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CLINICAL RESEARCH

The Elixhauser Comorbidity Method Outperforms the Charlson Index in Predicting Inpatient Death After Orthopaedic Surgery

Mariano E. Menendez MD, Valentin Neuhaus MD, C. Niek van Dijk MD, PhD, David Ring MD, PhD

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Abstract

Background Scores derived from comorbidities can help with risk adjustment of quality and safety data. The Charlson and Elixhauser comorbidity measures are well-known risk adjustment models, yet the optimal score for orthopaedic patients remains unclear.

Questions/purposes We determined whether there was a difference in the accuracy of the Charlson and Elixhauser comorbidity-based measures in predicting (1) in-hospital mortality after major orthopaedic surgery, (2) in-hospital adverse events, and (3) nonroutine discharge.

Methods Among an estimated 14,007,813 patients undergoing orthopaedic surgery identified in the National Hospital Discharge Survey (1990–2007), 0.80% died in the hospital. The association of each Charlson comorbidity measure and Elixhauser comorbidity measure with mortality was assessed in bivariate analysis. Two main multivariable logistic regression models were constructed, with in-hospital mortality as the dependent variable and one of the two comorbidity-based measures (and age, sex, and year of surgery) as independent variables. A base model that included only age, sex, and year of surgery also was evaluated. The discriminative ability of the models was quantified using the area under the receiver operating characteristic curve (AUC). The AUC quantifies the ability of our models to assign a high probability of mortality to patients who die. Values range from 0.50 to 1.0, with 0.50 indicating no ability to discriminate and 1.0 indicating perfect discrimination.

Results Elixhauser comorbidity adjustment provided a better prediction of in-hospital case mortality (AUC, 0.86; 95% CI, 0.86–0.86) compared with the Charlson model (AUC, 0.83; 95% CI, 0.83–0.84) and to the base model with no comorbidities (AUC, 0.81; 95% CI, 0.81–0.81). In terms of relative improvement in predictive performance, the Elixhauser measure performed 60% better than the Charlson score in predicting mortality. The Elixhauser model discriminated inpatient morbidity better than the Charlson measure, but the discriminative ability of the model was poor and the difference in the absolute improvement in predictive power between the two models (AUC, 0.01) is of dubious clinical importance. Both comorbidity models exhibited the same degree of discrimination for estimating nonroutine discharge (AUC, 0.81; 95% CI, 0.81–0.82 for both models).

Conclusions Provider-specific outcomes, particularly inpatient mortality, may be evaluated differently depending on the comorbidity risk adjustment model selected. Future research assessing and comparing the performance of the

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This work was performed at the Orthopaedic Hand and Upper Extremity Service, Massachusetts General Hospital, Boston, MA, USA.

M. E. Menendez (✉), V. Neuhaus, D. Ring
Orthopaedic Hand and Upper Extremity Service, Massachusetts General Hospital, Yawkey Center, Suite 2100, 55 Fruit Street, Boston, MA 02114, USA
e-mail: marianofurrer@gmail.com

C. N. van Dijk
Department of Orthopaedic Surgery, Academic Medical Center, Amsterdam, The Netherlands

Charlson and Elixhauser measures in predicting long-term outcomes would be of value.

Level of Evidence Level II, prognostic study. See the Instructions for Authors for a complete description of levels of evidence.

Introduction

Patients undergoing orthopaedic surgery often have multiple coexisting medical conditions (comorbidities) [13, 21, 24, 28, 39, 45, 58]. Preoperative risk assessment can help with decision-making and management strategies [11, 37, 50]. Several models for estimating risk based on coded comorbidities are currently in use for orthopaedic patients, but there is no consensus regarding the optimal approach [22, 37, 49, 51, 56, 57]. Selecting appropriate risk adjustment models can help hospitals contain costs while ensuring high levels of quality. Furthermore, inadequate comorbidity risk-adjustment might penalize practitioners and hospitals that care for the sickest patients [41].

Large administrative inpatient databases have been used to assess the effect of baseline comorbidity status on surgical care outcomes targeted in pay-for-performance initiatives such as mortality, morbidity, and discharge disposition [14, 22, 32–34, 37–39]. The Charlson Comorbidity Index [5] encompasses 19 medical conditions and is the most widely used comorbidity risk adjustment model in orthopaedic surgery. First reported in 1987 to predict 1-year mortality [5], this index subsequently was adapted for use with administrative databases [9]. The Elixhauser measure [12], a more recent model including 31 conditions, is believed to be a better predictor of mortality in patients with cardiac, gastrointestinal, hepatobiliary, and oncologic conditions [6, 18, 27, 52]. Several prevalent comorbidities such as hypertension, obesity, weight loss, and psychiatric disorders that are included in the Elixhauser model are not included in the Charlson model [12].

