD EDAC cohort, where it is evident that post-discharge hospital visits continue beyond 30 days, and do not reach baseline until about 80 days.

Principal diagnoses associated with post-discharge hospital visits

In Table 6, we show that the most frequent reasons (principal discharge diagnoses) associated with unplanned readmission within 30 days are mostly associated with the initial index admission.

Table 6. COPD EDAC: Top 25 (Most Frequent) CCS Categories Associated with Unplanned Readmission for COPD (January 1, 2022 – December 31, 2023)

Rank	CCS	CCS Description	Count	Percent	Cumulative	Cumulative Percent
1	127	Chronic obstructive pulmonary disease and bronchiectasis	17,869	20.5%	17,869	20.5%
2	131	Respiratory failure; insufficiency; arrest (adult)	13,551	15.6%	31,420	36.1%

Rank	CCS	CCS Description	Count	Percent	Cumulative	Cumulative Percent
3	2	Septicemia (except in labor)	10,355	11.9%	41,775	48.0%
4	99	Hypertension with complications and secondary hypertension	8,467	9.7%	50,242	57.7%
5	122	Pneumonia (except that caused by tuberculosis or sexually transmitted disease)	6,688	7.7%	56,930	65.4%
6	999	COVID-19	3,215	3.7%	60,145	69.1%
7	106	Cardiac dysrhythmias	1,826	2.1%	61,971	71.2%
8	157	Acute and unspecified renal failure	1,343	1.5%	63,314	72.8%
9	129	Aspiration pneumonitis; food/vomitus	1,197	1.4%	64,511	74.1%
10	153	Gastrointestinal hemorrhage	1,093	1.3%	65,604	75.4%
11	55	Fluid and electrolyte disorders	839	1.0%	66,443	76.4%
12	103	Pulmonary heart disease	825	0.9%	67,268	77.3%
13	100	Acute myocardial infarction	815	0.9%	68,083	78.2%
14	237	Complication of device; implant or graft	808	0.9%	68,891	79.2%
15	159	Urinary tract infections	790	0.9%	69,681	80.1%
16	95	Other nervous system disorders	651	0.7%	70,332	80.8%
17	108	Congestive heart failure; nonhypertensive	623	0.7%	70,955	81.5%
18	123	Influenza	615	0.7%	71,570	82.2%
19	109	Acute cerebrovascular disease	591	0.7%	72,161	82.9%
20	238	Complications of surgical procedures or medical care	585	0.7%	72,746	83.6%
21	226	Fracture of neck of femur (hip)	560	0.6%	73,306	84.2%
22	197	Skin and subcutaneous tissue infections	545	0.6%	73,851	84.9%
23	130	Pleurisy; pneumothorax; pulmonary collapse	516	0.6%	74,367	85.5%

Rank	CCS	CCS Description	Count	Percent	Cumulative	Cumulative Percent
24	50	Diabetes mellitus with complications	514	0.6%	74,881	86.0%
25	19	Cancer of bronchus; lung	485	0.6%	75,366	86.6%

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5.3.4a Attach Additional Validity Testing Results

5570-SupplementalAttachment-Spring2026_0.pdf

5.3.5 Interpretation of Validity Results

Data element validity is supported by evidence from the literature and long-term use of these specific claims-based data elements for other quality measures.

Both strong face validity and empiric validity testing results support the validity of the COPD EDAC measure. Ninety-two percent of TEP members voted in support of the face validity statement. Our empiric validity analysis shows a statistically significant association with the expected strength and in the expected direction with measures in the same causal pathway, which

supports the construct validity of the COPD EDAC measure. Lastly, validity of the outcome results show that the most frequent reasons (principal discharge diagnoses) associated with readmission for those in the COPD EDAC cohort are associated with the initial index admission for COPD. In addition, we provide evidence for the validity of the 30-day outcome. The interpretation of these results is discussed below.

Face validity

The validity of the COPD EDAC measure is supported by strong face validity results, as measured by systematic feedback from the TEP.

