# Chapter 2: Risk Adjustment Summary Report: Hospital Harm - Falls with Injury 

# Patient Safety Measure Development and Maintenance 

American Institutes for Research<br>University of California Davis<br>Clinician-Driven Quality Solutions

February 2024

## - AIR

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## Project

Patient Safety Measure Development and Maintenance
Contract Number: 75FCMC18D0027

## Task \& Deliverable

Chapter 6 Measure Testing
Deliverable 6-4 Risk Adjustment Methodology Report

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## 1. Introduction

This project, titled Patient Safety Measure Development and Maintenance, is performed under the Measure \& Instrument Development and Support (MIDS) contract for the Centers for Medicare \& Medicaid Services (CMS).

The goal of the project is to develop, maintain, re-evaluate, and implement patient safety measures for CMS's hospital-level quality reporting programs. Broadly, these programs range from the Hospital Inpatient Quality Reporting (IQR) Program to Hospital-Acquired Condition (HAC) Reduction Program, and the Promoting Interoperability (PI) Program.

This report is an independent chapter of the overall measure testing report and describes the rationale and methodology for a risk adjustment model for the Hospital Harm - Falls with Injury (HH-Falls) electronic clinical quality measure (eCQM). In this report, we explain risk factors selection, provide the model specification, summarize empirical findings, and present coefficient estimates.

We note that the baseline risk adjustment model presented in this chapter welcomes future update and refinement, as the number of hospitals (or test sites) participating in testing and model development is small. We aim to improve the model by augmenting hospitals and hence enlarging sample size to improve the model's generalizability to the full population in the future (during measure implementation).

## 2. Measure Description

HH - Falls assesses the number of inpatient hospitalizations where at least one fall with a major or moderate injury occurs among the total qualifying inpatient hospital days for patients aged 18 years and older. The initial population (IP) includes all inpatient hospitalizations with a length of stay less than or equal to 120 days ending during the measurement period for patients aged 18 years and older at the time of admission, and all payers. The measure denominator population is a subset of the IP, where encounters meeting denominator exclusion criteria are excluded. The measure numerator population is, in turn, a subset of denominator population where the patient has a fall that results in moderate or major injury. To qualify for the measure numerator, one harm event suffices.

Table 1 summarizes the measure's core components without delving into the technical details. For an in-depth review of the measure specification, please refer to Chapter 1: Measure Testing Summary Report.

Table 1: Measure Initial Population, Denominator Exclusion, Denominator, and Numerator

| Population | Description |
| :---: | :--- |
| Measure IP | Inpatient hospitalizations for patients aged 18 and older with a length of stay less than or <br> equal to 120 days that ends during the measurement period. |
| Denominator <br> Exclusion | Inpatient hospitalizations where the patient has a fall diagnosis present on admission. |
| Denominator | This measure includes all inpatient hospitalizations with a length of stay less than or equal to <br> 120 days ending during the measurement period for patients aged 18 years and older at the <br> time of admission, and all payers. The time period for data collection is inpatient <br> hospitalizations, which are defined as beginning at hospital arrival and including time in the <br> emergency department and observation when the transition between these encounters (if <br> they exist) and the inpatient encounter are within an hour or less of each other. |
| Numerator | Inpatient hospitalizations where the patient has a fall that results in moderate or major injury. <br> The diagnosis of a fall and of a moderate or major injury must not be present on admission. |

## 3. Rationale For Risk Adjustment

It is well understood that there are major risk factors for falls with injury, many of which are outside hospitals' control (e.g., age, frailty), which is why current practice guidelines emphasize risk assessment and mitigation. It is also well understood that misguided efforts to reduce fall rates to zero (i.e., by limiting patient activity or movement, installing bed or chair alarms) may cause other harms (e.g., adverse events due to immobility such as increased risk of pressure injury, functional decline, and venous thromboembolism) that are likely to exceed fall-related harms. ${ }^{1,2}$ In order to permit fair comparisons among hospitals that serve very different patient populations, risk-adjustment is used in the HH-Falls eCQM.

## 4. Streamlined Conceptual Model

Exhibit 1 is a simplified conceptual framework that guided our risk model development. Conceptually, risk factors for in-hospital falls with injury can be separated into two categories: 1) risk factors for falling, given hospitalization; and 2) risk factors for moderate or serious injury, given a fall. Some personal characteristics are risk factors for falling but are unlikely to affect the risk of injury given a fall, whereas other personal characteristics are risk factors for injury given a fall but are unlikely to affect the risk of falling.

Our review below focuses on risk factors for falls with injury in the inpatient setting; a much larger literature describes risk factors for falls in ambulatory settings (over several years). Patient attributes (demographics, comorbid conditions, clinical signs and symptoms, functional risk factors, and others) present at the start of care are integral components of the risk model, in that they directly influence the measured outcome and hospitals have less control.

[^0]Below, we discuss how patient risk factors for falling, patient risk factors for an injury given a fall, social risk factors, and mediators reflecting each component relates to the outcome of interest and whether they below to the risk model, and if so in what forms.