We therefore determined whether there was a difference in the accuracy of the Charlson and Elixhauser comorbidity-based measures in predicting (1) in-hospital mortality after major orthopaedic surgery, (2) in-hospital adverse events, and (3) nonroutine discharge.

Patients and Methods

All data were extracted from the National Hospital Discharge Survey (NHDS) database [4, 8]. The NHDS is an annual probability sample survey of discharges from nonfederal, general, and short-stay hospitals in the United States [8, 19]. Sample data then were weighted to produce annual estimates of inpatient care [8]. A maximum of seven medical diagnoses and four procedures were gathered and coded with the use of ICD-9-CM codes. Patient demographic information, hospital characteristics, and inpatient outcomes such as discharge disposition and hospital length of stay also were collected. Recognizing its utility to answer valuable clinical questions, the NHDS has been used extensively to analyze data associated with a wide range of diagnoses and procedures across different medical specialties [3, 25, 33, 34, 38, 44, 48]. Because of prior adequate data deidentification, our study was exempt from institutional review board approval.

Patients with a procedure code (ICD-9-CM) for primary TKA (81.84), primary THA (81.51), or spinal fusion (81.00 to 81.08) were included in the sample. Patients who underwent hip fracture (820.x) surgery also were included in the analysis. From a database with more than 500,000,000 patients treated between 1990 to 2007, an estimated 14,007,813 patients were identified and included in the analysis. The mean age of the patients was 66 $\pm$ 15 years, and female patients accounted for 62% of the study sample (Table 1). Overall, an estimated 0.80% of the included patients died during hospitalization. Mortality rates ranged from 0.30% for total joint arthroplasty and spinal fusion to 2.6% for operative treatment of hip fracture (Table 1).

Comorbidity burden was quantified using validated Charlson (adaptation by Deyo et al. [8]) and Elixhauser coding algorithms available for ICD-9-CM codes [9, 12, 43]. Dichotomous variables indicating the presence or absence of each Charlson and Elixhauser comorbidity were created, and their associations with mortality were assessed in bivariate analysis using chi-square tests. In addition, the original Charlson and the weighted Elixhauser scores, developed by van Walraven et al. [55], were computed and further stratified into groups (0, 1–2, 3–4, $\geq$ 5 and $<$ 0, 0, 1–4, $\geq$ 5, respectively). The Charlson weights assigned to each comorbidity range from +1 to +6, while the Elixhauser weights range from −7 to +12 [5, 55]. Comorbidity scores then can be calculated for each patient by summing the individual weights of all comorbidities. Continuous variables (age, days of care) of the stratified Charlson and Elixhauser groups were analyzed with ANOVA, and categorical data (sex, mortality, adverse events, discharge status) were analyzed with the chi-square test (Table 2). Chronic pulmonary disease (11%) and uncomplicated diabetes mellitus (11%) were the most frequently encountered comorbidities when using the Charlson/Deyo algorithm (Table 3). Among all 31 Elixhauser comorbidities, uncomplicated hypertension (38%) was the most prevalent condition, followed by chronic pulmonary disease (11%) and uncomplicated diabetes mellitus (11%) (Table 4).

Table 1. Characteristics of the study cohort (n = 14,007,813)

Parameter	Total cohort	Mortality cohort	p value
% of the total cohort	100	0.80	
Age (years)*	66 ± 15	81 ± 11	< 0.001
Age group (%)			< 0.001
≤ 50 years	15	0.10	
50–59	15	0.10	
60–69 years	22	0.20	
70–79 years	28	0.70	
80–89 years	16	2.0	
> 89 years	4.0	4.1	
Sex (%)			< 0.001
Male	38	0.70	
Female	62	0.80	
Procedure (%)			
Primary TKA	38	0.30	< 0.001
Primary THA	21	0.30	< 0.001
Spinal fusion	20	0.30	< 0.001
Surgery for hip fracture	21	2.6	< 0.001
Number of Charlson comorbidities (%)			
0	69	0.40	< 0.001
1 or 2	30	1.5	
≥ 3	0.90	4.7	
Number of Elixhauser comorbidities (%)			
0	32	0.30	< 0.001
1 or 2	54	0.80	
≥ 3	14	1.7	
≥ 1 adverse events (%)	32	1.7	< 0.001
Days of care (days)*	5.5 ± 5.6	11 ± 16	< 0.001

* Values are expressed as mean ± SD.