Construct Validity Testing

The validity of the COPD EDAC measure is further supported by the empiric construct validity results that demonstrate a correlation (in the expected strength and direction) between the COPD EDAC measure and other quality/cost measures in the causal pathway (see COPD EDAC Logic Model in the Supplemental Attachment), such as the Star Rating Readmission Group Score (without the HWR measures), the Patient Experience Group Score, and MSPB.

As expected, the magnitude of the associations (effect sizes) account for only a portion of the COPD EDAC construct, for the following reasons:

- Star Ratings Summary Score:
  - The Summary Score is a broad measure of quality that includes five domains with many quality measures, some of which are not in the same causal pathway (including outpatient measures).
  - None of the measures capture the MA population.
  - Some measures within the Summary Score capture a broader population (all adults, for example).
  - The timeframes of the measures overlap but are not perfectly aligned.
- Star Ratings Readmission Group Score:
  - There are measures in this group that have outcomes that conceptually overlap (post-discharge acute hospitalization use), but largely focus on other target populations
  - Measures in this group include only FFS admissions, compared with the COPD EDAC measure that includes both FFS and MA admissions.
  - There are outpatient measures in the Readmission Group whereas the COPD EDAC measure cohort includes admissions discharged from an inpatient stay only.
  - The COPD EDAC measure cohort overlaps with a small proportion of the HWR measure, and for that small proportion the HWR measure includes only the outcome of readmission.
  - The timeframe of the measures overlaps but is not perfectly aligned.
- Star Ratings Patient Experience Group Score
  - Patient Experience captures a cohort that includes all adults; COPD EDAC is only adults over age 65 with a qualifying diagnosis of COPD.
  - Patient Experience is patient-reported; COPD EDAC is claims-based
    - While on the same causal pathway, even if the two cohorts were exactly aligned, you would not expect a high correlation.
- MSPB

- MSPB includes only FFS beneficiaries.
- COPD is only a fraction of the cohort captured by MSPB.
- Cost and quality are not always aligned (higher cost can be associated with better, and worse quality). For example, improving post-discharge quality and reducing EDAC may result in appropriate shifting of services and related costs to the outpatient setting, or alternatively, improving inpatient care may result in reducing short- and long-term complications and reducing a proportion of costs.
- The timing of long-term cost savings may not align with performance periods.

However, because we know that (1) there are effective strategies that hospitals can implement to reduce post-discharge hospital use, and (2) hospitals have implemented quality improvement programs to improve readmission rates, which can be broad-based, we conclude with moderate certainty that the relationships we see between the Readmission Group and the COPD EDAC performance are directly related.

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, as shown by the time course of post-discharge hospital visits, the daily post-discharge utilization rate does not return to baseline after 30 days after the index admission and is therefore temporally associated with the index admission (Figure 5). 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 (Table 6). We note however, that seemingly unrelated diagnoses (such as a fall resulting in fracture, dehydration, delirium, or an exacerbation of another chronic condition) may also be caused by poor care coordination (e.g., lack of medication management) (Liang & Alper, 2018). In addition, through the literature, we show that there is a relationship between specific care processes and the outcome of post-discharge facility-based acute care utilization. As discussed in the evidence of measure importance (Section 2.2), interventions during and after a hospitalization can be effective in reducing utilization rates in geriatric populations and, particularly, for older patients with COPD. Lastly, there is also increasing evidence that hospitals have been able to reduce readmission rates through quality improvement initiatives (see Section 6.2.1 for details).

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5.4.1 Methods Used to Address Risk Factors

Statistical risk adjustment model with risk factors

5.4.2 Conceptual Model Rationale

The goal of risk adjustment is to adjust for case-mix differences across the 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. In pursuing a risk adjustment approach that best leverages the data, we used a framework based largely on individual ICD-10 codes for risk adjustment. 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 COPD EDAC measure adjusts for case-mix differences between 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 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. Please see Tab *COPD EDAC Risk Variable Complications of Care* in the Excel file entitled "*COPD EDAC_Data Dictionary.xlsx*" for the list of potential complications referred to in Step 3 of the algorithm.

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 intent is for this measure to adjust for patient demographic and clinical characteristics while illuminating important quality differences.

