HHS Public Access

Author manuscript

J Med Syst. Author manuscript; available in PMC 2019 September 18.

Published in final edited form as:

J Med Syst. ; 42(5): 81. doi:10.1007/s10916-018-0936-3.

Validation of the All Patient Refined Diagnosis Related Group (APR-DRG) Risk of Mortality and Severity of Illness Modifiers as a Measure of Perioperative Risk

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Abstract

The All Patient Refined Diagnosis Related Group (APR-DRG) is an inpatient visit classification system that assigns a diagnostic related group, a Risk of Mortality (ROM) subclass and a Severity of Illness (SOI) subclass. While extensively used for cost adjustment, no study has compared the APR-DRG subclass modifiers to the popular Charlson Comorbidity Index as a measure of comorbidity severity in models for perioperative in-hospital mortality. In this study we attempt to validate the use of these subclasses to predict mortality in a cohort of surgical patients. We

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Author Contributions Patrick J. McCormick has seen the study data, reviewed the analysis of the data, and approved the final manuscript. Hung-mo Lin has seen the study data, reviewed the analysis of the data, and approved the final manuscript. Stacie G. Deiner has seen the study data, reviewed the analysis of the data, and approved the final manuscript. Matthew A. Levin has seen the study data, reviewed the analysis of the data, and approved the final manuscript.

Conflict of Interest Patrick J. McCormick reported no conflicts of interest.
Hung-mo Lin reported no conflicts of interest.
Stacie G. Deiner reported no conflicts of interest.
Matthew A. Levin reported no conflicts of interest.

This work in part has been presented at the Annual Meeting of the American Society of Anesthesiologists, New Orleans, LA, October 12, 2014.

This article is part of the Topical Collection on *Systems-Level Quality Improvement*

Ethical Approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed Consent Informed consent was waived by the Mount Sinai Institutional Review Board (irb@mssm.edu) due to the retrospective nature of the study.

analyzed all adult (age over 18 years) inpatient non-cardiac surgery at our institution between December 2005 and July 2013. After exclusions, we split the cohort into training and validation sets. We created prediction models of inpatient mortality using the Charlson Comorbidity Index, ROM only, SOI only, and ROM with SOI. Models were compared by receiver-operator characteristic (ROC) curve, area under the ROC curve (AUC), and Brier score. After exclusions, we analyzed 63,681 patient-visits. Overall in-hospital mortality was 1.3%. The median number of ICD-9-CM diagnosis codes was 6 (Q1–Q3 4–10). The median Charlson Comorbidity Index was 0 (Q1–Q3 0–2). When the model was applied to the validation set, the c-statistic for Charlson was 0.865, c-statistic for ROM was 0.975, and for ROM and SOI combined the c-statistic was 0.977. The scaled Brier score for Charlson was 0.044, Brier for ROM only was 0.230, and Brier for ROM and SOI was 0.257. The APR-DRG ROM or SOI subclasses are better predictors than the Charlson Comorbidity Index of in-hospital mortality among surgical patients.

Keywords

Risk adjustment; Case mix; Diagnostic related group; Comorbidity; Perioperative mortality

Introduction

There have been several retrospective studies using comorbidity data, frequently taken from administrative sources, to predict outcomes in the perioperative period. One of the most popular comorbidity indices is the Charlson Comorbidity Index (CCI) [1], which has been used to develop postoperative outcome predictions for emergency general surgery [2], hip fracture surgery [3], ileostomy creation [4], transurethral re-section of the prostate [5], and many other surgical patient populations. The CCI can be generated from administrative diagnosis codes [6, 7].

Another available measure of a patient's disease burden are the All Patient Refined Diagnosis Related Group (APR-DRG) subclasses, which is used by several major US hospital systems [8]. The primary input to APR-DRG is a set of diagnosis codes and surgical procedure codes, generated by chart abstraction. Through a complex multi-phase algorithm, the APR-DRG grouper outputs a DRG and two modifiers: Risk of Mortality (ROM) and Severity of Illness (SOI). SOI is defined as "the extent of organ system loss of function or physiologic decompensation" and is categorized as minor, moderate, major, and extreme. ROM is the likelihood of in hospital mortality based on secondary diagnosis, age, principal diagnosis, and whether certain procedures were performed [9]. The Risk of Mortality and Severity of Illness subclasses are independent of each other. For example, acute cholecystitis has a high SOI, but a low ROM [10].