Multivariable binary logistic regression analyses were performed to assess the contributions of the individual Charlson (Table 5) and Elixhauser (Table 6) comorbidities to predicted in-hospital mortality, our primary response variable. Charlson and Elixhauser comorbidities with a p value less than 0.10 in bivariate analysis and present in at least 0.2 % of the population were included in the logistic regression modeling. Two main models were constructed; each of these regression models encompassed one of the two comorbidity-based scores, and age, sex, and year of surgery, as independent variables. A base model that included only age, sex, and year of surgery also was evaluated [27].

To determine which model best predicted inpatient mortality, receiver operating characteristic (ROC) curves were plotted and the regression models were compared on the basis of the area under the ROC curve (AUC) and its 95% CI [20, 54]. The AUC quantifies the ability of our models to assign a high probability of mortality to the patients who died [42]. Values range from 0.50 to 1.0, with 0.50 indicating no ability to discriminate and 1.0 indicating perfect discrimination. In general, values less than 0.70 are considered to show poor discrimination, values between 0.70 and 0.80 can be considered acceptable, and between 0.80 and 0.90 excellent. In addition to the absolute improvement in predictive performance, we calculated the difference between two AUCs in percent beyond the predictive power of the base model including age, sex, and year of surgery [47]. For instance, a difference in AUC between the Charlson and Elixhauser comorbidity scores of

Table 2. Charlson and Elixhauser comorbidity scores in the study cohort (n = 14,007,813)

Parameter	Charlson score				p value	Elixhauser score (van Walraven et al. [53])				p value
	0	1 or 2	3 or 4	≥ 5		< 0	0	1 to 4	≥ 5	
Age (years)*	64 ± 16	71 ± 13	75 ± 11	70 ± 15	< 0.001	64 ± 14	64 ± 15	69 ± 14	74 ± 13	< 0.001
Sex (%)					< 0.001					< 0.001
Male	39	37	40	43		29	41	38	36	
Female	61	64	61	57		71	59	63	64	
Mortality (%)	0.40	1.3	5.0	4.5	< 0.001	0.10	0.30	0.60	2.5	< 0.001
≥ 1 adverse events (%)	30	35	45	43	< 0.001	31	27	35	47	< 0.001
Days of care (days)*	5.2 ± 5.3	6.0 ± 5.7	8.1 ± 8.2	11 ± 16	< 0.001	4.9 ± 4.7	5.0 ± 4.9	5.5 ± 4.7	7.5 ±7.8	< 0.001
Discharge status (%)					< 0.001					< 0.001
Routine/discharged home	57	41	22	28		53	60	46	31	
Left against medical advice	0.10	0.10	0.20	0		0.10	0.10	0.20	0.10	
Transferred to short-term facility	7.4	9.3	9.7	11		7.9	7.2	8.5	10	
Transferred to long-term facility	20	31	48	38		23	19	28	39	
Alive, disposition not stated	13.0	15.0	14.0	17		15	13	15	15	
Died	0.40	1.3	5.0	4.5		0.10	0.30	0.60	2.5	
Not reported	1.8	2.1	1.6	2.1		1.6	1.7	2.2	2.4	

* Values are expressed as mean ± SD.

Table 3. Bivariate analysis of Charlson comorbidities in the study cohort (n = 14,007,813)

Comorbidity	Total cohort (%)	Mortality cohort (%)	p value
Myocardial infarction	2.4	3.8	< 0.001
Congestive heart failure	4.4	4.9	< 0.001
Peripheral vascular disease	0.9	1.3	< 0.001
Cerebrovascular disease	1.7	4.2	< 0.001
Dementia	1.0	1.9	< 0.001
Chronic pulmonary disease	11	1.2	< 0.001
Rheumatic disease	2.0	0.10	< 0.001
Peptic ulcer disease	0.80	0.60	< 0.001
Mild liver disease	0.20	0.90	0.015
Moderate/severe liver disease	0	3.1	< 0.001
Diabetes (no chronic complication)	11	0.50	< 0.001
Diabetes (chronic complication)	0.80	3.4	< 0.001
Hemiplegia or paraplegia	0.30	3.7	< 0.001
Renal failure	0.60	6.3	< 0.001
Any malignancy	0.70	3.5	< 0.001
Leukemia	0.20	2.1	< 0.001
Lymphoma	0.20	0.80	0.94
Metastatic solid tumor	0.40	4.9	< 0.001
AIDS/HIV infection	0.10	0	< 0.001