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 originally selected for the complementary COPD readmission measure, as described below. 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 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). 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. We note that frequencies were based on a 100% sample, but that all subsequent steps were based on a 70% sample. 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]); however, increases in the c-statistic did not meet these thresholds when additional variables were evaluated. 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. We did not include sex as a variable since sex can be considered a socio-demographic variable (Goodman et al., 2025).

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).

Economic Disadvantage

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 variables related to economic disadvantage and their overlap with clinical risk factors. Although some recent literature has evaluated the relationship between these variables 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 described below (and in the Supplemental Attachment) 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 Factors and Factors Related to Economic Disadvantage

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.

- **Comorbidities and economic disadvantage:** Economically disadvantaged patients 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 COPD (Celli & Wedzicha, 2019). 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, with worse baseline respiratory status and multimorbidity (Owens et al., 2022). These 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 economic disadvantage variables 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 admissions with the dual eligibility (DE) variable.
- **Differential care:** A second pathway by which economic disadvantage may contribute to post discharge acute care risk is that patients may not receive equivalent care within a facility (Lloren et al., 2019). For example, it is known that the implementation of evidence-based inpatient and transitional care for COPD varies across hospitals (Rojas et al., 2023), and it has been shown that for other conditions (acute myocardial infarction, pneumonia, and heart failures), that across almost all hospitals (>98% of hospitals with sufficient data for assessment), dually eligible patients have higher rates of post discharge hospital based care (readmission) when compared with patients who are not dually eligible patients in the same hospital (within hospital disparities), after accounting for comorbidities, and area level variables (Silvestri et al., 2022). It is known that individuals with economic disadvantage and chronic conditions including COPD have both lower rates of post-discharge follow up, and higher unadjusted readmission rates (Anderson et al., 2022).
- **Low-quality hospitals:** Economically disadvantaged patients 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 these 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; economically disadvantaged patients are known to have lower rates of follow-up after discharge and higher rates of post-discharge acute care (Anderson et al., 2022).
- **Residual risk:** Economically disadvantaged patients may experience worse health outcomes only partially under the control of the healthcare system. Some economic 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 (Chatterjee et al., 2022).

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 multi-hospital systems) to invest in mitigating these risks (Levinson et al., 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 such needs.

Economic Variables Used in Testing

Based on the available literature and given the limited availability of valid and reliable variables that can be tested in claims data, we selected dual eligibility as a variable for testing.

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. There is also a body of literature demonstrating differential health care and health outcomes among dually eligible beneficiaries (ASPE, 2020).

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5.4.2a Attach Conceptual Model

5570-SupplementalAttachment-Spring2026_0.pdf

5.4.3 Variable Distribution Across Measured Entities

Table 7 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 (see Tab 2). Table 7a shows the distribution of each risk variable at the hospital level.

Table 7. COPD EDAC: Frequency of ICD-10-Based Risk Variables and Adjusted OR with 95% Confidence Intervals (January 1, 2022-December 31, 2023)

Variable	Description	Percentage (%) (N=453,692)	OR (95% CI)
AGE	Age, mean (SD)	75.5 (7.21)	1.00 (1.00-1.00)
ICD-10 codes during the index admission			
IND_B9789	Other viral agents as the cause of diseases classified elsewhere	1.27	0.83 (0.81-0.85)

