Outcome-specific Charlson Comorbidity Indices for Predicting Poor Inpatient Outcomes Following Noncardiac Surgery Using Hospital Administrative Data

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Background: A need exists for adapting existing perioperative risk stratification methods such as the Charlson Comorbidity Index (CCI) for application with hospital administrative data in noncardiac surgery populations.

Objective: Develop and validate outcome-specific CCIs for predicting inpatient mortality, and cardiac and renal morbidity in noncardiac surgery patients using hospital administrative data.

Methods: We used hospital administrative data from the 2010 and 2011 California State Inpatient Database (SID) to develop (derivation cohort: 2010 SID, n = 177,280) and validate (validation cohort: 2011 SID, n = 179,145) 3 outcome-specific CCIs. Along with the 17 CCI comorbidities, the clinical importance and weighted point scores for age, male sex, race, emergent admission, and high-risk surgery were also determined from the coefficients of a logistic regression model. Cumulative outcome-specific CCI, CCI, and age-adjusted CCI (AACCI) scores were calculated for each patient. Receiver-operator characteristic curve analyses were used to determine the prognostic accuracy (area under the curve) of each outcome-specific CCIs, the CCI, and the AACCI. Risk was stratified according to cumulative point scores for each outcome-specific CCI, and posttest probabilities for each risk category were calculated.

Results: All outcome-specific CCIs showed good performance as a prognostic tools (area under the curve > 0.800 for all) and performed better than the CCI and AACCI. We attached clinical relevance to a given cumulative point score by determining posttest probabilities for each outcome-specific index.

Conclusions: We successfully adapted and validated 3 outcome-specific CCIs for use in noncardiac surgery patients based on ICD-9 and hospital admission data. Further validation of these outcome-specific CCIs is warranted.

Key Words: inpatients, mortality, morbidity, noncardiac surgery, Charlson Comorbidity Index

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Globally, over 200 million patients undergo noncardiac surgery each year, with between 0.5% and 3.0% of these patients experiencing a complication following their surgical procedure.[1] Complications following surgery are not only associated with increased patient morbidity and mortality, but also have an impact on hospital finances.[2] These potential implications highlight the need for developing new, or adapting existing perioperative risk stratification methods for application in noncardiac surgery populations.

The Charlson Comorbidity Index (CCI) is commonly used for risk stratification in inpatient and outpatient populations.[3] The CCI originally consisted of a series of 19 comorbid conditions, which was subsequently reduced to 17 comorbid conditions, with each comorbid condition allocated a weighted point score. An age-adjusted CCI (AACCI) has also been developed.[4] The advent of electronic medical information systems has allowed for the quick and easy identification of CCI comorbid conditions in large patient populations through the use of International Classification of Diseases (ICD) codes, which are routinely collected during inpatient hospital visits for medical billing purposes. Higher cumulative CCI scores have been linked to a higher risk of poor patient outcomes following several noncardiac surgery subspecialties such as general surgery, orthopedic surgery, and renal surgery.[5–7]

An attempt to adapt the CCI for application in a surgical population by Kork et al,[8] was published in 2015. However, this adaptation of the CCI requires the use of intraoperative patient data, and therefore it cannot be applied as a preoperative risk stratification tool. The study of Kork et al,[8] also included cardiac surgery patients and pediatric surgery patients, and so the relevance of the derived nomogram for use in adult noncardiac surgery populations remains debatable.

Our study sought to adapt and validate the outcome-specific CCIs for inpatient mortality, cardiac morbidity, and

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renal morbidity, which could be applied preoperatively using hospital administrative data for risk stratification in an adult noncardiac surgery population. We did not include cardiac surgery patients in this research as noncardiac surgery risk stratification methods cannot be applied in cardiac surgery populations, a restriction highlighted by the American Heart Association's guidelines for noncardiac and cardiac surgery risk stratification, which advocate different risk stratification methods for the 2 surgical populations.[9–11]

METHODS

Data Source, Data Description, and Outcome Definitions

This study involved the use of data from the 2010 and 2011 California State Inpatient Database (SID). The SID was obtained from the Healthcare Cost and Utilization Project and was sponsored by the Agency for Healthcare Research and Quality. The SID is an administrative database consisting of almost 100% of the state's inpatient discharge records contributed by data sources from 48 participating data organizations. Data comprising the SID are collected from both community and noncommunity hospitals, and include patient demographic information, clinically coded diagnoses, procedure codes, and discharge disposition of the patient. The SID also contains an indicator of whether each discharge diagnosis code was present on admission. Ethical approval for this study was waived by the Biomedical Research Ethics Committee of the University of KwaZulu-Natal, South Africa (Study Number: EXM267/15) in lieu of the data being available in the public domain.