Exhibit 1. Simplified Conceptual Model That Guided the Risk Adjustment Model Development


Note: This eCQM logic model is adopted from The World Falls Guidelines (WFG) Task Force, World guidelines for falls prevention and management for older adults: a global initiative. Age and Ageing, 51(9), 1-36. https://doi.org/10.1093/ageing/afac2

### 4.1 Social Factors

Social factors have been shown to have relatively little marginal impact on the risk of falls with injury in inpatient settings, except as shown in the conceptual model. As summarized by Noel (2021), non-Hispanic Black "(NHB) adults have higher bone mineral density (BMD), lower prevalence of osteoporosis, and lower rates of fracture compared with NHW adults. Research on Hispanic adults, however, is less clear, with conflicting evidence regarding BMD, osteoporosis, and fractures. Although Asian populations generally show lower BMD, higher prevalence of osteoporosis, and lower fracture rates compared with NHW adults, data are limited... there is considerable variation within these groups based on origin for genetic, lifestyle, social, cultural, and environmental factors. ${ }^{\prime 3}$ Social factors, such as race and ethnicity, were not coded consistently across a large proportion of the data to be considered for inclusion in the risk model. Additionally, because the impact of social factors on the risk of inpatient falls with injury appears to be mediated through clinical characteristics such as osteoporosis and other comorbidities, we adjust for those latter factors (rather than social factors) in our final model.

[^1]Some of the factors described below were tested but proved not to be independent risk factors for falls with injury in the available data. The risk-adjustment model will be updated annually (from the existing feature set) and additional risk factors will be added to the model as needed.

### 4.2 Age

Advanced age is recognized as a risk factor for falling and for fall-related injuries among hospitalized patients, although it may serve largely as a proxy for frailty and related concepts that cannot be measured directly. For example, the Network of Patient Safety Databases (NPSD) Falls Chartbook 2023 analyzed patient safety events from 2014 to 2022 and demonstrated that the residual harm after a fall, defined by the extent of harm to the patient after discovery of the incident and after any attempts to minimize adverse consequences, increased with age. ${ }^{4}$ Specifically, $38.7 \%$ of adults ( $18-64$ years) experienced residual harm compared to $56.8 \%$ of older adults ( $75-84$ years) and $61 \%$ of aged adults ( $85+$ years). ${ }^{4}$ The current risk model for AHRQ PSI 08, based on 11,536 in-hospital fall-associated fractures among over 58 million patients, estimates a nearly linear effect of age from $<40$ years to $>85$ years.

### 4.3 Weight Loss

Several studies have reported increased risk of harmful falls in patients with malnutrition and low BMI (Lackoff, 2019), especially in the older elderly population (>80 years) (Vivanti, 2010, Bellanti, 2022). ${ }^{5,6,7}$ Based on a systematic review and meta-analysis by Neri et al. (2020), obesity increases the risk of falls but is a protective factor for injury, given falls (due to greater bone mineral density and less kinetic energy transmission to bone). ${ }^{8}$ The current risk model for AHRQ PSI 08, based on 11,536 in-hospital fall-associated fractures among over 58 million patients, estimates an adjusted OR of 1.51 ( $95 \% \mathrm{Cl}$ : 1.44-1.58) for comorbid weight loss.

### 4.4 Delirium

Delirium is common among hospitalized older adults, "with studies suggesting that up to 31\% of older adults have delirium on hospital admission." In a systematic review, Sillner et al. (2019) reported that "the median risk of falling with delirium among the studies was $12 \%$ (range from $6 \%$ to $67 \%$ ) with smaller studies on the higher end of the range. ${ }^{9}$ The risk of falling was lower in

[^2]the comparison group without delirium in all studies (median 2\%, range 1\% to 47\%).Accordingly, the relative risk ( $R$ R) for falls with delirium was elevated and significant in all studies but one (median RR $=4.5$, range 1.4-12.6)." ${ }^{\prime 9}$ The current risk model for AHRQ PSI 08, based on 11,536 in-hospital fall-associated fractures among over 58 million patients, estimates an adjusted OR of 1.28 ( $95 \% \mathrm{Cl}$ : 1.20-1.37) for comorbid psychotic delirium.

### 4.5 Dementia

Patients with dementia have increased risk of falls during hospitalization. ${ }^{10,11,12,13,14}$ For example, a study by Jørgensen, et. al. (2015) demonstrated significantly increased odds of in-hospital fallrelated major injuries among individuals with dementia, compared with patients without dementia ( $\mathrm{OR}=2.34, \mathrm{Cl}: 1.87-2.92$ ). ${ }^{15}$ The use of psychotropic drugs, even at low defined daily dose ( 0.25 DDD), to treat symptoms of dementia further increases the risk of in-hospital falls (Sterke, 2012). ${ }^{16}$ The current risk model for AHRQ PSI 08, based on 11,536 in-hospital fallassociated fractures among over 58 million patients, estimates an adjusted OR of 1.72 ( $95 \% \mathrm{CI}$ : 1.64-1.81) for comorbid dementia.

### 4.6 Depression

Depression has been identified as one of the risk factors for falls. ${ }^{10,12,17}$ For example, the retrospective case-control study by Djurovic, 2021, confirmed that depression is a statistically significant risk factor for falls ( $\mathrm{P}<0.001$ ), recognizing "a causal link between depressive symptoms and the falls. ${ }^{17}$ Antidepressants are considered to be an independent risk factor for falls. For example, in the retrospective case-control study by Castaldi (2022), antidepressants had a significant correlation with increased risk of falls (OR: 2.18; CI 95\%: 1.32-3.59). ${ }^{18}$ The current risk

[^3]model for AHRQ PSI 08, based on 11,536 in-hospital fall-associated fractures among over 58 million patients, estimates an adjusted OR of 1.34 ( $95 \%$ CI: 1.28-1.39) for comorbid depression.

