Functional Status and Readmissions in Unilateral Hip Fractures

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ABSTRACT

Objectives: To test whether functional status is a robust predictor of acute care readmission risk in patients who have been discharged to an inpatient rehabilitation facility (IRF) following a unilateral hip fracture.

Study Design: Retrospective database study using a large administrative data set.

Methods: A retrospective analysis of data from the Uniform Data System for Medical Rehabilitation from the years 2002 to 2011 was performed, examining patients with an impairment of unilateral hip fracture. A basic prediction model based on functional status was compared with competing models incorporating medical comorbidities. C statistics were compared to evaluate model performance.

Results: There were a total of 433,154 patients: 32,783 (7.87%) patients were transferred back to an acute hospital, including 7937 (1.91%) transferred within 3 days, 16,150 (3.88%) transferred within 7 days, and 32,607 (7.83%) transferred within 30 days after IRF admission. The C statistics for the Basic Model are 0.710, 0.674, and 0.667 at days 3, 7, and 30, respectively. Compared with the Basic Model, the best performing Basic-Plus model was the Basic + Elixhauser Model with C statistic differences of +0.013, +0.014, and +0.019, and the best performing Age-Comorbidity Model was the Age + Elixhauser Model with C statistic differences of –0.110, –0.079, and –0.065 at days 3, 7, and 30, respectively.

Conclusions: Functional status is a robust and potentially modifiable risk factor for patients admitted to IRFs following a unilateral hip fracture.

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Hip fracture is a significant source of morbidity and mortality in older adults.[1-4] Recent epidemiological studies among Medicare beneficiaries have shown that hospital lengths of stay for patients with hip fractures have been decreasing in recent years, yet there has been a rise in the average comorbidity burden among this population[1] in diagnoses such as congestive heart failure,[1] which has been identified by CMS as a high-volume diagnosis for which the 30-day readmission rate may result in hospital payment penalties of 1% to 3% payment reduction.[5]

Significant research in recent years has been devoted to identifying patients who are at risk for an acute care readmission,[6] but despite this attention, the rate of readmissions has remained relatively unchanged, suggesting that this research has not resulted in actionable information that clinicians can use to reduce this rate.[7] This may be partly because studies have tended to repeatedly examine the same risk factors, such as medical comorbidities, which is the most often included risk factor in readmission prediction models[6] and also not modifiable. Conversely, many risk factors that are potentially modifiable have not been studied, such as functional status, which has been shown to be predictive of acute care readmissions in the burn and stroke populations,[8-10] despite it being one of the least studied predictors.[6]

Another limitation of prior readmissions work is that the populations of interest tend to not be well defined. For example, 30-day readmission rates have been commonly examined,[6] probably because 30 days is the time frame used by CMS. However, patients may return to the hospital within a much shorter time frame, such as a week or even a few days; these "bouncebacks" are likely a distinct population from patients who take almost a month to return to the hospital. Additionally, following hospitalization, patients may be discharged to markedly different and distinct levels of care, ranging from self-care at home to post acute care environments with around-the-clock nursing and possibly even daily physician visits. Among patients who have had a hip fracture, about 90% are discharged from an acute care hospital to a post acute care facility—about 20% of whom are transferred to an acute inpatient rehabilitation facility (IRF) from the hospital.[11]

Take-Away Points

- A high volume of previously published readmissions research has had little impact on readmission rates.
- Hospital readmission rates, risk-adjusted for demographic and medical characteristics of patients, are being monitored by health policy makers with planned financial penalties for hospitals with high readmission rates.
- Functional status, a risk factor not currently routinely in use by hospitals or CMS' risk adjustment models, is an important risk factor for an acute care readmission in patients who have had a unilateral hip fracture.

In this study, we sought to examine the role of functional status as a predictor of acute care readmissions in the unilateral hip fracture population at IRFs within multiple time windows of IRF admission (3, 7, and 30 days). There are no large-scale prior studies examining risk factors for readmissions in this population, but based on research in other populations[8-10,12] and a much smaller study that included orthopedic patients in general,[13] we hypothesized that functional status as measured by the FIM instrument—a proxy measure for the burden of care[14-18]—can be used to create relatively simple and strong models for predicting the risk of acute care readmissions in the unilateral hip fracture population at IRFs.