As this research involved derivation and validation of risk indices, it was decided that the 2010 dataset would be used as a derivation cohort while the 2011 dataset would be used as a validation cohort. The "VisitLink" variable in the 2010 and 2011 SID was used to identify unique patients who had undergone a noncardiac surgery procedure (177,280 and 179,145 unique patients in 2010 and 2011, respectively). Noncardiac surgery procedures were identified from ICD-9 codes recorded for the "Primary Procedure" variable for each patient.[12] Open intrathoracic, intraperitoneal, or suprainguinal vascular surgeries were considered high-risk surgical procedures.[13] Data related to patient age, sex, race, and emergent hospital admissions were also extracted from the SID. The ICD-9 codes used to identify patient comorbidities in this study were adapted from the study of Quan et al.[14] We did not include facility-level data in our study, as this study was performed for the purposes of developing risk-adjustment models. We therefore followed the standard approach of not including facility effects in the derived risk models.

To develop a risk stratification tool that could be applied preoperatively, the "Present on Admission" label in the SID was used to identify the preoperative presence of CCI comorbidities. The study endpoints were inpatient mortality following noncardiac surgery, incident myocardial infarction or congestive heart failure following noncardiac surgery (cardiac morbidity), and incident acute kidney injury following noncardiac surgery (renal morbidity). We chose to derive and validate a separate outcome-specific CCI for mortality, cardiac complications, and renal complications rather than using a composite of the aforementioned outcomes. This decision was based on 2 considerations. Firstly, not all cardiac and renal complications are fatal, and equating nonfatal and fatal complications has implications with regard to what level of perioperative risk patients are willing to accept before providing consent for their surgical procedure. Secondly, identifying the likelihood of a specific outcome rather than a composite outcome would allow attending physicians to efficiently institute outcome-specific preventative management during the perioperative period in at-risk patients. Inpatient death is recorded in the SID as a separate variable. Postoperative inpatient cardiac and renal morbidity was defined as the presence of ICD-9 codes for myocardial infarction,[14] congestive heart failure,[14] and acute kidney injury,[15] which were listed as "Not Present on Admission" in the SID. A similar method of defining adverse perioperative outcomes in the SID has been described elsewhere.[16] The proportions of comorbidities and other potentially important variables in the derivation and validation cohorts are presented descriptively.

Derivation and Validation of Outcome-specific CCIs

Each outcome-specific CCI was derived using the 2010 SID and an approach to convert coefficients to a score similar to that used to derive the Framingham Heart Study risk score.[17] Three logistic regression models including all potential predictors (all the CCI comorbidities, as well as other potentially important variables such as age, sex, race, emergent admission, and high-risk surgery) in each regression model were obtained-1 model for each outcome (inpatient mortality, cardiac morbidity, and renal morbidity). Hosmer-Lemeshow tests were performed on a random sample of 5000 patients from the derivation cohort for each outcome-specific CCI to determine model fit.[18] The random sample approach Hosmer-Lemeshow test was used due to reported limitations in the conventional Hosmer-Lemeshow test when applied to large study populations.[18] The results of the logistic regression analysis are presented as β-coefficients with P-values. A P-value <0.05 was considered statistically significant. The β-coefficients for each independent risk factor obtained from each of the 3 logistic regression analysis were then used to recalibrate weighted point scores for each variable included in each outcome-specific CCI.[17] This was done by using the smallest statistically significant β-coefficient in each logistic regression as a denominator and substituting each statistically significant β-coefficient from the regression analysis as a numerator. The resulting weighted point score for each risk factor included in the final model was rounded to the nearest integer. Those factors not identified to be independently associated with a specified outcome were given a point score of zero.[17]

