CBE ID

5575

Title

Excess Days in Acute Care (EDAC) After Hospitalization for Diabetes

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 Diabetes (hereafter "Diabetes EDAC") measure assesses days spent in acute care within 30 days of discharge from an inpatient hospitalization for diabetes. This measure is intended to improve care transition quality for discharged patients hospitalized for diabetes 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 Diabetes 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 diabetes. The Diabetes EDAC measure captures excess days in acute care within 30 days of discharge from a hospitalization for diabetes 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).

About one in three Medicare beneficiaries have been diagnosed with diabetes (Centers for Medicare & Medicaid Services [CMS], 2024) and short and long-term complications often result in hospital admission; there are roughly 8 million diabetes-related hospitalizations in adults each year (Dhatariya et al., 2024), with about half occurring in people older than 65 (AHRQ, 2018). Thirty-day readmission rates among patients with diabetes in the United States (U.S.) range from 16 percent to 20 percent (Soh et al., 2020; Rubin & Shah, 2021). In 2022, 32.4 million hospital inpatient days were directly attributable to diabetes with an estimated cost of approximately $96 billion including $67 billion attributed to individuals aged 65 or older. Extrapolating to readmissions in the Medicare population only, this amounts to approximately $12 billion per year of excess costs in this population (Parker et al., 2024).

EDAC measures capture a complete picture of acute-care post-discharge utilization that informs patients and the public about care quality and incentivize 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 Diabetes 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 of diabetes, 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, identifying re-hospitalizations for diabetes can help identify patients for whom ambulatory care has proven insufficient for adequate diabetes control. 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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1.11 Measure Webpage

None.

1.13 Data Dictionary

Attached

1.13a Attach Data Dictionary

5575-1.13a-Diabetes-EDAC-Data-Dictionary-Spring2026.xlsx

1.14 Numerator

The outcome for the Diabetes 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, *Diabetes 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, *Diabetes 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 *Diabetes EDAC Risk Variable Complications of Care* tab in the Excel file entitled *Diabetes 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 Diabetes EDAC cohort is defined as patients aged 65 years or older with a principal discharge diagnosis of diabetes, 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 Diabetes EDAC measure includes index admissions for patients who meet all the following criteria:

- **Principal discharge diagnosis of diabetes**

  - *Rationale:* Hospitalization specifically for diabetes is the target for measurement.
  - ICD-10 codes used to define the Diabetes EDAC cohort inclusion criteria are shown in Tab 1 of the Excel file entitled *Diabetes EDAC_Data Dictionary.xlsx.* During measure development we considered a cohort that included diabetes as a secondary diagnosis. However, due to the heterogeneity of this population and the cohort overlap with existing measures such as Heart Failure EDAC, CMS decided, based on this and the preference of the Technical Expert Panel (TEP), to specify this measure more narrowly, based on a principal discharge diagnosis of diabetes.
- **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).

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)
- Diabetes admissions within 30 days of discharge from a prior diabetes 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.
- **Diabetes admissions within 30 days of discharge from a prior diabetes index admission**

- *Rationale*: Additional diabetes 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.

Figure 2 (in the Supplemental Attachment) shows the final Diabetes EDAC cohort with inclusion and exclusions applied.

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

5575-1.18a.-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 Diabetes EDAC measures that were recently newly endorsed or re-endorsed by the Cost & Efficiency Recommendation Group, after considering the addition of MA admissions. Those measures include: hybrid Hospital-Wide Readmission [HWR] (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 Diabetes 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’).

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1.26 Minimum Sample Size

The measure does not have a minimum sample size.

2.1 Attach Logic Model

5575-SupplementalAttachment-Spring2026.pdf

2.2 Evidence of Measure Importance

About one out of every three Medicare beneficiaries has been diagnosed with diabetes (CMS, 2024) and short and long-term complications often result in hospital admission; there are roughly 8 million adults hospitalized with diabetes each year (AHRQ, 2018; Dhatariya et al., 2024), with about half occurring in people older than 65. In 2020, a Healthcare Cost & Utilization Project (HCUP) statistical brief found that, among Medicare beneficiaries, diabetes with complications ranked the fifth highest of principal diagnoses at index admission for the total number of 30-day readmissions and had the second highest readmission rate per 100 index admissions at 22.2% (Jiang & Barrett, 2024) with an estimated cost of $12 billion per year (Parker et al., 2024). In the long term, better management of diabetes and its complications, including during the peri-discharge period, can improve outcomes such as reducing rates of amputation, improving patient quality of life, and lowering healthcare costs (Friel et al., 2022; Boreland et al., 2015).

There is both a quality gap and a measurement gap for post-discharge outcomes for patients hospitalized for diabetes. The quality gap is illustrated by variation at the hospital level in risk standardized post-discharge acute care utilization for patients hospitalized for diabetes. In CORE's empirical analyses of Medicare beneficiaries in the Diabetes EDAC cohort, excess post-discharge acute utilization (unplanned readmissions, ED visits, observation stays) within 30 days at the hospital level ranged from -125 excess days in acute care per 100 discharges to 1,613 excess days in acute care per 100 discharges; the interdecile range was 142.8 excess days per 100 discharges. In terms of a measurement gap, there are no outcome measures in any federal programs that directly address post-discharge transitions of care for patients hospitalized for diabetes, nor are there any PQM-endorsed outcome measures that address this population.

