Targeting a High-Risk Group for Fall Prevention: Strategies for Health Plans

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ABSTRACT

Objectives: Although Medicare has implemented incentives for health plans to reduce fall risk, the best way to identify older people at high risk of falling and to use screening results to target fall prevention services remains unknown. We evaluated 4 different strategies using a combination of administrative data and patient-reported information that health plans could easily obtain.

Study Design: Observational study.

Methods: We used data from 1776 patients 75 years or older in 4 community-based primary care practices who screened positive for a fear of falling and/or a history of falls. For these patients, we predicted fall-related injuries in the 24 months after the date of screening using claims/encounter data. After controlling for age and gender, we predicted the number of fall-related injuries by adding Elixhauser comorbidity count, any claim for a fall-related injury during the 12 months prior to screening, and falls screening question responses in a sequential fashion using negative binomial regression models.

Results: Basic patient characteristics, including age and Elixhauser comorbidity count, were strong predictors of fall-related injury. Among falls screening questions, a positive response to, "Have you fallen 2 or more times in the past year?" was the most predictive of a fall-related injury (incidence rate ratio [IRR], 1.56; 95% CI, 1.25-1.94). Prior claim for a fall-related injury also independently predicted this type of injury (IRR, 1.41; 95% CI, 1.05-1.89). The best model for predicting fall-related injuries combined all of these approaches.

Conclusions: The combination of administrative data and a simple screening item can be used by health plans to target patients at high risk for future fall-related injuries.

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Reducing fall risk is one of the process measures used to determine the CMS 5-Star Ratings for Medicare Advantage plans, which are published annually, and to determine Medicare Advantage Quality Bonus Payments.[1] Moreover, with the passage of the Affordable Care Act, private insurers, Medicare, and Medicaid are likely to be required to provide coverage for new preventive health services graded A or B by the US Preventive Services Task Force (USPSTF),[2,3] including exercise or physical therapy and vitamin D supplementation for fall prevention (USPSTF grade B recommendations).[4] However, the best method to screen community-dwelling older adults for fall risk, and the best way to use the screening results to target preventive services for falls, remains unclear.

Several risk factors have been identified for falls among community-dwelling older adults,[5-7] with age and a history of falls being the 2 most commonly used risk factors to define high risk in fall intervention studies.[4] Other frequently reported risk factors for falls include a history of mobility problems, poor performance on office-based gait and balance testing such as the Get-Up-And-Go test, visual impairment, use of psychoactive medications, and female gender.[5,6,8] However, there is no consensus on a best single screening question, set of questions, or clinical tool to reliably identify older adults at increased risk for falls.[4]

Most clinical tools used to assess fall risk are performed in a primary care setting by a clinician,[8] requiring a face-to-face office visit, provider training in the use of the screening tool, and provider engagement in the screening process. However, this may not be the preferred approach for a health plan seeking to provide fall prevention services more widely to its at-risk members. Alternative approaches could include screening questions completed over the phone or by mail or the use of health plan administrative data to identify patients with risk factors for falls (eg, age, female gender, certain health conditions) or with a prior claim for a fall or a fall-related injury.

Take-Away Points

Among a high-risk population of community-dwelling older adults, the best model for predicting future fall-related injuries combined basic administrative data (age, gender, and comorbidity count), a prior claim for a fall-related injury, and patient response to the single item screener, "Have you fallen 2 or more times in the past year?"

- The most important influences on prediction were comorbidity count and response to the screening question.
- Given current Medicare incentives to reduce fall risk, health plans can use this information to target fall prevention interventions to the highest risk members without requiring a face-to-face office visit.

Our objective was to examine the predictive value of different possible screening approaches for fall risk that would be relevant to a health plan seeking to identify its older adult members at highest risk for falls and fall-related injuries. We assessed the value of 3 commonly used falls screening questions in combination with data from Medicare claims in predicting subsequent fall-related injuries in a cohort of high-risk community-dwelling older adults.

METHODS

Participants

We studied 1776 adults 75 years or older who screened positive for falls or fear of falling in 4 community-based primary care practices using 3 questions: 1) Have you fallen 2 or more times in the past 12 months? 2) Have you fallen and hurt yourself since your last visit to the doctor? 3) Are you afraid that you might fall because of balance or walking problems?

Participants were screened during 2006 and 2007 as part of the ACOVEprime study, a controlled trial of a practice-based quality improvement intervention to improve care for falls and urinary incontinence.[9]

This project was approved by the UCLA Institutional Review Board (IRB). The 4 participating sites either approved the project via their own IRB or by deferring to the UCLA IRB. A fifth site received approval to obtain claims only from decedents; thus, data from this site were excluded.

Data Source

We obtained Medicare claims data for calendar years 2005 to 2009 for all individuals who screened positive for at least 1 of the fall-related screening questions. We were unable to obtain claims data for screen-negative individuals as they were not included in the original ACOVEprime study, and the study sites did not retain registries of screen-negative individuals at the conclusion of ACOVEprime.

Medicare eligibility was determined based on the Master Beneficiary Summary File; fee-for-service Medicare claims data were obtained from MedPAR, outpatient, carrier, hospice, home health agency, and durable medical equipment files. For participants enrolled in a Medicare Advantage plan at the time of screening, we attempted to obtain both institutional and professional encounter data from participating health plans that had at least 50 members in the study. Of the 2022 individuals who were potentially eligible from the 4 sites, 77 were either not enrolled in Medicare or sites did not have a valid Medicare ID for the patient; we could not obtain managed care data for 169 patients. This left us with a final analytic cohort of 1776 patients.

