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Evaluating Comorbidity Indices for Predicting Post-Acute Outcomes

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Evaluating Comorbidity Indices for Predicting Post-Acute Outcomes

by

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Dedication

This dissertation is dedicated to aging populations living in developing countries and to my late grandparents, Ramshray Sharma and Anupa Sharma, for being my source of inspiration.

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Evaluating Comorbidity Indices for Predicting Post-Acute Outcomes

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Comorbidities are defined as acute or chronic medical conditions that an individual has in addition to his or her primary diagnosis. These comorbid conditions can affect a patient's prognosis across the continuum of care. Functional decline and the presence of comorbidities are common in older adults. Functional decline can be precipitated by the presence of comorbid conditions during acute hospitalization. Thus, poor management of comorbidities can lead to undesired outcomes such as preventable hospital readmissions. A valid comorbidity index is needed to adjust for adverse effects of comorbidities on post-acute outcomes. However, validation of various comorbidity indices on post-acute health outcomes has not been investigated using administrative data. The overarching goal of this study was to compare the performances of five comorbidity indices, including Charlson Comorbidity Index, Elixhauser Comorbidity Index, the Functional Comorbidity Index, the Hierarchical Condition Category, and Centers for Medicare and Medicaid Services Tier categories for predicting post-acute-relevant health outcomes. The health outcomes studied included functional status, community discharge, and 30-day acute

hospital readmission. Secondary analyses were conducted using 100% Medicare data for beneficiaries on fee-for-service plans in calendar year 2011. The Medicare Provider Analysis and Review file was linked to the Inpatient Rehabilitation Facilities-Patient Assessment Instrument file to retrieve admission and discharge Functional Independence Measure ratings. The Hierarchical Condition Category performed relatively better than the other comorbidity indices in predicting functional status at admission to post-acute inpatient rehabilitation, discharge functional gain during rehabilitation, and 30-day acute hospital readmission after discharge from rehabilitation. Our findings provide further evidence that medical diagnosis – including comorbidity burden – cannot be used as a proxy for patient's functional status or ability to live independently in the community, the two most important patient-centered outcomes in post-acute care.

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List of Abbreviations

ADL	Activity of Daily Living
ACA	Affordable Care Act
ARDS	Acute Respiratory Distress Syndrome
AUC	Area under Curve
CMG	Case-Mix Group
CMS	Centers for Medicare and Medicaid Services
CI	Confidence Intervals
COPD	Chronic Obstructive Pulmonary Disease,
Charlson	Charlson Comorbidity Index
DRG	Diagnosis Related Group
Elixhauser	Elixhauser Comorbidity Index
FCI	Functional Comorbidity Index
FIM	Functional Independence Measure
HCC	Hierarchical Condition Category
HMO	Health Maintenance Organization
HRRP	Hospital Readmissions Reduction Program
ICD-9-CM	International Classification of Diseases, 9th revision, Clinical Modification
IRF	Inpatient Rehabilitation Facility
IRF-PAI	Inpatient Rehabilitation Facility Patient Assessment Instrument
IOM	Institute of Medicine
LOS	Length of Stay(s)

MedPAR	Medicare Provider Analysis and Review
RIC	Rehabilitation Impairment Categories
ROC	Receiver operating characteristics
SNF	Skilled Nursing Facility
SF36	Short-Form-36
SD	Standard Deviation
Tier	Tier Comorbidity System
U.S.	United States
UTMB	The University of Texas Medical Branch

CHAPTER 1

Introduction

Comorbidity indices are commonly used for predicting health service utilization and mortality. Measuring the impact of comorbid conditions has also become a potential clinical marker for payment purposes and continuity of care across acute and post-acute care settings. However, limited studies have examined acute/post-acute patient-centered outcomes associated with comorbidity indices and evaluated the performance of current comorbidity indices for predicting inpatient rehabilitation outcomes.

Under the Affordable Care Act (ACA), the Centers for Medicare and Medicaid Services (CMS) have proposed various provisions to improve transition of care, reduce 30-day hospital readmission, and evaluate quality measures during acute and post-acute stays.[1] Two provisions within the ACA – the Hospital Readmission Reduction Program (HRRP) and the acute-post-acute 'bundled payment's initiative – call for developing standardized risk-adjustment methods and investigating the effect of comorbid conditions across the continuum of care, including the transitions among acute and post-acute care settings.[2] Currently, the U.S. healthcare system is fragmented across acute and post-acute care settings with no uniformity in measuring comorbidities or functional status.

Medicare claims data associated with acute hospitalizations currently do not contain information related to functional status. Unmeasured functional status during acute hospitalization can have a residual confounding effect on study outcomes in health service research using Medicare claims data. Each post-acute setting (e.g., inpatient rehabilitation facilities or skilled nursing facilities) evaluates functional status using different instruments and metrics. This inconsistency makes the comparison of functional status, as a quality indicator across post-acute settings, difficult, if not impossible.[3] One potential method to address this problem is to compare most commonly used comorbidity indices in the post-acute settings.

The overarching objective of this study was to compare the performances of five commonly used comorbidity indices, including the Charlson Comorbidity Index (CCI), Tier cormobidty system, Functional Comorbidity Index (FCI), Elixhauser Comorbidity Index (ECI), and Hierarchical Condition Category (HCC) for predicting post-acute functional outcomes, community discharge, and 30-day rehospitalization following discharge from inpatient rehabilitation facilities. Retrospective secondary analysis was conducted using data of Medicare beneficiaries on the fee-for-service plans receiving acute and post-acute inpatient rehabilitation services in 2011. The study sample included patients who received inpatient rehabilitation for stroke, hip fracture, or joint replacement, and directly admitted from acute hospital. International Classification of Disease, 9th revision, Clinical Modification (ICD-9) diagnostic codes were used to identify various comorbid conditions.

Specific Aim-1

There is a need to determine which comorbidity index, derived during the acute hospital stay, serves as the best predictive measure for functional status at admission to inpatient rehabilitation. Medicare claims data associated with acute hospitalizations contain no information related to functional status. Therefore, the first aim of this study was to compare the utility of various comorbidity indices as a proxy for functional status for hospitalized patients discharged directly to post-acute inpatient rehabilitation facilities. Indices included the Charlson Comorbidity Index (CCI), Tier cormobidty system (Tier), Functional Comorbidity Index (FCI), Elixhauser Comorbidity Index (ECI), and Hierarchical Condition Category (HCC).

Hypothesis: FCI will demonstrate the strongest association with functional status measured at admission to inpatient rehabilitation.

Specific Aim-2

Patients receiving post-acute rehabilitation often have medical comorbidities that may affect functional improvement and discharge destination. However, information is limited on the comparative performance of comorbidity indices to predict post-acute rehabilitation outcomes. The second aim of this study was to assess the relative contributions of the five comorbidity indices to predict functional gains in self-care, mobility, and community discharge after post-acute inpatient rehabilitation.

Hypothesis: FCI will demonstrate the best discriminatory ability for predicting functional gain and community discharge.

Specific Aim-3

Thirty-day readmission is an important quality indicator which can be affected by comorbidities, particularly during the transition from post-acute inpatient rehabilitation to the community. It is important to identify the most informative comorbidity index for predicting 30-day readmission following discharge from inpatient rehabilitation. Therefore, the third aim of this study was to evaluate the performances of five comorbidity indices to predict 30-day readmission, following discharge from inpatient rehabilitation.

Hypothesis: HCC will demonstrate the best discriminatory ability for predicting 30-day readmission.

CHAPTER 2

Background

Comorbidities

The risk of comorbidities increases with age, and with longer life expectancies, the prevalence of multiple chronic conditions has increased significantly among older U.S. adults.[4, 5] In the U.S., more than 25% of older adults have four or more chronic conditions, and approximately 68% of Medicare beneficiaries have two or more chronic conditions.[5] The most common chronic conditions in older adults are hypertension, diabetes, hyperlipidemia, ischemic heart disease, depression, arthritis, and stroke.[6] Older adults are also at risk for conditions acquired during hospitalizations, such as falls, urinary tract infection, pressure ulcers and frailty.[7, 8] These conditions can affect patients' physical functioning and may lead to poor health outcomes, longer hospitalizations, and increased healthcare costs.[9-12] Wolf and colleagues showed that average annual per capita Medicare costs of care for older adults with 4 or more chronic conditions were more than $13,900 compared to approximately $200 for those without chronic conditions.[13] Similarly, during post-acute inpatient rehabilitation, patients with a hospital-acquired infection have longer lengths of stay (28.2 days versus 13.3 days) and higher readmission rates (13.8% versus 8.2%) compared to patients without hospital-acquired infections.[12] By 2023, 157 million Americans will have more than one chronic condition, leading to an estimated increase in annual healthcare costs from $1.3 trillion to $4.2 trillion.[14]

Most research on comorbidities has been conducted in the context of acute care hospitalization. Health service researchers have stressed the importance of evaluating the validity of comorbidity indices for predicting rehabilitation outcomes in post-acute populations.[15-18] Adjusting for the impact of comorbidities at admission on health outcomes, such as functional gain, discharge destinations, and hospital readmission rates, is important to address the effect of confounding, to predict health care needs during transition of care, and to live independently in the community.

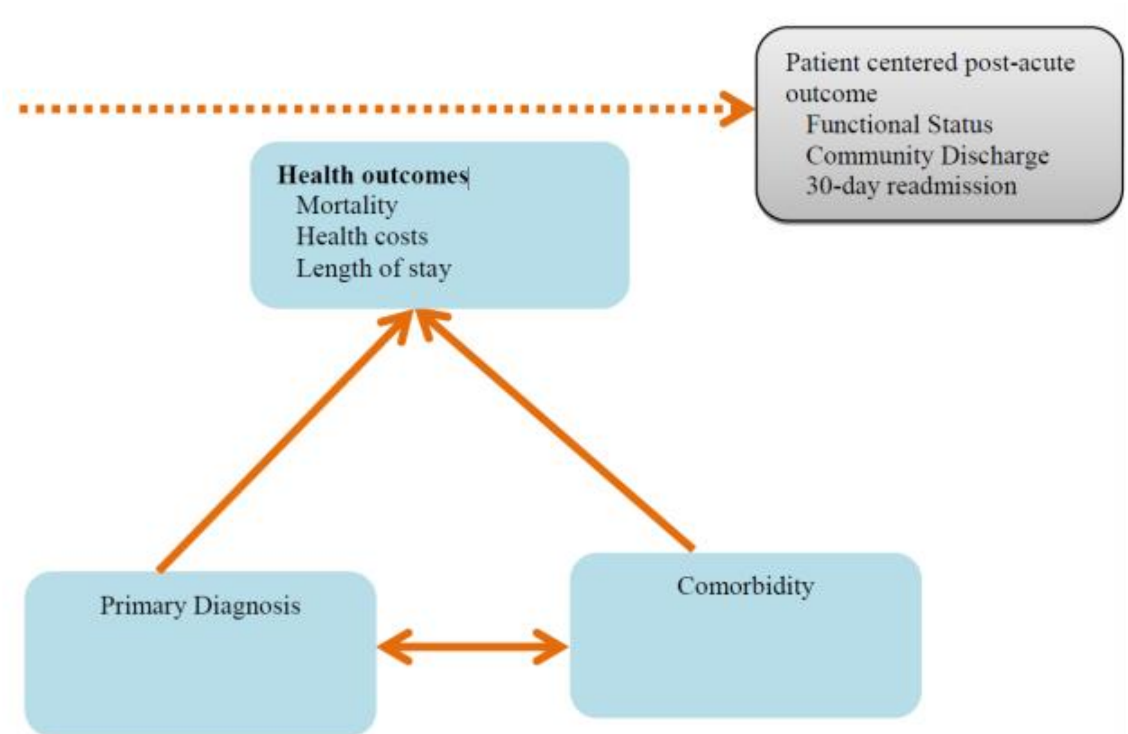


Figure 1: Conceptual model of the effect of comorbidity with post-acute outcomes

The evaluation of comorbidity indices in post-acute settings is useful conceptually and methodologically. As depicted in the conceptual model (Figure 1 and Figure 2), comorbid conditions are risk factors for adverse outcomes and are also associated with the primary diagnostic condition (rehabilitation impairment categories in the context of this study).[10] This conceptual model was based on findings from previous studies.[19 25] For example, Graham et al. demonstrated that the severity of diabetes was associated with lower functional status at discharge and lower likelihood of community discharge in patients with stroke.[25] In this example, diabetes is the comorbid condition, stroke is the rehabilitation impairment category, and functional status at discharge and community discharge are the outcomes. Thus, for this study a comorbid condition was operationally identified as a confounding factor influencing post-acute outcome variables such as functional status at discharge, community discharge, and hospital readmission.[11] Specifically, this study evaluated and compared the discriminatory ability of five comorbidity indices on patient centered outcomes including functional gain, community discharge, and 30-day readmission following inpatient rehabilitation. In the absence of information on discharge functional status from acute hospitals in administrative claims data from Medicare; this study also highlights the need to address the effect of residual confounding by functional impairment as shown in Figure 2.[20, 21]

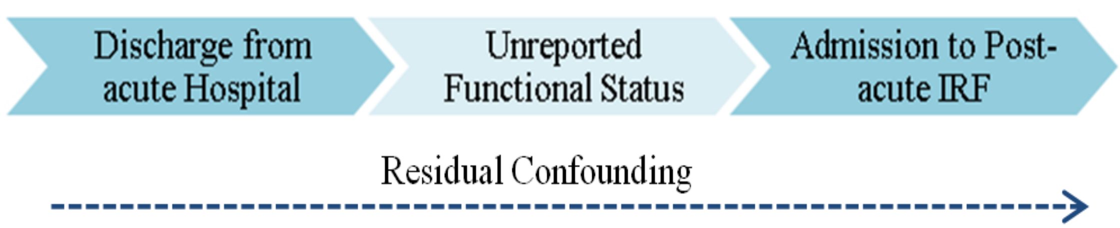


Figure 2: Residual confounding effect of missing functional status from acute hospital

Significance

This study addresses an important gap in the literature, since most existing comorbidity indices were developed in acute settings to predict mortality risk in patients with specific medical conditions. Therefore, it is unknown how the presence of comorbidities impacts other health outcomes across the continuum of care. With the growing interest in use of functional status in risk-prediction models, it is important to examine the potential association between comorbidity indices and functional status.[22] This study compared the performance of five comorbidity indices. Four of these indices are commonly used with Medicare data (Charlson Comorbidity Index, Elixhauser Comorbidity Index, Hierarchical Condition Category, and Tier Comorbidity System). The fifth comorbidity index is the Functional Comorbidity Index (FCI), which was adapted to use with Medicare data as part of this study. Each of the comorbidity indexes are described below.

Charlson Comorbidity Index: Charlson

The Charlson was developed to predict one-year all-cause mortality in patients with breast cancer using hospital medical records. It has been validated in various medical populations for predicting the risk of one-year mortality.[23-26] The Charlson has also been used in health-service studies to predict rehabilitation outcomes, but the results were inconsistent.[17, 24, 27-29] Studies have demonstrated significant associations between Charlson and 30-day readmission among patients who had orthopedic surgery in acute hospitals.[30, 31] However, its utility has not been tested in post-acute settings. The Deyo version of the Charlson Index was used in this study. Dichotomous indicators for each of the Charlson's 17 comorbidity conditions were included in the models described below (see Appendix A for detailed information related to all the comorbidity indices).

The Tier Comorbidity system: Tier

The Tier categories were developed by the CMS as part of the Prospective Payment System for Inpatient Rehabilitation Facilities and classify medical conditions into four categories (Tier1, Tier2, Tier3, or no Tier). Tier categories are based on the impact of these conditions on projected utilization of resources during an inpatient rehabilitation stay.[32] For example, medical conditions in Tier 1 have the highest severity and greatest impact, followed by conditions in the Tier 2 and Tier 3 categories, respectively. This classification is updated and published annually by the CMS in the Federal Register.[32, 33] Tier is commonly used in health service research. It was originally developed to predict resource utilization during inpatient rehabilitation.[32, 33] Previous research suggests that 25.6% of Medicare patients readmitted to acute hospitals within 30 days from an IRF belong to the Tier 1 category, compared to 9.9% in the no Tier category.[34] Tier was included as a single 4-level variable in the models described below.