Standards for hospital care for patients with diabetes are well established, including care at the peri-discharge period. The American Diabetes Association (ADA) Professional Practice Committee routinely releases their Standards of Care in Diabetes. Within their January 2026, Volume 49, Supplement 1 Standards of Care, the ADA explicitly dictates intervention strategies for an array of populations (American Diabetes Association Professional Practice Committee, 2026). Specifically for crossover in which clinical guidelines support the Diabetes EDAC measure, the ADA notes appropriate interventional strategies for both older adults (chapter 13) and diabetes care in the hospital (chapter 16). More specifically for hospital-based interventional strategies (chapter 16), the ADA notes a series of recommendations that connect to reducing readmissions for patients hospitalized for diabetes. They provide clear guidance for hospitals for how to transition patients hospitalized for diabetes from the hospital to an ambulatory setting to reduce future readmissions. For example, Recommendation 18 (chapter 16) states that a structured discharge plan should be tailored to the individual with diabetes, including medication reconciliation, education, and follow-up visits.

Evidence suggests that there is variation in the implementation of standard care, resulting in gaps of healthcare quality between hospitals (American Diabetes Association Professional Practice Committee, 2025). For example, a study of one health system that developed a tool to identify gaps across five hospitals showed variation in the structure, processes, resources, and leadership for diabetes care across their health system. Specifically, they found variation in glucose management, variation in training of providers on glucose management, and a lack of adequate resources for ambulatory care for patients with diabetes (Golden et al., 2017). Furthermore, patients themselves report gaps in care coordination (Colvin et al., 2023). One study highlights such a gap, stating that that 24% of patients at a tertiary university medical center who received an endocrinology consultation for diabetes were discharged with incorrect medication(s) and/or without discharge recommendations (Shah & Kulasa, 2021). Similarly, research on utilization of Diabetes Self-Management Education and Support (DSMES), which is an evidenced-based program to help people manage their diabetes (Centers for Disease Control and Prevention, 2024), shows that within two hospitals and a federally qualified healthcare clinic, fewer than 54% of patients who had a new type 2 diabetes diagnosis were referred to a DMSES program. For those patients that received DMSES in this study cohort, a significant reduction in A1c (1 hour, p=0.001; 8 or more hours, p=0.022) occurred based on time spent receiving DSMES (Alsayed et al., 2020).

There are evidence-based interventions and guideline-directed standards that hospitals can implement to reduce post-discharge acute care use. For example, one of the biggest risk factors for a readmission for diabetes is the lack of a post-discharge ambulatory visit (Rubin et al., 2023), and interventions around ensuring such a visit have shown that such follow up is associated with a reduced risk of post-discharge acute care utilization (Ostling, Wyckoff, & Ciarkowski, 2017). CORE has found in our empirical analyses in Medicare patients that the most common reason (captured by principal discharge diagnosis) after discharge for a diabetes hospitalization is itself, a diabetes complication, suggesting that better management of diabetes in the peri-discharge period can reduce excess post-discharge acute care utilization. We note that this measure is specified to capture patients admitted with a principal diagnosis of diabetes, which includes patients experiencing diabetic ketoacidosis, hypoglycemia, and severe hyperglycemia/hyperosmotic status. They are distinct from patients admitted for organ damage related to prolonged presence of diabetes (coronary artery disease, heart failure, stroke, kidney failure, peripheral vascular disease), who have been hospitalized for these other conditions and would be coded with a secondary diagnosis of diabetes. The hospitalizations for the Diabetes EDAC cohort may disproportionally represent those newly diagnosed, those with difficulty self-managing diabetes, and those with inappropriate dosing of medications, rather than a population who becomes ill because of a complication of long-standing diabetes. A 2023 study (Rubin et al., 2023) found that admissions with a principal, vs a secondary diagnosis, have unique risk factors for a readmission, and that specific interventions, such as inpatient diabetes consultation, are more effective in patients admitted with a principal vs. secondary diagnosis. See Section 6.2.1 for additional evidence for hospital-level interventions that impact Diabetes EDAC scores.

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.

The evidence presented above, including the prevalence of diabetes, variation in care and outcomes, and evidence-based interventions that can improve outcomes, underscores the importance and need for a quality measure to track hospital-level post-discharge acute care in this population. The goal of the Diabetes EDAC measure is to improve patient care by providing patients, physicians, and hospitals with information about hospital-level, risk-adjusted acute care use following hospitalization for diabetes.

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2.3 Anticipated Impact

As noted above in Section 2.2, diabetes is a common and costly condition, associated with high healthcare utilization, including post-discharge acute care. Because there are existing evidence-based standards of inpatient care designed for patients hospitalized with diabetes, and because there is variation in care and outcomes, we anticipate that a Diabetes EDAC measure will support hospital efforts to optimize the quality of care for patients hospitalized for diabetes, with a concomitant reduction in post-discharge, hospital-based acute care (please see the Diabetes 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 Diabetes EDAC Logic

Model in the Supplemental Attachment for details on activities, outputs, outcomes, and impact expected as a result of the implementation of the Diabetes 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. Importantly, among the long-term potential clinical benefits of this measure which could result from better in-hospital control of blood sugar in hospitalized patients are a reduction in short- and long-term complications of diabetes, including vascular and kidney disease, infection and even mortality. (Kodner et al., 2017; Pasquel et al., 2021; Blonde et al., 2022; American Diabetes Association Professional Practice Committee, 2026a; American Diabetes Association Professional Practice Committee, 2026b; Idrees et al., 2025)