Outcome

Our primary outcome measure was the count of fall-related injuries in the 24 months after the date of screening. Since we could not find a claims-based algorithm for fall-related injuries in the literature that was validated against medical records, we adapted an existing approach used for osteoporotic fractures.[10-13] We included specified combinations of *International Classification of Diseases, Ninth Revision, Clinical Modification* (*ICD-9-CM*) and Healthcare Common Procedure Coding System (HCPCS) codes for hip fractures, other selected nonvertebral fractures, inpatient head trauma, selected joint dislocations, and healthcare claims where an external cause of injury code ("E-code") for falls was used. A list of injuries with associated *ICD-9-CM* and E-codes and the coding hierarchy used has been described in prior work by this group.[13] We included claims for fall-related injuries in both the inpatient and outpatient settings in the 24 months after the individual screening date and conducted sensitivity analyses in which we only analyzed the first fall-related injury experienced by each participant. To avoid double counting fall-related injuries due to multiple claims for a single injury, a claim could only count toward defining a unique injury if there were no prior claims for a fall-related injury, or the claim occurred at least 30 days after a previous claim for a fall-related injury. In a robustness check, varying the length of the episode window around 30 days had little effect on the number of unique fall-related injuries identified.

Statistical Analysis

Because the data were obtained from a controlled multisite study, we began analyses using a model that adjusted for study site and ACOVEprime intervention group status. We also included a dichotomous variable identifying the few cases (N = 52; 2.9%) where there were missing claims

Table 1. Participant Characteristics

	Total (N = 1776) N (%) or Mean (SD)
Age	82.9 (5.3)
Female	1274 (72%)
Elixhauser score (comorbidity count)	2.9 (2.4)
Intervention group[a]	1175 (66%)
Study site	
A	987 (56%)
B	256 (14%)
C	209 (12%)
D	324 (18%)
Fallen twice in past 12 months	659 (37%)
Fallen and hurt self since last doctor's visit	420 (24%)
Afraid may fall because of balance/walking problems	1495 (84%)

[a]Participants were screened for fall risk as part of the ACOVEprime study, a controlled trial of a practice-based quality improvement intervention to improve care for falls and urinary incontinence.[9]

data in the 12-month period prior to the screening date since such cases might have a falsely low rate of comorbidities or claims-detected fall-related injury in the baseline period. We retained study site, intervention group, and the dichotomous variable adjusting for missing data in all subsequent models as an adjustment for study design.

Descriptive statistics were used to examine age, gender, and comorbidity count derived from Medicare claims using the Elixhauser method[14]; all of these variables were determined to have a potential relationship with fall-related injuries. We then included variables for age (as a continuous variable) and gender in the model, creating our base model. All additional predictors were added to this base model in a sequential fashion.

We included responses to the 3 falls-screening questions in 2 different ways. First, we included the response (yes/no) to each individual screening question without controlling for responses to the other 2 questions, which allowed us to examine the predictive value of each question individually. Second, we included the screening questions in the multivariate model as a 3-item set, with each response adjusted for response to the other 2 items. Next, we added to our baseline multivariate model a binary variable for the presence/absence of at least 1 fall-related injury during the 12 months prior to the date of screening using our claims-based outcome definition with and without controlling for screening question response. This allowed us to evaluate the utility of a model using only administrative data to predict future fall-related injuries and a model using both administrative and patient-reported information (patient demographics, screening item response, and prior claim for a fall-related injury).

For our primary analyses, we examined the count of fall-related injuries at 24 months after the date of screening using negative binomial regression models. Negative binomial regression was selected as the primary approach to allow all falls, including recurrent falls, in a given participant to be counted in the analyses and to account for the individual follow-up time of each participant based on available claims data.[15,16] Models were compared using Akaike's information criterion (AIC) and Bayesian information criterion (BIC), likelihood measures in which lower values indicate better fit and a penalty is paid for increasing the number of variables in the model.[17,18] A stronger penalty is paid for increasing the number of variables with BIC.[18,19]

Lastly, we compared observed and predicted total fall-related injuries by decile of predicted values and conducted Hosmer-Lemeshow χ^2 tests to examine goodness-of-fit for all models.[20] We also examined scatter plots of residuals versus predicted values with locally weighted polynomial regression (LOESS) smoothing curves for all models.[21]

We also conducted sensitivity analyses examining time to first fall-related injury for each participant during the 24 months after screening using Kaplan-Meier plots and Cox proportional hazards models. As both approaches resulted in similar findings, we present only the negative binomial models here. All statistical analyses were performed using STATA IC version 13 (Stata Corp LP, Texas Station, Texas).

RESULTS

Of the 1776 patients who screened positive for a fear of falling and/or a history of falls who had data available for analysis, the mean age and number of comorbidities were 82.9 years (SD = 5.3) and 2.9 (SD = 2.4), respectively; 72% of participants were women. The majority of the sample reported being afraid of falling due to balance or walking problems (84%). More than one-third reported 2 or more falls in the past year and about one-fourth reported having had a fall resulting in injury since their last visit to the doctor (Table 1).