A receiver operator characteristic (ROC) curve analysis was used to determine the prognostic accuracy of the outcome-specific CCIs versus the CCI and the AACCI in the derivation (2010 SID) and validation (2011 SID) cohorts. The results of the ROC curve analysis are presented as an "area under the curve" (AUC) with 95% confidence intervals. An

AUC for a prognostic test can range between 0.00 and 1.00, with AUC values approaching 1.00 indicative of tests with higher prognostic accuracy. The ROC analysis for each outcome-specific CCI was used to determine optimal and diagnostic cut-points, which were then used to classify patients as low, intermediate, or high risk for each outcome depending on their cumulative point scores. The optimal cut-off value is the point where the rate of true positives is maximized while minimizing the rate of false positives, thereby reflecting the point with the highest accuracy for prediction of a specified outcome. This was defined by ROC statistics using a 1:1 weighting of sensitivity and specificity and the point determined by the value with the minimum distance when using the formula: Distance $= \sqrt{[(1-\text{sensitivity})^2+(1-\text{specificity})^2]}$. This approach to calculating the optimal cut-off value is known as the "minimum Euclidean distance to the coordinate (0, 1) method," and is briefly explained in Supplemental Digital Content 1 (http://links.lww.com/MLR/B230). The diagnostic cut-off point was chosen at a specificity of 95% while maximizing sensitivity. Optimal and diagnostic cut-off points were determined following the manual transfer of ROC curve coordinate points obtained from the ROC analysis to a customized Microsoft Excel spreadsheet containing the aforementioned formula.

Pretest probabilities for each outcome-specific CCI were determined for low-risk, intermediate-risk, and high-risk categories and used in conjunction with the 2-step Fagan Nomogram[19] to estimate posttest probabilities for individual risk categories within each outcome-specific CCI. Fagan's nomogram is based on Bayes' theorem and allows for the probability of an outcome of interest occurring in a patient to be calculated (posttest probability), given a specified pretest probability (or the probability of an outcome occurring in a patient before the result of a test being investigated is known).[19] The original Fagan nomogram required likelihood ratios for tests to be calculated separately, and this step was later accounted for in an adaptation of the nomogram (The 2-step Fagan nomogram).[19] There is a separate axis for pretest probability, likelihood ratio, posttest probability in the 2-step Fagan nomogram. A posttest probability can be determined by drawing a straight line from the point on the pretest probability axis, which corresponds to the given observed pretest probability through the calculated likelihood ratio on the likelihood ratio axis, until the line meets a point on the posttest probability axis. This point is the posttest probability for the test under investigation.[19] An example showing the application of the 2-step Fagan nomogram to determine posttest probabilities is provided in Supplemental Digital Content 2 (http://links.lww.com/MLR/B231). All data analysis was performed using the Statistical Package for the Social Sciences version 22.0 (IBM Corp.).

RESULTS

Description of the Derivation and Validation Cohorts

A description of the derivation and validation cohorts is presented in Table 1. Of the 177,280 patients in the derivation cohort, 41.6% were male. Most patients in the derivation cohort were 60 years old or older (62.7%). Approximately one third of the derivation cohort was nonwhite. High-risk surgery was performed in 15.2% of cases, whereas 27.5% of cases were admitted to hospital as emergent cases. The 3 most prevalent comorbid conditions were uncomplicated diabetes (16.8%), chronic obstructive pulmonary disease (15.9%), and renal disease (8.1%). The proportions of males, elderly, and nonwhite patients in the validation cohort (n = 179,145) were similar to that observed in the derivation cohort, as were the proportions of patients undergoing high-risk surgery and emergent admissions. Uncomplicated diabetes, chronic obstructive pulmonary disease, and renal disease were also the most prevalent comorbidities in the validation cohort. The proportion of patients who suffered mortality and cardiac or renal morbidity in the derivation cohort was similar to that observed in the validation cohort (Table 1).