### 4.7 Psychosis/Psychotic disorders

Psychosis and psychotic disorders have been found risk factors for falls. Study findings demonstrate increased immobility as well as bone density loss associated with psychotic disorders. ${ }^{18,19}$ For example, in the multivariable analysis of predictors of fractures by Stubbs (2018), psychosis was an independent and significant predictor for fall-related fractures requiring hospitalization (HR: 2.05, $95 \% \mathrm{Cl} 1.53-2.73$ ). ${ }^{19}$ The current risk model for AHRQ PSI 08, based on 11,536 in-hospital fall-associated fractures among over 58 million patients, estimates an adjusted OR of 1.28 ( $95 \% \mathrm{Cl}$ : 1.20-1.37) for comorbid psychosis.

### 4.8 Other Neurologic Disorders

Neurological disorders put patients at a higher risk for injurious falls during hospitalization. These conditions include peripheral neuropathy, disorders of gait and balance ${ }^{10,12,17}$ epilepsy, including seizure disorder, ${ }^{12,20,21}$ Parkinson disease, multiple sclerosis, stroke, and other neurological disorders ${ }^{10,15,18,22,23,24}$ For example, a study by Forns, et al. (2021) comparing patients with Parkinson disease with (PDP) and without psychosis (PD), found that PDP patients had higher risk for falls and fractures than those without psychosis. ${ }^{\text {Error! Bookmark not defined. This }}$ effect was noted separately for falls (IRR = 1.48; 95\% CI, 1.43-1.54) and any fractures (IRR = 1.17; $95 \% \mathrm{Cl}, 1.08-1.27$ ) as well as for specific types of fracture, including pelvis and hip fractures. The current risk model for AHRQ PSI 08, based on 11,536 in-hospital fall-associated fractures among over 58 million patients, estimates adjusted odds ratios of 1.13 ( $95 \% \mathrm{Cl}$ : 1.07-1.19) for comorbid other neurologic disorders and 1.23 ( $95 \% \mathrm{Cl}: 1.14-1.31$ ) for seizures.

[^4]
### 4.9 Sex

In papers by Aryee (2017) and Hodgson (2023), male sex was associated with increased risk of falls. ${ }^{25,26}$ The current risk model for AHRQ PSI 08, based on 11,536 in-hospital fall-associated fractures among over 58 million patients, suggests that male sex is associated with higher risk of these adverse events up to 54 years, but lower risk above that age.

### 4.10 Surgery

Aryee (2017) reported that surgery was a statistically significant protective risk factor. ${ }^{26}$ Patients after a recent lower limb amputation may be at increased risk of falling, compared with other surgical and medical patients, according to IHI and VA Fall Prevention Group. ${ }^{27,28}$ The current risk model for AHRQ PSI 08, based on 11,536 in-hospital fall-associated fractures among over 58 million patients, estimates an adjusted OR of 0.063 ( $95 \% \mathrm{Cl}$ : 0.059-0.068) for medical patients, relative to surgical patients. However, this estimate must be interpreted in the context of other features in the model.

### 4.11 Bone disorders

In systematic reviews by Wildes (2015) and Frattura (2022), bone disorders including cancers involving bones were found to be significant risk factors for falls and falls with injuries. ${ }^{29,30}$ For example, Frattura's review of 11 papers on 1237 patients with osteoporosis undergoing TKA found "pre-operative fall prevalence ranged from $23 \%$ to $63 \%$, while post-operative values ranged from $12 \%$ to $38 \% .{ }^{30}$ In Jørgensen's (2015) analysis of administrative data on patients 65 years and older with in-hospital falls causing fractures or head injuries with need for surgery or intensive observation, osteoporosis was a significant risk factor for falls with injuries ( $O R=1.68$, $\mathrm{Cl}: 1.43-1.99) .{ }^{15}$

[^5]
### 4.12 Leukemia/lymphoma

Several studies found hematological and other cancers to be a risk factor for falls Lorca, 2019, Kong, 2014). ${ }^{31,32}$ For example, in the prospective study by Martí-Dillet (2023) of 6090 patients hospitalized with cancer, patients with hematological cancers had the second highest incidence of falls (24.8\%), after lung cancer. ${ }^{31}$ The current risk model for AHRQ PSI 08, based on 11,536 inhospital fall-associated fractures among over 58 million patients, estimates an adjusted OR of 1.44 ( $95 \%$ CI: 1.23-1.68) for leukemia and 1.22 ( $95 \% \mathrm{CI}$ : 1.06-1.39) for lymphoma.

### 4.13 Liver disease

Severe liver disease as well as management of severe liver disease increases risk of falls and bleeding due to injuries associated with falls. ${ }^{33,34,35}$ Acharya (2021) described gait abnormalities among patients with liver cirrhosis listed for deceased solitary liver transplant from 2011 to 2015: "abnormal tandem gait (TG) trended towards increased falls (OR 3.3, $\mathrm{P}=0.08$ ). 49\% had abnormal TG, $61 \%$ had cognitive dysfunction (CD), $32.7 \%$ had CD plus abnormal TG, $62 \%$ had prior overt hepatic encephalopathy (OHE), and $14.7 \%$ had falls." ${ }^{35}$ The current risk model for AHRQ PSI 08, based on 11,536 in-hospital fall-associated fractures among over 58 million patients, estimates an adjusted OR of 1.45 ( $95 \%$ CI: 1.30-1.63) for severe and 1.13 ( $95 \% \mathrm{Cl}$ : 1.051.21) for mild liver disease.