While there have been several small studies that used APR-DRG ROM for risk adjustment of outcome, there is little published work validating the use of ROM and SOI as predictors of perioperative mortality [11, 12]. Historically, most risk adjustment based on administrative data in the surgical and anesthesiology literature has used the Charlson Comorbidity Index (CCI) [1] as derived from ICD-9-CM diagnosis codes [13]. However, the

CCI performs only moderately well in the perioperative setting, with c-statistics ranging from 0.711 to0.881 [14].

Since APR-DRG information is generated for all hospitalized patients, the data are readily available for researchers without additional effort or cost. We hypothesized that the APR-DRG ROM alone or with SOI is a valid measure of perioperative risk with better performance than the Charlson comorbidity index.

Methods

This study was approved by the Icahn School of Medicine at Mount Sinai Institutional Review Board (New York, NY, USA; IRB@mssm.edu, 212–824–8200.) The study hypothesis was developed prior to data extraction. Our perioperative data warehouse contains data on all anesthetics performed at the Mount Sinai Hospital since 2002, and integrates patient data from the hospital data warehouse. Using the perioperative data warehouse, we identified inpatient visits among adults (18 years of age or older) where the patient had non-cardiac surgery between December 2005 and July 2013. We extracted the patient's discharge disposition, ICD-9-CM diagnosis and procedure codes, and APR-DRG data. Visits with a non-surgical APR-DRG code were excluded. For patients with repeated visits, only the first visit was retained in the data set. APR-DRG data was generated using the most current model at the time of the inpatient visit.

In order to generate Charlson Comorbidity Index (CCI) results similar to that of a manual chart review, administrative ICD-9-CM discharge diagnosis codes were supplemented with comorbidity data from the anesthesia information management system (AIMS). Anesthesiologists had an opportunity to select "hypertension", "heart failure", "coronary artery disease", "chronic obstructive pulmonary disease", and "asthma" comorbidities within the AIMS. The electronic anesthesia record also maintained a list of preoperative medications. A diabetes comorbidity was inferred from the presence of an oral hypoglycemic medication or insulin. Hypertension was inferred from the presence of an oral antihypertensive medication. A ICD-9-CM to comorbidity map [7] with revised diagnosis weights [15] was used. For the ROM and SOI variables, the "extreme" category was used as the reference. Two models were developed using the CCI. The first treated the CCI as a continuous variable, while the second model created a categorical variable stratifying CCI into a "0" reference category, "1, 2" category, "3–5" category, and "> = 6" category. The category cut points were based on the frequency distribution within the dataset.

Statistical analysis

Model development was performed using the holdout method. We randomly divided the dataset into training and validation cohorts in a 1:1 ratio. Logistic regression models were created with in-hospital mortality as the outcome variable and five sets of input variables: the ROM subclass, the SOI subclass, the ROM and SOI subclasses together, the CCI as a continuous value, and CCI grouped into categories. To compare the prediction models, we considered performance measures in three areas: the overall performance (generalized Nagelkerke's R^2 for binary outcome and scaled Brier score), discrimination ability (c-

statistic / ROC curve, and discrimination slope / box plot) and model calibration (calibration slope and Hosmer-Lemeshow test).

Calculations were performed using R version 3.3.2 (R Foundation for Statistical Computing, Vienna, Austria.) The R package *medicalrisk*[1] version 1.1 was used to determine Charlson Comorbidity Index values. The package *ROCR* version 1.0–7 was used to generate ROC curves, and the package *rms* version 5.0–0 was used to generate calibration curves.

Results

Data from 86,392 patient encounters were retrieved. After applying exclusion criteria, 62,486 patients remained, with one encounter for each. These encounters were randomly divided into a training (n = 31,193) and validation (n = 31,293) dataset (Fig. 1). Table 1 shows that there were no significant differences in either demographics or outcomes between the training and validation cohorts. Within the validation cohort, the mean age was 52.8 (SD 17.8), and the cohort was 60.9% female. Overall in-hospital mortality was 1.3%. The median [Q1–Q3] number of ICD-9-CM diagnosis codes was 6 [4–10], and the median Charlson Comorbidity Index was 1 [0–2]. Table 2 shows the characteristics in the validation cohort, stratified by in-hospital mortality versus survival.

