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Longitudinal Investigation of Rehospitalization Patterns in Spinal Cord and Traumatic Brain Injury among Medicare Beneficiaries

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Abstract

Objective—To model 12-month rehospitalization risk among Medicare beneficiaries receiving inpatient rehabilitation for SCI or TBI and to create two (SCI- and TBI-specific) interactive tools enabling users to generate monthly projected probabilities for rehospitalization based on an individual patient's clinical profile at discharge from inpatient rehabilitation.

Design—Secondary data analysis.

Setting—More than 1,100 inpatient rehabilitation facilities across the US.

Participants—Medicare beneficiaries receiving inpatient rehabilitation for SCI or TBI.

Main Outcome Measure—Monthly rehospitalization (yes/no) based on Medicare claims.

Results—Results are summarized through computer-generated interactive tools, which plot individual level trajectories of rehospitalization probabilities over time. Factors associated with the probability of rehospitalization over time are also provided, with different combinations of these factors generating different individual level trajectories. Four case studies are presented to demonstrate the variability in individual risk trajectories. Monthly rehospitalization probabilities for the individual high-risk TBI and SCI cases declined from 33–15% and 41–18%, respectively, over time, whereas the probabilities for the individual low-risk cases were much lower and stable over time: 5–2% and 6–2%, respectively.

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Conclusion—Rehospitalization is an undesirable and multifaceted health outcome. Classifying patients into meaningful risk strata at different stages of their recovery is a positive step forward in anticipating and managing their unique healthcare needs over time.

Keywords

Rehabilitation; Readmission; Longitudinal Studies; Spinal Cord Injury; Traumatic Brain Injury

The Affordable Care Act (ACA)¹ contains a comprehensive hospital “readmission reduction program” for Medicare beneficiaries. It is clear that responsibility for hospital readmissions is not limited to short-stay acute care hospitals. The 2014 *Final Rule* established 30-day rehospitalization rates as the next quality metric for inpatient rehabilitation facilities (IRFs).² These and other healthcare reform initiatives have prompted an extraordinary interest in 30-day readmissions in recent years. However, from a patient-centered approach, it is important to note that while the financial responsibility of a given provider may end, a person’s healthcare experiences and risk for hospitalization extend past the acclaimed 1-month threshold. Jencks and colleagues³ showed continued increases in cumulative readmission rates among Medicare beneficiaries for up to 1 year following an ‘index’ hospital stay: 20% at 30 days, 45% at 6 months, and 56% at 1 year.

Older adults who experience a traumatic spinal cord injury (SCI) or traumatic brain injury (TBI) often require intensive postacute care following hospital discharge.⁴ Not surprisingly, the same medical needs and functional deficits that promote direct referral to inpatient rehabilitation also place a patient at higher risk for a later rehospitalization.⁵ Compounding the newly-acquired health problems, are the disruptions in usual care and care continuity resulting from the series of transitions (e.g. community to hospital to inpatient rehabilitation and back to community or other intermediate setting) over a relatively short period of time. This common scenario represents a particularly vulnerable time for older adults with pre-existing chronic health conditions.⁶

The purpose of this study was to model 12-month rehospitalization risk among Medicare beneficiaries receiving inpatient rehabilitation for traumatic SCI or TBI. Our ultimate goal was to use the longitudinal Medicare data to create two (SCI- and TBI-specific) interactive tools enabling users to generate monthly projected probabilities for rehospitalization based on an individual patient’s clinical profile at discharge from inpatient rehabilitation.

Methods

Data source and participants

Data were obtained from the Centers for Medicare and Medicaid Services (CMS). Specific files included the 100% beneficiary summary, Medicare provider analysis and review, and inpatient rehabilitation facility-patient assessment instrument files (2010). The beneficiary summary file includes patient demographic and enrollment (Medicare eligibility) information. The Medicare provider analysis and review file contains claims data for all Medicare inpatient stays. The inpatient rehabilitation facility-patient assessment instrument includes the functional measures and social status variables collected during IRF stays. The

study was approved by the University's institutional review board and we had a data use agreement with the CMS. We selected Medicare beneficiaries who received IRF services for traumatic SCI or TBI and were discharged in 2010 and linked their assessment data to the inpatient claims and enrollment files. Patients were excluded if 1) the rehabilitation stay was not the initial admission for the given condition, 2) they enrolled in the Medicare Advantage plan during the study period, 3) they did not survive for 90 days past discharge, or 4) they had missing data on the predictor variables in the final condition-specific models. Figure 1 shows the flow diagram for both the SCI and TBI samples.