Table 2 shows incidence rates for fall-related injuries per 1000 person-years before and after screening. Eleven percent of participants had a claim for a fall-related injury in the 12

Table 2. Incidence Rates for Fall-Related Injuries Before and After Screening

	Total FRI	Person-Years of Observation	Incidence Rate (FRI per 1000 person-years)	N (%) With Any FRI
12 months before screening	223	1742	128	198 (11%)
24 months after screening	413	3166	130	341 (19%)

FRI indicates fall-related injury.

months prior to study entry and 19% had any claim for a fall-related injury during the 24-month study follow-up period.

Table 3 shows the 4 different models for predicting fall-related injuries. The greatest increase in predictive value for future fall-related injuries occurred with the addition of Elixhauser comorbidity count to the base model with a decrease in AIC of 22.7. Age and Elixhauser comorbidity count remained significant predictors of future fall-related injuries in all models.

Adding the response to the single-item screening question, "Have you fallen 2 or more times in the past year?" increased the predictive value of the model with age, gender, and comorbidity count more than the addition of a prior claim for a fall-related injury, with a decrease in AIC of 18.3 and 7.6, respectively. Adding prior claim for a fall-related injury to the model with patient demographics and response to the single-item screening question was most predictive of future fall-related injuries and further decreased the AIC by 3.1. The comparison of models by BIC was generally similar to the comparison using AIC and is provided in eAppendix 1 (available at **www.ajmc.com**). The comparison of models by relative likelihood of better fit is also provided in eAppendix 1.

In the final model, a 5-year increase in age was associated with a 22% relative increase in the expected number of fall-related injuries in a 2-year period, and each additional comorbid condition was associated with a 10% relative increase in the expected number of fall-related injuries. Observed and predicted fall-related injuries for the final model (Model 4 in Table 3) were similar across deciles of risk, as seen in the Figure. Plots of observed and predicted values for Models 1, 2, and 3 in Table 3 and Hosmer-Lemeshow test statistics for all models are provided in eAppendix 2, and plots of residuals versus predicted values for all models are provided in eAppendix 3.

Table 4 shows the number of fall-related injuries predicted by the model for an 85-year-old female with different combinations of risk factors. For example, an 85-year-old woman with 3 comorbid conditions and a prior fall-related injury who reports 2 or more falls in the last year is expected to have 0.45 fall-related injuries within the next 2 years. In contrast, another woman of the same age who has none of the 3 risk factors is expected to have 0.15 fall-related injuries within the next 2 years.

"Have you fallen 2 or more times in the past year?" was the only screening question that independently predicted fall-related injuries in multivariate models (for a positive response: incidence rate ratio (IRR), 1.56; 95% CI, 1.25-1.94). Neither, "Have you fallen and hurt yourself since your last visit to the doctor?" nor "Are you afraid that you might fall because of balance or walking problems?" was predictive of a fall-related injury (IRR, 1.15; 95% CI, 0.89-1.48; and IRR, 1.33; 95% CI, 0.98-1.82, respectively) in multivariate models. Prior claim for a fall-related injury also independently predicted future fall-related injuries (IRR, 1.41; 95% CI, 1.05-1.89), after adjusting for patient demographics and screening item response.

DISCUSSION

Taking the perspective of a health plan, we developed a model to identify patients at high risk for future fall-related injuries using a combination of administrative data and response to a simple single-question screening item that could be administered by mail or phone. The largest gains in prediction were seen with the addition of Elixhauser comorbidity count and response to the single-item screening question, "Have you fallen 2 or more times in the past year?" Adding the response to, "Have you fallen and hurt yourself since your last visit to the doctor?" to the model did not improve the model's ability to predict fall-related injuries. These findings are consistent with prior work showing that a history of multiple prior falls is a strong predictor of future falls.[5,22] In contrast, fear of falling added little to the regression modelling. This finding is similar to other multivariate analyses,[5] where fear of falling was a weakly positive predictor of future falls.

Practical Implications

These findings have practical implications for insurers seeking to identify those members at highest fall risk. Using plan administrative data and a one-item screener, health plans have the ability to use similar models