### 4.14 Coagulopathy

Coagulation disorders and anticoagulant medications put patients at a higher risk for developing bleeding after a fall. IHI and VA Fall Prevention Group identify coagulation issues that put the patient at risk for injury in the event of a fall such as bleeding, anticoagulant use, and abnormal platelet count. ${ }^{27,28}$ "Anticoagulants are commonly used in elderly patients to reduce the risk of potential stroke, but this potential benefit must be weighed against the risk of falls with potentially fatal bleeds." ${ }^{36}$ "In the regression model for the dependent variable of falling, anemia ( $O R=2.26, \mathrm{p}<0.001$ ) was associated with more than twice the risk of falling." ${ }^{37}$ The current risk

[^6]model for AHRQ PSI 08, based on 11,536 in-hospital fall-associated fractures among over 58 million patients, estimates an adjusted OR of 1.08 ( $95 \% \mathrm{Cl}$ : 1.02-1.15) for comorbid coagulopathies.

### 4.15 Medications POA

There are several classes of medications, referred to as a fall-risk increasing drugs (FRIDs), especially in adults who are greater than 65 years or older, that increase risks of falls. If these medications were administered at home, with persisting effects at admission to the hospital, then they are appropriate for risk-adjustment.

- Opioids ${ }^{38,39,40,41,42}$
- CNS depressants:
- Antipsychotics, hypnotics, opioids, benzodiazepines, antiepileptics ${ }^{40}$
- Active treatment on CNS agents ${ }^{26}$
- Antipsychotics, antidepressants, TCAs, SSRIs, benzodiazepines, short-acting benzodiazepines, long-acting benzodiazepines, antiepileptic ${ }^{38}$
- Sedatives, hypnotics, antidepressants including tricyclic antidepressants, selective serotonin reuptake inhibitors, and serotonin norepinephrine reuptake inhibitors ${ }^{39}$
- Antiparkinsonian agents, anti-anxiety agents and hypnotic agents ${ }^{43}$
- Anticonvulsant, benzodiazepine anticonvulsant, haloperidol, tricyclic antidepressant ${ }^{44}$

[^7]- Lorazepam ${ }^{45}$
- Sedatives, hypnotics, psychotropics, antiepileptics ${ }^{46}$
- Antihypertensives ${ }^{47,48}$
- Alpha blockers, alpha agonist, angiotensin-converting enzyme inhibitors (ACE-i), angiotensin receptor blockers (ARB), calcium channel blockers (CCB), beta blockers (BB), vasodilators ${ }^{43,49,50}$
- Diuretics (increase bone loss on loop diuretics ${ }^{38,44,47,51,52}$
- Antidepressants ${ }^{39,50,53,54,55}$


### 4.16 Mediating Factors

Several care processes and intermediate factors (or mediators) may also contribute to the occurrence of falls with injuries. These factors are largely within the hospital's control and are therefore not considered as risk factors. For example, in the NPSD Falls Chartbook 2023 analysis of patient safety reports from 2014 through 2022, $22.9 \%$ of in-hospital falls were associated with injury or residual harm among patients ambulating without assistance prior to falling, versus only $6.4 \%$ among patients ambulating with assistance. Error! Bookmark not defined. Assistance during

[^8]ambulation may not decrease the risk of falling, but it appears to reduce the risk of injury as the patient is assisted to the ground. Other mediating factors include keeping the bed in low position, keeping the call light and personal items in reach, educating the patient and family regarding fall risk, providing non-slip footwear, and visibly identifying each applicable patient as being at risk for fall (e.g., Falling Star).

## 5. Methodology

### 5.1 Data Sources

The final risk-adjustment model was estimated using Poisson regression with an exposure time offset term (Stay_days) run on the entire dataset. All risk factors were dichotomous (0/1) except for age. Data sources included:

- ICD-10-CM diagnosis codes for comorbidities present on admission, including obesity, weight loss or malnutrition, coagulation disorder, delirium, dementia, depression, seizures and epilepsy, leukemia or lymphoma, liver disease (moderate or severe), malignant bone disease, neurological movement disorders, other neurological disorders, osteoporosis, neuropathy, psychosis, and stroke (POA);
- Anesthesia record for surgery;
- EHR home medication list for antidepressants, antihypertensives, CNS depressants, diuretics, and opioids;
- EHR hospital medication record for anticoagulants; and
- EHR demographic fields for age, sex, race, ethnicity, and primary payer.


### 5.2 Model Development

Guided by the conceptual model, we developed the baseline risk adjustment model for HH-Falls using a 2 -step sequential process (A) feature selection followed by (B) risk adjustment (RA) model development as explained below.