Outcome variable

All-cause hospital readmissions (yes, no) were identified using claims information from the Medicare provider analysis and review file. The observation window extended from days 1 through 365 following discharge from inpatient rehabilitation. Any inpatient claim during that period from a short-stay acute or critical access hospital was coded as a rehospitalization. Note: an emergency department visit without being admitted to the hospital does not count as a rehospitalization.

Covariates

We examined several sociodemographic, clinical, and functional status variables for inclusion in the rehospitalization models based on risk factors commonly reported in readmission studies. Sociodemographic variables included age (years), sex, race/ethnicity (white, black, Hispanic, other), social support based on who the individual was living with prior to injury (family/friends, paid attendant, none), and initial entitlement for Medicare benefits due to disability (yes, no).

Clinical variables included tier comorbidity (none, tier 3, tier 2, tier 1), plegia status (quadriplegia, paraplegia, other) for SCI only obtained from the impairment group code in the IRF assessment file, number of hospitalizations in prior year derived from the claims data, hospital and IRF lengths of stay (days) also derived from the claims data, and discharged against medical advice (yes, no). Each patient is assigned to one of four tier comorbidity categories at admission.² Select comorbid conditions are grouped into specific tier categories based on the perceived impact they will have on an individual's resource utilization and healthcare needs during his or her rehabilitation stay. Tiers 1–3 affect reimbursement with tier 1 associated with the highest additional payments and tiers 2 and 3 with relatively lower additional payments, respectively.

Functional status variables included discharge cognition and motor scores calculated from the 18 items on the FIM instrument.⁷ The cognition subscale includes 5 items (comprehension, expression, social interaction, problem solving, and memory) scores range from 5–35. The motor subscale includes 13 items (eating, grooming, bathing, dressing upper, dressing lower, toileting, bladder, bowel, transfer bed /chair /wheelchair, transfer toilet, transfer tub / shower, walk / wheelchair, and stairs); scores range from 13–91.

Data analysis

This retrospective study examines a nationally representative longitudinal cohort with the goal of developing interactive tools that can be used to estimate individual level monthly rehospitalization probabilities across the first year post rehabilitation discharge for Medicare beneficiaries with SCI and TBI. The study goal was achieved by applying a combination of generalized linear mixed modeling (GLMM) and individual growth curve (IGC) analyses.^{8–10} First, random intercept GLMM was used to generate a logit based temporal profile for each individual based on the study covariates that contributed significantly to the model. All variables listed in Table 1 down through ‘discharged against medical advice’ were tested for inclusion in the initial GLMM models. The customary approach of including the main effects for variables producing significant interaction terms was employed. Type III sums of squares analysis based on a p-value level of less than 0.05 was used as a criterion in the model reduction process. Individual temporal profiles were generated from the reduced models and used in the IGC analysis.

Using IGC analysis, unconditional models (models free of covariates) associating outcome and time (estimated logits) were constructed.¹¹ A number of unconditional models were compared to determine which model optimally related outcome with time¹² within each sample. The Akaike Information Criterion (AIC) was used to identify the best fitting models. In both the SCI and TBI samples, a linear function produced the smallest AIC value. A linear function is defined by two growth parameters; initial status (intercept) and change in outcome over time (slope). Once the function that best described the underlying structure of the temporal data was identified, random effects were introduced into the modeling process as well as covariates to explain the variability in the random effects. This process produced two conditional models, one for the SCI sample and one for the TBI sample (which were subsequently reduced using a <0.05 alpha criterion based on a type III sums of squares analysis). Due to model convergence difficulties as a result of insufficient memory, only outcomes collected at months 1, 2, 4, 6, 8, 10, and 12 were included in the models. All analyses were conducted using SAS 9.4. It is important to note that the analysis performed is descriptive in the sense that results describe the data at hand, although this approach provides a comprehensive, individual level, understanding of the change in the probability of rehospitalization over time. Our ultimate goal was not to test a discrete (yes/no) hypothesis, but rather to model individual risks for rehospitalization over time based on various combinations of patient characteristics. In turn, we developed interactive tools from those models for others to use when assessing risks for patients with various demographic and clinical profiles.