Functional Comorbidity Index: FCI

The FCI was developed to predict physical function in the community-dwelling population using the 36-Item Short-Form Health Survey (SF-36).[35] However, it has never been adapted in the IRF setting using Medicare data. The FCI includes 18 comorbid conditions and shows significant associations with physical functioning.[15, 35, 36] The

Charlson and FCI demonstrated similar associations with function in an acute hospital setting in a small prospective cohort from Canada.[17] In comparison to Charlson, the FCI captures more chronic conditions (e.g., arthritis, hearing impairment, and degenerative disk disease) which have strong associations with physical performance.[35] Dichotomous indicators for each of the FCI 18 comorbidity conditions were included in the models described below.

We mapped these 18 conditions on the International Classification of Diseases, 9th Revision, Clinical Modification (ICD-9 CM) codes in the Medicare claims data. After acquiring ICD-9 codes for the FCI, a physician, physical therapist, occupational therapists, and nurse, working in the department of internal medicine at the University of Texas Medical Branch, were consulted for determining mapping accuracy between the FCI medical conditions and ICD-9 codes. In addition validation of ICD-9 codes for the FCI medical conditions was done by an experienced coder in the UTMB claims and billing department. Further operationalization was conducted by running the frequency of ICD-9 diagnostic codes associated with the 18 FCI conditions for patients with an index hospital stay for stroke, lower extremity fracture, or joint replacement in 2010. Frequency statistics and ICD-9 codes are reported in Table 1.

Table 1: Percentage of Patients after Validating FCI Condition Using the ICD-9 CM Codes from CMS Administrative Database.

Functional Comorbidity Index condition	**Stroke** (n =62,893)	**Lower Extremity Fractures** (n= 51,666)	**Joint Replacement** (n=39,893)
Arthritis (rheumatoid and osteoarthritis)	7.2	14.8	72.5
Osteoporosis	2.9	17.5	7.1
Asthma	2.7	4.1	8.7
COPD, ARDS	14.4	16.5	9.1
Angina	0.3	0.4	0.3
Congestive heart failure or heart disease	35.5	31.0	22.5
Heart attack	4.0	3.9	3.3
Neurological disease	19.6	2.6	1.6
Stroke or transient ischemic attack	83.5	0.4	0.1
Diabetes types I and II	31.3	21.4	25.0
Peripheral vascular disease	3.3	3.1	1.8
Upper gastrointestinal disease	1.3	0.7	0.3
Depression	6.7	8.9	11.4
Anxiety or panic disorders	2.5	4.1	5.0
Visual impairment	0.2	0.06	0.09
Hearing impairment	0.8	1.5	1.5
Degenerative disk disease	1.0	1.0	1.4
Obesity or BMI >30 kg/m^2	4.5	3.1	16.5

COPD= Chronic Obstructive Pulmonary Disease, ARDS= Acute Respiratory Distress Syndrome

Elixhauser Comorbidity Index: Elixhauser

The Elixhauser consists of 30 medical conditions that are shown to be associated with in-hospital mortality, length of stay, and hospital charges.[37] The Elixhauser was developed to predict health-service utilization and captures more comorbid conditions than the Charlson. A recent systematic review found that the Elixhauser has greater predictive ability than Charlson for short- and long-term mortality.[38] For this study, dichotomous indicators for each of Elixhauser's 30 comorbidity conditions were included in all the models described below.

Hierarchical Condition Category: HCC

The HCC was developed by the CMS to estimate annual expenditures for beneficiaries enrolled in the Medicare Advantage plans using demographic characteristics and diagnostic-based medical conditions documented in the patient claims from the previous year.[39] CMS has also included the HCC in a proposed risk adjustment model to predict unplanned 30-day readmission rates from inpatient rehabilitation facilities (IRF).[40] Li et al. compared the effectiveness of HCC with the Charlson and Elixhauser to predict in-hospital and six-month mortality in Medicare beneficiaries, and determined the HCC out-performed both the Charlson and Elixhauser indices.[41] Dichotomous indicators for each of the 70 HCC comorbidity conditions were included in the models discussed below.

Study Sample

The sample for this dissertation research consisted of Medicare beneficiaries, 66 years or older enrolled in the fee-for-service plans, with an acute stay immediately followed by an inpatient rehabilitation stay. The study sample included patients from three rehabilitation impairment categories (RIC) that captured 44% of the total IRF cases in 2011.[42] These patients are at high risk of having comorbidities and progression to disability.[32, 42, 43] The rehabilitation impairment categories were developed by the CMS based on the primary etiologic diagnosis for which the patient was admitted to IRF. The three RICs included in our study are stroke, lower extremity fracture, and joint replacement (see Table 2).

Table 2: ICD-9- CM Codes Associated with The Impairment Categories.

Rehabilitation Impairment Category	Diagnosis Related Group	ICD-9 Codes
Stroke	061, 062, 063	430, 431,432.0-432.9, 433-433.91, 434-434.91,436, 438.0-438.9
Lower extremity fracture	533, 534, 535, 536,537, 538	820.00-820.9, 821.00-821.11,821.20-821.39, 808.0-808.9, 823.02-823.92, 827.0-827.1, 828.0-828.1
Joint replacement	461, 462, 469, 470, 480, 481, 482	696.0, 7110.0, 714.0-714.2, 714.2, 714.30-714.33, 714.4,715.05-715.95, 715.06-715.96, 716.05-716.95, 716.06-716.96, 720.0, 996.4, 996.66, 996.67, 996.77-996.79

Our study sample included patients with acute injuries (stroke and lower extremity fracture) and persons receiving primarily elective procedures (lower extremity joint replacement) for a chronic condition. Most older adults hospitalized with stroke, hip fracture and joint replacement have multiple chronic conditions and were transferred to post-acute settings for further medical care and rehabilitation.[44] Among Medicare patients discharged from the acute hospital after stroke, more than half (55%) were not discharged directly to home and experienced residual physical and cognitive impairments, leading to a greater likelihood of long-term institutionalization.[45, 46] High rates of 30-day readmissions were reported in patients with hip and knee surgery and stroke in acute and post-acute settings.[34, 47, 48] In contrast to patients with stroke and lower extremity fracture, lower extremity joint replacement is an elective procedure for treating the symptoms of degenerative or arthritic changes usually in hip and knee joints. Addressing the risk of comorbidities before a joint replacement will reduce the risk of revision or post-surgery complications.[49, 50] Moreover, CMS has recently included knee and hip joint replacement among the acute hospital quality indicators for 30-day readmissions.[1] Thus, it is important to identify and adjust for appropriate comorbidities when modeling post-acute outcomes following these elective procedures.

Study Outcomes

FUNCTIONAL STATUS

The coexistence of comorbidities in hospitalized older adults with physical or cognitive impairment contributes to increased length of stay and delay in recovering functional independence.[51, 52] The presence of multiple comorbidities in diagnoses such as stroke and hip fracture is associated with increased likelihood of institutionalization, readmissions, mortality, and other adverse events.[8, 22, 53-60] Acute hospitalization is focused on stabilization of medical conditions, more than improvement in functional status. In 2005, the Institute of Medicine (IOM) stressed the need to gather data on performance-based quality measures across acute hospitals.[61] Currently, however, standardized data on patient functional status is not available in Medicare claims data associated with acute hospitalization.[61, 62] Establishing a comorbidity index as a proxy for functional status during acute care hospitalizations would be a valuable contribution for both health service researchers and clinicians. Since information on patient-level comorbidities is available in acute and post-acute settings, identifying a comorbidity index associated with functional status would also provide a mechanism for identifying functional status from acute to post-acute settings.

COMMUNITY DISCHARGE

Community discharge is an important performance indicator for IRF programs, consistent with the national quality strategy priorities for better-coordinated care and cost effectiveness, which is affected by patient medical needs, social support, functional status, and comorbid conditions.[63] Successful and timely discharge to the community may reduce the risk of complications, emergency visits, and readmissions. Older patients with multiple comorbidities may have poorer functional status and need additional care, including longer rehabilitation follow-up after discharge from an IRF because they need assistance with basic activities of daily living (ADL) and instrumental activities of daily living (IADL).[64] In most cases, these services are best provided in the person’s home environment. The Inpatient Rehabilitation Facility Patient Assessment Instrument (IRF-PAI) files contain information on patient discharge destinations, ranging from acute care to community settings.[65] Community discharge included patients discharged to a private home/apartment, board/care, assisted living, group home, and transitional living settings. Discharge to an institution included a skilled care nursing facility, intermediate care, acute hospital care, a sub-acute setting, and the chronic hospital alternate level of care and rehabilitation facility.

30 DAY ACUTE HOSPITAL READMISSION

Almost one out of ten older adults discharged from post-acute inpatient rehabilitation settings are readmitted to acute hospitals within 30 days of discharge.[34] Under the ACA, CMS has proposed a 30-day hospital readmission as a quality measure for IRFs.[1] Comorbidities and impaired functional status are associated with a higher risk of 30-day readmission rates in both acute and post-acute settings.[34, 57, 66] Despite high costs attributable to comorbidities and readmission, relatively little research has been done to identify the best comorbidity index to predict the risk of 30-day readmission after post-acute inpatient rehabilitation.

In this study, we have used all cause 30-day readmission as a primary outcome. The 30-day readmission is defined as admission to any short-stay acute hospital within 30-days of an IRF discharge because of clinical urgency, which is an unexpected event shown in Figure 3.[40] Any readmission within 30-days of discharge from an IRF, which was scheduled as a part of the patient plan or for a selective procedure, defined as a planned readmission.[40] Planned readmission is not a part of CMS quality measure and not included in our study outcome. This study has excluded program interruptions and transfers. For an example, any patient discharged from an IRF and readmitted to the same IRF within three consecutive calendar days is considered to have a program interruption, not readmission.[67] The 30-day readmission measure does not include patient's discharge from an IRF to a skilled nursing facility (SNF), home health or another IRF within 30 days. Transfer to the acute hospital on the same day of discharge from an IRF or the day after is not counted as a 30-day readmission measure.[40]

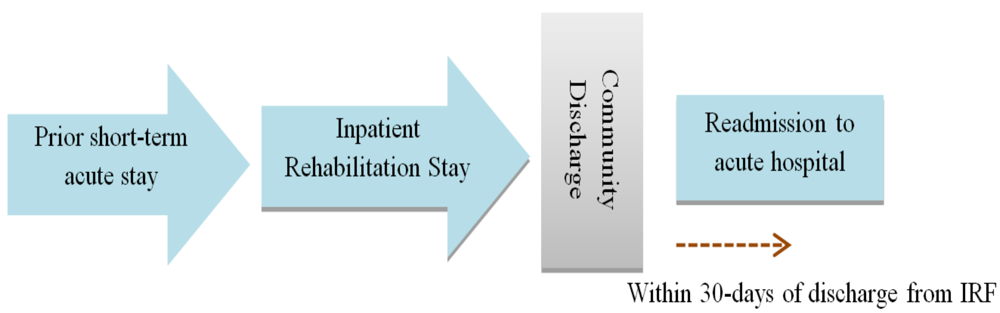


Figure 3: 30-day readmission following post-acute Inpatient Rehabilitation Facilities discharge

Policy Implications

With the implementation of ACA, both acute and post-acute providers are being held accountable for improving the coordination of care after discharge to address a patient’s continuing medical and functional needs. The U.S health care system is experimenting with moving from a fee-for-service model to a value-based purchasing system, which will incentivize providers to deliver the patient-centered quality of care at a lower cost. The CMS value-based purchasing includes three different models: pay-for-performance, accountable care organizations, and bundled payments. A bundled payment is one of the new hospital value-based purchasing programs to create an integrated delivery system. The principal objective of the bundled payment system is to improve quality of care by having a single prospective payment system, while encompassing the entire continuum of care through tracking a person's care needs after he or she leaves the hospital.[2] In bundled payment models, acute hospitals receive condition-specific predetermined expected costs for a clinically defined episode for projected health services that will be provided over an entire episode of care in multiple health care settings (acute hospital, IRF, nursing home, ambulatory care).[2] To select the appropriate post-acute setting after acute hospitalization, it is vital to assess comorbidities and the severity of functional impairment across the continuum of care. A lack of standardized reporting on functional status and comorbidities can limit efficient coordination between acute hospitals and post-acute care. Under the Hospital Readmissions Reduction Program, the CMS in 2012 started penalizing acute hospitals that had higher than expected levels of 30-day readmission rates.[1] The rates included adjustments for clinical factors, such as patient demographic attributes and comorbidities taken from the HCC.[1] Post-acute providers will also soon be subjected to financial penalties for greater-than-expected hospital readmission rates.[68] With the implementation of the Hospital Readmissions Reduction Program in post-acute settings such as IRFs, collaborations between acute and post-acute providers are increasing to improve discharge planning and post-acute care transitions across networks of providers.[69]

Summary

Measuring the burden of comorbidities for specific settings and functional outcomes is an important step in developing patient-centered risk-prediction models. Comorbidity indices are commonly used to predict health service utilization and mortality. However, limited studies have examined an association between comorbidity indices and rehabilitation-relevant outcomes or have compared the performance of current comorbidity indices in the post-acute inpatient rehabilitation setting.

The goal of the first part of this study, described in detail in Chapter 3 was to evaluate the association between comorbidity indices, derived from an acute hospital stay, with functional status at admission to post-acute inpatient rehabilitation. In the absence of the availability of a standardized functional status measure during an acute hospital stay, this study was designed to test and compare the utility of comorbidity indices as proxy measures of functional status. For the first aim, we linked hospital claims with post-acute assessments and followed a cohort of patients, admitted from acute hospitals. We examined comorbid conditions and functional status information available at the time of admission to inpatient rehabilitation. Because, the FCI was developed to predict physical function, we hypothesized that the FCI would demonstrate the strongest association with functional status measured at admission to inpatient rehabilitation.

Patients receiving post-acute rehabilitation often have medical comorbidities that may affect functional improvement and discharge destination. The goal of the second part of

this study was to compare the performances of the five comorbidity indices to predict functional gain and the likelihood of discharge to the community after receiving post-acute inpatient rehabilitation services for stroke, lower extremity fracture, or joint replacement. We hypothesized that the FCI would outperform the other indices in predicting functional gain and community discharge. The results of this study are reported in Chapter 4.

Comorbidity indices are commonly used in risk prediction models for 30- day readmission, though the performance of these comorbidity indices has not been tested in post-acute settings. The goal of the third part of this study was to compare the performances of the five comorbidity indices to predict 30-day hospital readmission following discharge from inpatient rehabilitation. CMS has begun to incorporate the HCC in the hospital risk prediction model for 30-day readmissions. Therefore, we hypothesized that the HCC would outperform the other indices in predicting 30-day hospital readmission following post-acute discharge. The findings of the third part of our study are reported in Chapter 5.

CHAPTER 3

Evaluating Comorbidity Indices to Predict Post-Acute Functional Status in Hospitalized Medicare Populations

Introduction

Acute hospitalization often accelerates loss of muscle mass and other physiologic declines in older adults due to prolonged immobilization.[70-72] Both physical and cognitive functioning can be affected.[51, 52] Poor functioning is associated with longer lengths of stay (LOS) in hospitals and increased likelihood of institutionalization, readmissions and mortality.[22, 53-57] Acute hospital stays are more focused on stabilization of medical conditions than maintaining or improving functional status. Accordingly, hospital claims records contain extensive information on medical diagnoses and procedures, but no function-related variables. Unlike post-acute care settings (inpatient rehabilitation facilities, skilled nursing facilities, and home healthcare), acute hospitals do not collect and submit standardized functional assessment data. In 2005, the Institute of Medicine (IOM) stressed the need to gather performance-based quality measures across acute hospitals. However, patient functional status is still missing as a quality indicator from these settings.[61, 62] There is growing interest in developing a ubiquitous functional status measure for use across the continuum of care (acute and post-acute care settings). The Alpha Functional Independence Measure (AlphaFIM®) was developed to measure patient functional status in acute care hospitals. However, it has not been implemented as a commonly used functional measure in US acute hospitals.[73] The Medicare post-acute payment reform demonstration has tested the use of the Continuity Assessment Record and Evaluation (CARE) tool. The CARE tool includes functional status items collected at the time of discharge from an acute hospital, at the time of admission in post-acute care settings, and discharge from post-acute care settings. However, the CARE tool is in the demonstration phases and a finalized version is not available.