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 Diabetes 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 diabetes in the cohort were seen at a hospital that performed at the mean of the best performing (1^{st}) decile of performance on the Diabetes EDAC measure (see Table 1), this would avoid about 410,483 days in acute care (estimated using 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 (approximately $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 (1^{st}) 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 (Parker et al., 2024), 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 Diabetes 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	**15.3**	**-124.5**	**-72.2**	**-45.1**	**-29.7**	**-17.1**	**-4.8**	**9.1**	**24.2**	**41.2**	**68.1**	**179.0**	**1,612.9**
N of Entities	**4,193**	**1**	**419**	**419**	**420**	**419**	**419**	**420**	**419**	**420**	**419**	**419**	**1**
N of Persons / Encounters / Episodes	**370,594**	**6**	**8,039**	**15,237**	**22,075**	**34,959**	**48,342**	**58,018**	**62,042**	**58,756**	**46,793**	**16,333**	**3**

As shown in Table 1a, Diabetes EDAC measure scores (excess days per 100 discharges) range from -124.5 to 1,612.9; the median is 1.6; the 10th percentile is -55.1 and the 90th percentile is 87.7. A hospital at the 10th percentile has 143 fewer excess days per 100 discharges compared with a hospital performing at the 90th percentile.

Table 1a. Diabetes EDAC: Hospital Distribution of Risk-Adjusted Measure Scores per 100 Discharges, January 1, 2022 – December 31, 2023 (N = 4,193)

Category	Value
Number of Hospitals	4,193
Mean (SD)	15.3 (80.6)
Range (min. to max.)	-124.5 to 1,612.9
10th Percentile	-55.1
25th Percentile	-29.5
50th Percentile	1.6
75th Percentile	40.3
90th Percentile	87.7

2.5 Health Care Quality Landscape

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

- The Diabetes 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 diabetes.
- While overlapping with part of the cohort and part of the outcome for the hybrid Hospital

Wide Readmission (hHWR) measure (CBE 2879e), the Diabetes 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 Diabetes

In addition, there are currently no publicly reported outcome measures that capture post-hospital discharge utilization for this population; for example, there is no diabetes readmission measure attributed to hospitals.

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 the Diabetes 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 Diabetes 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.

Diabetes 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) Economic disadvantage testing	Dates of Data: January 1, 2022-December 31, 2023 Total number of hospitals (with at least 1 admission): 4,193 Total number of admissions: 370,594 Male (n=206,900), 55.8% Female (n=163,694), 44.2% Dual eligible (DE) (n=96,190), 26.0% Total number of hospitals with at least 25 admissions: 2,342 (56% of total) Number of admissions within facilities with at least 25 admissions: 357,196 (96.4% of total)
CY2022: 1-year Medicare FFS and Medicare Advantage Dataset (January 1, 2022-December 30, 2022)	Cohort definition Risk variable selection Model performance testing (discrimination and calibration) Face validity Top 25 (Most Frequent) CCS Categories Associated with Unplanned Readmission for Diabetes	Dates of Data: January 1, 2022-December 30, 2022 Total number of hospitals (with at least 1 admission): 3,927 Total number of admissions: 172,139

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, and from CMS coding guidance.

Entity-Level Reliability

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, represent electronic data from structured fields, and are largely considered reliable (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).

Coding for diabetes has been shown to be more stable than for other chronic conditions: a 2025 study that examined coding for 17 chronic conditions found that coding of diabetes was among the most stable, with mean differences in prevalence between chart review and ICD-10 codes of 1.9%, 2.1%, and 1.1% (for the years 2002, 2015, and 2022) (Pan et al., 2025). Other quality measures, including those in the Healthcare Effectiveness Data and Information Set (HEDIS), have used ICD-10 codes to define the diabetes population (NCQA, 2026). The reliability of the data elements that define the cohort is further bolstered by the exclusive use of the principal diagnosis code, in light of CMS coding guidance for the use of such codes.

Other elements of the measure that are not specific to diabetes (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

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 diabetes, median signal-to-noise

reliability was 0.904. Signal-to-noise reliability ranged from a minimum of 0.668 to a maximum of 0.994; the 25th and 75th percentiles were 0.831 and 0.942, 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

5575-SupplementalAttachment-Spring2026.pdf

5.2.4 Interpretation of Reliability Results

Data Element Reliability

Data elements from Medicare claims that are used for reimbursement are generally considered reliable for use for quality measurement because they are collected using standardized coding and billing procedures and are subject to auditing. The additional evidence of stability of diabetes diagnosis coding over time further supports the reliability of the diagnosis codes that define qualifying index admissions (the cohort). The exclusive use of principal diagnosis codes to define the cohort, and the evidence of strong entity-level reliability, support the notion that the underlying data elements are also reliable.

Entity-Level Reliability

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	0.878	0.668	0.707	0.778	0.831	0.864	0.891	0.914	0.930	0.942	0.954	0.971	0.994
Mean Performance Score	17.57	-3.96	14.04	17.06	15.87	14.54	18.34	19.01	18.10	19.35	18.38	21.20	50.78
Number of Entities	2,342	17	242	231	231	237	226	240	235	231	238	231	1
Number of Persons / Encounters / Episodes	357,196	425	7,325	10,097	14,162	18,674	23,148	31,697	38,699	46,962	61,883	104,549	2,088

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	4,193 (100)	0.629 (0.311)	0.075-0.994	0.326	0.749	0.914
>=25	2,342 (56)	0.878 (0.082)	0.668-0.994	0.831	0.904	0.942

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.