Results

Descriptive summaries for the SCI (n = 1,815) and TBI (n = 7,760) samples are shown in Table 1. Given our focus on Medicare beneficiaries, both samples were older than the typical SCI and TBI study participants; mean ages for the two groups were 68 and 77 years, respectively. Table 1 also includes information on 1-year mortality and monthly rehospitalization rates. The monthly rates include multiple rehospitalizations for some patients. Cumulative first-time rehospitalization rates at 30 days, 90 days, 6 months, and 1

year for the SCI group were 23%, 35%, 45%, and 57%, respectively, and for the TBI group they were 20%, 32%, 42%, and 54%, respectively.

The reduced random intercept GLMM models for the TBI and SCI samples are presented in Tables 2 and 3, respectively.

The reduced conditional models of the TBI and SCI samples are presented in Tables 4 and 5, respectively. To aid in interpretation, all continuous covariates were centered about their respective means and, as a requirement of the analysis performed, each individual contributed at least three temporal measures.¹³

In addition to the results presented in Tables 4 and 5, the correlation between the slopes and intercepts was considered during modeling. However, for each sample, the correlation was negligible, meaning there was no discernible linear relationship between initial status and rate of change.

The narrow width of the 95% confidence intervals for the growth parameters and growth parameter/covariate associations attests to the precision of the estimates. It is important to recognize that the estimates presented in Tables 4 and 5 are reported in terms of logits, where the logit scale is centered about zero and ranges from negative infinity to positive infinity. Although the logit scale is interval and can be used to make direct comparisons between individual level results, these results are more interpretable if transformed into probabilities.

Due to the complexity of the information presented in Tables 4 and 5, two interactive tools were created, one for the TBI sample and the other for the SCI sample. The tools transform the information into user-friendly visual formats. The purpose of these interactive tools is to generate individual-level trajectories for probabilities of rehospitalization over time based on specified covariate values. The following cases highlight four possible trajectories, two representing the TBI sample and two representing the SCI sample. The covariate values examined for each case are summarized in Tables 6 and 7, and the corresponding trajectories for probability of rehospitalization are presented in Figures 2 and 3. An extensive amount of individual level information is provided by each tool; therefore, we encourage the user to investigate how different combinations of covariate values produce different trajectories. Both the TBI and SCI interactive tools used to generate these trajectories are available in an online supplement and can be accessed on the following website: <https://rehabsciences.utmb.edu/cldr/education-training/tools.asp>

Discussion

SCI and TBI are both acute, traumatic events with immediate and often dire health concerns. However, acute care for these conditions has improved substantially over the past 50 years.^{14–17} More individuals and those with more severe injuries are now surviving their initial hospital stay, receiving a relatively short course of postacute rehabilitation, and then being discharged back to the community. Moreover, both the numbers and percentages of older adults in the SCI and TBI inpatient rehabilitation populations have been increasing over the past 15 years.^{18,19} Thus, the challenge of managing, improving, and hopefully

preventing the chronic and secondary conditions associated with these acute injuries is mounting.^{20;21} A logical first step is identifying older patients at risk for poor outcome trajectories prior to discharge from postacute care.

To examine outcome trajectories, we modeled hospital readmission risk over the 12 months following discharge from inpatient rehabilitation in a national sample of Medicare beneficiaries with SCI and TBI. We produced estimates from the entire dataset as our goal was to provide a comprehensive summary rather than developing a predictive model, which would require splitting the data into training and validation samples. Several clinically-relevant variables were independent contributors to readmission risk in both populations: tier comorbidity, prior acute stays, IRF length of stay, and discharge functional status, with the latter three also demonstrating time-moderated effects. Thus, information from just a few easy-to-capture variables may be an important, yet practical, starting point for early identification of potentially at-risk patients. Interestingly, several sociodemographic variables were significant contributors to the TBI model, but not to the SCI model. These included age, sex, race/ethnicity, and disability benefits. Additional research is needed to assess potential mechanisms for the differential influence of sociodemographic characteristics across rehabilitation impairment groups.