Table 4. Bivariate analysis of Elixhauser comorbidities (n = 14,007,813)

Comorbidity	Total cohort (%)	Mortality cohort (%)	p value
Congestive heart failure	5.0	4.6	< 0.001
Cardiac arrhythmias	8.1	2.7	< 0.001
Valvular disease	3.0	1.1	< 0.001
Pulmonary circulation disorders	0.50	5.8	< 0.001
Peripheral vascular disorders	1.5	1.3	< 0.001
Hypertension (uncomplicated)	38	0.3	< 0.001
Hypertension (complicated)	1.9	2.1	< 0.001
Paralysis	0.70	2.6	< 0.001
Other neurologic disorders	1.9	1.6	< 0.001
Chronic pulmonary disease	11	1.2	< 0.001
Diabetes (uncomplicated)	11	0.50	< 0.001
Diabetes (complicated)	1.2	3.6	< 0.001
Hypothyroidism	7.6	0.30	< 0.001
Renal failure	1.3	5.0	< 0.001
Liver disease	0.60	1.2	< 0.001
Peptic ulcer disease (excluding bleeding)	0.70	0.10	< 0.001
AIDS/HIV infection	0.10	0	< 0.001
Lymphoma	0.20	0.70	0.56
Metastatic cancer	0.50	4.5	< 0.001
Solid tumor without metastasis	0.80	3.6	< 0.001
Rheumatoid arthritis/collagen vascular diseases	3.2	0.20	< 0.001
Coagulopathy	1.1	1.7	< 0.001
Obesity	4.8	0	< 0.001
Weight loss	0.70	9.0	< 0.001
Fluid and electrolyte disorders	7.6	2.2	< 0.001
Blood loss anemia	1.6	0.70	< 0.001
Deficiency anemia	0.90	0.20	< 0.001
Alcohol abuse	1.1	0.60	< 0.001
Drug abuse	0.70	0.70	0.18
Psychoses	0.70	0.50	< 0.001
Depression	4.4	0.40	< 0.001

0.80 and 0.90, when the baseline AUC is 0.75, corresponds to a 67% relative increase in AUC: 0.90–0.75 – 0.80–0.75/ 0.90–0.75 = 0.67. We calculated the relative improvement in predictive performance of the Elixhauser score to the Charlson score. Global model performance also was compared using the Nagelkerke pseudo R-square measure [35]. Our secondary outcome variables, in-hospital adverse events and nonroutine discharge, were analyzed in an analogous fashion to in-hospital mortality. In-hospital adverse events were defined by ICD-9 codes (Appendix), following a coding approach used in other studies [34, 38]. A nonroutine discharge was defined as discharge to a skilled nursing facility or rehabilitation center. So as to set stricter standards owing to the large weighted sample size, a p value less than 0.001 was used to define significance in all analyses.

Results

Elixhauser comorbidity adjustment provided better prediction of in hospital case-mortality (AUC, 0.86; 95% CI, 0.86–0.86) compared with the Charlson model (AUC, 0.83; 95% CI, 0.83–0.84) and the base model with no comorbidities (AUC, 0.81; 95% CI, 0.81–0.81) (Table 7). In terms of relative improvement in predictive ability, the Elixhauser model performed 60% better than the Charlson model. The base model already showed excellent discrimination and accounted for 12% of the variation (Nagelkerke R-square = 0.12). The further addition of the Charlson comorbidity score to the base model led to a 2% increase in the amount of variation explained. The inclusion of the Elixhauser score to the base model achieved greater discrimination than the base model alone and the model incorporating the Charlson index and explained 18% of the variability (Nagelkerke R-square = 0.18). The rates of in-hospital death, together with those of adverse events and nonroutine disposition, increased steadily with the number of comorbidities and index scores In multivariable logistic regression analysis, chronic renal failure (odds

Table 5. Logistic regression analysis of relation of Charlson comorbidities (n = 14,007,813)