1. Created contingency tables (see Table 2) for all the categorical features to identify any that had zero cells for either the positive or negative outcome. These features were not considered for feature selection due to anticipated model convergence problems (i.e., quasi-complete separation) in the RA model. For continuous variables, such as age, we ran locally weighted bivariate regressions (i.e., locally weighted scatterplot smoothing, or LOWESS) to understand the functional form of the relationship. This analysis confirmed that the risk of fall with injury was linearly related to age through nearly all the age distribution, from about 30 to 90 years of age (see Exhibit 2).
2. Obtained summary statistics such as event rate by facility, overall event rate, overall event rate based on encounter days, and unadjusted observed event rates by facility.
3. Randomly partitioned the full denominator data into a $70 \%$ training set and a $30 \%$ holdout test set. The hold out test set was used to evaluate the generalizability of the
features chosen. The feature selection algorithm was applied to the training set with 100 -fold cross-validation (CV).
4. Elastic net was developed by Zou and Hastie in 2005 by combining the advantages of least absolute shrinkage and selection operator (LASSO) and ridge regression ${ }^{56}$. Its main advantage is in handling multicollinearity. It outperforms LASSO in prediction accuracy and provides a unique solution due to the ridge regression penalty term. We ran elastic net feature selection algorithm using all the clinically justifiable features on the training set using 100 -fold cross-validation (CV) (see Exhibit 3). This step helped understand how many features get selected at different values of the regularization parameter (lambda) and to assess model fit on the training set. We extracted the final set of features chosen by the model where the regularization parameter (lambda) was set to lambda1se, i.e., "one-standard-error" (i.e., the largest lambda at which the mean squared error (MSE) is within one standard error of the minimum MSE). This rule is standard practice for improving generalization on hold-out test set (unseen data).
5. The elastic net model (where lambda is equal to lambda1se) with the selected features was evaluated on the hold-out test set and performance metrics obtained (see Exhibit 4).

Table 2: Contingency Table of Risk Factors

| Categorical Feature ${ }^{57}$ | \# Negative events | \# Positive Events | Event Rate (\%) |
| :--- | ---: | ---: | ---: |
| Male | 80499 | 49 | $0.03 \%$ |
| Female | 112813 | 37 | $0.02 \%$ |
| Obese (no) | 163668 | 77 | $0.04 \%$ |
| Obese (yes) | 29644 | 9 | $0.00 \%$ |
| Coag (no) | 147016 | 52 | $0.03 \%$ |
| Coag (yes) | 46296 | 34 | $0.02 \%$ |
| Weight loss (no) | 173153 | 47 | $0.02 \%$ |
| Weight loss (yes) | 20159 | 39 | $0.02 \%$ |
| Antidep (no) | 174193 | 70 | $0.04 \%$ |
| Antidep (yes) | 19119 | 16 | $0.01 \%$ |
| Anthyp (no) | 73718 | 39 | $0.02 \%$ |
| Anthyp (yes) | 155740 | 47 | $0.02 \%$ |
| CNS (no) | 37572 | 56 | $0.03 \%$ |
| CNS (yes) | 177511 | 15801 | 30 |
| coagdis (no) | 189199 | 67 | $0.02 \%$ |
| coagdis (yes) |  | 19 | $0.03 \%$ |
| delir (no) |  | 78 | $0.01 \%$ |

[^9]| Categorical Feature ${ }^{57}$ | \# Negative events | \# Positive Events | Event Rate (\%) |
| :---: | :---: | :---: | :---: |
| delir (yes) | 4113 | 8 | 0.00\% |
| demen (no) | 182285 | 70 | 0.04\% |
| demen (yes) | 11027 | 16 | 0.01\% |
| depress (no) | 176432 | 71 | 0.04\% |
| depress (yes) | 16880 | 15 | 0.01\% |
| diur (no) | 171631 | 70 | 0.04\% |
| diur (yes) | 21681 | 16 | 0.01\% |
| epil (no) | 185661 | 79 | 0.04\% |
| epil (yes) | 7651 | 7 | 0.00\% |
| leuk (no) | 188902 | 79 | 0.04\% |
| leuk (yes) | 4410 | 7 | 0.00\% |
| liver (no) | 190503 | 82 | 0.04\% |
| liver (yes) | 2809 | 4 | 0.00\% |
| bone (no) | 190917 | 84 | 0.04\% |
| bone (yes) | 2395 | 2 | 0.00\% |
| movement (no) | 190755 | 85 | 0.04\% |
| movement (yes) | 2557 | 1 | 0.00\% |
| neuroother (no) | 177568 | 64 | 0.03\% |
| neuroother (yes) | 15744 | 22 | 0.01\% |
| Opiods (no) | 171932 | 65 | 0.03\% |
| Opiods (yes) | 21380 | 21 | 0.01\% |
| Osteo (no) | 189751 | 83 | 0.04\% |
| Osteo (yes) | 3561 | 3 | 0.00\% |
| Neuropathy (no) | 183177 | 78 | 0.04\% |
| Neuropathy (yes) | 10135 | 8 | 0.00\% |
| Psychosis (no) | 190017 | 83 | 0.04\% |
| Psychosis (yes) | 3295 | 3 | 0.00\% |
| Stroke (no) | 184678 | 79 | 0.04\% |
| Stroke (yes) | 8634 | 7 | 0.00\% |
| Suicide (no) | 193284 | 86 | 0.04\% |
| Suicide (yes) | 28 | 0 | 0.00\% |
| Surgery (no) | 164572 | 75 | 0.04\% |
| Surgery (yes) | 28740 | 11 | 0.01\% |

Exhibit 2: Lowess Smoothing; Patient Age (x-axis) and Falls with Injury


Exhibit 3: Elastic net model feature selection (100-fold CV on 70\% Training Set)


Exhibit 4: Performance of elastic net model with selected features (Test Data)