Table 3. Sequential Models for Predicting Fall-Related Injuries

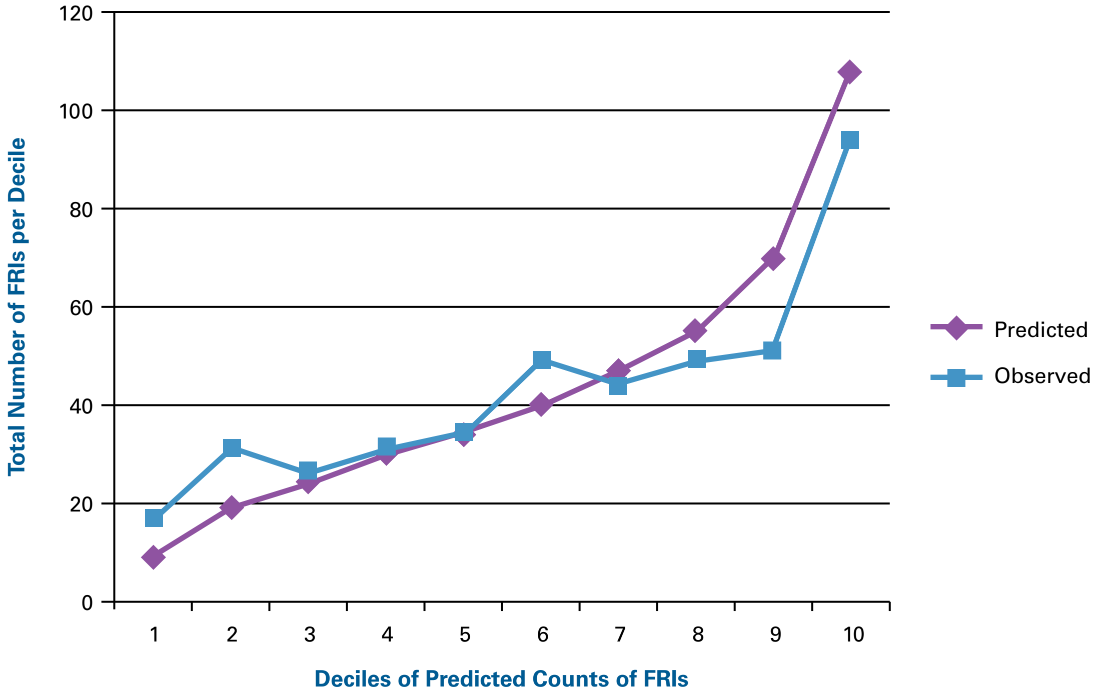
Model	IRR (95% CI)	AIC[a]	Change in AIC
Base model (age, gender)		2156.4	
Age (per additional 5 years)	1.22 (1.10-1.34)[b]		
Female gender	1.11 (0.87-1.43)		
1) Base + comorbidity count		2133.7	–22.7[c]
Elixhauser score (per additional comorbidity)	1.13 (1.08-1.18)[b]		
Age	1.22 (1.10-1.34)[b]		
Female gender	1.16 (0.90-1.48)		
2) Base + comorbidity count + prior FRI		2126.1	–7.6[d]
Claim for FRI in 12 months prior to screening	1.60 (1.20-2.13)[b]		
Elixhauser score	1.11 (1.06-1.16)[b]		
Age	1.22 (1.10-1.34)[b]		
Female gender	1.13 (0.88-1.45)		
3) Base + comorbidity count + Screening Question		2115.4	–18.3[d]
≥2 falls in the past year[e]	1.64 (1.32-2.03)[b]		
Elixhauser score	1.12 (1.07-1.17)[b]		
Age	1.22 (1.10-1.34)[b]		
Female gender	1.20 (0.94-1.54)		
4) Base + comorbidity count + screening question + prior FRI		2112.3	–3.1[f]
≥2 falls in the past year[e]	1.56 (1.25-1.94)[b]		
Claim for FRI in 12 months prior to screening	1.41 (1.05-1.89)[b]		
Elixhauser score	1.10 (1.05-1.15)[b]		
Age	1.22 (1.10-1.34)[b]		
Female gender	1.18 (0.92-1.51)		

AIC indicates Akaike information criterion; FRI, fall-related injury; IRR, incidence rate ratio.
[a]AIC is a likelihood measure in which lower values indicate better fit and a penalty is paid for increasing the number of variables in the model.[17]
[b]$P < .05$.
[c]Screening question, "Have you fallen 2 or more times in the past 12 months?"
[d]Change in AIC from base model.
[e]Change in AIC from model 1.
[f]Change in AIC from model 3.
All models also adjusted with study site, intervention group, and a dichotomous variable for presence of missing claims data in the 12 months prior to screening date.

to identify those at highest risk of fall-related injuries. While other multivariate models predicting fall risk exist,[5-7] our approach is novel in that we identify those at highest risk using available administrative data and without requiring a face-to-face office visit. We used age, gender, and Elixhauser comorbidity count to adjust for patient demographics and global disease burden in our models; however, health plans could use other conceptually similar markers of disease burden, such as the CMS Hierarchical Condition Categories (HCC) risk score, which uses age, gender, prior year diagnoses from Medicare claims, Medicaid dual eligibility, disability status, and institutionalization to risk-adjust Medicare program payments.[23] Although a prior claim for a fall-related injury independently predicted a future incident, including this variable only modestly improved model fit and also would require a health plan to undertake operationalizing a claims-based algorithm for determining fall-related injuries. There are several different ways a health plan could use this combination of administrative and questionnaire data to target fall-prevention interventions. Multifactorial falls reduction programs that include physical therapy designed to reduce fall risk[24] could be directly offered to those members at highest risk. Alternatively, a fall-risk profile could be provided to the primary care provider to alert him or her that the patient may need further evaluation or a more individualized intervention to prevent future falls.

How a health plan chooses to implement screening for fall risk also depends in part on the available resources ded-

■ **Figure.** Predicted vs Observed Fall-Related Injuries by Decile



FRI indicates fall-related injury.
Predicted and observed counts calculated using final model that includes age, gender, Elixhauser comorbidity count, screening question (≥2 falls in the past year), and prior claim for fall-related injuries (Model 4 in Table 3).

icated to screening and implementation of prevention activities. While contacting patients individually to ask about prior history of falls is more time- and resource-consuming than using administrative data alone, the responses to this screening question also more accurately identify those likely to utilize healthcare services for falls or fall-related injuries. Alternatively, a model that uses administrative data entirely—particularly one that includes a measure of global disease burden—can still reasonably identify those at risk for future fall-related injuries, but would encompass a broader population including those at lower risk.

Strengths and Limitations

This study has strengths and limitations. Our cohort is limited to screen-positive participants 75 years or older; thus, our models were fitted on a group at higher risk for fall-related injuries than the general Medicare patient population. It is possible that our model will be less accurate when applied to a geriatric population with a broader spectrum of fall risk. However, the study cohort is also an otherwise unselected patient population as the original study was a pragmatic trial. Participants did not need to be consented to participate since this study was part of a larger quality improvement intervention. Participants were screened in a clinic setting, not as part of a research protocol, and there were no other exclusion criteria, making our study sample highly generalizable to high-risk community-dwelling older adults.

