4.4.2 Conceptual Model Rationale for the Hybrid Hospital Wide Mortality (HWM) Measure

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

Approach to Variable Selection

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

The approach to risk adjustment differs from usual claims-based measures. The original claims-only HWM measure uses claims data to adjust for two aspects of risk: 1) case mix or how sick individual admitted patients are; and, 2) service mix or the proportion of admitted patients with various different principal discharge diagnoses.

The goal of the hybrid measure is to enhance risk adjustment using clinical data from the electronic health record (EHR). To select candidate variables for the Hybrid risk model, we began with the list of all administrative claims-based risk-adjustment variables included in the claims-only HWM measure, described below. We then added EHR-based risk variables, also described below.

Selecting Risk Variables

Candidate Comorbid Risk Variables

Our goal is to develop parsimonious models that include clinically relevant variables strongly associated with the risk of mortality in the 30 days following an index admission. For candidate variable selection, using the development sample we started with the CMS Condition Categories (CCs) grouper, used in previous CMS risk-standardized outcome measures, to group ICD-9 codes into comorbid risk adjustment variables.

To select candidate variables, a team of clinicians reviewed all CMS-CCs and combined some of these CMS-CCs into clinically coherent groups to ensure adequate case volume. Any combined CMS-CCs were combined using both clinical coherence and consistent direction of mortality risk prediction across the CMS-CC groups in the majority of the 15 divisions.

Potential Complications of Care During Hospitalization

Complications occurring during hospitalization are not comorbid illnesses and do not reflect the health status of patients upon presentation. In addition, they likely reflect hospital quality of care, and, for these reasons, should not be used for risk adjustment. Although adverse events occurring during hospitalization may increase the risk of mortality, including them as risk factors in a risk-adjusted model could lessen the measure's ability to characterize the quality of care delivered by hospitals. We have previously reviewed every CMS-CC and identified those which, if they were to occur only during the index hospitalization, are more likely than not to represent potential complications rather than pre-existing comorbidities. For example: fluid, electrolyte, or base disorders; sepsis; and acute liver failure are all examples of CMS-CCs that could potentially be complications of care.

For the claims-only HWM measure, we took a two-step approach to identifying complications of care. First, we searched the secondary diagnosis codes in the index admission claim for all patients in the measure and identified the presence of any ICD-9 code associated with a CMS-CC. If these codes appeared only in the index admission claim, we flagged them because they are potential complications of care. Next, we

determined if these potential complications of care were associated with a “present on admission” code. Any potential complication of care with an associated “present on admission” code was kept in the risk model; any potential complication of care without an associated “present on admission” code was removed under the assumption that it represented a complication of care. In this way, we supplemented the existing approach to identifying potential complications of care used in CMS’s publicly reported mortality measures by incorporating “present on admission” codes. Our analyses demonstrate that a majority of hospitals currently use “present on admission” codes across a majority of conditions. Therefore, we felt that a combined approach to excluding complications of care from the risk model that used both the existing methodology and “present of admission” codes allowed the measure to capture as many clinically appropriate risk variables as possible while simultaneously removing complications of care from the risk model.

Final Comorbid Risk Variable Selection

To inform variable selection, we used the development sample to create 500 bootstrap samples for each of the service-line divisions. (This analysis was performed prior to removing the divisions Other Non-Surgical Conditions and Other Surgical Procedures; therefore, this analysis was completed on 15 divisions. During ICD-10 re-specification, these divisions were added back to the measure.) For each sample, we ran a standard logistic regression model that included all candidate variables. The results were summarized to show the percentage of times that each of the candidate variables was significantly associated with 30-day mortality (at the p<=0.05 level) in the 500 bootstrap samples (for example, 90% would mean that the candidate variable was significant at p<=0.05 in 90% of the bootstrap samples). We also assessed the direction and magnitude of the regression coefficients.

We found that models containing all risk factors performed similarly to models containing a more limited set of “significant” risk factors, described below. We therefore used a fixed, common set of comorbidity variables in all of our models for simplicity and ease of implementation and analysis. We describe below the steps for variable selection.

a. The CORE Project Team reviewed the bootstrapping results and decided to provisionally examine risk adjustment variables at or above a 90% cutoff in one of the 15 service-line division models (in other words, retain variables that were significant at the p<=0.05 level in at least 90% of the bootstrap samples for each division). We chose the 90% cutoff because this threshold has been used across other measures and produced a model with adequate discrimination.
b. In order to develop a statistically robust and parsimonious set of comorbid risk variables, we then chose to limit the variables to those that met a 90% threshold in at least 13/15 divisions. This step resulted in the retention of 31 risk factors, including age and 19 comorbid risk variables. This resulted in C-statistics that did not change by more than 0.02 in any of the 15 divisions compared to models that contained all possible risk variables.