Acute illness and chronic conditions adversely affect functional independence.[8, 58-60] The information about comorbidities has potential value for approximating functional status during acute care hospitalizations. Several comorbidity indices have been developed to predict health care utilization and mortality.[23, 35, 37, 74] Among the most commonly used are the Charlson Comorbidity Index (Charlson), Elixhauser Comorbidity Index (Elixhauser), Functional Comorbidity Index (FCI), and Hierarchical Condition Category (HCC). However, none has been tested for their ability to predict functional status in Medicare beneficiaries using large administrative data.

Medicare claims data associated with acute hospitalizations contain no information related to functional status. Therefore in this study, we compared the utility of various comorbidity indices to predict functional status for hospitalized patients discharged directly to post-acute inpatient rehabilitation facilities. We used functional status at the time of admission to IRF as a proxy for discharge functional status from acute hospitals.

Materials and Methods

Source of Data: A retrospective secondary analysis of Medicare data was conducted using: Medicare Provider Analysis and Review (MedPAR) data files, the Inpatient Rehabilitation Facility-Patient Assessment Instrument (IRF-PAI) file, and the Beneficiary summary file for the calendar year 2011. Linking patients' hospital claims records with their immediate inpatient rehabilitation functional assessment data enabled us to examine the association between comorbidity burden during acute hospitalization and functional status at the time of IRF admission. A Data Use Agreement was established with the Center for Medicare and Medicaid (CMS). The study was approved by the University of Texas Medical Branch Institutional Review Board.

STUDY POPULATION

The population included Medicare beneficiaries, 66 years of age or older on the Medicare fee-for-service plan, with an acute hospital stay immediately followed by the post-acute inpatient rehabilitation stay. The study sample included patients from three rehabilitation impairment categories (RICs) representing 44% of IRF admissions in 2011: stroke, lower extremity fracture, and lower extremity joint replacement.[42] The study exclusion and inclusion criteria are shown in Figure 4. The study excluded patients living in non-community settings prior to IRF admissions (n=1,801), those who died during IRF stay (n= 222), not admitted for initial rehabilitation (n=7,313), patients with program interruptions during inpatient rehabilitation (n=1,748), and patients who stayed more than 30 days in the IRF (n=3,006). Also, for 157 cases there was no match in the beneficiary summary file. Further, we excluded patients younger than 66 years of age (n=19,115), and those on health maintenance organization (HMO) plans (n= 24,147). For this study, we excluded cases with repeated rehabilitation stays (n=4,549) and cases without a match in the MedPAR file for one year look back period (n=13,944). Thus, the final study sample included patients discharged from acute hospital to the IRF (n=105,441).

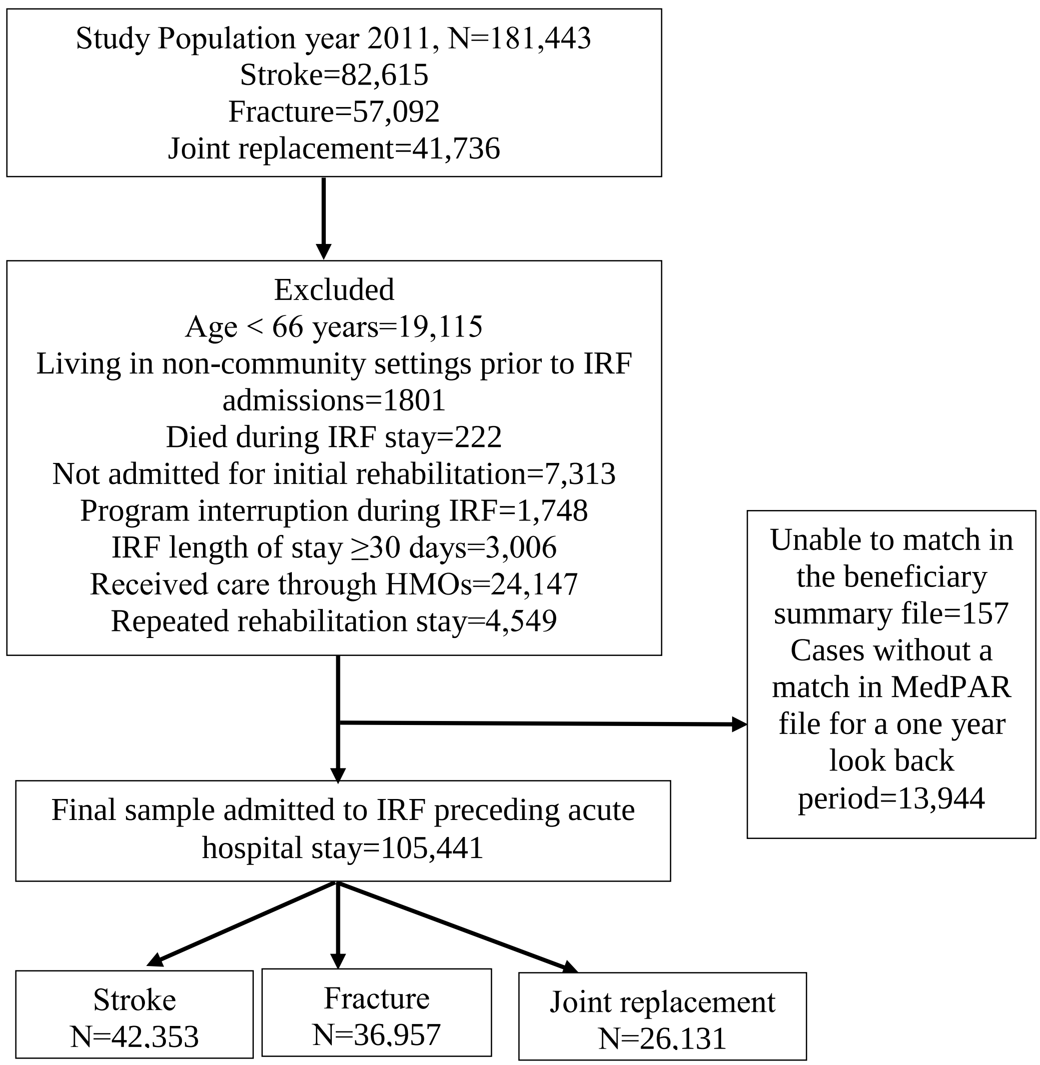


Figure 4: Flow chart of the study sample discharged from acute to Inpatient Rehabilitation Facilities.

VARIABLES

Outcome: The primary outcome was functional status at admission to post-acute inpatient rehabilitation which is a proxy for discharge functional status from acute hospitalization. The IRF-PAI functional status items are administered by rehabilitation clinicians within three days after inpatient rehabilitation admission and within three days before discharge. We examined self-care, mobility, and total motor scores from the FIM instrument. We included eight items in the self-care domain: eating, grooming, bathing, upper body dressing, lower body dressing, toileting, bladder management, and bowel management. The mobility domain included five items: bed to chair transfer, toilet transfer, and shower transfer, walking, and climbing stairs. The self-care score ranges from 8 to 56, and mobility score ranges from 5 to 35. The total motor score included both self-care and mobility domains, with scores ranging from 13-91. Items were scored on a 7-point ordinal scale, ranging from complete dependence (1) to complete independence (7).[75] The reliability and validity of the FIM instrument have been studied extensively in patients with stroke and other impairment categories.[76]

Demographic Variables: Patient demographic variables were extracted from the Medicare Beneficiary summary file, including age, gender, race/ethnicity, original Medicare benefits due to disability, and dual eligibility for Medicare and Medicaid. Age was used as a continuous variable. Since 85 % of the study sample was non-Hispanic white, race/ethnicity was categorized into non-Hispanic white and other (i.e., non-Hispanic black, Hispanic, and other races). Disability and dual eligibility were categorized into yes and no.

Comorbidity Indices: Tier Comorbidity, Charlson Comorbidity Index, Elixhauser Comorbidity Index, Functional Comorbidity Index (FCI), and Hierarchical Condition Category (HCC).

DATA ANALYSIS

Multivariate linear regression models were constructed to evaluate the impact of five comorbidity indices on functional status at admission to post-acute inpatient rehabilitation facilities. For the study sample, we computed seven models for each of the outcome variables: admission self-care, admission mobility, and admission motor ratings. The baseline model included age, gender, race/ethnicity, disability, dual eligibility, and acute length of stay (LOS). The second models included RIC with baseline demographic variables to show the variation explained by diagnostic category. In each of the five subsequent models, one of the comorbidity indices was added separately to the second model. Unstandardized regression coefficients and adjusted R^2 were compared across all models. R^2 reflects goodness-of-fit of a linear model. It measures how well the regression line approximates the real data points in the model and also determines the amount of total variation in the outcome variable explained by the model.[77] R^2 value can range from 0 to 1, with 0 indicating no statistical correlation between the data points and the line, and 1 indicating a perfect fit between the data points and the line.[77] We also ranked the adjusted coefficient estimates from the linear models to identify the top five comorbid conditions in each comorbidity index with functional status.

Results

The study sample included 105,441 patients discharged from acute hospitals who were admitted directly to an IRF on the same day. The mean age of the study population was 79.3 (standard deviation [SD] 7.6) years. The majority of patients were non-Hispanic white (85%) and female (64%). The mean LOS in an acute hospital was 5.1 days. Only 14% of the study sample was dual eligible (Medicare and Medicaid), and 10% were eligible for Medicare due to disability. Stroke was the largest impairment category of patients discharged to the IRF, representing 40% (n=42,353) of the study sample, followed by lower extremity fracture (35%, n=36,957), and lower extremity joint replacement (25%, n=26,131). Demographic and clinical characteristics stratified by impairment groups are shown in Table 3. The mean functional status of the total sample at the time of IRF admission was 26.4 (8.8) for self-care, 10.6 (3.8) for mobility, and 37.1 (11.7) for total motor score.

Table 3: Descriptive Characteristics of Study Population by Rehabilitation Impairment Category.

Variable	**Total**	**Stroke**	**Lower Extremity Fracture**	**Joint Replacement**
N (%)	105,441	42,353 (40.1)	36,957 (35.0)	26,131 (24.7)
Age mean ± (SD)	79.3 ± 7.6	78.9 ± 7.5	81.7 ± 7.5	76.6 ± 6.7
Female	67,794 (64.3)	23,257 (54.9)	26,689 (72.2)	17,848 (68.3)
Race/Ethnicity				
White	89,109 (84.5)	33,621(79.3)	32,997 (89.2)	22,491 (86.0)
Black	8,406 (7.9)	5,158 (12.1)	1,317 (3.5)	1,931 (7.3)
Hispanic	5,188 (4.9)	2,182 (5.1)	1,841 (4.9)	1,165 (4.4)
Other	2,738 (2.6)	1,392 (3.2)	802 (2.1)	544 (2.0)
Acute length of stay	5.1 ± 3.7	5.9 ± 4.7	5.2 ± 3.0	3.7 ± 2.1
Dual eligibility	15,216 (14.4)	7,474 (17.6)	5,096 (13.7)	2,646 (10.1)
Disability	10,875 (10.3)	4,742 (11.2)	3,306 (8.9)	2,827 (10.8)
Functional status (mean±SD)				
Self-care	26.4 (8.8)	24.4 (9.7)	25.4 (7.7)	31.0 (6.8)
Mobility	10.6 (3.8)	11.0 (4.3)	9.4 (3.0)	11.7 (3.4)
Total Motor Score	37.1 (11.7)	35.5 (13.3)	34.9 (9.9)	42.8 (9.3)

Values are presented as the mean ± standard deviation (SD) or N (%).

Figure 5 represents the R^2 estimates from the linear regression models predicting self-care, mobility, and total motor score. In predicting admission self-care, the base model with demographic variables explained 11% of the variance. Adding RIC to the base model explained 15.9% of the variance. The amount of explained variance increased marginally when the individual comorbidity indices were added to the base model with RIC: Charlson (0.2%), Tier (0.2%), FCI (0.7%), Elixhauser (1.4%), and HCC (1.8%). For admission mobility, the base model explained 5.6% and adding RIC to the base model explained 9% of the variance. The increases in variance explained with the addition of the comorbidity indices were minimal: Charlson (0.3%), Tier (0.3%), FCI (0.6%), Elixhauser (1.4%) and HCC (1.5%). For admission motor status (self-care plus mobility), the base model explained 10.8% of the variance and base model with RIC explained 14.2%o fthe variance. The increases in variance explained with the addition of the comorbidity indices were minimal: Charlson (0.3%), Tier (0.3%), FCI (0.6%), Elixhauser (1.6%), and HCC (1.9%).

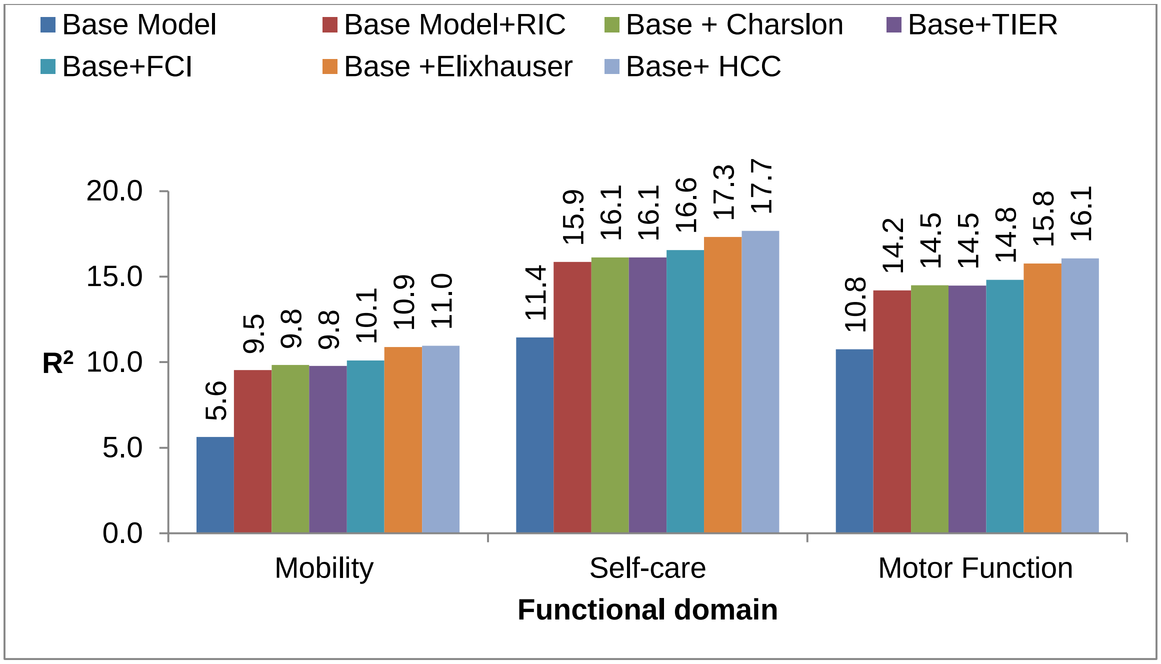


Figure 5: R^2 statistics for predicting self-care, mobility, and motor functional status in seven different models in all patients.

Table 4 summarizes the strength of associations between the top five medical conditions and functional status across all comorbidity indices. Paraplegia, hemiplegia, cerebral hemorrhage, cerebral palsy, neurological disease, diabetes, gastrointestinal disease, liver disease, traumatic amputation, depression, psychoses, dementia, obesity, weight loss, and HIV were strongly associated with patient functional status across all comorbidity indices.

Table 4: Coefficient Estimates for the Top Five Conditions in Each of the Comorbidity Indices.

HCC		**Elixhauser**		**FCI**		**Charlson**	
Medical Condition	**Coefficient (SE)**	**Medical Condition**	**Coefficient (SE)**	**Medical Condition**	**Coefficient (SE)**	**Medical Condition**	**Coefficient (SE)**
Paraplegia	-13.2 (10.8)	AIDS/HIV	-5.3 (2.2)	Neurological Disease	-2.2 (0.11)	Dementia	-8.0 (7.84)
Traumatic Amputation	-12.7 (7.6)	Paralysis	-4.7 (0.15)	Diabetes types I and II	-0.9 (0.07)	AIDS/HIV	-5.7 (2.14)
Hemiplegia/ Hemiparesis	-6.2 (0.25)	Other Neurologic Disorders	-2.9 (0.13)	Depression	-0.9 (0.10)	Hemi/ Paraplegia	-4.5 (0.67)
Cerebral Hemorrhage	-5.5 (0.17)	Weight Loss	-1.9 (0.19)	Upper Gastrointestinal Disease	-0.7 (0.33)	Cerebrovascular disease	-2.9 (0.17)
Cerebral Palsy/ Paralytic Syndrome	-5.3 (0.95)	Psychoses	-1.5 (0.22)	Obesity	-0.7 (0.12)	Mild Liver Disease	-1.9 (0.53)

The estimates were adjusted for patient characteristics (age, gender, race/ethnicity, disability, acute LOS, and dual eligibility) and rehabilitation impairment categories.