We used inpatient and outpatient claims to identify falls and fall-related injuries. Although many falls do not result in medical attention, and thus will not be captured in claims data, our claims-based outcome identified the falls that resulted in healthcare utilization. These falls are more likely to be associated with poor outcomes for patients and high costs for insurers, making this outcome highly relevant for health plans.

We also lack additional clinical information that may affect fall-related injuries, particularly information about osteoporosis, which is poorly coded in claims,[25] and use of medications that increase fall risk. Our claims-based outcome has also not been validated with medical record review, but is a pragmatic, clinically relevant, and thorough approach that is feasible for a health plan to recreate using its own administrative data.

Table 4. Predicted Fall-Related Injuries for an 85-Year-Old Female

Patient Characteristics			Predicted Number of FRIs (95% CI)[a]
Number of comorbid conditions	Prior claim for FRI	Screen for ≥2 falls[b]	
0	No	Negative	0.15 (0.12-0.19)
3	No	Negative	0.21 (0.18-0.24)
3	Yes	Negative	0.29 (0.20-0.38)
3	Yes	Positive	0.45 (0.33-0.58)
6	Yes	Positive	0.61 (0.44-0.78)

FRI indicates fall-related injury.
[a]Number of fall-related injuries predicted over 2 years.
[b]Screening question, "Have you fallen 2 or more times in the past 12 months?"

CONCLUSIONS

Using a simple falls screening question and routine administrative data, we were able to predict fall-related injuries in a sample of Medicare enrollees from 4 medical groups across the country. This combination of questionnaire and administrative data can be used to target fall prevention interventions to health plan members at highest risk for future fall-related injuries. Prospective studies of this approach within health plans will be needed to determine its ultimate clinical value.

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eAppendix 1

Table 1. Comparison of Models Predicting Fall-Related Injuries Using AIC and BIC

Model	**AIC[a]**	**Change in AIC**	**BIC[b]**	**Change in BIC**
Base model (age, gender)	2156.4		–11088.0	
1) Base + Elixhauser comorbidity count	2133.7	–22.7[c]	–11099.7	–11.7[c]
2) Base + Elixhauser comorbidity count + prior FRI	2126.1	–7.6[d]	–11101.8	–2.1[d]
3) Base + Elixhauser comorbidity count + screening question	2115.4	–18.3[d]	–11112.5	–12.8[d]
4) Base + Elixhauser comorbidity count + screening question + prior FRI	2112.3	–3.1[e]	–11110.1	+2.4[e]

AIC indicates Akaike information criterion; BIC, Bayesian information criterion; FRI, fall-related injury.
[a]Akaike Information Criterion (AIC) is a likelihood measure in which lower values indicate better fit and a penalty is paid for increasing the number of variables in the model.[1]
[b]Bayesian Information Criterion (BIC) is a likelihood measure in which lower values indicate better fit, and a stronger penalty is paid for increasing the model parameters than with AIC.[2]
[c]Change in AIC or BIC from the base model.
[d]Change in AIC or BIC from model 1.
[e]Change in AIC or BIC from model 3.

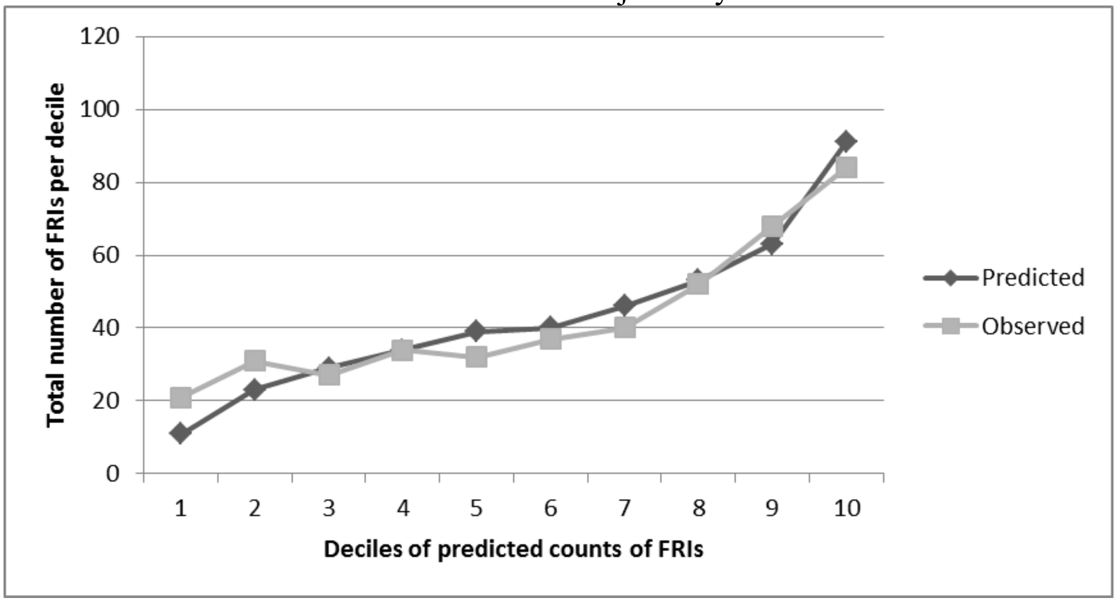
Table 2. Comparison of Models Predicting Fall-Related Injuries by Relative Likelihood of Better Fit