CCDE Risk Variable Selection

To select candidate clinical EHR variables, we began with the list of candidate CCDE variables shown below in Table 10 in the Tables and Figures attachment. The table includes all tested, candidate elements. Of those tested, ultimately ten variables were chosen for the final model.

Table 10. Candidate Specified CCDE Variable

Clinical Data Elements	Units of Measurement	Window for First Captured Values
Patient Characteristics		
Age	Years	---
First-Captured Vital Signs		
Diastolic Blood Pressure	mmHg	0-2 hours
Heart Rate	Beats per minute	0-2 hours
Oxygen Saturation	Percent	0-2 hours
Respiratory Rate	Breath per minute	0-2 hours
Systolic Blood Pressure	mmHg	0-2 hours
Temperature	Degrees Fahrenheit	0-2 hours
Weight	Pounds	0-24 hours
First-Captured Laboratory Results		
Anion Gap	mEq/L	0-24 hours
Bicarbonate	mmol/L	0-24 hours
BUN	mg/dL	0-24 hours
Chloride	mEq/L	0-24 hours
Creatinine	mg/dL	0-24 hours
Glucose	mg/dL	0-24 hours
Hematocrit	% red blood cells	0-24 hours
Hemoglobin	g/dL	0-24 hours
Platelet	Count	0-24 hours
Potassium	mEq/L	0-24 hours
Sodium	mEq/L	0-24 hours
WBC Count	Cells/mL	0-24 hours

First, we looked at how many admissions in our Clinical Hybrid Dataset were missing values for each CCDE. The non-surgical divisions had fewer than 10% of admissions that were missing values. However, in the surgical divisions, while vitals were missing in fewer than 10% of admissions, the laboratory result values were missing in 15% - 50% of admissions, depending upon division. For development purposes only, we imputed values for missing labs or vital signs, as described below.

For all admissions missing any vital signs and for admissions within the non-surgical divisions missing any laboratory result values, we used multiple imputations (imposing limits to ensure the imputed values were within clinical possibilities) with 5 copies of data with different imputations based on a multi-normal distribution.

For admissions within the surgical divisions missing any laboratory results, we randomly imputed a value within the normal range for that lab. For the normal ranges, see Table 11 Candidate Clinical EHR Risk Variable (CCDE) Mortality Association Modelling Approaches below. Rationale: Surgical patients that are missing initial labs are most likely elective surgical admissions that had the labs collected within 30 days PRIOR TO ADMISSION. It is less likely that a patient with an extremely abnormal lab value would undergo elective surgery without having the labs checked again on admission. This approach is for development purposes only.

Second, we selected which CCDE would be the most appropriate to include in the hybrid HWM measure. We approached risk variable selection from the perspective of ensuring a parsimonious list of clinical EHR variables that would minimize the hospital burden to report the data and provide face validity from a clinical perspective.

Therefore, we first sought to ensure that each candidate variable was modeled in a clinically appropriate way. For example, the laboratory value sodium has a U-shaped predictive association with mortality: Normal sodium levels are associated with a low risk of mortality, while both abnormally high and abnormally low levels are associated with an

increased risk of mortality. The association between each CCDE variable and mortality was reviewed by four clinicians and selected based on the best association. See Table 3 Candidate Clinical EHR Risk Variable (CCDE) Mortality Association Modelling Approaches for the approach used for each risk variable. In addition, we report the normal values used for imputing missing laboratory results within the surgical divisions.

Table 11. Candidate Clinical EHR Risk Variable (CCDE) Mortality Association Modelling Approaches

Candidate EHR Risk Variables	Normal Range	Modeling Approach
Age	-	Linear
Diastolic Blood Pressure	-	Splined, knot at 80
Heart Rate	-	Linear
Oxygen Saturation	-	Linear
Respiratory Rate	-	Splined, knot at 16
Systolic Blood Pressure	-	Splined, knot at 140
Temperature	-	Linear
Weight	-	Splined, knot at 180
Anion Gap	7-17	Splined, knot at 10
Bicarbonate	22-30	Splined, knot at 26
BUN	8-18	Splined, knot at 14 and 40
Chloride	96-106	Linear
Creatinine	0.5-1.2	Linear, but Winsorized at 5
Glucose	70-100	Splined, knot at 180
Hematocrit	37-52	Linear
Hemoglobin	12-18	Linear
Platelets	140-144	Splined, knot at 200
Potassium	3.3-5.0	Splined, knot at 4.0
Sodium	135-145	Splined, knot at 140
White Blood Count	4.0-10.0	Splined, knot at 7.0