Performance and discrimination

The overall performance of the model using ROM only, as measured by R^2 and Brier, was considerably better than the performance using the Charlson Comorbidity Index. All results are from model application to the validation dataset. R^2 for ROM only was 0.53, and Brier scaled was 0.230 versus R^2 of 0.19 and Brier of 0.044 for CCI (Table 2). When used as a categorical variable, CCI had the same R^2 and a similar Brier (0.031.) The model using ROM only had excellent discrimination. The c-statistic for the model using ROM only was0.974 (95% CI: 0.969–0.979) versus 0.865 (95% CI: 0.849–0.880) for Charlson continuous. A model with ROM and SOI had a similar c-statistic of 0.977 (95% CI: 0.973–0.982), as did a model with SOI only (c-statistic 0.965; 95% CI: 0.959–0.970). Figure 2 shows the ROC (discrimination) curves for all models plotted on the same axes.

Validation

Overall performance in the validation cohort was comparable to the training dataset, according to R^2 and Brier, for all indexes. The c-statistics were almost identical. Calibration intercepts were slightly below zero for the ROM-only and the Charlson models, reflecting systematic “too high” predictions. Calibration slopes were slightly above 1 for the ROM-only and the Charlson models, suggesting some underfitting for large scores. (Table 3).

Discussion

Our results show that use of the APR-DRG Risk of Mortality score or the use of the Severity of Illness score outperforms the Charlson Comorbidity Index for prediction of mortality in a mixed surgical population. Use of both subclasses together (SOI and ROM) improves overall

[1] http://cran.r-project.org/web/packages/medicalrisk/

performance but not significantly. The APR-DRG system is readily available at many institutions at no additional expense. APR-DRG is likely to continue to be accurate in future years since unlike CCI, APR-DRG is updated annually to handle new diagnostic and procedural codes. Additionally, APR-DRG is generated with a single algorithm, unlike CCI which has multiple published methods to classify comorbidities [6, 7, 16–18]. The single algorithm ensures that methodology is uniform.

Currently the most often used comorbidity composite is the Charlson comorbidity index. Charlson is a diagnosis based comorbidity index as opposed to a medication or outpatient data type index [19]. Generally diagnosis based indices outperform the latter, although performance varies by surgical population and by specific outcome (e.g. mortality, length of stay, development of complications). When used with abstracted chart data instead of administrative data, the Charlson age-comorbidity index (CACI) [20] has demonstrated good performance in its ability to predict mortality among emergency surgery patients with a c-statistic of 0.9 [2]. The Charlson index has also been combined with frailty and lab data to construct a risk model for elderly surgical patients [21]. Prediction of in-hospital mortality using administrative versions of the Charlson and different surgical populations vary from a c-statistic of 0.711 to 0.881 [14]. This variability underscores the need for a better comorbidity-based risk model.

Other indices to predict clinical endpoints have been developed but are not as commonly used as Charlson, likely due to added complexity. The goal of the Risk Stratification Indices [13] (RSIs) is to enable risk stratification across diverse populations using only administrative data. The RSIs were developed using diagnostic and procedure data from hospital inpatients over 65 years old from a United States Medicare database. The RSI for in-hospital mortality compared favorably to the Charlson comorbidity index. The Risk Quantification Indices [22] (RQIs) is a separate system that uses the American Medical Association Current Procedural Terminology (CPT) code, the American Society of Anesthesiologists Physical Status, and patient’s age or hospitalization status. The RQIs were developed from National Surgical Quality Improvement Project (NSQIP) data. A validation study using data from the Massachusetts General Hospital found that the RSIs had good discrimination but poor calibration, while 30-day mortality RQI had good discrimination and calibration [23].

Limitations

A limitation of comparing APR-DRG to the CCI is that APR-DRG’s subclasses are designed to measure more than just the quantity of comorbidities. The risk of mortality subclass was specifically designed to predict mortality, while the severity of illness subclass was designed to predict increased resource use due to the patient’s comorbidities and acute illness. ROM and SOI subclasses are not strictly comparable between DRGs. A patient with risk of mortality 3 in a cardiac surgery DRG has a different risk of death than a risk of mortality 3 in a general surgery DRG. However, for perioperative use frequently a narrow range of DRGs is profiled (e.g. only orthopedic cases, or urology cases.) Since the APR-DRG is often available from the same data source as CCI, mortality risk models such as those cited above should consider using APR-DRG ROM and/or SOI instead of CCI.