Discussion

Our study is the first to examine and compare the ability of commonly used comorbidity indices, derived from acute hospitalizations, to predict functional status at admission to inpatient rehabilitation facilities. We utilized functional status measurement at admission to inpatient hospitalization as a proxy for discharge hospitalization because functional status is not routinely assessed in acute hospital stays. Our results suggest that currently available comorbidity indices cannot substitute for functional status measurement, as their predictive validity is weak. In our study, demographic factors alone explained approximately 10% of the variation in functional status scores and the RIC increased the variation by 4%. An additional 2% of the variance was explained by various comorbidity indices. This small increase may be a result of the fact that most of these comorbidity indices lack functional components and do not include any standardized measures for patient functional status.[22, 54]

We found that the HCC outperformed other comorbidity indices in predicting functional status. There may be several explanations for this finding. First, the HCC comorbidity index incorporates more medical conditions than the other indices. The HCC includes 70 comorbidities; Elixhauser, includes 30, FCI has 18, the Deyo version of Charlson includes 17 comorbidities, and Tier has four categories.[35, 37, 74, 78] Further, each of the comorbid conditions for HCC has a greater number of associated ICD-9-CM codes compared to the Elixhauser, Charlson, and FCI indices. For instance, Table 5 illustrates the fact that the ICD-9-CM codes used for Elixhauser, FCI, and Charlson are specific and cover less of the whole spectrum of disease and severity of conditions compared to HCC.

Nevertheless, the association between HCC and functional status was modest. These results are consistent with a recent study by Noyes et al. suggesting that HCC lacks conditions which reflects patients' functional status.[79]

We found that the Tier, Charlson, FCI, Elixhauser and HCC indices added little explanatory power to models that included demographic and RIC to predict patient functional status at the time of IRF admission. Tier is used to determine prospective payments for IRF stay. Schneider et al. (2013) did not find significant correlations between Charlson, Elixhauser, and Tier indices and changes in functional status using FIM or community discharge among patients with burn-related conditions.[28] However, the Charlson and Elixhauser indices were not developed to predict functional status. The weak association between FCI and functional status was an unexpected result in our study. Although the FCI was developed to predict physical functioning using clinical records, it has never been adapted for use in acute settings, using Medicare data. The current findings on Charlson and FCI are consistent with a previous study that has shown both Charlson and FCI performed equally as well in predicting functional outcome in patients with stroke using a small sample from an acute hospital in Montreal, Canada.[17] To our knowledge, ours is the first study that has adapted FCI to use ICD-9-CM codes from the administrative dataset. Although Elixhauser and FCI include a comprehensive set of comorbid conditions, they do not include hospital-acquired conditions such as pressure ulcers, falls, or catheter-associated urinary tract infection which are preventable quality indicators that might affect function and that CMS has tied to hospital reimbursement.[80]

Our study found that some medical conditions with highest predictive values for functional status were included in more than one comorbidity index. For example, hemiplegia/paralysis is included in the HCC, Elixhauser, and Charlson indices (Table 4); neurological condition/disease is included in the Elixhauser and Charlson; and HIV is included in both the Elixhauser and Charlson. In the future, health services researchers could use combinations of these medical conditions to develop a new comorbidity index that is a better predictor of functional status after acute care hospitalization.[81] That said, factors beyond comorbidities may play a more influential role in patient functional status and may limit the explanatory power of any comorbidity index. Immobility and prolonged periods of bed rest associated with acute care hospitalization, for example, can be detrimental to functional independence and contribute to hospital associated disability, thus obscuring the relationship between comorbidity and function. [70-72]Thus, our results also support the need for developing a standardized instrument to measure functional status at acute hospital discharge. This information may help target initiatives aimed at early mobilization and prevention of functional decline.

Table 5: ICD-9-CM Conditions Included in the Various Comorbidity Indices for Stroke.

Medical Condition	ICD-9-CM
HCC95 - Cerebral Hemorrhage	094.87, 430, 431, 432.0, 432.1, 432.9
HCC96 - Ischemic Stroke	433.01, 433.11, 433.21, 433.31, 433.81, 433.91, 434.01, 434.11, 434.91, 436
HCC100 - Hemiplegia	342.00, 342.01, 342.02, 342.10, 342.11, 342.12, 342.80, 342.81, 342.82, 342.90, 342.91, 342.92, 343.1, 343.4, 438.20, 438.21, 438.22
Elixhauser - Paralysis	342.0, 344.X, 438.2-438.5
FCI - Stroke	430, 431, 434, 434.01, 434.10, 434.11, 434.90, 434.91, 435, 435.1, 435.3, 435.8, 435.9, 436, 997.02
Charlson - Hemiplegia	344.1, 342.X
Charlson - Cardiovascular disease	430.X, 441.X, 785.4

HCC: Hierarchical Condition Category; Elixhauser: Elixhauser Comorbidity Index; FCI: Functional Comorbidity Index; Charlson: Charlson Comorbidity Index.

This study has some limitations. First, we did not use weights in calculating the comorbidity indices. Some indices do not have weights, and those with weighting schemes were developed for different outcomes. For example, Charlson weights were developed to predict mortality, HCC weights were developed to estimate cost in the Medicare Advantage patient population, and weights for Tier were developed for IRF patients for prospective payments. The original Elixhauser method did not assign weights. Second, our study was limited to three rehabilitation impairment categories, and thus the findings may not be generalizable to patients with other types of impairments. However, our sample was diverse and captured approximately 44% of total IRF admissions. Another limitation is that we included only medical comorbidities present at the time of admission, so we may have missed such hospital-acquired conditions as pressure ulcers, falls, and urinary tract infections, which can influence patient functional status during or after an acute stay. We have not included number of days in the Intensive Care Unit (ICU) and Critical Care Unit (CCU) during hospitalization, where prolonged immobility may greatly influence functional status. Future studies will need to be conducted to examine the impact of ICU/CCU stays on functional status.

Our study also has several strengths. We used national data on all Medicare fee-for-service beneficiaries admitted to IRF from an acute hospital. We linked the MedPAR claims data with IRF assessment data to evaluate concurrent comorbidity burden and functional status. Examining the association of comorbidity indices during acute hospitalization to predict IRF admission functional status was novel. To our knowledge, this is the first study to adapt the FCI using ICD-9 diagnostic codes for patients with an index hospital stay.

Conclusion

Current comorbidity indices are better suited for predicting LOS than functional status. The primary finding of this study suggests that Tier, Charlson, FCI, Elixhauser and HCC do not have a good ability to predict functional status at discharge from the acute care setting. In the current study, we identified the top five medical conditions that had the most influence on patient functional status across all comorbidity indices. Future research should determine the effectiveness of combining these medical conditions into a single index or developing weighting schemes specific to functional status outcomes.

CHAPTER 4

Comparing Comorbidity Indices to Predict Post-Acute Rehabilitation Outcomes

Introduction

Discharge to the community and gain in functional status are important patient-centered outcomes for persons receiving inpatient rehabilitation. Under the *Affordable Care Act*, the Centers for Medicare and Medicaid Services (CMS) have identified functional status as a future quality measure for inpatient rehabilitation facilities (IRFs).[32] The *Improving Medicare Post-Acute Care Transformation* (IMPACT) *Act* mandates uniform reporting of patient functional assessments across post-acute care settings (inpatient rehabilitation facilities, skilled nursing homes, home healthcare, and long term acute care hsopitals) to improve coordination of care and outcomes for Medicare beneficiaries.[82]

In 2012, 1,166 IRFs in the U.S. provided rehabilitation services to over 373,000 Medicare fee-for-service patients.[83] The majority of IRF patients are 65 years or older with multiple comorbidities. Approximately 41% of patients have one or more “Tier” comorbidities.[83] Tier comorbidities are used by CMS to assign IRF patients into 4 categories, based on severity of the comorbidities related to cost incurred.[83] Comorbidities increase the risk of developing secondary complications and negatively impact discharge functional status, length of stay, discharge destination, 30-day hospital readmission, and mortality.[57, 58, 84] Graham and colleagues have reported that patients with Tier-level diabetes (e.g., diabetes with renal manifestation, peripheral circulatory disorder or polyneuropathy) have longer

IRF- lengths of stay and worse functional outcomes compared to patients without diabetes or diabetes without a Tier classification.[58]

In addition to the CMS Tier classification developed for IRF prospective payment[32], several standardized comorbidity indices exist.[23, 35, 37, 85] The Charlson and Elixhauser comorbidity indices estimate mortality risk in hospitalized patients. Their association with post-acute rehabilitation-relevant outcomes is largely unknown. The Functional Comorbidity Index (FCI), was developed to predict physical function using clinical records.[35] The FCI has not been tested in IRF settings for its association with functional or other rehabilitation outcomes. Hierarchical Condition Category (HCC) has been used by the CMS for risk adjustment in capitated payments for Medicare Advantage plans.[39] However, the HCC has not been tested for its ability to predict rehabilitation-relevant outcomes in post-acute settings. The purposes of our study were to assess the relative contributions of the five comorbidity indices, listed above, to predict functional gains in self-care and mobility and likelihood of community discrage in patients receiving inpatient rehabilitation services. The study hypothesis was that the Functional Comorbidity Index would perform better than the other indices in predicting the functional gain and community discharge for patients receiving inpatient rehabilitation services.

Materials and Methods

Source of Data: Secondary analyses of Medicare data for 2011 were conducted using the Beneficiary Summary File, the Medicare Provider Analysis and Review File (MedPAR) and the Inpatient Rehabilitation Facility-Patient Assessment Instrument (IRF-PAI) file.[75] A Data Use Agreement was established with the CMS. The study was approved by the UTMB Institutional Review Board.

STUDY POPULATION

The study eligible sample included 181,443 from one of the three most common rehabilitation impairment categories (RICs): stroke (n=82,615), lower extremity fracture (n=57,092), and lower extremity joint replacement (n=41,736). These impairment categories represented 44% of IRF admissions in 2011.[42] The study excluded patients living in non-community settings prior to IRF admissions (n=1,801), those who died during their IRF stay (n=222), those not admitted for initial rehabilitation (n=7,313), patients with program interruptions during inpatient rehabilitation (n=1,748), and patients who stayed more than 30 days in the IRF (n=3,006). Also, for 157 cases there was no match in the beneficiary summary file. Further, we excluded patients younger than 66 years of age (n=19,115), and those on health maintenance organization (HMO) plans (n=24,147). For this study, we excluded cases with repeated rehabilitation stay (n=4,549) and cases without a match in the MedPAR file for a one year look-back period (n=14,110). Thus, the final study sample included patients discharged from IRF to the community (n=105,275) as shown in Figure 6. Patients from three RIC included in the study sample were: stroke (n=41,984), lower extremity fracture (n=36,861), and lower extremity joint replacement (n=26,430).

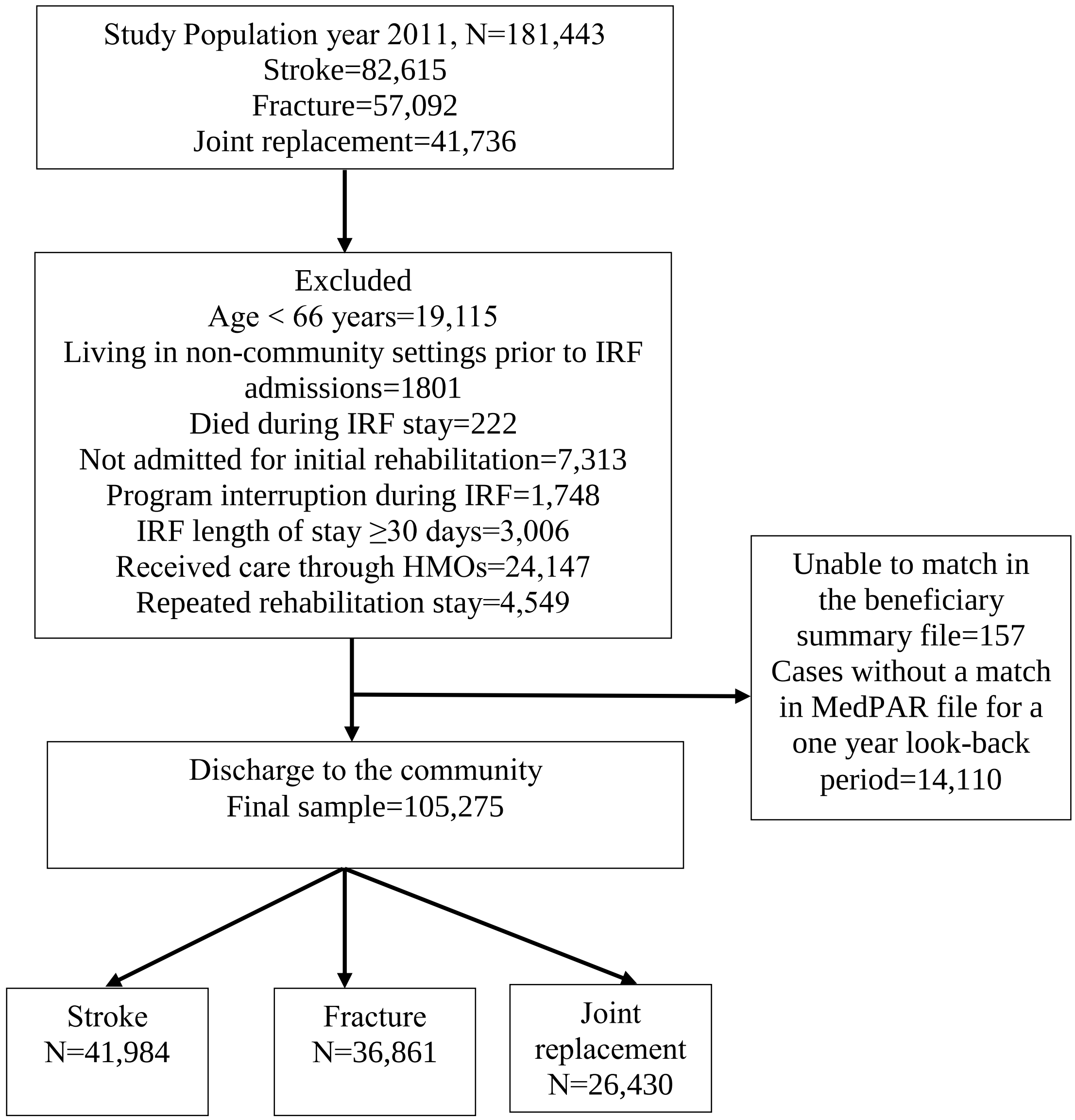


Figure 6: Flow chart of the study sample discharged from the Inpatient Rehabilitation Facilities.

VARIABLES

The primary study outcomes were functional gain and community discharge status. The functional gain was determined using the IRF-PAI file, which includes items from the *Functional Independence Measure* (FIM®) instrument.[75] The IRF-PAI is administered within three days of admission and three days before discharge. The IRF-PAI includes 18 items, out of which items comprising self-care (8 items: eating, grooming, bathing, upper body dressing, lower body dressing, toileting, bladder management and bowel management) and mobility subscales (5 items: bed to chair transfers, toilet transfers, shower transfers, walking, and climbing stairs.) were examined. Each item is rated on a 7-point scale, ranging from complete dependence (level 1) to complete independence (level 7). Codes of "0" indicating an activity did not occur at the time of admission, were re-coded as a "1."[32] The self-care subscale rating ranged from 8 to 56, and mobility from 5 to 35. Changes in the self-care and mobility ratings between IRF admission and discharge were defined as a functional gain. The discharge destinations in the IRF-PAI were categorized as a community versus institutionalization.[65] Community discharge included patients discharged to private home/apartment, board/care, assisted living, group home, and transitional living settings. Discharge to non-community settings included skilled nursing facility, intermediate care, acute hospital, sub-acute setting, chronic hospital, rehabilitation facility, and any other settings.