METHODS

We analyzed data from the Uniform Data System for Medical Rehabilitation (UDSMR), a data repository of IRF patients discharged from 2002 to 2011, which contains demographic, functional, medical, and facility data from approximately 70% of the IRFs in the United States. This data is routinely collected as part of the IRF Patient Assessment Instrument, as required by CMS. Inclusion criteria were for the subject to be 18 years or older with an impairment code of unilateral hip fracture and admission to IRF. Subjects were excluded if they were not transferred directly from acute care to an IRF, if they died at the IRF, or if they came from a zero-onset facility.[19] The primary outcome variable in this study was the probability of a discharge from the IRF to an acute care hospital.

The FIM instrument ("FIM"), a valid and reliable tool for assessing functional status in the IRF setting,[20-25] has 2 components: motor and cognitive. The motor domain, which was used in this study, consists of 13 items, including eating, dressing, grooming, bathing, toileting, sphincter control, bowel and bladder management, transfers, and locomotion. It is typically administered to patients by a combination of nursing and therapy staff. Each item is rated with a 7-level ordinal scale from completely dependent (1) to independent (7), with a FIM motor total score range of 13 to 91.

The UDSMR data was analyzed using Stata version 12.1 (StataCorp, College Station, Texas). Logistic regression analysis was used to create all models. We first developed models based on functional status, called "Basic Models," which included the Basic Model and Basic-Plus Models. The Basic Model used 2 predictors—FIM motor score and gender—and the odds of transfer to an acute care hospital was the dependent variable. Next, we compared the performance of the Basic Model with models that added comorbidity data (the Basic-Plus Models) and with models that included only gender and comorbidities (Gender-Comorbidity Models). Comorbidities are the most often included predictor in hospital readmission models, which is why models incorporating comorbidities were selected for comparison with the Basic Models. Three different comorbidity scoring systems were used in the analysis: the Elixhauser comorbidity index,[26,27] the Deyo-Charlson comorbidity index,[28,29] and the Medicare comorbidity tier system.[30,31] Consequently, we developed 3 Basic-Plus Models and 3 Gender-Comorbidity Models. See Table 1 for a description of the predictors incorporated into each of the 7 models. For each model, we investigated performance at 3 days, 7 days, and 30 days into the rehabilitation stay. Thus, there were a total of 18 comparisons of the Basic Model with competing models incorporating comorbidity data (ie, 18 opportunities to reject our hypothesis). Generalizability of the models was tested with bootstrap resampling using 1000 samples rather than single subsample cross-validation. Model predictive ability was assessed using the C statistic for each model.

We hypothesized that the Basic Model would perform similarly to the Basic-Plus Models and better than the Gender-Comorbidity Models at all 3 time points. The area under the receiver operator curve (C statistic) was used to test model performance. A C statistic of 0.5 indicates that a model predicts an outcome no better than random chance, and a C statistic of 1 indicates a model has perfect discrimination. There are no established guidelines for the interpretation of C statistics, but the original readmission prediction models for CMS had C statistics

Table 1. Logistic Regression Models

Basic Model	Sex, FIM motor score
Basic + Elixhauser	Sex, FIM motor score, 29 Elixhauser index comorbidities
Basic + Deyo	Sex, FIM motor score, 2 Deyo-Charlson comorbidity index sum scores[a]
Basic + CMS Tiers	Sex, FIM motor score, CMS comorbidity tier classification
Gender + Elixhauser	Sex, 29 Elixhauser index comorbidities
Gender + Deyo	Sex, 2 Deyo-Charlson comorbidity index sum scores[a]
Gender + CMS Tiers	Sex, CMS comorbidity tier classification

FIM indicates Functional Independence Measure.
[a]Deyo-Charlson comorbidity index sum scores are calculated as follows: The first sum score is based on the total of a patient's comorbidities that are on the Deyo-Charlson index. The second sum score is a patient's total points from the Charlson index.

in the range of 0.605 to 0.676[32]—similar to most readmission risk models published in the medical literature.[6] We preselected a C statistic difference of 0.05 as a clinically meaningful difference in model discrimination ability. If any Basic-Plus Model met this C statistic threshold at any time point, it would be considered evidence opposed to our hypothesis. Likewise, any failure of the Basic Model to outperform any of the Gender-Comorbidity Models by at least +0.05 would be considered evidence against our hypothesis.

RESULTS

Patient Characteristics

The UDSMR database included 433,154 adult patients with unilateral hip fractures admitted for at least 1 night between 2002 and 2011. We excluded 10,133 patients who were not admitted to inpatient rehabilitation directly from an acute hospital; 626 patients who died in rehabilitation; and 5791 who were from zero-onset facilities. The final sample size was 416,604 patients from 1127 IRFs. Of these, 32,783 (7.87%) patients were transferred back to an acute hospital: they included 7937 (1.91%) transferred within 3 days, 16,150 (3.88%) transferred within 7 days, and 32,607 (7.83%) transferred within 30 days after IRF admission. Table 2 shows the study population's demographic, medical, and facility data.