This study is also limited due to the use of administrative data for model input. A limitation that APR-DRG shares with the Charlson comorbidity index is that diagnostic and procedure codes are not available until the end of a patient's inpatient stay. Administrative data is more limited than chart abstracted data. For example, this study focuses on inpatient mortality because our institution does not routinely conduct 30-day or 1-year followup for inpatient surgical admissions. Another limitation with administrative data is that the degree of comorbidity may reflect the quality of clinical documentation. A recent study found that improved surgical documentation results in higher APR-DRG subclass rankings [24]. Finally, administrative data are generally more specific but less sensitive than a manual chart review. Our study incorporated comorbidity data from the anesthesia record to offset the limitation of relying on ICD-9-CM codes alone. Our study may under-state the degree that CCI performance lags more sophisticated methods.

This study shows that the APR-DRG ROM or SOI subclasses are better predictors than the Charlson Comorbidity Index of in-hospital mortality among surgical patients. There was no statistical difference between using the subclasses individually or in combination.

Funding

Departmental sources only.

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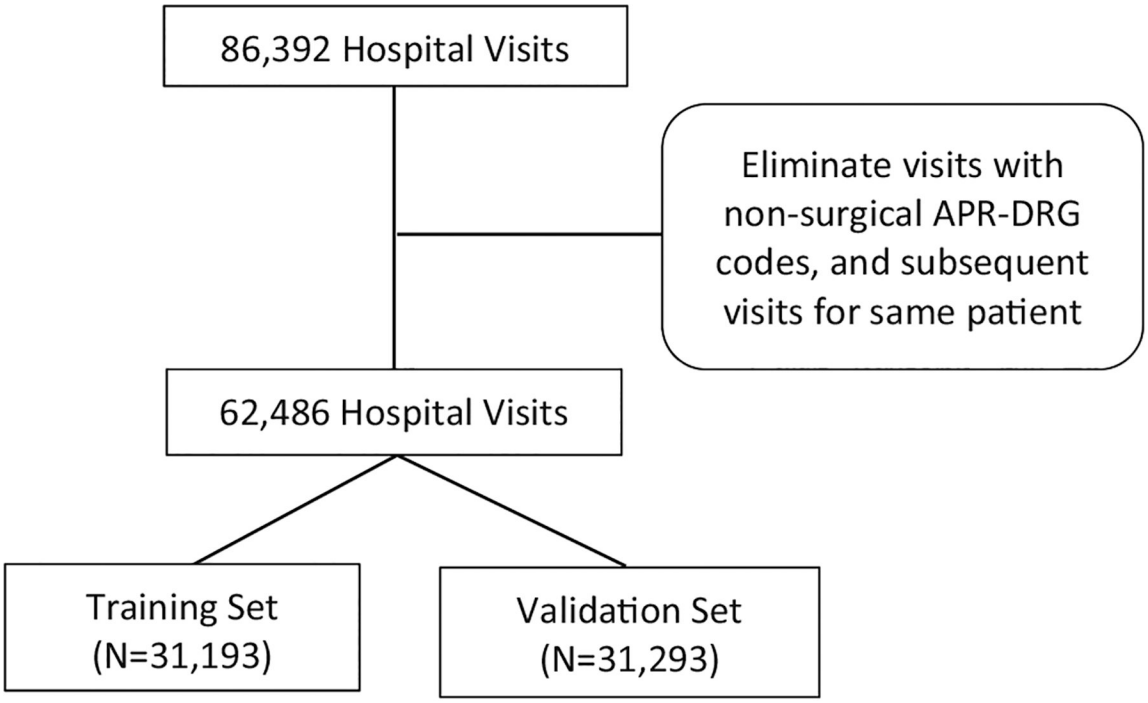

Fig. 1.
Flow of hospital visit selection and separation into training and validation sets