Based upon this information, we selected a standard set of clinically coherent risk variables in order to ensure that each division-level risk model included key laboratory results and vital signs data (see final list of EHR risk variables above, in Section 2b3.1.1). As with prior hybrid measures that use EHR data in their risk model, we did not include risk variables if they were strongly correlated with another variable. For example, we selected systolic blood pressure but not diastolic blood pressure, as these variables were highly correlated and provided very similar risk predictions. Using a standard set of clinically selected variables produced improved c-statistics compared to the models based purely upon stepwise selection. We also tested allowing the risk variables to vary across the 15 divisions (using stepwise selection) but still forcing in clinical variables and found that the model discrimination (c-statistic) was very similar, in some cases identical, to using a standard set of variables. Therefore, we proceeded with a common set of 10 clinical risk variables plus age across all divisions for the remainder of the risk model development work. for

Service-Line Adjustment

We use the AHRQ CCS grouper to group all ICD-10 **principal discharge diagnoses** into clinically coherent categories (categories have been somewhat modified as described below). For all AHRQ principal discharge diagnosis code CCSs with sufficient volume (CCSs with fewer than 100 admissions are excluded), we also included a discharge diagnosis-specific indicator in the model. This ensures that the principal discharge diagnosis for each patient is also included in the risk model, in addition to the 20 comorbid risk variables described above.

Rationale: Discharge diagnosis categories differ in their baseline mortality risks and hospitals will differ in their relative distribution of these discharge diagnosis categories

(service mix) within each division.[3,4,5] Therefore, adjusting for principal discharge diagnosis categories levels the playing field across hospitals with different service mixes. See the data dictionary for the CCSs (tabs HWM Non-SurgCohortDiv CCS and HWM SurgicalCohortDiv CCS) that comprise each of the divisions in this measure and Tables 13-14 for the parameter estimates for the CCS categories for each division.

CCS modifications: Note that in addition to using the AHRQ CCS grouper to define the CCS categories in each division (see section S.7 of the submission form), we made two types of modifications: (1) We modified selected CCS highly heterogenous CCS categories to create more homogenous CCS risk variable groups, and so increased the face validity of risk model, described below, and (2) we combined low-mortality CCSs (those with mortality rate of 1% or lower), also described below.

Heterogenous CCSs: In parallel with our approach during measure development in ICD and in response to feedback from our TEP and Technical Workgroup, we addressed heterogeneity within specific AHRQ CCS groups where the risk of mortality varied significantly across the different ICD-10 diagnoses within the CCS. We calculated the correlation between mortality rates grouped by principal discharge diagnosis ICD-10 code within each CCS. We identified any CCS with an intra-class correlation (ICC) score >0.05 as having high heterogeneity. (The ICC is used in this context to identify heterogeneity of mortality risk across ICD-10 codes within the ICC. The value 0.05, or 5%, is a conventional threshold for accounting for between-group heterogeneity.) To address the heterogeneity, three clinicians independently, and through consensus, modified the highly heterogeneous CCSs using clinically informed recategorizations, by either splitting the CCSs into more than one CCS, moving ICD-10 codes to more clinically coherent CCSs, or removing from inclusion ICD-10 codes where quality of care less likely impacts survival, and/or where there were a small number of patients. During ICD-10 respecification, we identified 44 highly heterogeneous CCSs and made modifications to 20 of them, as described in the data dictionary, tab “HWM_CCS_Modifications.”

Low-mortality CCSs: During initial measure development, the patient-level risk models for two divisions (the “Other” surgical and non-surgical divisions) did not converge due to the large number of CCS category codes in these divisions, and due to low mortality rates associated with some of the CCSs in these divisions (which are used for service-line risk adjustment). However, the TEP and Patient and Family Caregiver Workgroup had a strong interest in retaining these admissions (more than half a million admissions) in the measure. To address this issue, within each division, CCSs with low mortality rates (those less than or equal to 1%) are combined into one independent group, which reduces the total number of risk variables (CCS category codes) in the model.

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