Comorbidity	Coefficient (β)	Standard error	Wald chi-square	Odds ratio	95% CI		p value
					Lower	Upper	
Myocardial infarction	1.4	0.010	18017	3.9	3.9	4.0	< 0.001
Congestive heart failure	1.3	0.0080	27778	3.5	3.5	3.6	< 0.001
Peripheral vascular disease	0.022	0.026	0.73	1.0	1.0	1.1	0.40
Cerebrovascular disease	1.2	0.012	9793	3.3	3.2	3.4	< 0.001
Dementia	−0.34	0.020	284	0.71	0.69	0.74	< 0.001
Chronic pulmonary disease	0.35	0.0080	1723	1.4	1.4	1.4	< 0.001
Rheumatic disease	−1.8	0.064	751	0.17	0.15	0.20	< 0.001
Peptic ulcer disease	−0.50	0.039	162	0.61	0.56	0.66	< 0.001
Diabetes (no chronic complication)	−0.49	0.012	1589	0.61	0.60	0.63	< 0.001
Diabetes (chronic complication)	1.5	0.018	6856	4.3	4.2	4.5	< 0.001
Hemiplegia or paraplegia	0.45	0.027	276	1.6	1.5	1.7	< 0.001
Renal failure	1.5	0.016	8036	4.3	4.2	4.4	< 0.001
Any malignancy	0.81	0.020	1562	2.2	2.2	2.3	< 0.001
Leukemia	0.43	0.042	107	1.5	1.4	1.7	< 0.001
Metastatic solid tumor	1.5	0.023	4369	4.5	4.3	4.7	< 0.001

ratio [OR], 4.3; 95% CI, 4.2–4.4; $p < 0.001$), complicated diabetes mellitus (OR, 4.3; 95% CI, 4.2–4.5; $p < 0.001$), and myocardial infarction (OR, 3.9; 95% CI, 3.9–4.0; $p < 0.001$) were the Charlson conditions associated with the greatest odds of in-hospital death (Table 5). Weight loss (OR, 5.0; 95% CI, 4.8–5.1; $p < 0.001$), pulmonary circulation disorders (OR, 4.5; 95% CI, 4.4–4.7; $p < 0.001$), and chronic renal failure (OR, 4.4; 95% CI, 4.3–4.6; $p < 0.001$) had the highest adjusted odds of inpatient mortality in the Elixhauser algorithm (Table 6).

Although the Elixhauser measure (AUC, 0.65; 95% CI, 0.65–0.65) was 100% more accurate than the Charlson measure (AUC, 0.64; 95% CI, 0.64–0.64) in predicting adverse events in terms of relative improvement, the discriminative ability of the model was poor and the difference in the absolute improvement in predictive power between the two models (AUC, 0.01) is of dubious clinical importance (Table 7).

The Elixhauser and Charlson models showed the same degree of discrimination for nonroutine discharge prediction after major orthopaedic surgery (AUC, 0.81; 95% CI, 0.81–0.81 for both scales) (Table 7).

Discussion

Surgical mortality and morbidity rates are important parameters of in-hospital quality of care [11, 37, 50]. Given the increasing age and complexity of patients undergoing orthopaedic surgery, it is necessary to appropriately adjust for patient risk, recognizing that the underlying nature of some patients' conditions may make them more likely than others to experience poor outcomes. We therefore assessed and compared the two most commonly used comorbidity risk adjustment models in orthopaedic surgery, the Charlson and Elixhauser measures, regarding their ability to predict in-hospital death, adverse events, and nonroutine discharge.

Our results should be interpreted after taking into account numerous factors. Despite access to large numbers and associated power, administrative databases have several recognized limitations [14, 23, 29]. First, the NHDS dataset is based on billing data from ICD-9-CM codes, and such a coding system may not fully capture the patient population of interest [1]. In particular, it has been suggested that administrative databases tend to underreport chronic medical conditions that are considered less acute in the perioperative orthopaedic surgery setting [16, 31, 33, 34, 39]. Second, the possibility of errors in coding of the diagnoses and procedures cannot be avoided [7]; however, misclassification mistakes distribute evenly in large-scale studies [53]. Third, the NHDS database does not include data regarding the timing of diagnoses, which hinders the differentiation of baseline comorbidities from complications [36]. Analyses of risk-adjusted mortality rates should adjust mortality rates only for baseline comorbid diseases, not complications that arise from surgery [15]. The degree to which this issue influenced our results is unclear, although it has been reported that the majority of common diagnoses are comorbidities rather than adverse events [15, 30, 36]. Fourth, the NHDS enabled only ascertainment of inpatient outcomes, and thus postdischarge complications