Patient demographic variables included age, gender, race/ethnicity, disability, and dual eligibility. Age was used as a continuous variable. Race/ethnicity was categorized as non-Hispanic white and other (i.e., non-Hispanic black, Hispanic and other). Disability was dichotomized (yes/no). Disability referred to beneficiaries who qualified for Medicare disability benefits. Medicaid dual eligibility was dichotomized (yes/no). Dual eligible beneficiaries include patients who receive benefits from both Medicaid and Medicare.

Comorbidity Indexes: Tier Comorbidity, Charlson Comorbidity Index, Elixhauser Comorbidity Index, Functional Comorbidity Index (FCI), and Hierarchical Condition Category (HCC).

DATA ANALYSIS

Descriptive statistics for patient demographic and functional characteristics were stratified by rehabilitation impairment categories (stroke, lower extremity fractures, and lower extremity joint replacement). Separate linear regression models were computed to assess the impact of each comorbidity index on functional gain during post-acute inpatient rehabilitation. Six models were computed to test for gains in self-care and six models for gains in mobility. The baseline model included age, gender, race/ethnicity, disability, dual eligibility, rehabilitation impairment categories, and admission functional scores. Five subsequent models were computed for self-care with one of the comorbidity indices included in each model. The same procedure was followed in computing six regression models for gains in mobility. Variance explained (R^2) values were compared across the models for both outcomes.

Logistic regression models were computed to examine the associations between each comorbidity index and discharge to the community. Seven receiver operating characteristics (ROC) curves were constructed to differentiate patients discharged to the community compared to institutional settings. Two models were computed without comorbidity indices. The first model included age, gender, race/ethnicity, disability, dual eligibility, length of stay and rehabilitation impairment categories. The second model added discharge functional status to show the discriminatory ability explained by functional status. In each of the subsequent models, a comorbidity index was added. The *C*-statistic was used to quantify the discrimination ability of the models.[86] All statistical analyses were performed using SAS 9.3 (SAS Institute, Cary, NC).

Results

The sample included 105,275 patients discharged from an inpatient rehabilitation facility in 2011. Patient characteristics are presented in Table 6 stratified by the rehabilitation impairment group. The mean age of the study sample was 79.3 (SD = 7.6) years. The majority of patients were non-Hispanic white (84.6%) and female (64.4%). The mean IRF length of stay was 13.0 (SD = 5.1) days, 10.2% of the cases were eligible for Medicare due to disability, and 14.4 % were dual-eligible. Stroke was the largest impairment category of patients receiving rehabilitation representing 40.1% of the sample, followed by lower extremity fracture (35%), and lower extremity joint replacement (24.7%). The mean functional gain for the total sample was 13.0 (SD = 7.7) points for self-care and 9.8 (SD = 5.4) points for mobility. Approximately 73% of the patients in the sample were discharged to the community after inpatient rehabilitation.

Table 6: Descriptive Characteristics of the Sample by Impairment Category

Variable	**Total**	**Stroke**	**Lower Extremity Fracture**	**Joint Replacement**
Total number of patients, *n* (%)	105,275	41,984 (40.1)	36,861 (35.0)	26,430 (24.7)
Age, mean (SD)	79.3 ± 7.6	79.0 ± 7.5	81.8 ± 7.5	76.6 ± 6.7
Female *n* (%)	67,839 (64.4)	23,098 (55.0)	26,657 (72.3)	18,084 (68.4)
Race/Ethnicity *n* (%)				
White	89,079 (84.6)	33,387 (79.5)	32,935 (89.3)	22,757 (86.1)
Black	8,300 (7.8)	5,074 (12.1)	1,303 (3.5)	1,923 (7.2)
Hispanic	5,170 (4.9)	2,145 (5.1)	1,836 (4.9)	1,189 (4.5)
Other	2,633 (2.5)	1,347 (3.2)	751 (2.0)	535 (2.0)
Length of stay	13.0 ± 5.6	14.7 ± 6.6	13.4 ± 4.5	9.7 ± 3.6
Dual eligibility	15,159 (14.4)	7,427 (17.6)	5,059 (13.7)	2,637 (10.1)
Disability	10,785 (10.2)	4,676 (11.1)	3,275 (10.7)	2,834 (10.7)
Admission functional status, mean (SD)				
Self-care	26.4 (8.8)	24.4 (9.7)	25.4 (7.7)	31.0 (6.8)
Mobility	10.6 (3.8)	11.0 (4.3)	9.4 (3.0)	11.7 (3.4)
Total motor score	37.1 (11.7)	35.5 (13.3)	34.9 (9.9)	42.8 (9.3)
Discharge functional status, mean (SD)				
Self-care	39.5 (10.4)	36.1 (11.8)	39.2 (7.7)	45.3 (6.3)
Mobility	20.5 (6.6)	19.3 (7.2)	19.3 (6.0)	24.1 (4.9)
Motor score	60.1 (16.4)	55.4 (18.4)	58.6 (14.5)	69.5 (10.4)
Functional gain, mean (SD)				
Self-care	13.0 (7.7)	11.6 (8.0)	13.7 (7.6)	14.2 (6.9)
Mobility	9.8 (5.4)	8.2 (5.3)	9.8 (5.2)	12.3 (4.7)
Motor	22.9 (11.8)	19.8 (12.2)	23.6 (11.5)	26.6 (10.1)
Community Discharge, *n* (%)	76,574 (72.7)	27,380 (65.2)	25,295 (68.6)	23,899 (90.4)

Figure 7 shows the R^2 values from the linear regression models predicting functional gains for self-care and mobility. The base model explained 9.9% of the variance in gain for self-care. The amount of explained variance increased marginally when the individual comorbidity indices were added: Charlson (0.2%), Tier (0.3%), FCI (0.7%), Elixhauser (1.1%) and HCC (2.8%). The base model explained 10.9% of the variance in mobility. The increases in variance explained with the addition of the comorbidity indices were minimal: Charlson (0.4%), Tier (0.6%), FCI (0.7%), Elixhauser (1.6%) and HCC (2.8%).

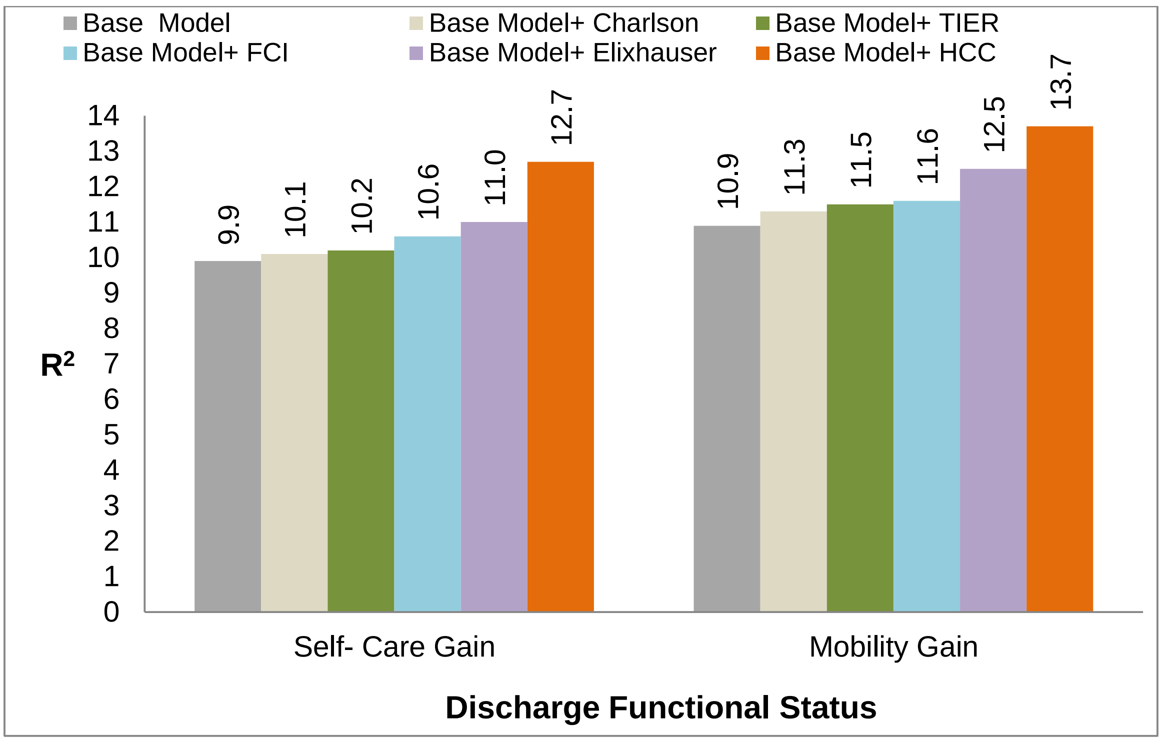


Figure 7: R^2 values for predicting functional gain in six different models in all patients.

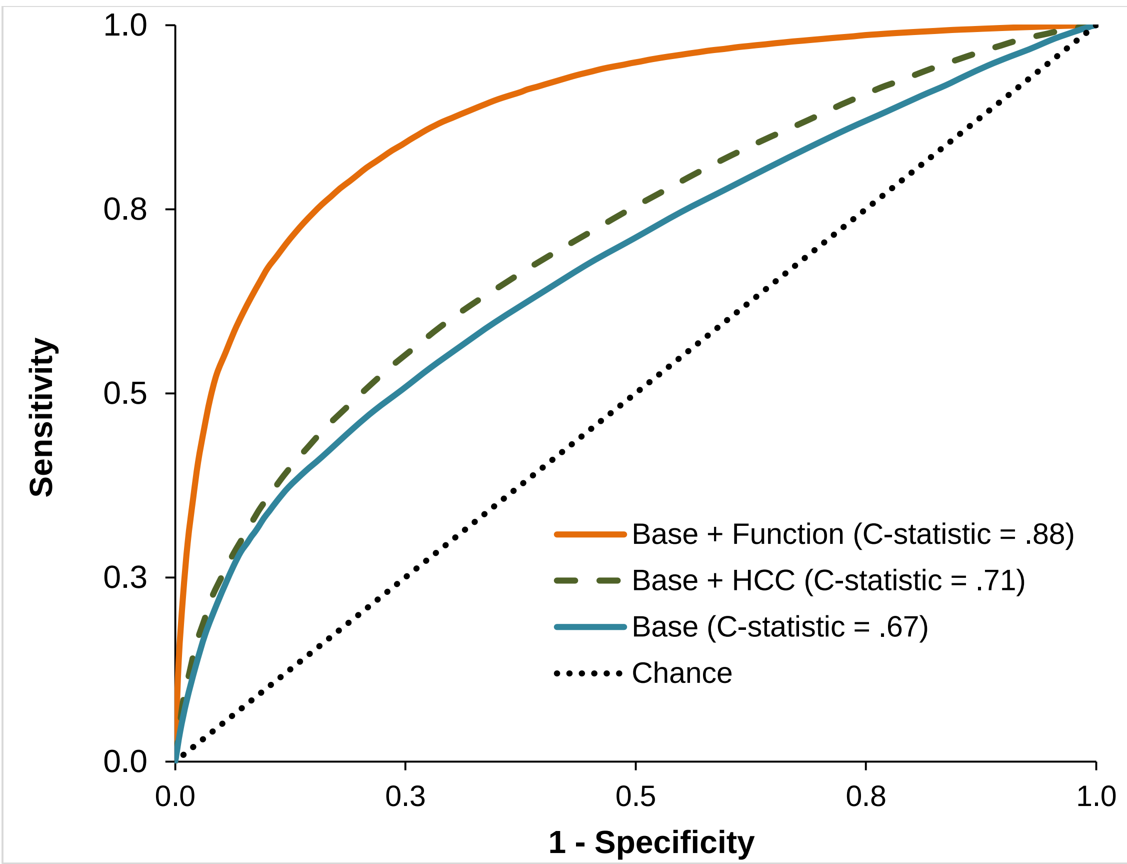
Table 7 reports the *C*-statistics from the logistic regression models predicting community discharge. The *C*-statistic for the base model including age, race/ethnicity, and disability, length of stay, dual eligibility, and impairment was 0.67. The *C*-statistic increased to 0.87 after adding discharge functional status to the base model.

Table 7: Results of Logistic Regression Analysis for Predicting Community Discharge

Model	**C-statistic**	**95% CI**
Base Model	0.67	0.67-0.67
Base Model + Discharge Function	0.87	0.87-0.88
Base Model + Discharge Function + Charlson	0.87	0.87-0.88
Base Model + Discharge Function + Tier	0.87	0.87-0.88
Base Model + Discharge Function + FCI	0.87	0.87-0.88
Base Model + Discharge Function + Elixhauser	0.87	0.87-0.88
Base Model + Discharge Function + HCC	0.87	0.87-0.88

Baseline models included age, gender, race, and disability, and dual eligibility, length of stay and impairment group. Charlson: Charlson Comorbidity Index; CMS-Tier: Tier; FCI: Functional Comorbidity Index; Elixhauser: Elixhauser Comorbidity Index; CMS-HCC: Hierarchical Condition Category

Figure 8 shows the areas under curves (AUC). The AUC for the base model was 0.67. The AUC increased by 4 points after adding the HCC to the base model. The AUC increased by 21 points after adding the HCC to the base model. None of the comorbidity indices were associated with a statistically significant or clinically meaningful increase in *C*-statistic values.



—Base Model: age, gender, race/ethnicity, disability, dual eligibility, length of stay, impairment group (Area under the curve: 0.67)

-----Base Model + HCC comorbidity index (Area under the curve: 0.71)

—Base Model + Discharge Function (Area under the curve: 0.88

Figure 8: Receiver Operating Characteristic curves comparing the performance of different models for predicting community discharge.

Discussion

Patients receiving post-acute inpatient rehabilitation often have medical comorbidities that may affect functional improvement and discharge destination. In this study, the performances of five comorbidity indices were examined to determine if there were any statistically significant or clinically important differences in their ability to predict functional gains in self-care and mobility ratings, or to predict community discharge following inpatient rehabilitation. The a-priori hypothesis that the Functional Comorbidity Index would outperform the other indices in terms of functional gain and community discharge was not supported. Adding comorbidity information from the CMS Tier, Charlson, FCI, and Elixhauser indices added little to a base model of demographic and clinical factors in predicting patient functional gain. The inclusion of the HCC to the base model explained an additional 2.8% of the variance in self-care and mobility functional gain. The slightly better performance of HCC may have two possible explanations. First, the HCC comorbidity index includes more medical conditions (70) than the other indices: Elixhauser (30), FCI (18), Deyo version of Charlson (17) and Tier (4 levels).[35, 37, 39, 78] Second, the HCC has more ICD-9 codes per condition than the Elixhauser or Charlson. These factors may have made the HCC an index that is more sensitive to clinical outcomes.

The weak association between acute care primary diagnoses and resource utilization in post-acute care is well established.[87] IRFs and other post-acute settings were exempt from the acute care hospital prospective payment system because Diagnosis Related Groups (DRG) are not strongly associated with resource utilization in these settings.[87] The IRF prospective payment system was originally developed using Function Related Groups, now termed as Case-Mix Groups (CMGs).[88] Based on this history, it is not surprising that comorbidity indices such as the Charlson, derived from medical conditions more prevalent in acute care settings, were minimally associated with rehabilitation-relevant outcomes in older Medicare patients.[89]

The FCI was created with the goal of establishing a comorbidity index sensitive to physical function as an outcome. Groll and colleagues[35] state that the underlying premise in developing the FCI was that "*diagnoses associated with physical function*" would be different than those associated with mortality and that the FCI "*would perform better than indices designed with mortality as the outcome of interest.*"[35] page-599

Although the Functional Comorbidity Index was developed to predict physical function, our results indicate that the conditions included in the FCI are not strong predictors of gain in self-care, mobility or community discharge. One reason for the lack of association with functional gain for the FCI may be that it was developed and validated using samples of community-based adults, and had limited information on severity.