Model	**AIC[a]**	**Change in AIC**	**Relative Likelihood of Better Fit[b]**
Base	2156.4		
1	2133.7	–22.7[c]	0.00001 (base model compared with model 1)
2	2126.1	–7.6[d]	0.02 (model 1 compared with model 2)
3	2115.4	–18.3[d]	0.0001 (model 1 compared with model 3)
4	2112.3	–3.1[e]	0.21 (model 3 compared with model 4)

AIC indicates Akaike information criterion; FRI, fall-related injury.
[a]Akaike Information Criterion (AIC) is a likelihood measure in which lower values indicate better fit and a penalty is paid for increasing the number of variables in the model.[1]
[b]Relative likelihood of better fit of the model = $\exp((AIC_{min} - AIC)/2)$ where AIC_{min} is the minimum AIC.[3]
[c]Change in AIC from base model.
[d]Change in AIC from model 1.
[e]Change in AIC from model 3.

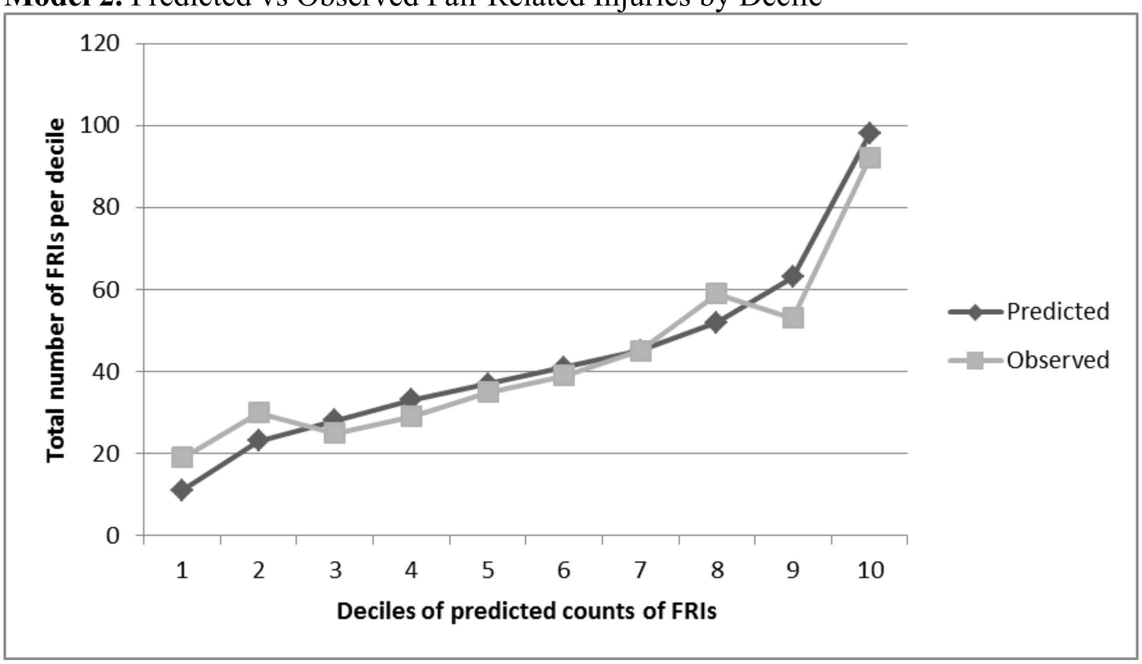
eAppendix 2

Model 1. Predicted vs Observed Fall-Related Injuries by Decile



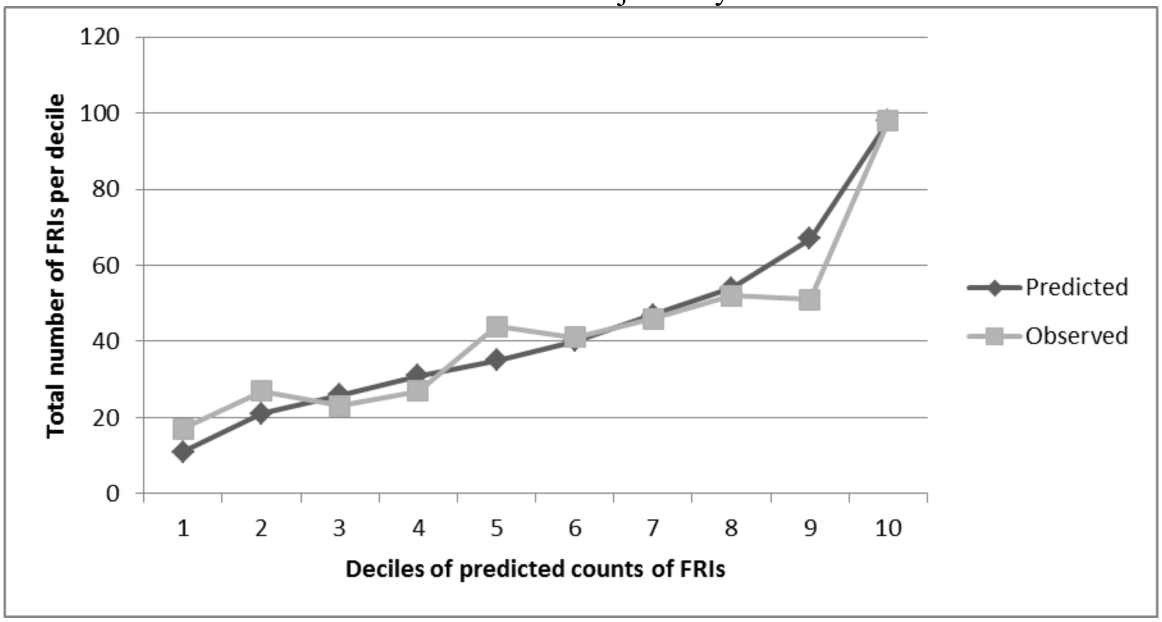
FRI indicates fall-related injury.
Predicted and observed counts calculated using model that includes age, gender, and Elixhauser comorbidity count (Model 1 in Table 3).