## ROC - P: 25, N: $57994 \quad$ Precision-Recall - P: 25, N:


6. We also ran a least absolute shrinkage and selection operator (LASSO) on the split data for feature selection. LASSO selected more features and had poorer performance on the hold-out test set. The clinical team reviewed the features selected by LASSO and noticed that several features were collinear. Therefore, we decided to use the features selected by elastic net for the RA model.
7. The final risk-adjustment model was a Poisson model with an offset for patient stay days, accounting for the fact that in-hospital falls followed a Poisson distribution with stay days as an indicator of exposure time. The RA model coefficients were estimated on the entire dataset using the set of features selected by elastic net through 100-fold CV and testing on the hold-out test set. Feature selection and RA model performance were evaluated using a variety of metrics such as C-statistics, area under the precision-recall curve and calibration plots.
8. The risk-adjustment model was also tested with additional social drivers of health variables (race, Medicaid insurance, Hispanic ethnicity, race), considered individually and collectively. See Section 7 for results.
9. After feature selection with 100 -fold cross-validation and testing on the hold-out test set, the final RA model only included these risk factors - age (in linear form), weight loss or malnutrition POA, delirium POA, dementia POA, and other neurological disorders POA. We tested RA models, without performing feature selection, by including all the clinical factors and found three statistically significant features which were age, weight loss and home opioid medication but no meaningful improvement in any metric of model performance (e.g., AUC, Brier score, AIC/BIC).

### 5.3 Model Performance

Overall model discrimination as assessed by C-statistic. The C-statistic is the area under the receiver-operator curve (i.e., AUC) that measures the discriminative ability of a model. It also describes the probability that a randomly selected patient who experienced a fall with injury had
a higher expected value than a randomly selected patient who did not experience that event. The AUC for the elastic net was 0.781 on the hold-out test set and 0.852 for the final Poisson RA model run on the entire data. These values indicate strong discrimination performance, relative to a random classifier with $\mathrm{AUC}=0.5$.

The precision-recall (PR) curve and the area under the curve (AUPRC). The PR curve and AUPRC are less sensitive to data imbalance or class imbalance (i.e., very rare events) than the AUC. Given the low overall event rate for this measure, it was advisable to check the values of AUPRC. The AUPRC was 0.00166 on the hold-out test set (elastic net), indicating poor prediction at the individual patient level but reasonable performance relative to a random classifier with AUPRC=0.00043.

The RA model calibration was assessed across deciles of patient risk using Hosmer-Lemeshow plots (see Exhibit 5). The deciles of risk are ten mutually exclusive groups containing equal numbers of discharges, ranging from very low-risk patients (according to the model) to high-risk patients. We do not provide Hosmer-Lemeshow test statistics because, given the large sample size of our data, the null hypothesis is almost always rejected. Moreover, the plots provide more detail on model fit than the overall Hosmer-Lemeshow statistic. Because over 53\% of events occurred in the highest-risk decile, and nearly $76 \%$ occurred in the highest-risk quintile, the decile analysis is statistically unstable.

Exhibit 5: Hosmer-Lemeshow Decile Calibration Plot (Final Risk Adjustment Model)


A preferred approach in this situation is to estimate calibration belts suggested by Nattino et al. (2017). ${ }^{58}$ Calibration belts are an advance over the conventional Hosmer-Lemeshow plot, as the latter has the limitation of undue sensitivity to the choice of bins and extreme fluctuations in the

[^10]observed-to-expected ratios in bins with few harm events. The null hypothesis of perfect calibration is never rejected at the $95 \%$ confidence level ( $p=0.052$ ) (see Exhibit 6).

Exhibit 6: Calibration belt (Final Risk Adjustment Model)
Falls calibration (Poisson)


## 6. Risk Adjustment Model Specification

Table 3 shows the coefficient estimates, standard errors, and 95\% confidence interval using data points from the full denominator population.

Table 3: Final Risk Model Coefficient Estimates, Standard Error, and Odds Ratios

| Risk Adjuster | Estimate | Standard <br> Error | Odds Ratio <br> (95\% CI) |  |
| :--- | :--- | ---: | ---: | ---: |
| Age | $0.019^{* *}$ | 0.007 | 1.019 | $(1.006,1.034)$ |
| Weight Loss | $0.740^{* *}$ | 0.226 | 2.096 | $(1.341,3.257)$ |
| Delirium | 0.194 | 0.383 | 1.214 | $(0.530,2.424)$ |
| Dementia | 0.338 | 0.305 | 1.403 | $(0.750,2.501)$ |
| Other neurological disorders | 0.240 | 0.261 | 1.271 | $(0.747,2.087)$ |

Notes: ${ }^{* * *} \mathrm{p}<0.0001$; $^{* *} \mathrm{p}<0.001$; ${ }^{*} \mathrm{p}<0.01$; Cstat $=0.8522$; BrierScore $=0.0004$

Table 4 shows the denominator count as well as observed and risk-adjusted measure performance rates for every hospital included in the analysis. We calculated risk-adjusted measure rate as:

$$
\frac{\text { observed measure rate }}{\text { Expected measure rate }} \times \text { sample average },
$$

where the expected measure rate came from the risk-adjustment model and the sample average stands in for the observed measure rate in the reference population.