The weak association between CMS Tier and rehabilitation outcomes in this study is consistent with previous research.[28, 90, 91] Schneider et al. reported poor performance for the CMS Tier, Charlson, and Elixhauser in predicting functional gain and community discharge in patients with burn-related conditions.[28] Horn and colleagues likewise found that the Charlson and Tier indices had weak correlations with discharge FIM motor ratings and community discharge among patients with spinal cord injury.[91]

The relationship between rehabilitation outcomes and comorbidity indices is complex and has not been widely or carefully studied. The majority of research on comorbidity indices and health outcomes has occurred in acute care settings. The HCC is a reliable measure for estimating costs, but it lacks specific information on medical conditions associated with a patient's functional status.[79] The Elixhauser and Charlson indices include comprehensive sets of comorbid conditions based on ICD-9-CM codes and are useful in predicting hospital-related outcomes such as mortality, acute length of stay and hospital payment.[37, 78, 92] Neither of these indices were strongly associated with rehabilitation-related outcomes in the current study.

There is growing interest in the role of multi-morbidity, chronic conditions and functional status in post-acute care settings as the result of health care reform. [82] The presence of multiple chronic conditions creates challenges for administrators and clinicians providing post-acute rehabilitation. Evidence-based practice guidelines typically focus on a single condition and fail to address the multiple comorbidities encountered by clinicians providing inpatient rehabilitation to older patients with stroke and hip fracture. The Institute of Medicine and Department of Health and Human Services recently issued a report describing the need for practice guidelines to address the impact of multiple morbidities when making treatment decisions for older adults.[93]

The increasing attention concerning the role of multi-morbidity and functional status in health care reform[82] (e.g., IMPACT Act) reflects the need for research to better understand the multifaceted relationships among physical and cognitive function status and comorbid conditions. An improved understanding of this relationship could help clinicians, investigators and administrators make better health care decisions. A logical place to begin exploring the relationship between multimorbidity and functional status is to evaluate existing comorbidity indexes. Our results suggest a weak relationship among the five comorbidity indices examined and the self-care, mobility and community discharge. Additional research is needed to test other domains of functional status such as cognition and to explore alternative approaches to operationalizing comorbidity.

In a recent study using visual analytics methods, Bhavanai and colleagues found that small clusters or pairs of comorbid conditions were associated with a higher risk of hospital readmission for patients with hip fracture who received post-acute rehabilitation.[94] The comorbidity clusters were more powerful predictors of readmission than a single comorbidity or larger pre-defined groups of comorbidities such as the Charlson or Elixhauser. Methods such as those used by Bhavnani and colleagues might help identify small clusters or unique combinations of comorbidities from existing indexes, such as the HCC, that are sensitive to positive (discharge to community) or negative outcomes (readmissions) in patients from specific impairment groups.[94]

Limitation: This study has several limitations. First, the study methods did not use a single score for the comorbidity indices or outcome-specific weights. Separate indicators for the comorbid conditions for each specific index were included in the regression models. Thus, true head-to-head comparisons of the scoring methods of each index were not conducted. The study was also limited to three impairment categories, and the findings may not be generalizable to patients with other rehabilitation impairments or medical diagnoses. Strengths of the study include the large national sample of Medicare beneficiaries and the availability of information on functional status and rehabilitation outcomes contained in the Medicare IRF-PAI files.

Conclusion

The results suggest that the addition of comorbid diagnoses from the Charlson, Functional Comorbidity Index, Elixhauser, Hierarchical Condition Category, and CMS Tier comorbidity indices do not significantly predict functional gain in self-care and mobility. Information from the comorbidity indices was also not associated with discharge setting for patients receiving inpatient rehabilitation related to stroke, lower extremity fracture and or joint replacement. Research is needed to develop an index or methods better able to use chronic conditions and comorbidities to predict post-acute rehabilitation-relevant outcomes.

CHAPTER 5

Evaluating Comorbidity Indices for Predicting 30-Day Readmission in Medicare Fee-for-Service Beneficiaries following Inpatient Rehabilitation

Introduction

Approximately 371,000 Medicare fee-for-service patients received intensive medical rehabilitation in 1,165 inpatient rehabilitation facilities (IRFs) throughout the country in 2011.[42] Almost 12% of beneficiaries discharged from post-acute inpatient rehabilitation are readmitted to acute hospitals within 30 days of discharge.[83] Unadjusted 30-day rehospitalization rates following post-acute inpatient rehabilitation ranges from 5.8% for patients with joint replacement to 18.8% for patients with debility.[34] Facility-level readmission rates are now an important quality indicator linked to financial penalties in acute care hospitals. In 2011, Medicare spent $24 billion to treat patients readmitted to acute care hospitals.[95]

Thirty-day hospital readmission is associated with multidimensional factors and directly affected by the comorbidities, chronic conditions, and functional limitations in acute and post-acute settings.[96] The presence of comorbidities increases with age. In the U.S., 21% of Medicare beneficiaries aged 65 years and older had four or more chronic conditions and approximately 68% of Medicare beneficiaries had two or more chronic conditions in 2011.[5] Comorbdities and functional status are the strongest predictors of longer length of hospilization, risk of instiutionzalization, higher healthcare cost, and moratlity in older adults. Therefore, in order to predict readmission rates, adjustment for the confounding effect of comorbidities on 30-day readmission is needed. Several readmission risk prediction models use comorbidity indices, which were developed to predict mortality and morbidity in acute settings.[97, 98] However, most readmission risk models lack important patient-level clinical variables (e.g., functional status). There is wide agreement that data reflecting patient functioning could improve the accuracy of readmission risk models.[22, 99] The relationship between specific comorbidity indices, functional status, and 30-day acute-care readmission has not been extensively studied using administrative data in patients receiving post-acute inpatient rehabilitation.[23, 35, 37, 74]

Understanding the impact of comorbidity and function on readmission risk after discharge from inpatient rehabilitation is important for several reasons. First, under the Affordable Care Act, the Centers for Medicare and Medicaid Services (CMS) has proposed 30-day hospital readmission as one of the national quality measures for inpatient rehabilitation facilities.[68] Under the Hospital Readmission Reduction Program (HRRP), CMS penalizes acute care hospitals that have excessive readmissions rates.[1] Post-acute providers will soon be subject to financial penalties for greater-than-expected hospital readmissions.[68]

Recently, CMS has included the Hierarchical Condition Category (HCC) variables in a risk adjustment measure to predict unplanned 30-day readmission from post-acute inpatient rehabilitation facilities.[40] However, HCC was not developed to predict post-acute outcomes and has not been tested for its ability to predict 30-day readmission in a post-acute population. Second, investigating the effect of comorbid conditions throughout acute or post-acute transitions has implications for the bundled payment initiative.[2] In some bundled payment models, acute hospitals receive predetermined reimbursements for health-related services provided over an episode of care.[2] The ability to account for the effect of comorbidities will help facilities accurately estimate the hospital quality measures, such as readmission and functional status, needed for patients as they transition between levels of care over an episode of care.

A recent systematic review found that the addition of functional status improves the performance of readmission risk models in acute hospitals.[22] Despite the high cost associated with comorbidities, functional limitations and readmission,[47, 57, 66] little research has been done to identify the best comorbidity index and the associated impact of functional status for assessing readmission risk in post-acute care. Current reforms in post-acute health care and the growing aging population provide incentives to identify comorbidity indices that are associated with readmission. A recent study by Shih and colleagues suggested that traditional comorbidity indices, such as the Charlson and Elixhauser, demonstrated weak associations with readmission to an acute hospital during medical rehabilitation or discharged from IRFs for medically complex patients.[96] Functional status and gender were the best predictors of transfer or readmission from an IRF to an acute hospital.[96] Shih et al. used data from the Uniform Data System, which includes 70% of IRFs in the United States.[100]

The purpose of this study was to evaluate the utility of five comorbidity indices in predicting 30-day hospital readmission following post-acute inpatient rehabilitation. The CMS has incorporated the HCC in the hospital risk prediction model for 30-day readmissions;[40] therefore we hypothesized that HCC would outperform other indices in predicting 30-day hospital readmission.

Materials and Methods

Source of Data: Secondary analyses of Medicare data were conducted using the Beneficiary Summary File, the Medicare Provider Analysis and Review File (MedPAR) and the Inpatient Rehabilitation Facility-Patient Assessment Instrument (IRF-PAI) file from 2011. The MedPAR files were linked to the IRF-PAI file to retrieve admission and discharge functional assessment information.[75]

STUDY POPULATION

The study cohort included Medicare fee-for-service beneficiaries who had an inpatient rehabilitation stay and were discharged in 2011. The method for selecting patients with 30-day readmission was explained in a previously published paper by Ottenbacher and colleagues in 2014. [34] The cohort included patients 66 years of age or older, who survived 30 days after discharge from inpatient rehabilitation, who had one of the three most common rehabilitation impairment categories (RICs): stroke, lower extremity fracture and lower extremity joint replacement.[83] As shown in the Figure 11, the study had an eligible sample of 181,443 patients for three RIC that included stroke (n=82,615), lower extremity fracture (n=57,092), and lower extremity joint replacement (n=41,736). The study excluded patients living in non-community settings prior to IRF admissions (n=1,801), those who died during IRF stay (n= 222), those not admitted for initial rehabilitation (n=7,313), patients with program interruptions during inpatient rehabilitation (n=1,748), and patients who stayed more than 30 days in the IRF (n=3,006). Also, for 157 cases there was no match in the beneficiary summary file. Further we excluded patients younger than 66 years of age (n=19,115), and those on health maintenance organization (HMO) plans (n= 24,147). For this study we excluded cases with repeated rehabilitation stay (n=4,549) and cases without a match in the MedPAR file for a one year look back period (n=14,110) leaving a sample of 105,275 patients. We also excluded the patients transferred to acute hospitals, and nursing homes and other non-community settings on the same day after discharge from inpatient rehabilitation, and those who did not survive for 30 days post-IRF discharge (n=29,693). Thus, the final study sample included patients discharged to the community (n=75,582), as shown in Figure 9.

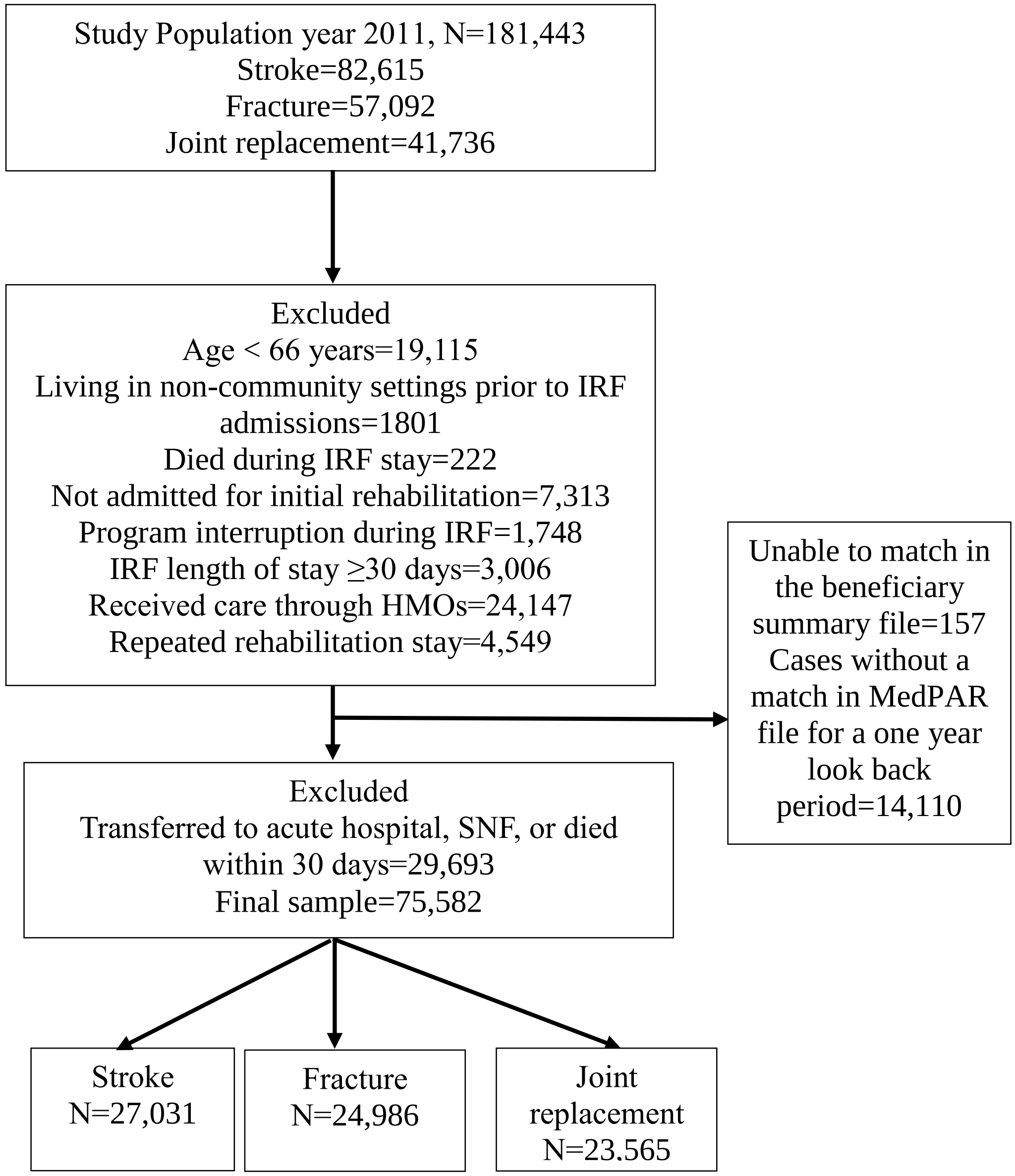


Figure 9: Flow chart of the study sample discharged from Inpatient Rehabilitation Facilities to community.

VARIABLES

Outcome Variable: The primary outcome of the study was 30-day readmission to acute hospitals following discharge from the IRF to the community.[40] Community settings included home, board-and-care, transitional living and assisted living residences.[65]

Predictor Variables: Patient demographic variables included age, gender, race/ethnicity, disability and dual eligibility for Medicare and Medicaid. Age was used as a continuous variable. Because 85% of the study sample was non-Hispanic white, race/ethnicity was dichotomized into non-Hispanic white and other. Disability and dual eligibility were dichotomized into yes and no. Disability was categorized as yes or no based upon whether or not the beneficiary originally qualified for Medicare benefits due to disability rather than age. Dual eligible beneficiaries receive full benefits from both Medicaid and Medicare. Dual eligible beneficiaries were more likely to be non-white, with less income and less education and had more chronic conditions.[101]

Functional status: Information on functional status was obtained using the IRF-PAI data file, which uses items from the Functional Independence Measure (FIM) instrument.[75] The FIM instrument includes 18 items in the following domains: self-care (eating, grooming, bathing, upper body dressing, lower body dressing, toileting, bladder management, and bowel management); mobility (bed to chair transfer, toilet transfer, shower transfer, walking, and climbing stairs); and cognition (comprehension, expression, social interaction, problem solving and memory). Each item is rated on a 7-point scale, ranging from complete dependence to complete independence. Ratings range from 18 to 126, with higher scores indicating better function. The self-care ratings range from 8 to 56; mobility and cognition ratings range from 5 to 35. The overall discharge FIM rating was used in the logistic regression analyses for this study. The reliability and validity of the FIM instrument have been studied extensively in post-acute care settings.[76]

Comorbidity Indexes: Tier Comorbidity, Charlson Comorbidity Index, Elixhauser Comorbidity Index, Functional Comorbidity Index (FCI), and Hierarchical Condition Category (HCC).

DATA ANALYSIS

Descriptive statistics of patient demographic, functional status and hospital readmission were stratified by rehabilitation impairment category (RIC). Logistic regression models were computed to examine the discriminative ability of the five comorbidity indices to predict 30-day readmission. Seven receiver operating characteristics (ROC) curves were constructed to differentiate patients readmitted to the hospital versus not readmitted. The baseline models included demographic variables including age, gender, race/ethnicity, disability, dual eligibility, length of stay, and RIC. In the second model, the overall discharge functional status rating was added along with the base model to illustrate the discriminatory ability of functional status. In each of the five subsequent models, one of the comorbidity indices was added separately to the model including functional status. The C-statistics were used to measure the overall predictive ability of each comorbidity index across all models. All analyses were performed using SAS 9.3 (SAS Institute, Cary, NC).

