ORIGINAL ARTICLE

Impact of Comorbidities on Stroke Rehabilitation Outcomes: Does the Method Matter?

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ABSTRACT. Berlowitz DR, Hoenig H, Cowper DC, Duncan PW, Vogel WB. Impact of comorbidities on stroke rehabilitation outcomes: does the method matter? Arch Phys Med Rehabil 2008;89:1903-6.

Objectives: To examine the impact of comorbidities in predicting stroke rehabilitation outcomes and to examine differences among 3 commonly used comorbidity measures—the Charlson Index, adjusted clinical groups (ACGs), and diagnosis cost groups (DCGs)—in how well they predict these outcomes.

Design: Inception cohort of patients followed for 6 months.

Setting: Department of Veterans Affairs (VA) hospitals.

Participants: A total of 2402 patients beginning stroke rehabilitation at a VA facility in 2001 and included in the Integrated Stroke Outcomes Database.

Interventions: Not applicable.

Main Outcome Measures: Three outcomes were evaluated: 6-month mortality, 6-month rehospitalization, and change in FIM score.

Results: During 6 months of follow-up, 27.6% of patients were rehospitalized and 8.6% died. The mean FIM score increased an average of 20 points during rehabilitation. Addition of comorbidities to the age and sex models improved their performance in predicting these outcomes based on changes in c statistics for logistic and R^2 values for linear regression models. While ACG and DCG models performed similarly, the best models, based on DCGs, had a c statistic of .74 for 6-month mortality and .63 for 6-month rehospitalization, and an R^2 of .111 for change in FIM score.

Conclusions: Comorbidities are important predictors of stroke rehabilitation outcomes. How they are classified has important implications for models that may be used in assessing quality of care.

Key Words: Cerebrovascular accident; Comorbidity; Rehabilitation; Risk adjustment.

THE IMPORTANCE OF monitoring outcomes of stroke rehabilitation is increasingly recognized.[1] As purchasers and consumers seek to maximize the effectiveness and value of care, outcomes assessments are being used for a variety of purposes, including describing quality of care,[2] comparing different venues or models of care such as traditional Medicare versus managed care,[3,4] and examining temporal trends in care.[5] When examining such outcomes, baseline characteristics of patients that may affect the outcomes of interest, such as acute illness severity, comorbidities, functional status, and age, must be considered, typically through the process of risk adjustment.[6,7] This adjustment helps ensure that differences in outcomes reflect the care provided and not the underlying baseline characteristics, or illness severity, of the patients. Developing better approaches to risk adjustment are essential to understanding rehabilitation outcomes and maximizing care.

When performing risk adjustment, comorbidities are often an important consideration. However, studies of stroke rehabilitation outcomes often have not considered such comorbidities[8] or have not found them to be important predictors of the outcomes.[9,10] When comorbidities have been used, there has been no consensus on the approach to use, resulting in a wide variety of different approaches, including counts of the number of comorbidities,[5] the Charlson Index,[2] grouping comorbidities into 3 tiers based on costliness of care,[4] or using comorbidities in the Elixhauser index[11] as individual explanatory variables.[3,12] In recent years, a variety of different systems for describing the comorbidity burden have been developed and are being used widely in health services research. These systems vary in their basic approach to classifying comorbid diseases and in the weights that they may assign. The extent that these systems differentially impact predictions of stroke rehabilitation outcomes remains uncertain.

We examine the impact of comorbidities on predicting stroke rehabilitation outcomes. We consider 3 different outcomes measures that have been used frequently in past research: 6-month mortality, 6-month rehospitalization, and change in FIM score.[13] We also consider 3 different methods for describing comorbidities: the Charlson Index,[14] ACGs,[15] and DCGs.[16] We selected these 3 approaches because they are widely used, they are available as pre-existing packages that can be readily used with databases incorporating ICD-9-CM codes, and they are likely to be used by researchers in future studies.

We address the following 3 questions. First, do measures of comorbidity improve predictions of stroke rehabilitation out-

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List of Abbreviations

ACG	adjusted clinical group
CI	confidence interval
DCG	diagnosis cost group
ICD-9-CM	*International Classification of Diseases, Ninth Revision, Clinical Modification*
ISOD	Integrated Stroke Outcomes Database
VA	Veterans Affairs

comes compared with models that consider only age and sex? Second, are there differences among the 3 comorbidity measures in how well they predict these outcomes? Third, do comorbidity measures appear to be more important in predicting medical outcomes such as mortality and rehospitalization than functional outcomes such as change in FIM score? In addressing these questions, we provide information that is useful in improving outcomes measurement for stroke rehabilitation.