Overall, the time variable (month) demonstrated a negative effect, indicating that the risk for rehospitalization decreases over time in both impairment groups. This is also evident from the unadjusted values listed in Table 1. The four case studies emphasize how different patient profiles can affect both the initial rehospitalization risk and the slope of the time effect. To date, 30-day rehospitalization rates have dominated the healthcare reform conversations and literature,^{22;23} but recent interest has turned to alternative payment models such as accountable care organizations²⁴ and bundled payment initiatives.²⁵ These alternative models extend the responsibility for patient outcomes and costs beyond discharge from the inpatient facility. As payment structures and patient management shift from fee-for-service and short-term perspectives to more quality performance and long-term perspectives, it becomes increasingly important to anticipate the changing health needs and healthcare experiences of individuals over time. Stratifying patient risks at discharge may inform transitional care plans and targeting of resources for selective follow-up services. Ideally, this could lead to better patient outcomes and experiences as well as better provider quality performance ratings.

Prior studies including adults of all ages consistently report lower 1-year rehospitalization rates than we observed in our study of older adults with either SCI (57%) or TBI (54%). Davidoff and colleagues²⁶ followed SCI patients from a single comprehensive healthcare system in the mid 1980s and reported a 1-year rehospitalization rate of 39%. This value likely underestimates the true rate as patients lost to follow-up were excluded and only readmissions back to the same health system were captured. Mahmoudi et al.²⁷ examined SCI model systems network data from 1990–2000 and reported an overall 1-year rehospitalization rate of 31%. However, hospital admissions were obtained through patient self report and these authors acknowledged the inherent problems with patients lost to follow-up in prospective longitudinal studies. Nakase-Richardson et al.²⁸ examined more than 20 years of data (1988–2009) from the TBI model systems network and reported an

overall 1-year rehospitalization rate of only 20%. Subsequently, Dams O'Connor and colleagues⁸ used the TBI model systems data to examine longer-term rehospitalization rates. They reported relatively higher rates in the first year (28%) that decreased in year 2 (23%) and then remained consistent in years 5 (22%) and 10 (23%). The TBI model systems' rehospitalization outcome is also based on patient self-report and likely affected by sample attrition, and the sample includes younger patients. Recently, Saverino and colleagues²⁹ used administrative health records for a population-level study of Ontario, Canada residents discharged from an acute hospital with TBI from 2003–2010. The combined 1-year rehospitalization rate was 23% for the entire sample and 36% for those aged 65 years or older. Their sample was not limited to patients requiring intensive postacute rehabilitation. More than half of the 65+ year old patients were discharged home following the index acute hospital stay, which may partially explain the difference in our respective rehospitalization rates.

Limitations

The assumptions for and relationships from this study were limited to Medicare fee-for-service beneficiaries who received inpatient rehabilitation following acute hospitalization for SCI or TBI. Trajectories generated by the interactive tools are based on data captured from those who met the inclusion/exclusion criteria. Consequently, our results are intended to only provide a description of the data, although the technique used is comprehensive and demonstrates the extensive variability in rehospitalization over time within the representative samples. In other words, our intent was to describe the entire dataset, not to create a predictive model, wherein splitting the sample into training and validation samples would be required. Although, this would be a logical approach for future research. Caution should be exercised when generalizing to other populations or extrapolating beyond the typical range of data, i.e. entering covariate values that are unlikely to represent a real individual. Also, relationships between covariates and the growth parameters do not imply causality. Trajectories are mathematical representations based on the associations between identified covariates and the growth parameters. Other factors potentially related to rehospitalization were not available in the claims data (e.g., TBI severity) and thus, were not included in our models. Thus, individuals with SCI or TBI not included in the study may not be constrained to the corresponding trajectories. In addition, the analysis involves a “double estimation” process. First, a set of temporal logits is estimated per individual using a generalized linear mixed model. Then, patterns in the logits are evaluated by way of IGC analysis. Such an estimation process introduces additional error; although, error remains relatively small due to the large study sample. Lastly, the transformation from logits to probabilities requires a transformation from an infinite scale (logits) to a bounded scale (0 to 1 for probabilities). Trajectories on the logit scale will not directly mirror trajectories conformed to probabilities. Based on these complex modeling issues and the descriptive focus of this study, comparisons between trajectories should be made based on practical clinical relevance rather than statistical inference.