Results

The study sample included 75,582 patients discharged from an IRF in 2011. The mean age of the study sample was 78.6 (SD 7.4) years. The majority of patients were non-Hispanic white (84.2%) and female (64.9 %). Only 13.2% of the sample was dual eligible (Medicare and Medicaid), and 10% were originally eligible for Medicare due to disability. Demographic and clinical characteristics of study sample were stratified by readmission as shown in Table 8. Stroke was the largest rehabilitation impairment category, representing 35.7% (n=27,031) of the sample, followed by lower extremity fracture 33.0% (n=24,986) and lower extremity joint replacement 31.1% (n=23,565). Approximately 10.4% of the sample was readmitted to an acute hospital within 30 days of discharge from post-acute inpatient rehabilitation. Patients with stroke had the highest readmission rate (14.0%), followed by those with lower extremity fracture (10.3%) and lower extremity joint replacement (6.5%). Readmitted patients had longer IRF length of stay [13.3 (SD 5.6) vs. 12.3 (SD 5.1) days] and had lower functional status ratings at the time of IRF admission in self-care [26.0 (SD, 8.6) vs. 28.8 (SD 7.9)], mobility [10.7 (SD 3.7) vs. 11.5 (SD 3.7)] and cognitive domains [22.0 (SD 7.3) vs. 24.6 (SD 6.8)]. Readmitted patients were discharged with lower functional status scores in the self-care [39.2 (SD, 9.9) vs. 43.5 (SD 7.4)], mobility [20.4 (SD 6.2) vs. 23.1 (SD 5.0)] and cognitive domains [26.4 (SD 6.7) vs. 29.0 (SD 5.5)].

Table 8: Descriptive Characteristics of the Study Sample by Readmission Status.

Variable	**All Patients** n=75582	**No Readmission** 67653 (89.5)	**Readmission** 7929 (10.4)	***p* value***
Age in years (mean±SD)	78.6 ± 7.4	78.5 ± 7.4	79.3 ± 7.6	0.04
Female	49086 (64.9)	44165 (65.2)	4921 (62.0)	<.0001
Male	26496 (35.0)	23488 (34.7)	3008 (37.9)	
Race/Ethnicity				
White	63685 (84.2)	57129 (84.4)	6556 (82.6)	<.0001
Black	5992 (7.9)	5230 (7.7)	762 (9.6)	
Hispanic	3844 (5.0)	3413 (5.0)	431 (5.4)	
Other	1985 (2.6)	1811 (2.6)	174 (2.1)	
Dual eligibility	10026 (13.2)	8706 (86.8)	1320 (13.1)	<.0001
Disability	7788 (10.3)	6801 (87.3)	987 (12.6)	<.0001
Impairment Category				
Stroke	27031 (35.7)	23224 (85.9)	3807 (14.0)	<.0001
Lower extremity fracture	24986 (33.0)	22406 (89.6)	2580 (10.3)	0.2980
Joint replacement	23565 (31.1)	2203 (93.4)	1542 (6.5)	<.0001
Length of stay (mean±SD)	12.4 ± 5.1	12.3 ± 5.1	13.3 ± 5.6	<.0001
Functional Status (mean±SD)				
Admission Self-care	28.5 ± 8.0	28.8 ± 7.9	26.0 ± 8.6	<.0001
Admission Mobility	11.4 ± 3.7	11.5 ± 3.7	10.7 ± 3.7	0.8537
Admission Cognitive	24.3 ± 6.9	24.6 ± 6.8	22.0 ± 7.3	<.0001
Admission Function Total	63.8 ± 15.5	64.5 ± 15.3	58.2 ± 16.5	<.0001
Discharge Self-care	43.0 ± 7.8	43.5 ± 7.4	39.2 ± 9.9	<.0001
Discharge Mobility	22.9 ± 5.2	23.1 ± 5.0	20.4 ± 6.2	<.0001
Discharge Cognitive	28.7 ± 5.7	29.0 ± 5.5	26.4 ± 6.7	<.0001
Discharge Function Total	94.6 ±16.2	95.6 ± 15.4	85.9 ± 20.2	<.0001

*Chi-square tests for categorical variables and *t* tests for continuous variables. *P* value was compared between readmission and non-readmission group.

The C-statistic for each model predicting 30-day readmission is presented in Table 9. The C-statistic for the base model including demographic variables and length of stay was 0.60. When discharge functional status was added to the base model, the C-statistic increased by 5 points. The C-statistics increased minimamlly when the individual comorbidity indices were added: Charlson (1point), Tier (1point), FCI (1point), Elixhauser (3 points) and HCC (3 points).

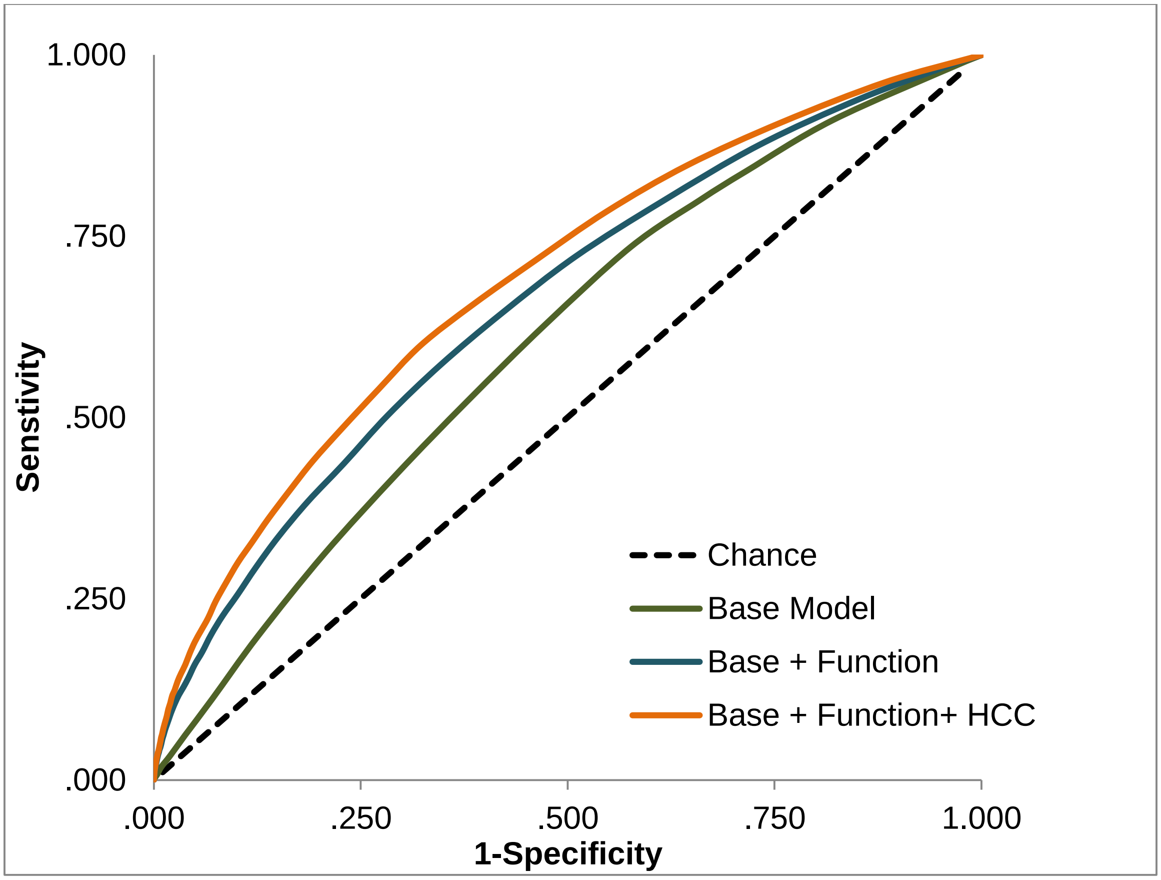
Table 9: C- Statistics Associated with Readmission for Each Logistic Regression model.

Model	**C Statistics**
Base model	0.60 (0.60-0.61)
Base model +Function	0.65 (0.65-0.66)
Base Model + Charlson	0.66 (0.66-0.67)
Base Model + Tier	0.66 (0.66-0.67)
Base Model + FCI	0.66 (0.66-0.67)
Base Model + Elixhauser	0.68 (0.67-0.69)
Base Model + HCC	0.68 (0.67-0.69)

Base models included age, gender, race, disability, dual eligibility, length of stay, and impairment group (Stroke, Lower extremity fracture, Joint replacement).

Charlson: Charlson Comorbidity Index; FCI: Functional Comorbidity Index; Tier: CMS-Tier Comorbidity System; Elixhauser: Elixhauser Comorbidity Index; CMS-HCC: Hierarchical Condition Category. Function: Discharge Functional Independence Measure score

Figure 10 shows the areas under curves (AUC). The AUC for the base model was 0.60. The AUC increased by 5 points after adding discharge function to the base model. The AUC increased by 3 points after adding the HCC to the base model with discharge function.



—Base Model: age, gender, race/ethnicity, disability, dual eligibility, length of stay, impairment group (Area under Curve: 0.604)
—Base Model + Discharge Functional Status (Area under Curve: 0.657)
—Base Model + Discharge Functional Status + HCC (Area under Curve: 0.683)

Figure 10: Receiver operating characteristic curve to compare the performance of different models for predicting 30-day readmission.

Discussion

We compared the discriminatory ability of models containing discharge functional status and five comorbidity indices to predict 30-day readmission in a large national sample of Medicare beneficiaries with stroke, lower extremity fracture and lower extremity joint replacement discharged from inpatient rehabilitation. Our results suggest that models containing HCC and Elixhauser performed marginally better than those containing other comorbidity indices. The addition of discharge functional ratings improved the discriminatory utility of the models to the same magnitude as the addition of the best-performing comorbidity index HCC. The Tier, Charlson or the FCI comorbidity indices added minimally to a model that included demographic information and discharge functional status. Previous studies have documented an increased risk of readmission due to poor functional status in acute settings.[66, 98, 102] The study hypothesis that HCC would outperform the other comorbidity indices was supported by the results.

Our findings regarding the Charlson, Tier, and Elixhauser indices are consistent with the results from Shih and colleagues.[96] This study extended the work of Shih et al., and others, by examining patients with stroke, lower extremity fracture, and joint replacement from the Medicare fee-for-service population.[28, 35, 96] In addition to including a broader and more representative sample of Medicare FFS patients receiving rehabilitation services, we included 100% of the IRFs in the United States. We also evaluated two new comorbidity indices with specific relevance to readmission and post-acute care: the Functional Comorbidity Index and Hierarchical Condition Category. Specifically, we examined the following comorbidity indices: the Charlson Comorbidity Index (Charlson), Elixhauser Comorbidity Index (Elixhauser), Functional Comorbidity Index (FCI), Hierarchical Condition Category (HCC) and “Tier” comorbidity groups used in the IRF prospective payment system. In addition, we analyzed the impact of patient clinical factors such as disability (eligibility for Medicare due to disability), length of stay, and dual eligibility for Medicare and Medicaid on 30-day readmission following inpatient rehabilitation.

Our study adds new information regarding the HCC and FCI comorbidity indices for predicting 30-day readmission following post-acute inpatient rehabilitation. Adding the HCC to the model including function increased the C-statistic from 0.65 to 0.68 for readmission. Interpretation of C-statistics higher than 0.70 are considered good and clinically relavant, and C-statistics higher than 0.80 are considered strong.[86] The slightly better performance of HCC and Elixhauser is likely attributable to the fact that these measures include more medical conditions than the other indices. The HCC includes 70 acute and chronic conditions.[18] The Elixhauser includes 30.[17] In contrast; the FCI has only18; the Deyo version of the Charlson Index includes 17 comorbidities.[32, 39] The Tier Index includes 951 total diagnostic codes and condenses these into four categories.[32] Moreover, the CMS Tier system was developed to estimate projected health resource utilization during the rehabilitation stay and not for longer-term care needs.[83]

Given the established association between functional status and hospital readmission[66], the weak association between the FCI and readmission in our results requires some explanation. The FCI was developed to capture the physical domain of the Short-Form -

36 (SF-36) but has not been validated in acute or post-acute settings using administrative data.[35] The physical domain of the SF-36 is a patient-reported outcome measure that does not capture other aspects of functional status such as self-care and cognition. This may limit its sensitivity in reflecting performance-based functional status. The FCI was developed in a younger (mean age, 55 years), non-institutionalized sample with a primary diagnosis of osteoporosis and spine problems, whereas our study sample included older patients (mean age 79) with stroke, fracture or joint replacement who received intense inpatient medical rehabilitation.[35] The FCI includes a comprehensive set of chronic conditions that may be good predictors of functional status in outpatient settings, but the FCI does not include conditions such as pressure ulcers, urinary tract infection, renal failure, septicemia, pneumonia, or arrhythmia which are associated with readmission and are also common among older Medicare patients discharged from inpatient settings.[95]

The majority of the current risk adjustment models – including those developed by CMS for the acute hospital readmission reduction program, do not include functional status information or conditions specific to functional impairment.[22, 103] The current CMS risk adjustment model for hospital-level readmission rates includes age, gender, and HCC conditions but lacks functional information. This CMS risk adjustment model reported a C-statistic ranging from 0.62 -0.67 for readmission for different patient diagnostic cohorts.[103] One reason the current risk adjustment models lack the functional component is that most were developed for acute settings which generally do not collect functional data. Chuang and colleagues found that limitations in activities of daily living (ADL) at the time of discharge from acute hospitals were a significant predictor of 30-day hospital readmission in the stroke population.[102] Coleman et al. reported an increase of 6% in C-statistics (0.77 vs 0.83) and better predictive ability for acute hospital readmissions after adding self-reported variables, including information on functional status, self-rated health, visual impairment and assistance with ADL to the model.[7]

Standardized functional measures are required for payment in post-acute settings and, thus, this data could be added to hospital readmission risk models for post-acute care.[82] We found that the addition of functional information to the base model improved the prediction of the model by an increase of 5% (C- statistics 0.60 vs. 0.65) for inpatient rehabilitation facilities.

Readmission rates are affected not only by medical diagnostic conditions, but also by the complex interaction between the severity of the medical condition and patient functioning. This is a complex relationship that ICD-9-CM codes do not capture well.[104] Current comorbidity indices use ICD-9-CM codes to identify patient medical complications; this system cannot adequately identify the severity and granularity of medical conditions.[104, 105] ICD-9-CM codes have 3-5 digits which lack details about sites of etiology, severity and specificity of conditions, whereas ICD-10 codes can have 3-7 digits and address these concerns. Future study is recommended to adapt these comorbidity indices using ICD-10 codes, which will be implemented in the U.S. health care system beginning October 2015.[105]

Older patients with multiple chronic conditions may have poor functional status and require a continuum of care including longer rehabilitation follow-up after discharge from an IRF because they need assistance with ADLs and instrumental ADLs. There is a need for more sophisticated research approaches to better understand the complex relationships among both physical and cognitive function and comorbid conditions. Multiple chronic conditions or multimorbidity may affect health outcomes differently than simply aggregating comorbidities together.[106, 107] Some of the medical conditions in existing comorbidity indices may not be relevant in specific populations. In a recent study using a combination of sophisticated visual analytic computer modeling and quantitative methods, Bhavanai and colleagues found that small clusters of chronic conditions were more powerful predictors of readmission than simply aggregating comorbidities.[94] Future research is needed to understand the complex relationship between multimorbidity and functional status and to help identify comorbid conditions sensitive to hospital readmission. Understanding this relationship could help providers and administrators identify interventions that prevent or reduce hospital readmission.

Limitation: Despite access to large administrative data and applying a conservative method for selecting the sample and readmission variable, our study has several limitations. First, we did not weight the individual conditions within the comorbidity indices. Some indices do not apply weights, and those with weighting schemes were developed for specific outcomes. For example, Charlson Index weights are based on mortality risk. Second, our analyses were limited to three impairment groups, and may not be generalizable to patients in other impairment groups. Furthermore, we may have missed previously existing conditions.[108] Finally, readmission can be affected by patient socioeconomic status, discharge planning, and support systems. We included dual-eligibility status as a proxy for low socioeconomic status, but recognize that this is an inadequate measure. Thus, our study is limited by its lack of information on post-inpatient rehabilitation discharge status, social support or caregiver information.