Regression Model Results

The coefficients for the logistic regressions of the Basic Model at each time point are shown in Table 3. Table 4 shows the C statistics for each model at each time point. The C statistics for the Basic Model are: 0.710, 0.674, and 0.667 at days 3, 7, and 30, respectively. The Basic-Plus Model C statistics were marginally better at each time point, though not by the threshold of 0.05 that was chosen a priori to establish superiority. The best performing comparison model was the Basic + Elixhauser Model at 3 days, which with a C statistic of 0.723, was only 0.013 greater than that of the Basic Model at this same time point. The Basic Model performed substantially better than the 3 Gender-Comorbidity Models at each time point. The best performing Gender-Comorbidity Model was the 30-day Gender + Elixhauser Model with a C statistic of 0.602, which was 0.065 lower than the 30-day Basic Model.

DISCUSSION

This study provides evidence that functional status can be used to create a robust readmission prediction model, and that models based on functional status outperform those based on comorbidity data in the unilateral hip fracture population admitted to an IRF. This study is unique not only because there are no other large-scale studies examining readmission risk factors in this particular patient population, but also because it relied on functional status, compared the functional status model with models based on medical comorbidities, and did this in multiple time frames following acute care discharge. The C statistics of the models based on functional status are as good or better than many of the previously published readmission models.[6] While we do not have a method to study the reason that functional status predicts readmission risk, we suspect that it is at least in part because functional status is a proxy measure for health, and a better proxy measure than an enumeration of comorbidities alone.

One of the most recent studies examining readmission risks with one of the better predictive models found that comorbidities were not a significant predictor of readmission risk, and posited that this is because it is severity rather than presence of comorbidities that is important,[33] a supposition that the findings in this study support. Our results are also consistent with prior research on readmission risk in the burn and stroke populations.[8-10,12] Sicker patients are likely more disabled, and functional status as measured by the FIM instrument has been shown to be strongly related to the total hours of burden of care a patient requires.[15] The findings in this study suggest both a novel approach to the clinical management and stratification of readmission risk, and a novel approach to adjusting readmission rates in CMS's assessment of hospital quality.

Our findings suggest that clinicians may be able to reduce readmission rates using efforts aimed at improving functional independence even while the patient is at an acute care facility, an approach that has been shown to improve outcomes in critical care patients and improve hospital financial operating margins.[34-41] Such a functional status improvement effort could include not only more intensive physical and occupational therapy, but also standardized protocols to ensure consistent assessments of pain and its impact on therapy participation, nutritional optimization, and efforts designed to regulate sleep/wake cycles. Such an approach would be complementary to previously studied readmission prevention efforts such as close physician follow-up[42] or a specialized case management program.[43] These previously studied readmission prevention efforts have attempted to reduce readmission rates by providing more personalized care to high-risk patients, something that is likely also important in hip fracture patients in an IRF.

In addition to clinical implications, this study also has important health policy implications. New federal policy initiatives, such as penalizing hospitals for readmissions, assume that statistical models can effectively adjust readmission rates for the level of readmission risk associated with particular patients. Without such models, hospitals may be unfairly penalized for providing care to high-risk patients. This presents a significant problem for healthcare facilities given that federal policy initiatives with financial penalties based on risk-adjusted readmission rates are moving forward without regard for whether or not the statistical models needed to effectively risk-adjust a hospital's readmission rate have yet been developed. However, like most published readmission models, the risk adjustment algorithms that have been developed are based largely on age and comorbidity data.[32]

To our knowledge, a specific hip fracture readmission model has not been developed for use by Medicare in adjusting hospital readmission rates; the closest similar population for which a particular model has been published by CMS is the total hip and knee arthroplasty population.[44] This readmission risk adjustment model has 33 predictor variables and a C statistic of 0.65, compared with our Basic Model, which has only 2 predictors