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. Throughout the course of 2023 and 2024, we held four 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 Diabetes 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. Diabetes 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
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
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
TEP Members Active only during Creation of Cohort Definition		
Matt Cheung, PhD, RPh *Dates of TEP service: 2023-2024*	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

Name and Credentials	Organization (if applicable) and Role	Location
Ryan Merkow, MD, MS *Dates of TEP service: 2023-2024*	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

Empiric (Construct) Validity

We also explored validation through meaningful comparisons of the Diabetes 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 Diabetes EDAC 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 Diabetes EDAC measure score, as described below.

We examined correlations between Diabetes 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 Diabetes 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 Diabetes 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 Diabetes 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 Diabetes 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 Diabetes 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 Diabetes 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).

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5.3.4 Validity Testing Results

Data Element Validity

Literature supports the validity of ICD-10 codes used to identify a diabetes cohort. For example, a 2016 systematic review that examined the validity of ICD-10 coding for diabetes in hospital discharge data compared with medical records or other acceptable references, found sensitivity in included studies ranged from 59.1% to 92.6%, specificity ranged from 95.5-99%, positive predictive value (PPV) ranged from 62.5%-96%, negative predictive value (NPV) ranged from 90.8%-99% and kappa ranged from 0.6 to 0.9 (Khokhar et al., 2016). A more recent 2022 study found diabetes coding missing in about 5-15% of claims, compared with medical records (Ren et al., 2022). These studies did not focus only on principal diagnoses and therefore we would expect higher values for the codes used to define the cohort, which require a principal diagnosis. In addition, as discussed previously, 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 Diabetes EDAC measure as specified, can distinguish between better and/or worse performance across hospitals?"* Ten TEP members responded to the TEP survey; 9 out of 10 (90%) agreed (strongly agreed, agreed, or somewhat agreed) with the face validity of the measure, indicating support for the validity of the Diabetes 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. Diabetes EDAC: Technical Expert Panel (TEP) Face Validity Voting Results

Response Category	Number	Frequency
Strongly Agree	4	40.0%
Agree	2	20.0%
Somewhat Agree	3	30.0%
Somewhat Disagree	0	0.0%
Disagree	1	10.0%
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 Diabetes 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 measures (such as the Hospital-Wide Readmission measure, and measures that capture readmission following chronic obstructive pulmonary disease [COPD] or coronary artery bypass grafting [CABG] surgery), 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) Diabetes 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 Diabetes EDAC measure scores and the Readmission Group Score. We further hypothesized that removing the HWR measure (whose cohort overlaps with the Diabetes 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 Diabetes 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 Diabetes 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 Diabetes EDAC measure scores.

We eliminated other comparator measures for the following reasons:

- Measures related to diabetes but without data for the correct setting (outpatient vs inpatient, or health plan vs inpatient), such as poor HbA1C control, relative resource use for diabetics.
- Measures related to diabetes where the hospital is not the accountable entity (e.g. Diabetes Hospital Admissions per 100,000 Population (PQI 16)).
- Measures related to diabetes that were in the logic model but for which no data were available at the time of testing, or with data that were voluntarily reported (e.g. Hypo/Hyperglycemia eCQMs).

Analysis of Construct Validity

Table 5 provides Pearson correlation coefficients that show the relationship between the Diabetes EDAC measure score and related measures. Pearson correlation coefficients between the Diabetes EDAC measure and the comparator measures (Readmission Group Score, Readmission Group Score excluding HWR, and the Patient Experience Group Score) were -0.254, -0.232, and -0.175, respectively (all p-values <.0001). Pearson correlation coefficients between the Diabetes EDAC measure and the Summary Score, with and without the Readmission Group, were -0.233 and -0.146, respectively (p<.0001). Pearson correlation coefficients between the Diabetes EDAC measure scores and MSPB were 0.080, p-value .0002. 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 Diabetes EDAC measure.

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

Comparison Measure	Number of Hospitals	Pearson Correlation Coefficient	p-value
Star Rating Standardized Readmission Group Scores	2,252	-0.254	<.0001
Star Rating Standardized Readmission Group Scores Excluding Hospital-Wide Readmission	2,231	-0.232	<.0001
Star Rating Standardized Summary Scores	2,252	-0.233	<.0001
Star Rating Standardized Summary Scores Excluding Readmission Group Score	2,252	-0.146	<.0001
Star Ratings Standardized Patient Experience Group Score	2,238	-0.175	<.0001
Medicare Spending Per Beneficiary	2,225	0.080	.0002

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 Diabetes 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. Diabetes EDAC: Top 25 (Most Frequent) CCS Categories Associated with Unplanned Readmission for Diabetes (January 1, 2022 – December 30, 2022)

Rank	CCS	CCS Description	Count	Percent	Cumulative	Cumulative Percent
1	50	Diabetes mellitus with complications	4286	23.54%	4,286	23.54%