Model 2. Predicted vs Observed Fall-Related Injuries by Decile



FRI indicates fall-related injury.
Predicted and observed counts calculated using model that includes age, gender, Elixhauser comorbidity count, and prior claim for FRI (Model 2 in Table 3).

Model 3. Predicted vs Observed Fall-Related Injuries by Decile



FRI indicates fall-related injury.
Predicted and observed counts calculated using model that includes age, gender, Elixhauser comorbidity count, and screening question (≥2 falls in the past year) (Model 3 in Table 3).

Table 3. Comparison of Observed vs Predicted Fall-Related Injuries by Model

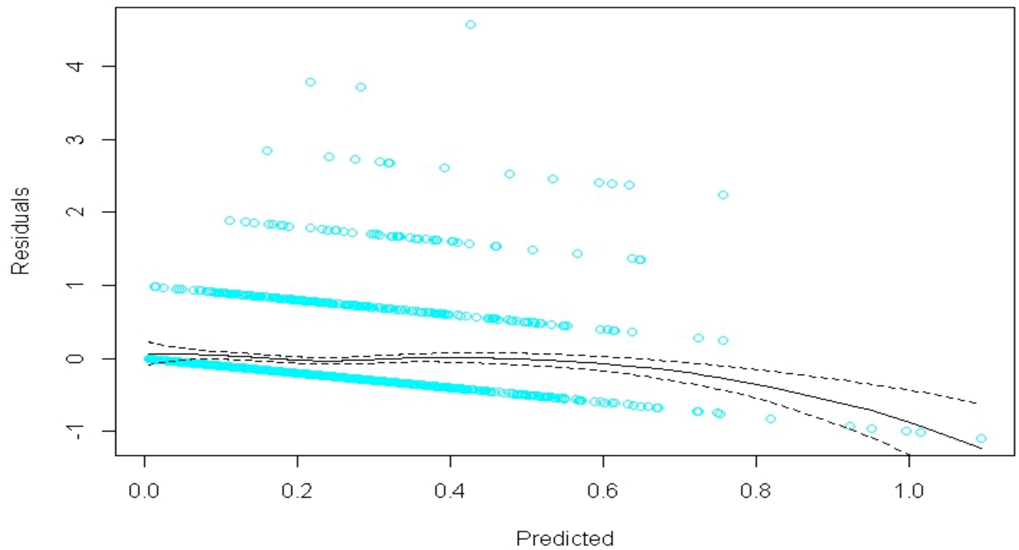
Model		**Hosmer-Lemeshow χ^2 Test Statistics**	***P***
1	Base (age, gender) + comorbidity count	15.25	.05
2	Base + comorbidity count + prior FRI	12.41	.13
3	Base + comorbidity count + screening question	12.43	.13
4	Base + comorbidity count + screening question + prior FRI	18.74	.02

Graphically, observed and predicted fall-related injuries are similar in all models. Significant or near-significant Hosmer-Lemeshow test statistics for Models 1 and 4 may be in part related to large sample size.[4]

eAppendix 3

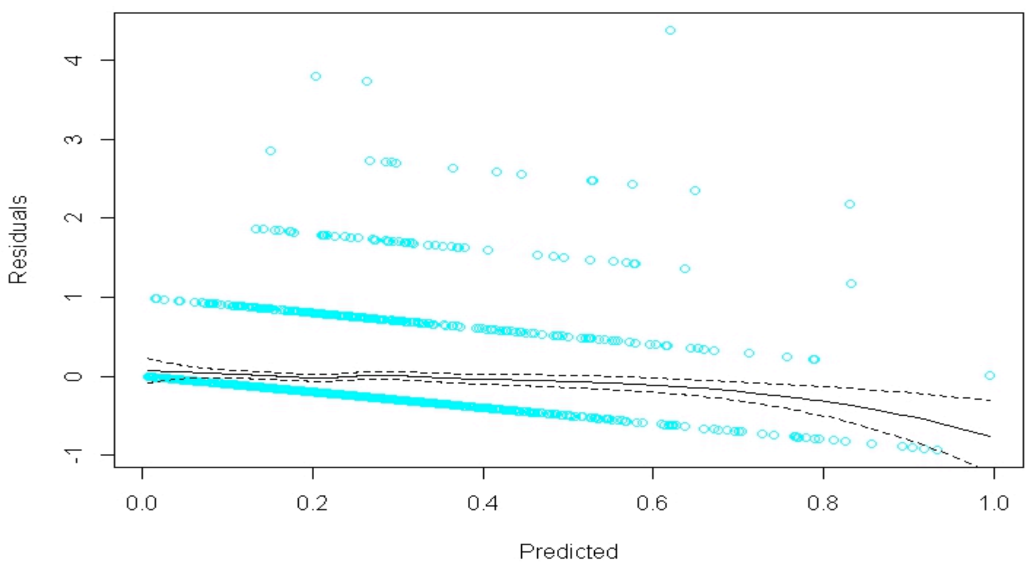
The eAppendix Figures show scatter plots of residual values versus predicted fall-related injuries for individual patients (blue circles) as well as locally weighted polynomial regression (LOESS) smoothing curves (solid black lines) with 95% CIs (dashed lines) for each model.[5] For all models, the LOESS curves show residuals centered around 0 except for the few subjects with high predicted values.