Table 2. Patient Characteristics

Number of subjects	416,604
Number of facilities	1127
Age, mean years (SD)	78.2 (11.05)
Male, number (%)	120,458 (28.91%)
Race/ethnicity, number (%)	
Caucasian	365,896 (89.36%)
African American	17,184 (4.20%)
Latino/Hispanic	18,031 (4.40%)
Asian	4857 (1.19%)
American Indian/Alaskan	1491 (0.36%)
Hawaiian/Pacific Islander	1189 (0.29%)
Multi-racial	811 (0.20%)
Married, number (%)	162,493 (39.00%)
Living alone, number (%)	147,198 (35.33%)
Employed pre-injury, number (%)	22,124 (5.31%)
Primary payer source, number (%)	
Medicare	367,067 (88.11%)
Medicaid	6999 (1.68%)
Workers compensation	4533 (1.09%)
Unreimbursed	2865 (0.69%)
Commercial	30,939 (7.43%)
Other	4200 (1.01%)
Number of comorbidities, mean (SD)	7.64 (2.60)
Onset days, mean (SD)	6.96 (11.75)
Length of IRF stay, mean days (SD)	13.27 (5.84)
Operating beds, mean (SD)	44.16 (35.08)
FIM motor rating at admission, mean (SD)	36.41 (10.58)
FIM motor rating at discharge, mean (SD)	59.02 (15.19)
Discharge disposition, number (%)	
Community	293,478 (70.44%)
Acute facility	32,783 (7.87%)
Skilled nursing/subacute	85,015 (20.41%)
Other	5238 (1.28%)

FIM indicates Functional Independence Measure; IRF, inpatient rehabilitation facility.

and a C statistic of 0.667 (C statistic difference of 0.017) . Even the most complex model developed in this study for 30-day readmissions has only 31 predictors, the Basic + Elixhauser Model, and has a C statistic of 0.686, outperforming CMS's model by a C statistic margin of 0.036. This level of difference does not reach our threshold for clinically meaningful when used in assessing the risk for an individual patient, but if a readmission model is applied to hundreds or thousands of patients to estimate hospital-level performance, such a difference may be important.

The readmission risk models presented here may not be directly suitable for application for such a risk adjustment, given that they rely on data from a functional status measure readily available in IRFs but not in many

■ **Table 3.** Odds Ratios for the Basic Model

	3 days	7 days	30 days
Female gender	0.671 (0.640-0.703)	0.698 (0.675-0.722)	0.732 (0.714-0.750)
FIM motor score	0.928 (0.925-0.930)	0.942 (0.940-0.944)	0.945 (0.944-0.947)
Constant	0.021 (0.020-0.022)	0.047 (0.045-0.049)	0.098 (0.095-0.101)

FIM indicates Functional Independence Measure.
Odds ratios for the predictors in the Basic Model obtained from logistic regression. The constant represents the odds for a male with a FIM motor score of 35.
Data presented as coefficient (95% CI).

■ **Table 4.** C Statistics for Each Model

	Basic Model	Basic-Plus Models			Gender-Comorbidity Models		
	Gender + FIM	Basic + Elixhauser	Basic + Deyo	Basic + CMS Tiers	Gender + Elixhauser	Gender + Deyo	Gender + CMS Tiers
3 days	0.710	0.723	0.712	0.711	0.600	0.576	0.559
7 days	0.674	0.688	0.681	0.676	0.595	0.581	0.563
30 days	0.667	0.686	0.679	0.677	0.602	0.587	0.585

FIM indicates Functional Independence Measure.
See Table 1 for model descriptions.

acute care hospitals. However, simpler functional status measures designed for acute care facilities and based on the FIM instrument have been developed.[45,46]

Limitations

This study must be interpreted within the context of its limitations. The data used in this study were obtained from a large administrative database, with medical comorbidity data obtained from *International Classification of Diseases, Ninth Revision, Clinical Modification* codes rather than from a medical record review, which might allow the capture of more granular information. However, a study of a sample size this large would be almost impossible to carry out without the use of such a data source. Well-studied approaches specifically designed to handle comorbidity data obtained from large administrative data sets were used. Additionally, data regarding the management of hip fracture during the acute care stay were not available (eg, type of operation, postoperative complications), which may help to further risk-stratify patients. Finally, this study was conducted in patients transferred to an IRF following their acute care stay—a sizable minority of the hip fracture population, nearly 20%.[11] However, we are unable to be sure how well our findings generalize to the rest of the unilateral hip fracture population.

CONCLUSIONS

Functional status as measured by the FIM instrument motor domain is a relatively strong and potentially modifiable risk factor for acute care readmission from an IRF in the unilateral hip fracture population. Future research may help to inform whether rehabilitation efforts in the acute care setting are able to reduce readmission risks. Such lines of future research might include intervention-based studies in which therapeutic programs are geared towards early mobilization in the acute care setting, a strategy that has been shown to improve intensive care unit outcomes in critically ill patients.[40]

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