2	2	Septicemia (except in labor)	2438	13.39%	6,724	36.94%
3	238	Complications of surgical procedures or medical care	1604	8.81%	8,328	45.75%
4	99	Hypertension with complications and secondary hypertension	1350	7.42%	9,678	53.16%
5	157	Acute and unspecified renal failure	790	4.34%	10,468	57.50%
6	237	Complication of device; implant or graft	773	4.25%	11,241	61.75%
7	153	Gastrointestinal hemorrhage	422	2.32%	11,663	64.07%
8	159	Urinary tract infections	374	2.05%	12,037	66.12%
9	122	Pneumonia (except that caused by tuberculosis or sexually transmitted disease)	353	1.94%	12,390	68.06%
10	55	Fluid and electrolyte disorders	320	1.76%	12,710	69.82%
11	95	Other nervous system disorders	313	1.72%	13,023	71.54%
12	197	Skin and subcutaneous tissue infections	290	1.59%	13,313	73.13%
13	100	Acute myocardial infarction	257	1.41%	13,570	74.54%
14	109	Acute cerebrovascular disease	248	1.36%	13,818	75.91%
15	131	Respiratory failure; insufficiency; arrest (adult)	226	1.24%	14,044	77.15%
16	106	Cardiac dysrhythmias	196	1.08%	14,240	78.22%
17	117	Other circulatory disease	147	0.81%	14,387	79.03%
18	129	Aspiration pneumonitis; food/vomitus	134	0.74%	14,521	79.77%
19	59	Deficiency and other anemia	120	0.66%	14,641	80.43%
20	155	Other gastrointestinal disorders	112	0.62%	14,753	81.04%
21	226	Fracture of neck of femur (hip)	104	0.57%	14,857	81.61%
22	135	Intestinal infection	101	0.55%	14,958	82.17%
23	146	Diverticulosis and diverticulitis	92	0.51%	15,050	82.67%
24	248	Gangrene	91	0.50%	15,141	83.17%
25	201	Infective arthritis and osteomyelitis (except that caused by tuberculosis or sexually transmitted disease)	88	0.48%	15,229	83.66%

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Agency for Healthcare Research and Quality. (2019, November). Clinical Classifications Software (CCS) for ICD-10-PCS (beta version). Healthcare Cost and Utilization Project (HCUP). Agency for Healthcare Research and Quality. https://www.hcup-us.ahrq.gov/toolssoftware/ccs10/ccs10.jsp

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5.3.4a Attach Additional Validity Testing Results

5575-SupplementalAttachment-Spring2026_0.pdf

5.3.5 Interpretation of Validity Results

Both strong face validity and empiric validity testing results support the validity of the Diabetes EDAC measure. Ninety 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 Diabetes EDAC measure. Lastly, validity of the outcome results show that the most frequent reasons (principal discharge diagnoses) associated with readmission for those in the Diabetes EDAC cohort are associated with the initial index admission for diabetes. In addition, we provide evidence for the validity of the 30-day outcome. Data element validity is supported by evidence from the literature. The interpretation of these results is discussed below.

Face Validity

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

Construct Validity Testing

The validity of the Diabetes EDAC measure is further supported by the empiric construct validity results that demonstrate a correlation (in the expected strength and direction) between the Diabetes EDAC measure and other quality/cost measures in the causal pathway (see Diabetes 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 Diabetes 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 Diabetes EDAC measure, that includes both FFS and MA admissions.
  - There are outpatient measures in the Readmission Group whereas the Diabetes EDAC measure cohort includes admissions discharged from an inpatient stay only.
  - The Diabetes 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; Diabetes EDAC is only adults over age 65 with a qualifying diagnosis of diabetes.
  - Patient Experience is patient-reported; Diabetes 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.
  - Diabetes 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 Diabetes 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 most of the reasons identified for readmissions within 30-days post-discharge (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 diabetes. 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).

References

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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 Diabetes 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 *Diabetes EDAC Risk Variable Complications of Care* in the Excel file entitled "*Diabetes 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 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 of readmission, 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).

The process described above for identifying risk variables resulted in the selection of 46 variables. We then reviewed this list and made the following minor adjustments for face validity, resulting in a final list with 42 variables:

- *Laterality:* When an ICD-10 code identified a variable that indicated a laterality (e.g. a left or right side of the body), we ensured that the same code for the other side of the body, and codes identified as bilateral and unspecified for laterality, were included. For example, the pre-index (in the prior 12 months) ICD-10 code for “Pain in left foot” (M79.672) was selected during the bootstrapping step, and we added “Pain in right foot” (M79.671) and “Pain in unspecified foot” (M79.673).
- *Deduplication:* During bootstrapping, three ICD-10 codes were selected that overlapped with the MCC frailty variable (history code Z89.421 and index codes E44.0 and E43); we removed the overlapping codes from the list of selected variables.

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; 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 diabetes (Soh et al., 2020). Patients who have lower income/education/literacy or unstable housing may have a worse general health status and may present for their hospitalization with a greater severity of underlying illness (Owens et al., 2022). These 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 (Lusk, et al., 2022). 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).
- **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 (Lusk 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

5575-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. Diabetes 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=370,594)	OR (95% CI)
AGE	Age, mean (SD)	75.1 (7.17)	1.00 (1.00-1.00)
ICD-10 codes during the index admission			
IND_B9561	Methicillin susceptible Staphylococcus aureus infection as the cause of diseases classified elsewhere	2.87	0.81 (0.80-0.82)
IND_C7951	Secondary malignant neoplasm of bone	0.57	1.29 (1.25-1.33)
IND_D631	Anemia in chronic kidney disease	13.44	1.32 (1.31-1.33)
IND_D638	Anemia in other chronic diseases classified elsewhere	4.27	1.22 (1.21-1.24)
IND_D649	Anemia, unspecified	10.21	1.13 (1.12-1.14)
IND_E860	Dehydration	12.40	0.97 (0.96-0.98)
IND_E871	Hypo-osmolality and hyponatremia	13.44	1.12 (1.11-1.13)
IND_I10	Essential (primary) hypertension	35.81	0.82 (0.81-0.82)
IND_I447	Left bundle-branch block, unspecified	0.92	1.07 (1.04-1.09)
IND_I96	Gangrene, not elsewhere classified	5.20	1.18 (1.17-1.20)
IND_N400	Benign prostatic hyperplasia without lower urinary tract symptoms	8.76	0.94 (0.93-0.95)
IND_R188	Other ascites	0.60	1.64 (1.59-1.68)
IND_T380X5A	Adverse effect of glucocorticoids and synthetic analogues, initial encounter	0.95	1.26 (1.23-1.29)
IND_T383X6A	Underdosing of insulin and oral hypoglycemic [antidiabetic] drugs, initial encounter	1.70	0.91 (0.89-0.93)
IND_Z515	Encounter for palliative care	2.75	0.97 (0.95-0.98)