Variable	Description	Percentage (%) (N=453,692)	OR (95% CI)
IND_C3411	Malignant neoplasm of upper lobe, right bronchus or lung	0.53	1.17 (1.14-1.21)
IND_D649	Anemia, unspecified	9.01	1.10 (1.09-1.10)
IND_D751	Secondary polycythemia	0.74	0.74 (0.71-0.77)
IND_E875	Hyperkalemia	4.99	1.22 (1.21-1.23)
IND_F17210	Nicotine dependence, cigarettes, uncomplicated	24.00	0.91 (0.90-0.92)
IND_G629	Polyneuropathy, unspecified	2.90	1.02 (1.01-1.03)
IND_G928	Other toxic encephalopathy	1.16	1.11 (1.09-1.14)
IND_I480	Paroxysmal atrial fibrillation	11.47	1.19 (1.18-1.19)
IND_I4891	Unspecified atrial fibrillation	7.97	1.14 (1.14-1.15)
IND_I5031	Acute diastolic (congestive) heart failure	0.90	1.20 (1.17-1.23)
IND_J101	Influenza due to other identified influenza virus with other respiratory manifestations	1.25	0.85 (0.83-0.87)
IND_J209	Acute bronchitis, unspecified	5.57	0.84 (0.83-0.85)
IND_J90	Pleural effusion, not elsewhere classified	2.34	1.25 (1.23-1.26)
IND_Z515	Encounter for palliative care	4.12	0.85 (0.83-0.86)
IND_Z66	Do not resuscitate	14.25	0.91 (0.90-0.92)
IND_Z720	Tobacco use	0.97	0.88 (0.86-0.90)
IND_Z7984	Long term (current) use of oral hypoglycemic drugs	10.83	0.90 (0.90-0.91)
IND_Z87891	Personal history of nicotine dependence	42.66	0.93(0.92-0.93)
ICD-10 codes in the 12 months prior to admission			
PRE_D649	Anemia, unspecified	27.46	1.16 (1.16-1.17)
PRE_E440	Moderate protein-calorie malnutrition	4.09	1.10 (1.09-1.11)
PRE_E871	Hypo-osmolality and hyponatremia	15.06	1.13 (1.12-1.13)
PRE_F17210	Nicotine dependence, cigarettes, uncomplicated	30.35	1.07 (1.07-1.08)
PRE_F32A	Depression, unspecified	20.42	1.03 (1.03-1.04)
PRE_F410	Panic disorder [episodic paroxysmal anxiety]	2.76	1.11 (1.10-1.12)
PRE_F419	Anxiety disorder, unspecified	28.53	1.09 (1.09-1.10)
PRE_H9190	Unspecified hearing loss, unspecified ear	3.05	1.07 (1.06-1.08)
PRE_I160	Hypertensive urgency	4.01	1.08 (1.07-1.09)
PRE_I509	Heart failure, unspecified	33.27	1.15 (1.14-1.15)
PRE_J440	Chronic obstructive pulmonary disease with (acute) lower respiratory infection	26.27	1.08 (1.07-1.08)
PRE_J449	Chronic obstructive pulmonary disease, unspecified	82.98	1.05 (1.04-1.06)
PRE_J8410	Pulmonary fibrosis, unspecified	6.66	1.11 (1.10-1.12)
PRE_J90	Pleural effusion, not elsewhere classified	19.79	1.17 (1.17-1.18)