Table 4: Denominator Count and Observed and Risk-adjusted Measure Rates Per 1000 Qualified Inpatient Encounters

| Facility | Number of <br> Events | Denominator <br> Count (sum of <br> days in hospital) | Observed Measure <br> Rate (per 1000 <br> encounter days) | Risk-adjusted <br> Measure rate |
| :---: | ---: | ---: | ---: | ---: |
| 1 | 16 | 73,597 | 0.2174 | 0.2575 |
| 2 | 7 | 121,102 | 0.0578 | 0.0650 |
| 3 | 2 | 55,458 | 0.0361 | 0.0451 |
| 4 | 0 | 3,597 | 0.0000 | 0.0000 |
| 5 | 11 | 229,966 | 0.0478 | 0.0497 |
| 6 | 4 | 67,844 | 0.0590 | 0.0530 |
| 7 | 2 | 43,412 | 0.0461 | 0.0375 |
| 8 | 11 | 108,704 | 0.1012 | 0.0935 |
| 9 | 17 | 269,922 | 0.0630 | 0.0585 |
| 10 | 1 | 12,655 | 0.0790 | 0.0708 |
| 11 | 5 | 128,945 | 0.0388 | 0.0428 |
| 12 | 10 | 43,742 | 0.2286 | 0.1861 |

Note: risk-adjusted measure rate = observed measure rate / expected measure rate sample averages. Expected measure rate was resulted from the risk-adjustment model and sample average serves as the proxy for the observed measure rate in the reference population.

## 7. Social Risk Factors

There may exist disparities in the rate of in-hospital falls. According to a report from the Leapfrog Group, the rate of in-hospital falls with hip fracture is significantly higher for patients insured by Medicare and Medicaid than for privately insured patients. ${ }^{59}$ This analysis also found the rate of in-hospital fall with hip fracture is also significantly lower for Non-Hispanic Black and Hispanic patients than for White patients.

Using data from the 12 test sites, we conducted a social disparities analysis. Our results align with the literature as we found:

[^11]- Hispanic patients have significantly lower risk of fall with injury (OR=0.36; 95\% CI, 0.100.91 ) than non-Hispanic patients, after adjusting for age and other factors in the riskadjustment model.
- Black patients ( $\mathrm{OR}=0.48 ; 36 ; 95 \% \mathrm{Cl}, 0.24-0.88$ ) and patients of "other" race (OR=0.47; $95 \% \mathrm{Cl}, 0.23-0.89$ ) have significantly lower risk of fall with injury than patients of White or "unknown" race, after adjusting for age and other factors in the risk-adjustment model.
- Racial/ethnic differences are likely to reflect known variation in the prevalence of osteoporosis, as we find very few false negative cases (see above).
- Risk of fall with injury is unrelated to Medicaid or uninsured status (OR=0.99), or dual eligibility among Medicare beneficiaries, after adjusting for age and other factors in the risk-adjustment model.

See Tables 5-8 below for results (individually and collectively).
Table 5: Social Drivers of Health Analysis - Race

| Variable | Estimate | Std. Error | z value | Pr $(>\|\mathbf{z}\|)$ | Odds Ratio | U CL | L CL |
| :--- | ---: | ---: | ---: | :--- | ---: | ---: | ---: |
| Age | 0.015 | 0.007 | 2.131 | $0.033^{*}$ | 1.015 | 1.001 | 1.029 |
| Weight Loss | 0.755 | 0.225 | 3.350 | $0.001^{* * *}$ | 2.128 | 1.362 | 3.307 |
| Delirium | 0.179 | 0.382 | 0.468 | 0.640 | 1.196 | 0.523 | 2.387 |
| Dementia | 0.360 | 0.306 | 1.177 | 0.239 | 1.433 | 0.766 | 2.556 |
| Other neurological disorders | 0.251 | 0.261 | 0.961 | 0.337 | 1.285 | 0.755 | 2.109 |
| Race: White | REF |  |  |  |  |  |  |
| Race: Black | -0.682 | 0.330 | -2.069 | $0.039^{*}$ | 0.506 | 0.251 | 0.926 |
| Race: Other | -1.014 | 0.330 | -3.074 | $0.002^{* *}$ | 0.363 | 0.180 | 0.665 |
| Race: Unknown | -0.328 | 0.720 | -0.456 | 0.648 | 0.720 | 0.118 | 2.306 |

Notes: ${ }^{* * *}$ p<0.0001; ** p < 0.001; *p < 0.01; Cstat = 0.8603; BrierScore = 0.0004; AIC: 1340.7***

Table 6: Social Drivers of Health Analysis - Medicaid Insurance

| Variable | Estimate | Std. Error | z value | $\operatorname{Pr}(>\mid \mathbf{z \|})$ | Odds Ratio | U CL | LCL |
| :--- | ---: | ---: | ---: | :--- | ---: | ---: | ---: | ---: |
| Age | 0.017 | 0.007 | 2.363 | $0.018^{*}$ | 1.017 | 1.003 | 1.032 |
| Weight Loss | 0.747 | 0.226 | 3.305 | $0.001^{* * *}$ | 2.110 | 1.350 | 3.282 |
| Delirium | 0.188 | 0.383 | 0.490 | 0.624 | 1.206 | 0.527 | 2.410 |
| Dementia | 0.358 | 0.306 | 1.170 | 0.242 | 1.431 | 0.764 | 2.555 |
| Other neurological disorders | 0.248 | 0.261 | 0.951 | 0.342 | 1.282 | 0.753 | 2.106 |
| Medicaid | -0.241 | 0.267 | -0.900 | 0.368 | 0.786 | 0.455 | 1.303 |