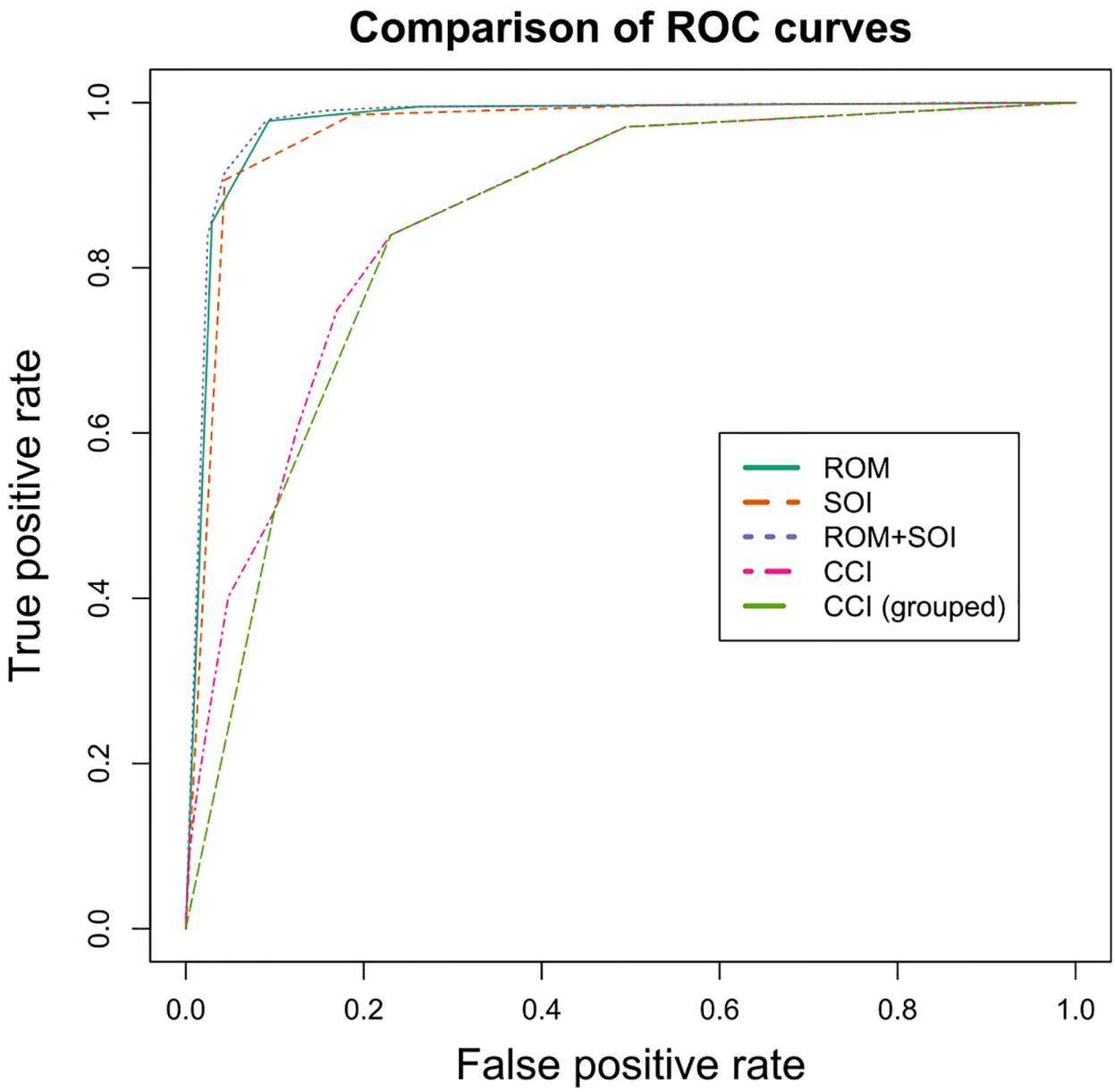

Fig. 2.
Receiver-operator characteristic (ROC) curves for each model. ROM = Risk of Mortality, SOI = Severity of Illness, CCI = Charlson Comorbidity Index

Table 1

Patient Demographics and Clinical Characteristics Stratified by Training and Validation Cohorts

Characteristic	Training	Validation	*P* Value
n	31,193 (50%)	31,293 (50%)	
Age	52.8 (17.8)	52.9 (17.8)	0.21
Female	19,073 (61.1%)	18,965 (60.6%)	0.17
ASA PS >2	13,643 (43.7%)	13,770 (44%)	0.51
Emergency	3113 (10%)	3169 (10.1%)	0.54
ICD-9 Dx Codes	6 [4–10]	6 [4–10]	0.87
CCI	0 [0–2]	1 [0–2]	0.44
CCI Group			0.48
0	15,612 (50%)	15,631 (50%)	
1,2	8294 (26.6%)	8200 (26.2%)	
3–5	4077 (13.1%)	4185 (13.4%)	
≥6	3210 (10.3%)	3277 (10.5%)	
APR-DRG SOI			0.29
Minor	13,938 (44.7%)	13,811 (44.1%)	
moderate	11,089 (35.5%)	11,292 (36.1%)	
Major	4390 (14.1%)	4468 (14.3%)	
Extreme	1776 (5.7%)	1722 (5.5%)	
APR-DRG ROM			0.92
Minor	22,824 (73.2%)	22,825 (72.9%)	
moderate	5111 (16.4%)	5187 (16.6%)	
Major	2014 (6.5%)	2028 (6.5%)	
Extreme	1244 (4%)	1253 (4%)	