Variable	Description	Percentage (%) (N=453,692)	OR (95% CI)
PRE_J9600	Acute respiratory failure, unspecified whether with hypoxia or hypercapnia	9.49	1.04 (1.04-1.05)
PRE_J9602	Acute respiratory failure with hypercapnia	12.92	1.05 (1.05-1.06)
PRE_J9620	Acute and chronic respiratory failure, unspecified whether with hypoxia or hypercapnia	8.24	1.06 (1.06-1.07)
PRE_J9621	Acute and chronic respiratory failure with hypoxia	33.08	1.07 (1.07-1.08)
PRE_J9622	Acute and chronic respiratory failure with hypercapnia	16.78	1.07 (1.07-1.08)
PRE_M542	Cervicalgia	9.66	1.08 (1.07-1.09)
PRE_M7989	Other specified soft tissue disorders	11.39	1.12 (1.11-1.13)
PRE_R0689	Other abnormalities of breathing	5.84	1.08 (1.07-1.09)
PRE_R079	Chest pain, unspecified	38.98	1.12 (1.11-1.13)
PRE_R0902	Hypoxemia	32.39	1.00 (0.99-1.00)
PRE_R1084	Generalized abdominal pain	5.24	1.18 (1.17-1.19)
PRE_R627	Adult failure to thrive	2.82	1.22 (1.20-1.23)
PRE_R918	Other nonspecific abnormal finding of lung field	46.98	1.08 (1.08-1.09)
PRE_T380X5A	Adverse effect of glucocorticoids and synthetic analogues, initial encounter	6.27	1.12 (1.11-1.13)
PRE_Z0000	Encounter for general adult medical examination without abnormal findings	21.13	0.96 (0.95-0.97)
PRE_Z1231	Encounter for screening mammogram for malignant neoplasm of breast	12.73	0.82 (0.81-0.83)
PRE_Z515	Encounter for palliative care	5.76	1.11 (1.10-1.12)
PRE_Z716	Tobacco abuse counseling	3.50	1.11 (1.10-1.12)
PRE_Z7951	Long term (current) use of inhaled steroids	25.68	1.08 (1.08-1.09)
PRE_Z7952	Long term (current) use of systemic steroids	12.20	1.15 (1.14-1.16)
PRE_Z9114	Patient's other noncompliance with medication regimen	3.67	1.25 (1.24-1.26)
PRE_Z9119	Patient's noncompliance with other medical treatment and regimen	3.51	1.18 (1.16-1.19)
PRE_Z9981	Dependence on supplemental oxygen	34.82	1.09 (1.08-1.09)
ICD-10 codes either during the index admission or 12 months prior to admission			
C3490	Malignant neoplasm of unspecified part of unspecified bronchus or lung	5.74	1.18 (1.17-1.19)
E1122	Type 2 diabetes mellitus with diabetic chronic kidney disease	16.54	1.15 (1.14-1.15)
N184	Chronic kidney disease, stage 4 (severe)	5.08	1.19 (1.18-1.20)
N2581	Secondary hyperparathyroidism of renal origin	3.13	1.19 (1.18-1.20)

Variable	Description	Percentage (%) (N=453,692)	OR (95% CI)
Other risk variables			
MCCFI	Multiple Chronic Conditions Frailty Index	62.18	1.23 (1.22-1.24)
HX_SA	Sleep-disordered breathing	27.45	0.94 (0.93-0.95)
HX_MV	History of mechanical ventilation	16.77	1.07 (1.06-1.07)
MA	MA (versus FFS)	53.32	0.98 (0.97-0.98)

Table 7a. COPD EDAC: Hospital-Level Distribution of Risk Variables (Hospitals with >= 25 admissions, N=2,960)

Variable	Mean	Std Dev	Median	25th Percentile	75th Percentile	Min	Max
AGE	76	2	75	74	76	70	83
Variable	**Mean (%)**	**Std Dev (%)**	**Median (%)**	**25th Percentile (%)**	**75th Percentile (%)**	**Min (%)**	**Max (%)**
C3490	5.3	3.8	5.1	3.1	7.1	0	79.4
E1122	15.7	6.3	15.6	11.5	19.5	0	44.7
IND_B9789	1.1	1.9	0	0	1.7	0	20.7
IND_C3411	0.5	0.9	0	0	0.7	0	23.4
IND_D649	8.6	5.2	8	5.3	11.2	0	49.3
IND_D751	0.8	1.2	0	0	1.1	0	12.1
IND_E875	4.6	3.1	4.2	2.6	6.4	0	25
IND_F17210	23.9	9.4	24.4	17.9	30.1	0	62.3
IND_G629	2.8	2.3	2.5	1.1	3.9	0	28
IND_G928	1	1.5	0.4	0	1.5	0	16.2
IND_I480	10.4	5.4	10.3	6.7	14.1	0	30.8
IND_I4891	8.2	4.7	7.5	4.7	10.7	0	37.3
IND_I5031	0.9	1.3	0.5	0	1.4	0	23.7
IND_J101	1.3	1.5	0.9	0	2	0	14.3
IND_J209	5.5	6	3.8	1.8	7.1	0	60.8
IND_J90	2.3	2.2	2	0.8	3.2	0	25.3
IND_Z515	3.6	4	2.9	0.7	5.2	0	59
IND_Z66	15	10.3	13	7.3	20.8	0	72.4
IND_Z720	1.2	3	0	0	1.1	0	43.8
IND_Z7984	10.8	5.4	10.5	7.3	14	0	38.5
IND_Z87891	41.2	12.8	42.7	34.8	49.6	0	81.6
N184	4.9	2.9	4.7	3	6.5	0	22.2
N2581	2.8	2.5	2.5	0.8	4	0	17.2
PRE_D649	26.3	7.7	26.4	21.4	31	2.4	58.8
PRE_E440	3.7	3.2	3.1	1.4	5.3	0	28.1