Model 1



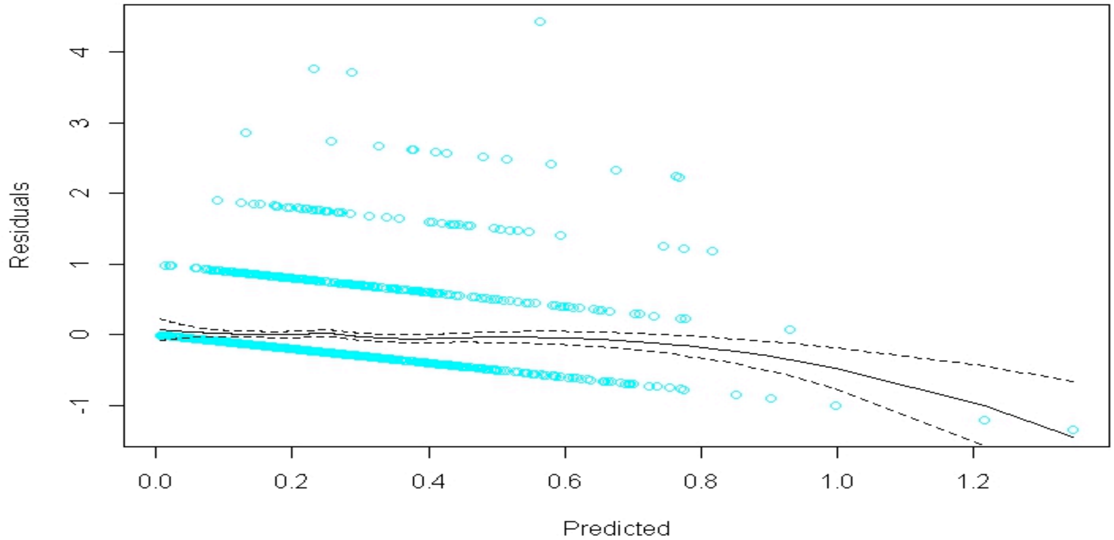
Predicted counts and residuals calculated using model that includes age, gender, and Elixhauser comorbidity count (Model 1 in Table 3).

Model 2



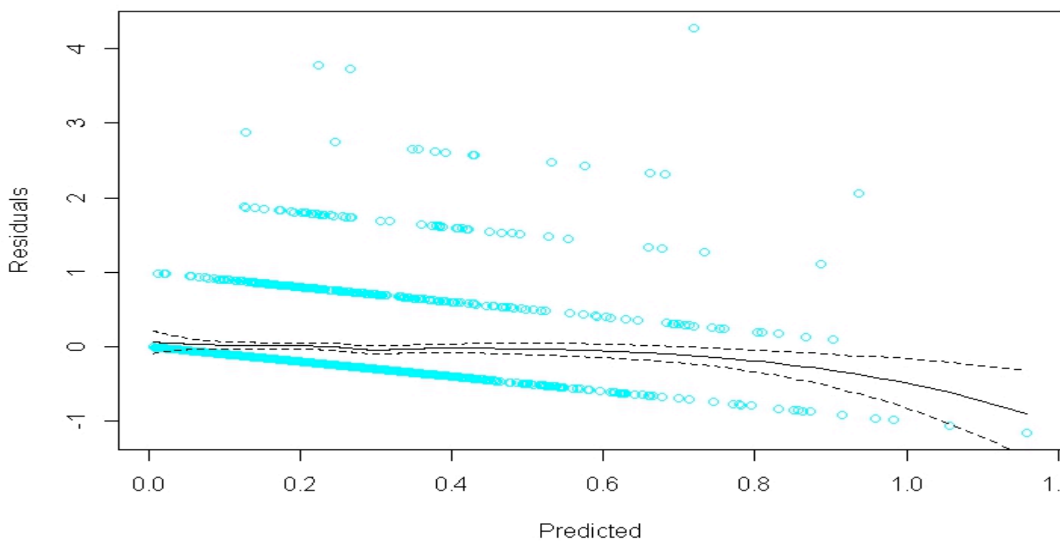
Predicted counts and residuals calculated using model that includes age, gender, Elixhauser comorbidity count, and prior claim for fall-related injury (Model 2 in Table 3).

Model 3



Predicted counts and residuals calculated using model that includes age, gender, Elixhauser comorbidity count, and screening question (≥2 falls in the past year) (Model 3 in Table 3).

Model 4



Predicted counts and residuals calculated using model that includes age, gender, Elixhauser comorbidity count, screening question (≥2 falls in the past year), and prior claim for fall-related injury (Model 4 in Table 3).

eAPPENDIX REFERENCES

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3. Burnham KP, Anderson DR. *Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach*. 2nd ed. New York, NY: Springer-Verlag; 2003.

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