Statistics expressed as *count (%), mean (SD), or median [Q1–Q3]* as appropriate

Dx diagnosis, *CCI* Charlson Comorbidity Index, *APR-DRG* All Patient Refined-Diagnosis Related Group, *ROM* Risk of Mortality, *SOI* Severity of Illness

Table 2

Validation Cohort Patient Demographics and Clinical Characteristics Stratified by In-Hospital Mortality

Characteristic	In-Hospital Mortality	Survived to Discharge	*P* Value
n	406 (1.3%)	30,887 (98.7%)	
Age	67.9 (15.2)	52.7 (17.7)	< 0.0001
Female	190 (46.8%)	18,775 (60.8%)	< 0.0001
ASA PS >2	397 (97.8%)	13,373 (43.3%)	< 0.0001
Emergency	152 (37.4%)	3017 (9.8%)	< 0.0001
ICD-9 Dx Codes	26 [19–33]	6 [4–9]	< 0.0001
CCI	6 [3–8]	0 [0–2]	< 0.0001
CCI Group			< 0.0001
0	12 (3%)	15,619 (50.6%)	
1,2	53 (13.1%)	8147 (26.4%)	
3–5	136 (33.5%)	4049 (13.1%)	
≥6	205 (50.5%)	3072 (9.9%)	
APR-DRG SOI			< 0.0001
Minor	1 (0.2%)	13,810 (44.7%)	
moderate	5 (1.2%)	11,287 (36.5%)	
Major	32 (7.9%)	4436 (14.4%)	
Extreme	368 (90.6%)	1354 (4.4%)	
APR-DRG ROM			<0.0001
Minor	2 (0.5%)	22,823 (73.9%)	
moderate	7 (1.7%)	5180 (16.8%)	
Major	50 (12.3%)	1978 (6.4%)	
Extreme	347 (85.5%)	906 (2.9%)	

Statistics expressed as *count (%), mean (SD), or median [Q1–Q3]* as appropriate

Dx diagnosis, *CCI* Charlson Comorbidity Index, *APR-DRG* All Patient Refined-Diagnosis Related Group, *ROM* Risk of Mortality, *SOI* Severity of Illness

Table 3

APR-DRG ROM, SOI, ROM+SOI, and Charlson model C-statistics and Brier Scores

Validation dataset (*N* = 31,293): Observed mortality rate is 1.30%									
ROM		1.32%	0.010	0.230	0.53	0.974	0.23	−0.03	1.05
SOI		1.29%	0.010	0.184	0.49	0.965	0.18	0.02	1.01
ROM+SOI		1.30%	0.010	0.257	0.55	0.977	0.25	0.00	1.03
Charlson		1.32%	0.012	0.044	0.19	0.865	0.05	−0.02	1.04
	Categorical	1.34%	0.012	0.031	0.19	0.850	0.03	−0.03	1.05

APR-DRG All Patient Refined Diagnosis Related Group, *ROM* Risk of Mortality, *SOI* Severity of Illness

Model details:

ROM: logit(in-hospital mortality) = − 0.9537 −7.2897*(minor==1) – 5.5044*(moderate==1) – 2.6967*(major==1) (REF = Extreme)

SOI: logit(in-hospital mortality) = − 1.3146 −7.1284*(minor==1) – 5.8010*(moderate==1) – 3.9317*(major==1) (REF = Extreme)

ROM + SOI: logit(in-hospital mortality) = −0.8404 – 5.0272*(ROM minor==1) – 3.6630*(ROM moderate==1) – 1.8176*(ROM major==1) – 2.7483*(SOI minor==1) – 2.0508*(SOI moderate==1) – 1.8974*(SOI major==1)

Charlson Index: logit(in-hospital mortality) = − 5.5806 + 0.3851*index

Charlson Index (categorical): logit(in-hospital mortality) = − 7.0158 + 2.2172 (score==1, 2) + 3.6417 (score==3–5) +4.3045 (score > =6)