PRE_E871	14.6	5.8	14.3	10.6	18.1	0	41.7
PRE_F17210	30.4	9.6	30.7	23.8	36.7	0	66
PRE_F32A	19.6	7.6	19.4	14.8	24.2	0	57.1
PRE_F410	2.6	2.2	2.4	1	3.7	0	23.8
PRE_F419	27.6	8.5	27.4	22.2	32.8	0	71.4
PRE_H9190	2.9	2.5	2.6	1.2	4	0	25
PRE_I160	3.6	3.1	3	1.5	5.1	0	27.4
PRE_I509	33	8.8	32.7	27.2	38.3	7.4	71.8
PRE_J440	26.1	9.2	25.5	20.5	30.8	0	84.4
PRE_J449	82.4	6.5	83.1	78.9	86.6	41.4	100
PRE_J8410	6.6	4.5	5.7	3.5	8.6	0	34.5
PRE_J90	18.9	7.2	18.8	14.2	23.1	0	55.2
PRE_J9600	8.9	6.1	7.8	4.4	12.2	0	43.8
PRE_J9602	12.1	6.6	11.5	7.5	16.2	0	42.9
PRE_J9620	7.7	5.3	7	3.8	10.5	0	39.2
PRE_J9621	31.6	10.7	32.2	25.2	38.6	0	69.4
PRE_J9622	15.8	7.7	15.4	10.6	20.7	0	49.6
PRE_M542	9.3	4.2	9	6.5	11.7	0	34.6
PRE_M7989	10.5	5.5	10	6.7	13.8	0	43.8
PRE_R0689	5.5	5.4	4.4	2.5	7.1	0	85.7
PRE_R079	36.7	14	35.6	27.3	45	0	99.3
PRE_R0902	32.4	10.4	31.7	25.3	38.8	2.4	91.2
PRE_R1084	4.9	3.3	4.4	2.7	6.6	0	28.1
PRE_R627	2.7	2.5	2.3	0.9	3.8	0	38.4
PRE_R918	45.4	15	45.4	35.5	55.3	0	96.3
PRE_T380X5A	5.4	4.1	4.9	2.4	7.8	0	29.4
PRE_Z0000	20.5	10.4	19.3	13.2	26.6	0	69.2
PRE_Z1231	12.5	4.9	12.3	9.4	15.2	0	46.2
PRE_Z515	5.1	4.6	4.1	1.8	7.2	0	59
PRE_Z716	3.4	3.6	2.5	0.8	4.7	0	25.9
PRE_Z7951	24.1	12.6	23.5	14.6	32.4	0	84.6
PRE_Z7952	11.6	6.6	11	6.9	15.4	0	50
PRE_Z9114	3.4	3.2	2.8	1.2	4.6	0	31.3
PRE_Z9119	3.2	2.7	2.8	1.3	4.6	0	22.2
PRE_Z9981	34.4	9.9	34.3	28.4	40.3	0	84.4

5.4.3a Attach Descriptive Statistics for Risk/Case-mix Variables

5570-SupplementalAttachment-Spring2026_1.pdf

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

Table 7 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 (see Tab 2).

Economic Disadvantage

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

To understand the incremental impact of the dual eligible (DE) variable on the COPD EDAC measure, we assessed the following: prevalence among the cohort and among hospitals, unadjusted outcome rates, association with the unadjusted outcome, odds ratios in a bivariate and multivariable model, model calibration, 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).

As shown in Table 8, 25.7% of admissions for patients hospitalized for COPD were dually eligible and mean unadjusted days in acute care were higher for admissions for patients with vs. without the DE variable (207 vs. 150, respectively). At the hospital level, the median proportion of admissions for patients with the DE variable was 22.4% among the 4,397 hospitals with at least one qualifying inpatient admission (25^{th} percentile, 14.3%, 75^{th} percentile, 33.3%).