Table 6. Logistic regression analysis of Elixhauser comorbidities (n = 14,007,813)

Comorbidity	Coefficient (β)	Standard error	Wald chi-square	OR	95% CI		p value
					Lower	Upper	
Congestive heart failure	1.01	0.0080	17580	2.8	2.7	2.8	< 0.001
Cardiac arrhythmias	0.71	0.0070	9150	2.0	2.0	2.1	< 0.001
Valvular disease	−0.45	0.016	827	0.64	0.62	0.66	< 0.001
Pulmonary circulation disorders	1.51	0.018	7217	4.5	4.4	4.7	< 0.001
Peripheral vascular disorders	−0.013	0.021	0.38	1.0	0.95	1.0	0.54
Hypertension (uncomplicated)	−0.95	0.0090	11075	0.39	0.38	0.40	< 0.001
Hypertension (complicated)	−0.86	0.018	2234	0.43	0.41	0.44	< 0.001
Paralysis	1.4	0.022	3715	3.9	3.7	4.0	< 0.001
Other neurologic disorders	0.40	0.016	589	1.5	1.4	1.5	< 0.001
Chronic pulmonary disease	0.20	0.0090	548	1.2	1.2	1.2	< 0.001
Diabetes (uncomplicated)	−0.16	0.012	167	0.85	0.83	0.87	< 0.001
Diabetes (complicated)	1.4	0.015	8818	3.9	3.8	4.0	< 0.001
Hypothyroidism	−0.78	0.018	1801	0.46	0.44	0.48	< 0.001
Renal failure	1.5	0.016	9112	4.4	4.3	4.6	< 0.001
Liver disease	0.67	0.034	377	1.9	1.8	2.1	< 0.001
Peptic ulcer disease (excluding bleeding)	−2.4	0.11	449	0.091	0.073	0.11	< 0.001
Metastatic cancer	1.1	0.023	2196	2.9	2.7	3.0	< 0.001
Solid tumor without metastasis	0.77	0.019	1587	2.2	2.1	2.2	< 0.001
Rheumatoid arthritis/collagen vascular diseases	−0.73	0.034	468	0.48	0.45	0.51	< 0.001
Coagulopathy	0.18	0.021	77	1.2	1.2	1.2	< 0.001
Obesity	−2.2	0.081	747	0.11	0.092	0.13	< 0.001
Weight loss	1.6	0.013	14868	5.0	4.8	5.1	< 0.001
Fluid and electrolyte disorders	0.55	0.0080	4750	1.7	1.7	1.8	< 0.001
Blood loss anemia	−0.69	0.027	667	0.50	0.48	0.53	< 0.001
Deficiency anemia	−2.18	0.071	955	0.11	0.10	0.13	< 0.001
Alcohol abuse	−0.066	0.033	4.0	0.94	0.88	1.00	0.046
Psychoses	−1.16	0.049	561	0.31	0.28	0.34	< 0.001
Depression	−0.0080	0.022	0.15	1.0	1.0	1.0	0.70

Table 7. Elixhauser and Charlson comorbidity method discrimination for inpatient outcomes after orthopaedic surgery

Model	Mortality		Adverse events		Nonroutine discharge	
	AUC (95% CI)	R-square	AUC (95% CI)	R-square	AUC (95% CI)	R-square
Base model (age, sex, year of surgery)	0.81 (0.81–0.81)	0.12	0.64 (0.63–0.64)	0.066	0.81 (0.81–.81)	0.35
Base model + Charlson score	0.83 (0.83–0.84)	0.14	0.64 (0.64–0.64)	0.067	0.81 (0.81–0.82)	0.36
Base model + Elixhauser score	0.86 (0.86–0.86)	0.18	0.65 (0.65–0.65)	0.077	0.81 (0.81–0.82)	0.36

AUC = area under the receiver operating characteristic curve.

and readmissions were not captured. Fifth, we performed risk-adjustment using administrative data only; inclusion of clinically relevant variables such as the American Society of Anesthesiologists (ASA) score or the Frailty Index developed by the Canadian Study of Health and Aging may have improved model performance [24, 40, 58]. Finally, we did not perform any clinical data abstraction from medical records, which is considered the gold standard risk adjustment method in these comparisons [10]; thus, we were able to compare the Charlson and Elixhauser measures only for their relative performance.