Conclusion

Our results suggest that the HCC and Elixhauser perform slightly better than Charlson, FCI, and Tier in predicting 30-day readmission for Medicare beneficiaries receiving inpatient rehabilitation services. Our findings also indicate that risk assessment may be improved by adding information on discharge functional status to risk prediction models. Adding functional status with comorbidity indices provides additional information to providers that allow them to better address the needs of older adults. Our results offer preliminary evidence in support of the HCC to help identify patients with higher risk of readmission during post-acute inpatient rehabilitation. Comorbidity indices have been developed to predict specific outcomes for different populations in different hospital settings. Improving pre-discharge risk prediction by using the most informative comorbidity indices and information on functional status has the potential to help target high-risk patients and improve the post-acute allocation of resources and coordination of care, and to contribute to lowering readmission rates.

CHAPTER 6

Summary and Conclusion

To our knowledge, this was the first investigation and series of studies to evaluate the performance of five comorbidity indices to predict acute/post-acute functional status, community discharge, and 30-day hospital readmissions using the 100% Medicare data. The main findings indicate that none of the five comorbidity indices, including the Charlson, Elixhauser, Tier, Functional Comorbdity Index, and Hiearchial Condtion Category were strong predictors of acute/post-acute functional status, community discharge, or 30-day hospital readmissions. The Hierarchical Condition Category outperformed the other comorbidity indices in predicting functional status, community discharge, and hospital readmissions in post-acute inpatient rehabilitation settings. The better performance of the Hierarchical Condition Category may be explained by having a greater number of ICD-9 codes for comorbid conditions compared to the Charlson and Elixhauser. Given that most of these comorbidity indices were developed for different populations and for predicting health care cost and mortality, the *C* statistics observed in our study (range 0.60–0.68) were not unexpected.

The first study (specific aim 1) evaluated the performance of the five comorbidity indices measured during acute hospitalization to predict functional status in self-care and mobility domains at post-acute inpatient rehabilitation admission. Results suggest that the Tier, Charlson, Functional Comorbidity Index, and Elixhauser Indices were not strong predictors of functional status at discharge from acute care settings. The HCC performed slightly better than the other comorbidity indices in predicting self-care and mobility functional status. Functional status is the key missing component in existing standardized risk models for health outcomes in acute settings. Our results did not support a-priori hypothesis that the Functional Comorbidity Index would outperform other comorbidity indices for predicting discharge functional status after acute care. The underperformance of Functional Comorbidity Index may be related to the following factors. First, the Functional Comorbidity Index was developed in a community-based population which includes more of the chronic conditions normally present in an outpatient population, but omits other important comorbid conditions commonly found in acute and post-acute patient populations. Our study sample included patients receiving medical treatment in acute hospitals. Second, the Functional Comorbidity Index was not validated by using ICD-9 codes in administrative data. We tried to address this by adapting Functional Comorbidity Index using ICD-9 codes so that it could be applied to Medicare data. The Functional Comorbidity Index was validated for physical functioning using self-reports based on the short-form-36 (SF-36) measure.[35] In our study, the performance-based functional status (FIM) measure was used to evaluate functional status, including self-care, mobility, and cognitive functioning.[75] Further study is recommended to develop a post-acute outcome-specific comorbidity index which can serve as a proxy for functional status in acute settings.

Our second study (sepecific aim 2) compared the discriminatory ability of the five comorbidity indices (Tier, Charlson, Elixhauser, Functional Comorbidity Index and Hierarchical Condition Category) to predict functional gain and likelihood of community discharge following post-acute inpatient rehabilitation. The results suggest that none of the comorbid indices strongly predicted functional gain. However, the Hierarchical Condition Category performed slightly better than the other comorbidity indices for predicting functional gain. The study results suggest that comorbidity information from the Tier, Charlson, Functional Comorbidity Index, Elixhauser, and Hierarchical Condition Category indices do not improve the discriminatory ability of the model in classifying community discharge. Adding discharge functional status increased the discriminatory ability of the model. Our study results do not support our a-priori hypothesis that the Functional Comorbidity Index would outperform the other comorbidity indices. The weak association between medical conditions and rehabilitation outcomes is well established. IRFs were exempted from the diagnostic-related group (DRG)-based prospective payment system for acute hospitals and the inpatient rehabilitation facilities prospective payment system is based on Case-Mix Groups (CMGs), which include a patient’s age and admission functional status.[87 88]

In our third study (specific aim 3), the performance of the Tier, Charlson, Elixhauser, Functional Comorbidity Index, and Hierarchical Condition Category were compared for their discriminatory ability to predict the risk of 30-day hospital readmission. The findings of this study suggested that the Elixhauser and Hierarchical Condition Category performed slightly better than Tier, Charlson, and FCI; however, none of them have a good discriminatory ability for 30-day acute hospital readmissions after discharge from post-acute inpatient rehabilitation settings. The study results support our a-priori hypothesis that the Hierarchical Condition Category would outperform the other comorbidity indices. The Hierarchical Condition Category performed slightly better than other comorbidity indices though it still lacked good discriminative properties. The C-statistic above 0.70 is considered to be good and clinically relevant. The HCC was developed to estimate costs and was included in the CMS risk adjustment model to predict unplanned 30-day readmission rates. The discriminatory ability of Hierarchical Condition Category from this study was consistent with current CMS risk adjustment model for predicting 30-day readmission.[109]

Future Recommendations

Multiple chronic conditions, or multimorbidity, may affect patient-centered health outcomes in the post-acute population differently than a simple aggregation of comorbidities.[106, 107, 110] Some of the diagnostic conditions in existing comorbidity indices may not be relevant in our study sample. The interaction of the cluster of chronic conditions with functional decline might be more substantial than the effect of individual comorbidity indices.[94, 106, 110, 111] Future research is needed to understand the complex relationship between multimorbidity and functional status and to help identify comorbid conditions that are sensitive to rehabilitation outcomes and hospital readmission.

Current comorbidity indices use ICD-9-CM codes to identify patient medical complications; this system cannot adequately capture the granularity of medical conditions.[104, 105] The ICD-9-CM codes have only 3-5 digits, and lack information about site of etiology, severity, and specificity of conditions. The ICD-10 codes that will be introduced in October 2015 have 3-7 digits and address these issues. [105] In 2005, Quan and colleagues found that comorbidity indices, including Charlson and Elixhauser with ICD-10 codes, outperformed existing ICD-9-CM codes for predicting mortality using administrative data.[112] Future study is recommended to adapt these comorbidity indices using ICD-10 codes.

The impact of comorbid conditions on health outcomes is multifaceted and needs to be better understood. The ability of a single comorbidity index to predict outcomes for various medical conditions is limited. Thus, use of comorbidity indices should be considered in the context of specific outcomes. An index might be good for predicting mortality, but have limited utility in predicting physical function. Also, current comorbidity indices use diagnostic codes that are limited in their ability to capture disability and the components of functional status. Further research is needed to determine performance-based functional status during acute hospitalization along with controlling for the potential confounding effects of comorbid conditions. Including standard and uniform measures of functional status in acute and post-acute settings could improve our ability to predict quality related outcomes such as discahrge setting and hospital readmission. Research that integrates functional status information with targeted and sensitive data on patient comorbid conditions has the potential to improve transitions and health outcomes.

Appendix-A Medical conditions in the Charlson Comorbidity Index (Deyo version)

Items	Comorbidity Conditions	Source/Data File	Definition
1	Myocardial infarct	MedPAR / IRF-PAI	Yes/No
2	Congestive heart failure	MedPAR / IRF-PAI	Yes/No
3	Peripheral vascular disease	MedPAR / IRF-PAI	Yes/No
4	Cerebrovascular disease	MedPAR / IRF-PAI	Yes/No
5	Dementia	MedPAR / IRF-PAI	Yes/No
6	Chronic pulmonary disease	MedPAR / IRF-PAI	Yes/No
7	Rheumatic disease	MedPAR / IRF-PAI	Yes/No
8	Peptic Ulcer disease	MedPAR / IRF-PAI	Yes/No
9	Mild Liver Disease	MedPAR / IRF-PAI	Yes/No
10	Diabetes without chronic complication	MedPAR / IRF-PAI	Yes/No
11	Diabetes with chronic complication	MedPAR / IRF-PAI	Yes/No
12	Hemiplegia/paraplegia	MedPAR / IRF-PAI	Yes/No
13	Moderate or severe renal disease	MedPAR / IRF-PAI	Yes/No
14	Malignant tumor	MedPAR / IRF-PAI	Yes/No
15	Moderate or severe liver disease	MedPAR / IRF-PAI	Yes/No
16	Metastatic solid tumor	MedPAR / IRF-PAI	Yes/No
17	AIDS	MedPAR / IRF-PAI	Yes/No

Appendix-B Medical conditions in the Elixhauser Comorbidity Index

Items	Comorbid Conditions	Source/Data File	Definition
1	Congestive Heart Failure	MedPAR / IRF-PAI	Yes/No
2	Cardiac Arrhythmia	MedPAR / IRF-PAI	Yes/No
3	Valvular Disease	MedPAR / IRF-PAI	Yes/No
4	Pulmonary Circulation Disorder	MedPAR / IRF-PAI	Yes/No
5	Peripheral Vascular Disorder	MedPAR / IRF-PAI	Yes/No
6	Hypertension, uncomplicated/complicated	MedPAR / IRF-PAI	Yes/No
7	Paralysis	MedPAR / IRF-PAI	Yes/No
8	Other neurological disorders	MedPAR / IRF-PAI	Yes/No
9	Chronic Pulmonary Disease	MedPAR / IRF-PAI	Yes/No
10	Diabetes, uncomplicated	MedPAR / IRF-PAI	Yes/No
11	Diabetes, complicated	MedPAR / IRF-PAI	Yes/No
12	Hypothyroidism	MedPAR / IRF-PAI	Yes/No
13	Renal failure	MedPAR / IRF-PAI	Yes/No
14	Liver disease	MedPAR / IRF-PAI	Yes/No
15	Peptic ulcer disease excluding bleeding	MedPAR / IRF-PAI	Yes/No
16	AIDS/HIV	MedPAR / IRF-PAI	Yes/No
17	Lymphoma	MedPAR / IRF-PAI	Yes/No
18	Metastatic cancer	MedPAR / IRF-PAI	Yes/No
19	Solid tumor without metastasis	MedPAR / IRF-PAI	Yes/No
20	Rheumatoid arthritis	MedPAR / IRF-PAI	Yes/No
21	Coagulopathy	MedPAR / IRF-PAI	Yes/No
22	Obesity	MedPAR / IRF-PAI	Yes/No
23	Weight loss	MedPAR / IRF-PAI	Yes/No
24	Fluid / electrolyte disorders	MedPAR / IRF-PAI	Yes/No
25	Blood loss – anemia	MedPAR / IRF-PAI	Yes/No

26	Deficiency Anemia	MedPAR / IRF-PAI	Yes/No
27	Alcohol Abuse	MedPAR / IRF-PAI	Yes/No
28	Drug Abuse	MedPAR / IRF-PAI	Yes/No
29	Psychoses	MedPAR / IRF-PAI	Yes/No
30	Depression	MedPAR / IRF-PAI	Yes/No

Appendix-C Medical conditions in the Functional Comorbidity Index

Items	Functional Comorbidity Index	Source/Data File	Definition
1	Arthritis (rheumatoid and osteoarthritis)	MedPAR / IRF-PAI	Yes/No
2	Osteoporosis	MedPAR / IRF-PAI	Yes/No
3	Asthma	MedPAR / IRF-PAI	Yes/No
4	COPD, ARDS	MedPAR / IRF-PAI	Yes/No
5	Angina	MedPAR / IRF-PAI	Yes/No
6	Congestive heart failure or heart disease	MedPAR / IRF-PAI	Yes/No
7	Heart attack	MedPAR / IRF-PAI	Yes/No
8	Neurological disease	MedPAR / IRF-PAI	Yes/No
9	Stroke or transient ischemic attack	MedPAR / IRF-PAI	Yes/No
10	Diabetes types I and II	MedPAR / IRF-PAI	Yes/No
11	Peripheral vascular disease	MedPAR / IRF-PAI	Yes/No
12	Upper gastrointestinal disease	MedPAR / IRF-PAI	Yes/No
13	Depression	MedPAR / IRF-PAI	Yes/No
14	Anxiety or panic disorders	MedPAR / IRF-PAI	Yes/No
15	Visual impairment	MedPAR / IRF-PAI	Yes/No
16	Hearing impairment	MedPAR / IRF-PAI	Yes/No
17	Degenerative disk disease	MedPAR / IRF-PAI	Yes/No
18	Obesity or BMI >30 kg/m^2	MedPAR / IRF-PAI	Yes/No

Appendix-D Medical conditions in the Hierarchical Condition Category

HCC number	Description	HCC number	Description	HCC number	Description
1	HIV/AIDS	**57**	Schizophrenia	**108**	Vascular disease
2	Septicemia sepsis	**58**	Major depressive, bipolar& paranoid disorder	**110**	Cystic fibrosis
6	Opportunistic infections	**70**	Quadriplegia	**111**	COPD
8	Metastatic cancer & acute leukemia	**71**	Paraplegia	**112**	Fibrosis of Lung & Chronic Lung Disorder
9	Lung & other severe cancers	**72**	Spinal Cord Injury	**114**	Aspiration & specified bacterial pneumonia
10	Lymphoma & other cancers	**73**	ALS/MND	**115**	Pneumococcal pneumonia, empyema, lung abscess
11	Colorectal, bladder, & cancers	**74**	Cerebral Palsy	**122**	Proliferative diabetic retinopathy/vitreous hemorrhage
12	Breast, prostate & other cancers	**75**	Myasthenia Gravis, GB syndrome	**124**	Exudative macular degeneration
17	Diabetes with acute complication	**76**	Muscular dystrophy	**134**	Dialysis status
18	Diabetes with chronic	**77**	Multiple sclerosis	**135**	Acute renal failure

	complication				
19	Diabetes without complication	**78**	Parkinson & Huntington disease	**136**	Chronic kidney disease, stage 5
21	Protein calorie malnutrition	**79**	Seizure disorder& convulsion	**157**	Pressure ulcer with necrosis of muscle, tendon or bone
22	Morbid obesity	**80**	Coma, brain compression/anoxic damage	**158**	Pressure ulcer with full thickness skin loss
23	Significant endocrine metabolic disorder	**82**	Respirator dependence/ tracheostomy status	**161**	Chronic ulcer of skin, except pressure
27	End stage liver disease	**83**	Respiratory arrest	**162**	Severe skin burn
28	Cirrhosis of Liver	**84**	Cardio- respiratory failure & shock	**166**	Severe head injury
29	Chronic hepatitis	**85**	Congestive heart failure	**167**	Major head injury
33	Intestinal obstruction, perforation	**86**	Acute myocardial failure	**169**	Vertebral fracture without SCI
34	Chronic pancreatitis	**87**	Unstable angina & acute IHD	**170**	Hip fracture / dislocation
35	Inflammatory bowel disease	**88**	Angina pectoris	**173**	Traumatic amputation
39	Bone/joint muscle infection/necrosis	**96**	Specified heart arrhythmias	**176**	Complicated of specified Implanted device/graft

40	RA/inflammatory connective tissue disease	**99**	Cerebral hemorrhage	**186**	Major organ transplant or replacement status
46	Severe hematological disorder	**100**	Ischemic or unspecified stroke	**188**	Artificial openings for feeding or elimination
47	Disorder of immunity	**103**	Hemiplegia/ hemiparesis	**189**	Amputation, lower limb amputation
48	Coagulation Defects & hematological disorder	**104**	Monoplegia		
54	Drug / alcohol psychosis	**106**	Atherosclerosis/ulceration/gangrene		
55	Drug / alcohol dependence	**107**	Vascular disease with complication		

Appendix-E List of comorbidities in the TIER classification system, 2011.

Tier categories were developed by the Centers for Medicare and Medicaid Service to classify patients receiving inpatient rehabilitation based on the level of severity and resource utilization. The link below reports ICD-9-CM codes for 951 medical conditions included in the Tier categories.

http://www.udsmr.org/Documents/Appendix_C_List_of_Comorbidities.pdf

Example of conditions in each of the Tier category.

Tier Category	Severity	Example
1	High	Edema of Larynx
2	Moderate	Pharyngeal Dysphagia
3	Low	Diabetes with circulatory disorders
0	No	Diabetes with ketoacidosis

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