Variable	Description	Percentage (%) (N=370,594)	OR (95% CI)
IND_Z66	Do not resuscitate (DNR)	8.61	0.93 (0.92-0.94)
IND_Z7984	Long term (current) use of oral hypoglycemic drugs	29.55	0.85 (0.85-0.86)
IND_Z79899	Other long term (current) drug therapy	27.99	0.91 (0.90-0.91)
ICD-10 codes in the 12 months prior to admission			
PRE_E1010	Type 1 diabetes mellitus with ketoacidosis without coma	3.93	1.26 (1.24-1.27)
PRE_E1151	Type 2 diabetes mellitus with diabetic peripheral angiopathy without gangrene	38.03	1.02 (1.02-1.03)
PRE_E860	Dehydration	17.75	1.12 (1.12-1.13)
PRE_E875	Hyperkalemia	19.36	1.17 (1.17-1.18)
PRE_E876	Hypokalemia	16.72	1.17 (1.17-1.18)
PRE_F17210	Nicotine dependence, cigarettes, uncomplicated	11.57	1.09 (1.08-1.10)
PRE_I739	Peripheral vascular disease, unspecified	38.42	1.07 (1.06-1.08)
PRE_I96	Gangrene, not elsewhere classified	14.02	1.05 (1.04-1.06)
PRE_J90	Pleural effusion, not elsewhere classified	14.18	1.29 (1.28-1.30)
PRE_R000	Tachycardia, unspecified	10.99	1.13 (1.12-1.14)
PRE_R1110	Vomiting, unspecified	4.59	1.15 (1.14-1.17)
PRE_R296	Repeated falls	8.89	1.14 (1.13-1.15)
PRE_Z1231	Encounter for screening mammogram for malignant neoplasm of breast	9.39	0.91 (0.90-0.92)
PRE_Z7952	Long term (current) use of systemic steroids	3.45	1.21 (1.19-1.22)
PRE_Z9114	Patient's other noncompliance with medication regimen	5.17	1.19 (1.18-1.20)
PRE_Z9119	Patient's noncompliance with other medical treatment and regimen	3.42	1.15 (1.14-1.17)
ICD-10 codes either during the index admission or 12 months prior to admission			
E11649	Type 2 diabetes mellitus with hypoglycemia without coma	21.90	1.14 (1.13-1.15)
J449	Chronic obstructive pulmonary disease, unspecified	24.67	1.11 (1.11-1.12)
COMB1: IND_I70261 IND_I70262 IND_I70263 PRE_I70261 PRE_I70262 PRE_I70263	Atherosclerosis of native arteries of extremities with gangrene, right leg Atherosclerosis of native arteries of extremities with gangrene, left leg Atherosclerosis of native arteries of extremities with gangrene, bilateral legs	12.99	1.28 (1.27-1.29)

Variable	Description	Percentage (%) (N=370,594)	OR (95% CI)
COMB2: IND_M86171 IND_M86172 IND_M86179	Other acute osteomyelitis, right ankle and foot Other acute osteomyelitis, left ankle and foot Other acute osteomyelitis, unspecified ankle and foot	9.41	0.82 (0.81-0.83)
COMB3: IND_I70221 IND_I70222 IND_I70223 PRE_I70221 PRE_I70222 PRE_I70223	Atherosclerosis of native arteries of extremities with rest pain, right leg Atherosclerosis of native arteries of extremities with rest pain, left leg Atherosclerosis of native arteries of extremities with rest pain, bilateral legs	10.61	1.12 (1.11-1.13)
COMB4: PRE_M79672 PRE_M79671 PRE_M79673	Pain in left foot Pain in right foot Pain in unspecified foot	23.25	1.03 (1.03-1.04)
COMB5: PRE_I70201 PRE_I70202 PRE_I70203	Unspecified atherosclerosis of native arteries of extremities, right leg Unspecified atherosclerosis of native arteries of extremities, left leg Unspecified atherosclerosis of native arteries of extremities, bilateral legs	14.70	1.02 (1.02-1.03)
Other risk variables			
MA	MA (versus FFS)	54.76	1.09 (1.08-1.10)
MCCFI	Multiple Chronic Conditions Frailty Index	68.12	1.29 (1.28-1.30)

Table 7a. Diabetes EDAC: Hospital-Level Distribution of Risk Variables (Hospitals with >= 25 admissions, N=2,342)

Variable	Mean	Std Dev	Median	25th Percentile	75th Percentile	Min	Max
AGE	75	1	75	74	76	71	82
Variable	**Mean (%)**	**Std Dev (%)**	**Median (%)**	**25th Percentile (%)**	**75th Percentile (%)**	**Min (%)**	**Max (%)**
IND_Z515	2.6	2.7	2.1	0.4	3.7	0	35.7
IND_D631	12.1	6.8	11.4	7.3	16.3	0	43.6
PRE_E1010	4.3	3.6	3.6	1.9	6	0	31
IND_Z66	9.3	6.8	7.9	4.1	12.8	0	43.2
IND_I10	36.6	8.5	36.1	30.9	41.7	3.6	82.1
IND_R188	0.6	0.8	0	0	0.9	0	7.3
PRE_I739	35.3	11.9	35.5	27.5	42.6	0	97.2