TABLE 1. Distribution of Patient Characteristics/Comorbidities in the Derivation and Validation Cohorts Expressed as a Frequency (%)

Patient Characteristic/ Comorbidity	Derivation Cohort (n = 177,280)	Validation Cohort (n = 179,145)
Age <49 y old	33,284 (18.8)	34,078 (19.0)
Age 50–59 y old	32,862 (18.5)	33,675 (18.8)
Age 60–69 y old	44,531 (25.1)	45,707 (25.5)
Age 70–79 y old	40,052 (22.6)	39,944 (22.3)
Age 80–89 y old	23,961 (13.5)	23,173 (12.9)
Age >90 y old	2590 (1.5)	2568 (1.4)
Male sex	73,829 (41.6)	74,565 (41.6)
Nonwhite race	55,006 (31.0)	57,629 (32.2)
Emergent admission	48,697 (27.5)	49,806 (27.8)
High-risk surgery	26,986 (15.2)	28,884 (16.1)
Myocardial infarction	229 (0.1)	234 (0.1)
Congestive heart failure	8654 (4.9)	8627 (4.8)
Peripheral vascular disease	12,694 (7.2)	12,981 (7.2)
Cerebrovascular disease	292 (0.2)	356 (0.2)
Dementia	573 (0.3)	547 (0.3)
Chronic obstructive pulmonary disease	28,109 (15.9)	28,570 (15.9)
Rheumatologic disease	5163 (2.9)	5234 (2.9)
Nonmetastatic malignancy	14,151 (8.0)	13,673 (7.6)
Peptic ulcer disease	1622 (0.9)	1539 (0.9)
Mild liver disease	5356 (3.0)	5979 (3.3)
Uncomplicated diabetes	29,794 (16.8)	30,852 (17.2)
Complicated diabetes	8336 (4.7)	8620 (4.8)
Hemiplegia or paraplegia	1434 (0.8)	1406 (0.8)
Renal disease	14,331 (8.1)	15,168 (8.5)
Moderate or severe liver disease	452 (0.3)	452 (0.3)
Metastatic malignancy	4372 (2.5)	4299 (2.4)
HIV/AIDS	222 (0.1)	248 (0.1)
Inpatient mortality	1543 (0.9)	1419 (0.8)
Inpatient cardiac morbidity	1855 (1.0)	1710 (1.0)
Inpatient renal morbidity	4136 (2.3)	4013 (2.2)

Derivation of Outcome-specific CCIs

Mortality-specific CCI

The results of the logistic regression analysis (Table 2) revealed that there was no independent association between