We found that the Elixhauser comorbidity risk adjustment model performed numerically better than the Charlson model in predicting in-hospital mortality after major orthopaedic surgery. Although differences in the AUC values between the two comorbidity-based measures

were small, it has been noted that even slight improvements in the AUC for such indexes can translate into quantifiable reductions in confounding bias [46]. Overall, the AUC values for inpatient mortality for the Charlson and Elixhauser comorbidity-based measures in our study were comparable to or slightly higher than those described in other patient populations [6, 18, 27, 52]. Consistent with a study by Nikkel et al. [39] in patients with hip fractures, the Elixhauser weight loss or malnutrition comorbidity was the major factor influencing mortality. We found some comorbidities (eg, hypothyroidism, obesity, uncomplicated diabetes, hypertension) to be associated with decreased odds of inpatient mortality. It is counterintuitive that these comorbidities would protect against inpatient death. It may be that these comorbidities are most common in patients with less overall infirmity compared with the average orthopaedic inpatient.

The occurrence of in-hospital adverse events after major orthopaedic surgery was slightly more accurately predicted with the Elixhauser comorbidity index. However, in line with the study by Gordon et al. [17] looking at the influence of the Elixhauser and Charlson measures on reoperations after THA, the predictive accuracy of both models to detect adverse events was poor (AUC values < 0.70). An AUC value approximating 0.70 is considered acceptable for discrimination and validation of methods for ongoing use [18]; we therefore could not validate the Charlson or Elixhauser measures in terms of predicting perioperative complications after major orthopaedic surgery. There may be something beyond measurable comorbidities that is yet unaccounted for in orthopaedic inpatient morbidity.

Both comorbidity indexes provided clinically relevant insight for estimating nonroutine discharge after orthopaedic surgery; the Elixhauser score was no better than the Charlson score. This finding suggests that the Charlson and Elixhauser indexes are valid prediction tools for healthcare resource use risk adjustment, and researchers should choose between them based more on their availability and comfort with the method [2].

The Elixhauser measure has not been introduced in orthopaedic surgery research until recently [17, 26, 39, 57, 59, 60], perhaps because of scarce reported comparisons with the Charlson model [17] and concerns regarding the inclusion of too many explanatory variables (31 variables), therefore requiring a relatively large sample size [27]. The main attractiveness of the use of large administrative databases for medical research lies in the possibility of studying rare occurrence events, such as inpatient mortality, that otherwise would be difficult to investigate in small population studies [14].

Testing comorbidity risk adjustment measure performance in orthopaedic surgery is worthy of future study. Further research comparing the Charlson and Elixhauser methods with the less accessible (costwise) risk adjustment methods of Disease Staging (Thomson Medstat Inc, Ann Arbor, MI, USA) and All Patient Refined Diagnosis Related Groups (3M Health Information Systems, Wallingford, CT, USA) is warranted [36]. In addition, we currently are testing and validating a specific comorbidity-based measure for outcome prediction after orthopaedic surgery. The Elixhauser comorbidity measure outperformed the widely used Charlson measure in predicting inpatient mortality and morbidity after major orthopaedic surgery, and its more extensive use in claims-based studies should be considered. Future research assessing and comparing the performance of these measures in predicting long-term outcomes would be of value.

Appendix

List of ICD-9 codes included to identify adverse events

Adverse events	ICD-9 codes
Postoperative shock	998.0
Hematoma or seroma	998.1
Disruption of wound	998.3
Postoperative infection	998.5
Acute posthemorrhagic anemia	285.1
Complications not elsewhere classified	997
Acute renal failure	580, 584
Acute myocardial infarction	410
Ventricular arrhythmias and cardiac arrest	427.4, 427.5
Pneumonia and pulmonary congestion	482, 485, 486, 514, 5184
Iatrogenic postoperative hypotension	458.29
Pulmonary embolism	415.1
Induced mental disorders	291, 292, 293
Cerebrovascular disease	430, 431, 432, 433, 434, 435, 436
Fat embolism	958.1
Pulmonary insufficiency after trauma, surgery, transfusion, or acute respiratory distress syndrome	518.5, 518.7, 518.81
Thrombotic events	451.1, 451.2, 453.2, 453.4, 453.8, 453.9
Intubation and mechanical ventilation	96.04, 96.07
Transfusion of blood (components)	99.0
Conversion of cardiac rhythm	99.6

ICD-9 = International Classification of Diseases, 9th Revision.

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