Bivariate odds ratios for admissions for patients with and without the DE variable (not adjusting for other covariates) show higher odds of EDAC for dually eligible patients (1.46 [95% CI: 1.43-1.48], however most of the risk is attenuated after the addition of the other risk variables in the model (1.10 [95% CI: 1.10-1.11], demonstrating the overlap between the DE variable and the clinical risk variables in the final model.

We also examined model calibration for the DE variable to determine if the risk model (without including DE) performs well for admissions with and without the DE variable (see Figure 6 in the Supplemental Attachment). The results show that the model is well-calibrated for both sets of admissions.

Table 8. COPD EDAC: Proportion of Admissions and Unadjusted Outcomes for Admissions with vs. without Dual Eligibility (January 1, 2022 - December 31, 2023, N=453,692)

Variable	N	Patient Prevalence (%)	Mean Unadjusted Days in Acute Care (SD) per 100 Discharges
Dual Eligible (DE)	116,726	25.7	207 (418)
Not Dual Eligible	336,966	74.3	150 (354)

Impact on Measure Scores

While admission-level, unadjusted days in acute care for dually eligible patients are higher than for patients who are not dually eligible, we also know that the patient-level risk conferred by economic and clinical risk variables overlap. Therefore, we wanted to additionally understand the impact of the DE variable at the hospital level on the risk-adjusted COPD EDAC measure score. To do so, we calculated measure scores with and without the DE variable in the risk model and then calculated the differences in measure scores and the correlation between measure scores (Table 9 below, and Figure 7 in the Supplemental Attachment).

Results show that measure scores calculated with and without the DE variable in the risk model are highly correlated (correlation coefficient 0.9997), and differences between measure scores are very small (Table 9). We also examined the hospital-proportion of admissions of patients within the measure cohort with DE and the distribution of hospital measures scores (Figure 8 in the Supplemental Attachment) and found that the distribution of measure scores within quintiles of the hospital proportion of admissions for patients in the measure cohort with DE overlaps across quartiles. This means hospitals in the fifth quintile can perform as well as hospitals in the first through fourth quintiles, concluding that most of the impact of the DE variable is accounted for within our empirically based risk model that uses primarily clinical risk variables to adjust the measure score.

Table 9. COPD EDAC: Differences in Measure Scores and Correlation Between Measure Scores, for Measure Scores Calculated with and without Dual Eligibility (DE) (January 1, 2022-December 31, 2023)

Variable	Median Differences in Measure Scores	IQR (25^{th} percentile to 75^{th} percentile)	Pearson Correlation Coefficient
DE	0.22	-0.74 to 0.98	0.9997 (p<0.0001)

Conclusion

Overall, our results show that economically disadvantaged patients have a higher risk of the EDAC outcome, but that there is little impact at the hospital level on measure scores due to an empirically derived risk model which addresses most of the influence on the EDAC outcome for these patients. Patients who are dually eligible have higher unadjusted rates of the outcome, but the impact of the DE variable on measure scores is minimal: measure scores calculated with and without the DE variable are highly correlated (near 1), and differences between measure scores calculated with and without the DE variable are small. In addition, the distribution of measure scores across quintiles of the hospital proportion of admissions for patients in the cohort with DE overlap. We also found that the model is well calibrated for admissions for patients with, and without, the DE variable. These empiric results support the decision to not adjust the measure for the DE variable. Adjusting for the DE variable may also mask signals that arise from systematic differences in the quality of care between hospitals serving more versus fewer dually eligible patients and would hold hospitals that serve these patient population to different standards of care. We also note that this measure is not in a pay-for-performance program.

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

5570-SupplementalAttachment-Spring2026_2.pdf

5.4.5 Calibration and Discrimination

Methods

To assess model performance, we assessed model discrimination and calibration.

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. We assess calibration for all admissions, and for important subsets (admissions for patients with and without dual eligibility, and Medicare Advantage vs. Medicare FFS).