Notes: ${ }^{* * *}$ p<0.0001; ${ }^{* *}$ p < 0.001; *p < 0.01; Cstat $=0.8498$; BrierScore $=0.0004$; AIC: 1349.4***

Table 7: Social Drivers of Health Analysis - Hispanic Ethnicity

| Variable | Estimate | Std. Error | z value | $\operatorname{Pr}(>\mid \mathbf{z \|})$ | Odds Ratio | U CL | LCL |
| :--- | ---: | ---: | ---: | :--- | ---: | ---: | ---: | ---: |
| Age | 0.016 | 0.007 | 2.371 | $0.018^{*}$ | 1.017 | 1.003 | 1.031 |
| Weight Loss | 0.744 | 0.226 | 3.292 | $0.001^{* * *}$ | 2.104 | 1.345 | 3.271 |
| Delirium | 0.176 | 0.383 | 0.461 | 0.645 | 1.193 | 0.521 | 2.381 |


| Variable | Estimate | Std. Error | z value | Pr(>\|z|) | Odds Ratio | U CL | LCL |
| :--- | ---: | ---: | ---: | :--- | ---: | ---: | ---: |
| Dementia | 0.341 | 0.305 | 1.115 | 0.265 | 1.406 | 0.752 | 2.506 |
| Other neurological disorders | 0.252 | 0.261 | 0.967 | 0.334 | 1.287 | 0.756 | 2.114 |
| Hispanic | -1.276 | 0.514 | -2.481 | $0.013^{*}$ | 0.279 | 0.085 | 0.673 |

Notes: ${ }^{* * *} \mathrm{p}<0.0001$; ${ }^{* *} \mathrm{p}<0.001$; ${ }^{*} \mathrm{p}<0.01$; Cstat $=0.8586$; BrierScore $=0.0005$; AIC: 1336.0***
Table 8: Social Drivers of Health Analysis - Combined (Race, Medicaid Insurance, Hispanic Ethnicity)

| Variable | Estimate | Std. Error | z value | $\operatorname{Pr}(>\|\mathbf{z}\|)$ | Odds Ratio | U CL | L CL |
| :--- | ---: | ---: | ---: | :--- | ---: | ---: | ---: | ---: |
| Age | 0.013 | 0.007 | 1.807 | $0.071^{+}$ | 1.013 | 0.999 | 1.028 |
| Weight Loss | 0.756 | 0.226 | 3.344 | $0.001^{* * *}$ | 2.129 | 1.362 | 3.311 |
| Delirium | 0.171 | 0.382 | 0.447 | 0.655 | 1.186 | 0.518 | 2.367 |
| Dementia | 0.355 | 0.307 | 1.159 | 0.247 | 1.426 | 0.761 | 2.549 |
| Other neurological disorders | 0.266 | 0.261 | 1.020 | 0.308 | 1.305 | 0.767 | 2.145 |
| Medicaid | -0.006 | 0.273 | -0.022 | 0.982 | 0.994 | 0.569 | 1.667 |
| Hispanic | -1.033 | 0.538 | -1.922 | $0.055^{+}$ | 0.356 | 0.105 | 0.910 |
| Race: White | REF |  |  |  |  |  |  |
| Race: Black | -0.739 | 0.332 | -2.228 | $0.026^{*}$ | 0.478 | 0.236 | 0.878 |
| Race: Other | -0.756 | 0.346 | -2.188 | $0.029^{*}$ | 0.469 | 0.226 | 0.887 |
| Race: Unknown | 0.447 | 0.720 | 0.620 | 0.535 | 1.563 | 0.256 | 5.015 |

Notes: ${ }^{* * *} \mathrm{p}<0.0001$; ${ }^{* *} \mathrm{p}<0.001$; ${ }^{*} \mathrm{p}<0.01 ; ~ \dagger \mathrm{p}<0.05$; Cstat $=0.8630$; BrierScore $=0.0005$; AIC: $1333.6^{* * *}$

## 8. Conclusion

Using EHR data from 12 hospitals with varying bed size, geographic location, and EHR system, we developed a baseline risk adjustment model for HH-Falls. Importantly, the risk model developed is still in its preliminary stage due to the small sample of hospitals. Risk-adjusted measure rates move closer to a state where comparison of hospital performance is affected as little as possible by factors other than the quality of care.

Acknowledging these limitations, we consider this exercise an important innovation in hospital outcome measures using EHR data on two fronts:

1. Developing a risk adjustment methodology for eCQMs responds to the preference of care providers and stakeholders that physiological data captured at the start of encounter can be valuable for adjusting patient-level risk factors in hospital outcome measures. In this sense, we took a step toward developing a risk-adjusted eCQM that takes full advantage of the rich physiological information existent in the medical record and recorded at the beginning of the episode of care. These data are used by clinicians to evaluate how sick patients are and to guide their treatment plans in real time. The face validity of these data and their use for risk adjustment are well-justified.
2. Use of EHR data in risk adjustment provides new efficiencies in future eCQM development and implementation, in that EHR data are already documented during the process of care and hence, data collection incurs minimal burden on providers. Maximizing the utility of EHR data elements for risk adjustment improves feasibility and data element reliability, and potentially improves harmonization across measures.

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