METHODS

Study Sample and Database

Our study sample consisted of patients beginning stroke rehabilitation in an inpatient setting at a VA medical center in 2001. Patients were identified through their presence in the VA ISOD.[17] The ISOD is a collection of VA clinical and administrative data on patients identified by a clinician as having a stroke, thus avoiding issues with the validity of ICD-9-CM stroke codes, and evaluated with the FIM. Included in the ISOD are FIM data from the Functional Status Outcomes Database, demographics, health care utilization, inpatient and outpatient diagnostic data from the National Patient Care Database, mortality data from the Beneficiary Identification and Records Locator Subsystem, pharmacy data from the Pharmacy Benefits Management database, and health status in the form of the Veterans RAND 36-Item Health Survey collected as part of the Large Survey of Veterans. We supplemented the ISOD with data from its component databases to ensure that information on diagnoses and outcomes included the entire period of interest. A number of studies have supported the reliability and validity of the component databases used in creating the ISOD, particularly the diagnostic data used in describing comorbidity.[18,19]

Outcome Measures

We evaluated 3 different outcome measures. First, we considered 6-month mortality. Second, we evaluated 6-month rehospitalization. Rehospitalization was considered present when a patient was readmitted to an acute medical-surgical unit after initiation of rehabilitation. Thus, rehospitalization could occur only after a patient was discharged home or transferred to a rehabilitation or long-term care unit. We only considered events occurring after 3 days of either initiating rehabilitation (for mortality) or of transfer to a rehabilitation or long-term care unit (for rehospitalization). This acknowledges the fact that serious events, such as venous thromboembolism in a patient with hemiplegia, occurring shortly after initiation of rehabilitation or transfer out of an acute medical-surgical unit are unlikely to reflect the quality of rehabilitation care. Longer-term, though, one would expect the rehabilitation team to ensure appropriate care measures such as receipt of anticoagulation when indicated. Our final outcome measure was change in FIM score from the initiation of rehabilitation to its completion. The FIM is an 18-item instrument that captures aspects of motor and cognitive function. Each item is scored on a 7-point ordinal scale, with a 7 indicating independence, so that the maximum possible score is 126. Change in FIM was operationalized as discharge FIM minus admission FIM. One study has suggested that a change in FIM score of 22 represents a clinically important difference in patients with stroke receiving inpatient rehabilitation.[20] Because of the different ways that outcomes were determined, the number of patients in each sample differed slightly. For example, patients without a discharge FIM score could not contribute an observation to the change in FIM score but would be considered for mortality and rehospitalization.

Measures of Comorbidity

We used 3 different measures of comorbidity that vary in how they conceptualize this construct. The Charlson Index consists of a weighted count of 17 serious medical conditions that was originally developed to predict 1-year mortality among hospitalized patients but has since been widely used in health services research.[14] We operationalized the Charlson Index using the Deyo modification that assigns specific ICD-9-CM codes to each diagnosis.[21]

ACGs were originally developed to predict ambulatory care visits among patients of health maintenance organizations but have since been widely used to describe the extent of medical problems and their likely effects on health care resource use.[15] Each ICD-9-CM code for a patient is assigned to 1 of 32 mutually exclusive adjusted diagnosis groups that groups diagnoses based on their similarity on a number of characteristics including expected persistence of the condition, likelihood of requiring hospitalization, or need for specialty referral. Examples of adjusted diagnosis groups are chronic medical unstable conditions and psychosocial recurrent or persistent stable conditions. Based on age, sex, and the number and pattern of adjusted diagnosis groups, each patient is then assigned to 1 of 93 different ACGs. We used ACG, version 6.0,[a] in these analyses.

DCGs were originally developed to predict future costs for Medicare beneficiaries.[16] Each ICD-9-CM code is first grouped into diagnostic clusters of clinically related disorders. Clusters are subsequently grouped into hierarchical condition categories that consider the severity and expected costliness of related disorders. Examples of hierarchies are congestive heart failure and diabetes mellitus with chronic complications. Hierarchies may be further clustered into aggregated condition categories. We used DxCG, release 6.0,[b] in conducting the analyses.

For each measure of comorbidity, we considered different variations. For the Charlson Index, we evaluated both an unweighted count of conditions and a version incorporating the weights from the original publication. For ACGs and DCGs, we examined weighted versions using coefficients derived from other samples and settings as well as unweighted versions in which coefficients were determined by the regression model. We report results from the models with the best performance based on their c statistic or R^2. These were a weighted Charlson, an unweighted ACG model that uses individual adjusted diagnosis groups, and an unweighted DCG model that considers each individual aggregated condition category.

Data Analyses

We modeled each of the 3 outcome measures using a linear regression model for the change in FIM score and a logistic regression model for rehospitalization and mortality. While we followed usual practice in our analyses of change in FIM scores by using linear regression techniques, total FIM scores and differences in FIM scores are not linear equal-interval measures, and hence the assumptions underlying standard regression techniques are not fully met. For each outcome, we compared a model that included just age and sex as independent variables with a model that added information on comorbidity using 1 of the 3 case-mix systems. We evaluated the R^2 for linear regression models and the c statistic for logistic regression models. These analyses were performed using SAS.[c]

We created CIs for each c statistic and R^2 using a bootstrap method from Stata/SE version 9.2.[d] We randomly sampled cases