Conclusion

Rehospitalization is an undesirable health outcome. It is also a complex multifaceted outcome that is difficult to predict. The risk trajectories generated from the interactive tools attached to this report enable users to obtain visual estimates of an individual's monthly projected probabilities for rehospitalization over the year following discharge from inpatient rehabilitation. Classifying patients with SCI and TBI into meaningful risk strata at different stages of their recovery can improve clinicians' ability to anticipate and manage the unique healthcare needs of their patients over time with the ultimate goal of reducing unnecessary rehospitalizations.

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List of Abbreviations

ACA	Affordable Care Act
AIC	Akaike Information Criterion
CMS	Centers for Medicare and Medicaid Services
GLMM	generalized linear mixed model
IGC	individual growth curve
IRF	inpatient rehabilitation facility
SCI	spinal cord injury
TBI	traumatic brain injury

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Figure 1.
Flow diagram for SCI and TBI sample selections.

Figure 2.
Individual level trajectories for TBI case studies.

Figure 3.
Individual level trajectories for SCI case studies.

Table 1

Patient characteristics for the SCI and TBI samples.

	SCI	TBI
N	1,815	7,760
Age	67.8 (15.3)	76.8 (11.4)
Male	60.1%	51.6%
Race/ethnicity		
White	78.7%	86.0%
Black	11.7%	5.6%
Hispanic	5.9%	5.3%
Other	3.8%	3.2%
Social support		
Family/friends	68.0%	65.9%
Paid attendant/other	1.5%	0.9%
None	30.5%	33.2%
Disability entitlement	42.3%	18.5%
Tier comorbidity		
No tier	58.2%	55.2%
Tier 3	21.1%	20.6%
Tier 2	15.2%	20.7%
Tier 1	5.6%	3.6%
Plegia category		
Other	39.4%	
Paraplegia	22.6%	
Quadriplegia	37.9%	
Prior hospitalizations	1.8 (1.4)	1.7 (1.3)
Length of stay, hospital	8.5 (9.4)	7.7 (6.6)
Length of stay, IRF	19.5 (12.9)	14.9 (8.0)
Discharge FIM cognition	29.2 (5.5)	23.7 (6.9)
Discharge FIM motor	49.7 (19.5)	58.4 (16.4)
Discharged against medical advice	0.3%	0.2%
Died within 1 year	8.3%	10.9%
Rehospitalization		
Month 1	22.5%	20.4%
Month 2	11.8%	9.9%
Month 3	10.3%	9.3%
Month 4	9.9%	8.1%
Month 5	7.3%	7.8%
Month 6	8.7%	6.8%
Month 7	9.0%	6.6%
Month 8	8.0%	6.5%
Month 9	7.4%	6.3%

	SCI	TBI
Month 10	7.2%	5.9%
Month 11	7.4%	5.5%
Month 12	7.9%	6.9%

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Table 2

Reduced Random Intercept Generalized Linear Mixed Model for the TBI Sample.

Covariate	F-Value	P-Value
Month	89.85	<.001
Age at admission	5.41	.020
Race	2.71	.043
Disability benefits	6.22	.013
Tier comorbidity	13.52	<.001
Prior acute stays	338.16	<.001
Hospital LOS	0.22	.648
IRF LOS	13.47	<.001
Discharge against medical advice	4.87	.027
Discharge cognitive FIM	1.95	.162
Discharge motor FIM	99.58	<.001
Time* Prior acute stays	7.22	<.001
Time*Hospital LOS	4.08	<.001
Time*IRF LOS	23.80	<.001
Time* Discharge cognitive FIM	2.27	.034
Time* Discharge motor FIM	24.27	<.001

Table 3

Reduced Random Intercept Generalized Linear Mixed Model for the SCI Sample.