J449	24.9	8.7	24.4	18.8	30.1	0	78.6
IND_T380X5A	0.9	1.2	0.5	0	1.4	0	20.8
PRE_Z1231	9.3	4	8.9	6.7	11.4	0	32.3
PRE_Z9114	5.1	3.3	4.6	3	6.7	0	36.7
PRE_Z9119	3.4	2.5	3.1	1.7	4.6	0	20
PRE_I96	13.1	6.2	12.9	9.2	16.7	0	40.5
PRE_J90	13.6	5.1	13.6	10.4	16.7	0	41.4
IND_E860	13.4	6.9	12.5	8.6	17	0	60.3
IND_E871	13.8	6.7	12.8	9.4	17.2	0	53.8
IND_N400	8.5	4.1	8.3	5.8	11	0	26.8
IND_Z7984	29.9	10	29.8	23.9	36	0	96.4
IND_I96	5.4	4.6	4.2	2.2	7.5	0	34.5
PRE_Z7952	3.3	2.7	2.9	1.5	4.5	0	45.3
IND_D649	10.3	5.4	9.6	6.5	13.3	0	53.8
PRE_E860	18.3	6.5	17.7	14	21.9	0	53.6
IND_D638	4	3.4	3.4	1.7	5.7	0	28.6
E11649	21.8	6.8	21.7	17.3	26	0	53.8
PRE_E875	18.6	5.6	18.6	15.1	22.1	0	46.4
IND_I447	0.9	1.1	0.6	0	1.4	0	8.3
PRE_E876	16.8	6.2	16.7	12.7	20.6	0	47.3
IND_T383X6A	1.8	2.2	1.2	0	2.6	0	16.7
IND_Z79899	27.8	22.7	25	6.3	45.4	0	96
IND_B9561	3.1	2.7	2.6	1.3	4.3	0	22.6
PRE_F17210	11.6	5.5	11.2	7.7	14.8	0	40.3
IND_C7951	0.6	1	0	0	0.9	0	17
PRE_R000	10.9	5.6	10	7	13.9	0	44.8
PRE_E1151	35.3	10.8	35.6	28.6	42.3	3.4	78.6
PRE_R1110	4.6	2.9	4.2	2.8	6.1	0	25
PRE_R296	8.9	4.4	8.5	6.1	11.2	0	37
comb1	11.3	7.3	10.7	5.9	15.4	0	54.8
comb2	9.5	6	8.5	5.3	12.5	0	50
comb3	8.9	7.2	7.7	3.8	12.2	0	69.8
comb4	22.2	7.9	22	16.8	26.9	0	59.5
comb5	13.2	7.6	12.6	7.8	17.6	0	54.8

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

5575-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 Diabetes 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, 26.0% of admissions for patients hospitalized for diabetes were dually eligible and mean unadjusted days in acute care were higher for admissions for patients with vs. without the DE variable (202 vs. 162, respectively). At the hospital level, the median proportion of admissions for patients with the DE variable was 21.3%, among the 4,193 hospitals with at least one qualifying inpatient admission (25th percentile, 11.9%, 75th percentile, 33.3%)

Table 8. Diabetes EDAC: Proportion of Admissions and Unadjusted Outcomes for Admissions with vs. without Dual Eligibility (January 1, 2022 - December 31, 2023, N=370,594)

Variable	N	Patient Prevalence (%)	Mean (SD) Unadjusted Days in Acute Care per 100 Discharges
Dual Eligible (DE)	96,190	26.0	202 (430)
Not Dual Eligible	274,404	74.0	162 (385)

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: 1.09-1.11], 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 5 in the Supplemental Attachment). The results show that the model is well-calibrated for both sets of admissions.

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 Diabetes 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 0.9998), 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. Diabetes EDAC: Median Difference in Measure Scores and Correlation Between Measure Scores Calculated with and without Dual Eligibility (DE) (January 1, 2022-December 31, 2023)

Variable	Median Differences in Measure Scores	IQR (25th percentile to 75th percentile)	Pearson Correlation Coefficient
DE	0.25	-0.91 to 1.01	0.9998 (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

5575-SupplementalAttachment-Spring2026_2.pdf

5.4.5 Calibration and Discrimination

Methods

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

To assess discrimination, we computed two discrimination statistics, the **c-statistic** and **predictive ability**. The c-statistic is the probability that predicting the outcome is better than chance, which is a measure of how accurately a statistical model is able to distinguish between a patient with and without the outcome. Predictive ability measures the ability to distinguish high-risk subjects from low-risk subjects; therefore, for a model with good predictive ability, we would expect to see a wide range in observed outcomes between the lowest and highest deciles of predicted outcomes. To calculate the predictive ability, we calculated the range of mean observed outcomes between the lowest and highest predicted deciles of outcome 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 (those undergoing amputation vs. no amputation, those undergoing dialysis vs. no dialysis at the index admission, those with Type 1 vs. Type 2 diabetes, and Medicare Advantage vs. Medicare FFS).

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

Results

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

For original measure development using CY2022 data, the c-statistic was 0.68 in the development sample, and 0.70 in the validation sample (Table 10). Predictive ability ranged from 1.66%-13.23% in the derivation sample, and 1.22%-14.43% in the validation sample.