Results

Please see Table 10, and Figures 6, 9, 10, and 11 in the Supplemental Attachment for the model testing results. The results are also described below.

The C-statistic, calculated using CY2022/2023 data, was 0.662 (Table 10). Predictive ability ranged from 0.75 to 3.87 mean acute care days across predicted-risk deciles.

Table 10. COPD EDAC: Model Testing Statistics (January 1, 2022 – December 31, 2023)

C-Statistic	Predictive Ability (Mean Acute Care Days)
0.662	0.75-3.87

Risk decile plots show that higher deciles of the predicted outcomes are associated with higher observed outcomes in both CY2022 and the CY2022/2023 dataset (Figures 9 and 10). We also found good calibration for important subsets of patients, including admissions for Medicare Advantage vs. Medicare FFS beneficiaries, and admissions for patients who are dually eligible vs those who are not. Please see Figure 6 and Figure 11 in the Supplemental Attachment.

5.4.5a Attach Calibration and Discrimination Testing Results

5570-SupplementalAttachment-Spring2026_3.pdf

5.4.6 Interpretation of Risk/Case-mix Factor Findings

Discrimination

The C-statistic of 0.662 indicates acceptable model discrimination for a post-discharge hospital utilization measure. The model's predictive ability, reflected in the range of mean acute care days between the lowest and highest predicted-risk deciles, indicates that the model distinguishes higher-risk patients from lower-risk patients.

Calibration

Higher deciles of predicted risk are associated with higher observed outcomes, indicating good model calibration.

Overall Interpretation

Interpreted together, these diagnostic results indicate that the risk-adjustment model adequately accounts for differences in patient characteristics, or case mix.

5.4.7 Final Approach to Address Risk Factors

Statistical risk adjustment model with risk factors

6.1.1 Current Status

Not in use

6.1.2 Current or Planned Use(s)

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

6.1.4 Attributes for Accountability Use

The target population includes Medicare beneficiaries enrolled in Medicare Advantage or Fee-for-Service. The accountable entity is the hospital, and the care setting is inpatient. This EDAC measure is a risk-adjusted outcome measure that is appropriate for a range of accountability programs; the existing implemented EDAC measures are in a pay-for-reporting program. The measure is not adjusted for economic disadvantage (dual eligibility [DE]) as we have shown empirically that there is little impact at the hospital level on measure scores due to an empirically derived risk model which addresses most of the influence on the EDAC outcome for these patients (please see Section 5.4.4). Adjusting for the DE variable may also mask signals that arise from systematic differences in the quality of care between hospitals serving more versus fewer dually eligible patients and would hold hospitals that serve these patient population to different standards of care.

6.2.1 Actions of Measured Entities to Improve Performance

Hospitals seeking to improve their performance on the COPD EDAC measure must implement comprehensive strategies that enhance discharge planning, strengthen post-discharge care coordination, and reduce unnecessary acute care utilization. Since this measure captures ED 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. Strategies that are specific to patients hospitalized for COPD are outlined within Section 2.2, as well as displayed within the COPD EDAC Logic Model (see Supplemental Attachment).

One of the important actions hospitals can take to reduce excess acute care utilization following COPD 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 self-management support, 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 patient self-management support include educating patients at discharge on their medication, diagnosis, proper inhaler use and therapeutic regimen. To reduce complications and avoidable acute care visits, hospitals can also equip patients with written 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 fragmentation is one of the main causes of high EDAC rates (Snow et al., 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 effectiveness of transitional care interventions, especially those targeting older or frail adults discharged from hospital to home, in reducing 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 (Le Berre et al., 2017).

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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6.2.5a Potential Unintended Consequences

All quality measures have the potential for unintended consequences. Early discharge, contributing to post-discharge mortality, is a conceptual concern for readmission measures. The COPD EDAC measure mitigates this by accounting for survival time. We note that if implemented, this measure will not be in a pay-for-performance program. CMS is committed to monitoring unintended consequences, including changes in coding practice and outcomes.

7.1 Supplemental Attachment

5570-SupplementalAttachment-Spring2026_1.pdf

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