Covariate	F-Value	P-Value
Month	29.01	<.001
Tier comorbidity	15.64	<.001
Prior acute stays	72.47	<.001
IRF LOS	1.46	.227
Discharge motor FIM	65.60	<.001
Plegia	9.97	<.001
IRF LOS*Month	8.84	<.001
Discharge motor FIM*Month	11.81	<.001
Prior acute stays*Month	2.90	.008

Table 4

The Reduced Conditional Model for the TBI Sample.

Parameter	Estimate	P-Value	Lower 95% CI	Upper 95% CI
Intercept	-2.280	<.001	-2.300	-2.260
Month	-0.076	<.001	-0.077	-0.075
Age at admission	0.006	<.001	0.005	0.007
Gender = Female	-0.023	.032	-0.040	-0.002
Gender = Male (Reference)	0			
Race = Black	-0.044	.060	-0.090	0.002
Race = Hispanic	0.096	<.001	0.050	0.140
Race = Other	-0.310	<.001	-0.370	-0.250
Race = White (Reference)	0			
Disability benefits = Yes	0.170	<.001	0.130	0.200
Disability benefits = No (Reference)	0			
Tier comorbidity = 1	0.410	<.001	0.353	0.472
Tier comorbidity = 2	0.042	.004	0.014	0.070
Tier comorbidity = 3	0.270	<.001	0.240	0.300
Tier comorbidity = None (Reference)	0			
Prior acute stays	0.180	<.001	0.170	0.180
Hospital LOS	0.017	<.001	0.015	0.018
IRF LOS	-0.028	<.001	-0.029	-0.026
Discharge cognitive FIM	-0.017	<.001	-0.018	-0.015
Discharge motor FIM	-0.027	<.001	-0.027	-0.026
Month* IRF LOS	0.003	<.001	0.003	0.003
Month*Hospital LOS	-0.003	<.001	-0.003	-0.002
Month*Discharge cognitive FIM	0.002	<.001	0.002	0.002
Month* Discharge motor FIM	0.002	<.001	0.002	0.002
Month* Prior acute stays	0.014	<.001	0.013	0.015

Table 5

The Reduced Conditional Model for the SCI Sample.

Parameter	Estimate	P-Value	Lower 95% CI	Upper 95% CI
Intercept	-2.200	<.001	-2.230	-2.160
Month	-0.079	<.001	-0.081	-0.077
Tier comorbidity = 1	0.980	<.001	0.890	1.070
Tier comorbidity = 2	0.170	<.001	0.110	0.230
Tier comorbidity = 3	0.350	<.001	0.300	0.400
Tier comorbidity = None (Reference)	0			
Prior acute stays	0.170	<.001	0.150	0.180
IRF LOS	-0.024	<.001	-0.025	-0.022
Discharge motor FIM	-0.031	<.001	-0.032	-0.030
Plegia = Para	0.350	<.001	0.300	0.400
Plegia = Quad	-0.091	<.001	-0.140	-0.041
Plegia = Other (Reference)	0			
Month*IRF LOS	0.003	<.001	0.003	0.003
Month* Discharge motor FIM	0.002	<.001	0.002	0.002
Month* Prior acute stays	0.008	<.001	0.007	0.010

Table 6

Covariate Values for Cases 1 and 2 from the TBI Sample.

Covariate	Case #1	Case #2
Age	68	80
Sex	Female	Male
Race/ethnicity	Black	Hispanic
Disability benefits	No	Yes
Tier comorbidity	None	1
Prior acute stays	0	4
Hospital LOS	6	12
IRF LOS	17	12
Discharge cognition FIM	29	19
Discharge motor FIM	64	49

Table 7

Covariate Values for Cases 3 and 4 from the SCI Sample.

Covariate	Case #3	Case #4
Tier comorbidity	None	1
Prior acute stays	0	3
IRF LOS	15	17
Discharge motor FIM	64	41
Plegia	None	Para