Risk decile plots show that higher deciles of the predicted outcomes are associated with higher observed outcomes in both CY2022 (development and validation datasets) and the CY2022/2023 dataset (Figures 9 and 10). Overfitting results are shown in Table 10; $\gamma 0$ is -0.06 and $\gamma 1$ is 0.96. We also found good calibration for important subsets of patients, including for those undergoing amputation vs. no amputation, those undergoing dialysis vs. no dialysis at the index admission, those with Type 1 vs. Type 2 diabetes, Medicare Advantage vs. Medicare FFS, and those who are dually eligible vs those who are not. Please see Figure 6 and Figures 11-14 in the Supplemental Attachment.

Table 10. Diabetes EDAC: Model Testing Statistics (January 1, 2022 – December 30,

2022)

Sample	C-Statistic	Predictive Ability (%)	Overfitting (γ0, γ1)
Development (n=120,716)	0.68	1.66 – 13.23	0.00, 1.00
Validation (n=51,427)	0.70	1.22 – 14.43	-0.06, 0.96

5.4.5a Attach Calibration and Discrimination Testing Results

5575-SupplementalAttachment-Spring2026_3.pdf

5.4.6 Interpretation of Risk/Case-mix Factor Findings

Discrimination

C-statistics show good model discrimination. Predictive ability results show a wide range between the lowest decile and highest decile, indicating the ability to distinguish high-risk subjects from low-risk subjects.

Calibration

Higher deciles of the predicted outcomes are associated with higher observed outcomes, which show a good calibration of the model for all patients, and for important subsets of patients.

Over-fitting (γ0, γ1)

If γ0 is substantially far from zero and γ1 is far from one in validation data, there is potential evidence of over-fitting. Our testing results show that in the validation sample, γ1 is close to one and γ0 is close to zero, indicating that we do not see evidence of overfitting and that the model performs well with “new” data.

Overall Interpretation

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

5.4.7 Final Approach to Address Risk Factors

Statistical risk adjustment model with risk factors

6.1.1 Current Status

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

The research and guidelines discussed in section 2.2., along with the variation in Diabetes EDAC scores across hospitals provided in section 2.4, indicate there is room for quality improvement and targeted efforts to reduce excess post-discharge acute care through improvements in patient care. These efforts can ultimately result in better long-term outcomes for patients with diabetes and cost savings (see the Diabetes EDAC Logic Model in the Supplemental Attachment).

The use of outcome measurement to drive quality improvement is not prescriptive; there are many evidence-based processes that facilitate improved outcomes. Using outcomes as the basis for quality improvement allows hospitals to determine the root causes of poor performance and implement tailored interventions that address the underlying goals of their quality improvement programs. Below we discuss the evidence-base that hospitals can consider when implementing activities to reduce EDAC for patients hospitalized for diabetes.

Numerous studies have found an association between the quality of inpatient or transitional care and readmission rates and ED visits for a wide range of conditions including diabetes. Safely transitioning patients after hospital discharge requires a complex series of tasks, including but not limited to timely and effective communication between providers, prevention of and response to complications, patient education about post-discharge care and self-management, and timely follow-up (AHRQ, 2020). Suboptimal transitions contribute to a variety of adverse outcomes post-discharge including ED evaluation, need for observation, and readmission (AHRQ, 2019). Variation in the care of patients' diabetes while hospitalized is associated with poor outcomes; for example, patients who are discharged with blood glucose near or at hypoglycemic levels have higher levels of 30-day readmission and post-discharge mortality (Spanakis et al., 2019). Interventions during care transitions, such as discharge medication reconciliation, are an opportunity for reducing the incidence of post-discharge hospital events for diabetic patients (Gosmanov, Mendez, & Umpierrez, 2022).

A 2023 review of interventions aimed at reducing readmissions for patients with type 2 diabetes concluded that interventions both at the peri-discharge period and those that start at the index admission are effective (Cai & Islam, 2023). Study authors identified common effective strategies including multidisciplinary teams, dedicated care teams, certified diabetes educator appointments post-discharge, and hospital protocol development and implementation, among others. Similarly, a 2021 review found that interventions including inpatient diabetes education, inpatient diabetes management service, inpatient/outpatient care coordination, and medication adjustment, were effective at reducing the risk of readmissions/ED visits for patients discharged after hospitalization for diabetes (Rubin & Shah, 2021). In addition, a recent 2025 systematic review and meta-analysis found that nurse-led interventions resulted in significantly lower odds of emergency department visits after discharge, compared with usual care (relative risk 0.63; 95% CI, 0.49–0.81; P = 0.0003) (Sakashita et al., 2025).

While most studies have been retrospective, there have been a few randomized controlled, prospective trials. The largest randomized controlled trial, published in 2020, found that patients randomized to receive care at a specialized multidisciplinary diabetes program had significantly lower rates of unplanned readmissions 30 days after discharge compared with patients who were randomized to a standard primary care setting (7% vs. 19%, respectively, p=0.02) (Bhalodkar et al., 2020).

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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 Diabetes 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

5575-7.1-Supplemental-Attachment-and-Methodology-Report-Spring2026.zip

Developer POC email

Lisa.Suter@yale.edu

Measure Developer POC

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

The measure developer is different from the measure steward

Yes

Steward Address

Raquel Myers
Windsor Mill, MD
United States

Steward Organization

Centers for Medicare & Medicaid Services

Steward Organization URL

https://www.cms.gov/

Steward POC email

Raquel.Myers@cms.hhs.gov