

Acute Myocardial Infarction (AMI) Excess Days in Acute Care (EDAC) Measure Conceptual Model

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

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

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

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

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

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

Selection of Clinical Risk Variables

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

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

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

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

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

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

Social Risk Factors

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

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

Conceptual Model for Clinical and Social Risk Factors

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

1. **Comorbidities and social risk:** Patients with social risk factors may have worse health at the time of hospital admission and patient comorbidities are known risk factors for post-discharge acute care use in patients hospitalized for AMI (Rashidi, Whitehead, & Glass, 2021). Patients who have lower income/education/literacy or unstable housing may have a worse general health status and may present for their hospitalization with a greater severity of underlying illness (Owens et al., 2022). These social risk factors, which are characterized by patient-level or neighborhood/community-level (as proxy for patient-level) variables, may contribute to worse health status at admission due to competing priorities (restrictions based on job, lack of childcare, etc.), lack of access to care (geographic, cultural, or financial), or lack of health insurance. Given that these risk factors all lead to worse general health status, this causal pathway should be largely accounted for by current clinical risk adjustment. We note that patient comorbidities and social risk factors overlap in their contribution to a higher risk of the outcome, as shown by our empirical evidence (see Section 5.3) demonstrating the attenuating impact of model variables on the odds ratios for each social risk factor (ADI; DE).
2. **Differential care:** A second pathway by which social risk factors may contribute to post-discharge acute care risk is that patients may not receive equivalent care within a facility (Downing et al., 2018). For AMI specifically, we know from empirical evidence that across almost all hospitals (99% of hospitals with sufficient data for assessment), patients with dual eligibility have higher rates of post-discharge hospital-based care (readmission) when compared with non-dual eligible patients in the same hospital (within-hospital disparities), after accounting for comorbidities, and area-level variables (Silvestri et al., 2022).
3. **Low-quality hospitals:** Patients with social risk factors may receive care at lower-quality hospitals. Patients of lower income, lower education, or unstable housing may not have the same access to high-quality facilities, in part, because such facilities may be less likely to be found in geographic areas with large populations of patients with social risk factors (Fahrenbach et al., 2020). Thus, patients with low income may be more likely to be treated in lower-quality hospitals, which can contribute to an increased risk of readmission. In addition, or alternatively, low-quality hospitals may not implement evidence-based interventions to reduce the risk of readmission,

such as post-discharge follow-up; patients with social risk factors are known to have lower rates of follow-up after discharge and higher rates of post-discharge acute care (Anderson et al., 2022).

4. **Residual risk:** Patients with social risk factors may experience worse health outcomes only partially under the control of the healthcare system. Some social risk factors, such as income or wealth, may affect the likelihood of readmission without directly affecting health status at admission or the quality of care received during the hospital stay. For instance, while a hospital may make appropriate care decisions and provide tailored care and education, a lower-income patient may still have a worse outcome post-discharge due to competing economic priorities or a lack of access to care outside of the hospital (Downing et al., 2018). However, for AMI, it has been shown that in older patients, income is less of a predictor of the outcome of readmission compared with younger patients (Khera et al., 2018).

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

Social Risk Factor Variables Used in Testing

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

Dual-eligible Status

Dual eligibility for Medicare and Medicaid is available at the patient level in the Medicare Master Beneficiary Summary File. The eligibility threshold for aged 65 or older Medicare patients considers both income and assets. For the dual-eligible (DE) indicator, there is a body of literature demonstrating differential health care and health outcomes among beneficiaries (ASPE, 2020).

Area Deprivation Index (ADI)

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

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

The 17 components are listed below:

- Population aged ≥ 25 y with < 9 y of education, %

- Population aged ≥ 25 y with at least a high school diploma, %
- Employed persons aged ≥ 16 y in white-collar occupations, %
- Median family income, \$
- Income disparity
- Median home value, \$
- Median gross rent, \$
- Median monthly mortgage, \$
- Owner-occupied housing units, % (homeownership rate)
- Civilian labor force population aged ≥ 16 y unemployed, % (unemployment rate)
- Families below the poverty level, %
- Population below 150% of the poverty threshold, %
- Single-parent households with children aged < 18 y, %
- Households without a motor vehicle, %
- Households without a telephone, %
- Occupied housing units without complete plumbing, % (log)
- Households with more than one person per room, % (crowding)

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

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