TABLE 2. Weighted Point Scores for Each Outcome-specific CCI

Patient Characteristics/ Comorbidity	Mortality-specific CCI			Cardiac-specific CCI			Renal-specific CCI			Original CCI and AACCI	
	β-Coefficient	*P*	Weighted Point Score	β-Coefficient	*P*	Weighted Point Score	β-Coefficient	*P*	Weighted Point Score	CCI Weighted Point Score	AACCI Weighted Point Score
Age <49 y old	Reference group	N/A	0	Reference group	N/A	0	Reference group	N/A	0	NI	0
Age 50–59 y old	0.731	<0.001	8	0.819	<0.001	5	0.528	<0.001	17	NI	1
Age 60–69 y old	1.110	<0.001	12	1.459	<0.001	10	0.889	<0.001	28	NI	2
Age 70–79 y old	1.555	<0.001	17	1.944	<0.001	13	1.080	<0.001	34	NI	3
Age 80–89 y old	1.893	<0.001	20	2.399	<0.001	16	1.286	<0.001	40	NI	4
Age >90 y old	2.430	<0.001	26	2.769	<0.001	18	1.560	<0.001	49	NI	5
Male sex	0.233	<0.001	2	0.150	0.002	1	0.437	<0.001	14	NI	NI
Nonwhite race	0.112	0.056	0	−0.027	0.623	0	−0.021	0.563	0	NI	NI
Emergent admission	1.266	<0.001	13	0.721	<0.001	5	0.385	<0.001	12	NI	NI
High-risk surgery	1.929	<0.001	21	0.988	<0.001	7	1.208	<0.001	38	NI	NI
Myocardial infarction	1.183	<0.001	13	0.129	0.663	0	0.122	0.600	0	1	1
Congestive heart failure	0.845	<0.001	9	0.925	<0.001	6	0.630	<0.001	20	1	1
Peripheral vascular disease	0.770	<0.001	8	0.665	<0.001	4	0.326	<0.001	10	1	1
Cerebrovascular disease	0.253	0.534	0	0.241	0.515	0	0.052	0.868	0	1	1
Dementia	0.479	0.029	5	−0.073	0.762	0	−0.098	0.621	0	1	1
Chronic obstructive pulmonary disease	0.224	<0.001	2	0.310	<0.001	2	0.264	<0.001	8	1	1
Rheumatologic disease	0.151	0.321	0	0.195	0.128	0	0.079	0.422	0	1	1
Nonmetastatic malignancy	−0.028	0.477	0	−0.041	0.328	0	0.046	0.085	0	2	2
Peptic ulcer disease	0.326	0.026	3	0.172	0.291	0	0.317	0.004	10	1	1
Mild liver disease	0.230	0.065	0	−0.173	0.244	0	0.190	0.023	6	1	1
Uncomplicated diabetes	−0.085	0.202	0	0.203	<0.001	1	0.268	<0.001	8	1	1
Complicated diabetes	−0.054	0.271	0	0.170	<0.001	1	0.069	0.012	2	2	2
Hemiplegia or paraplegia	0.678	<0.001	7	0.264	0.010	2	0.210	0.004	7	2	2
Renal disease	0.391	<0.001	4	0.231	<0.001	2	0.755	<0.001	24	2	2
Moderate or severe liver disease	0.668	<0.001	7	0.137	0.222	0	0.408	<0.001	13	3	3
Metastatic malignancy	0.094	<0.001	1	0.020	0.326	0	0.032	0.011	1	6	6
HIV/AIDS	0.137	0.132	0	0.095	0.429	0	−0.115	0.248	0	6	6

AACCI indicates age-adjusted Charlson Comorbidity Index; CCI, Charlson Comorbidity Index; N/A, not applicable; NI, not included in original CCI or AACCI.

the following comorbidities and inpatient mortality following noncardiac surgery: cerebrovascular disease, rheumatologic disease, nonmetastatic malignancy, mild liver disease, diabetes (uncomplicated and complicated), and HIV infection. All other comorbidities included in the CCI were associated with a higher risk of inpatient mortality following noncardiac surgery. Age, male sex, emergent admission, nonwhite race, and high-risk surgical procedures were also associated with a higher risk of postoperative inpatient mortality (Table 2). The results of the Hosmer-Lemeshow test for the mortality model indicated appropriate model fit ($P=0.220$).

None of the CCI comorbidities that were included in the mortality-specific CCI retained their original weighted points score. Furthermore, the points score weighting for each of the age categories utilized in the AACCI was also not retained in the mortality-specific CCI. The maximum cumulative point score that could theoretically be obtained for an individual patient was 121 points, versus maximum cumulative point scores of 29 and 34 points for the CCI and AACCI, respectively (Table 2).

An ROC curve analysis of cumulative point scores in the derivation cohort yielded an AUC of 0.896, 0.785, and 0.824 for the mortality-specific CCI, CCI, and AACCI,

TABLE 3. Prognostic Accuracy and Posttest Probabilities of Outcome-specific CCIs Versus the CCI and AACCI

Cohort	Outcome	Index	Area Under the Curve (95% CI)
Derivation	Inpatient mortality	Mortality-specific CCI	0.896 (0.888–0.903)
		CCI	0.785 (0.773–0.797)
		AACCI	0.824 (0.814–0.834)
	Cardiac morbidity	Cardiac-specific CCI	0.837 (0.829–0.846)
		CCI	0.739 (0.728–0.751)
		AACCI	0.799 (0.791–0.808)
	Renal morbidity	Renal-specific CCI	0.818 (0.811–0.824)
		CCI	0.766 (0.759–0.774)
		AACCI	0.780 (0.773–0.787)
Validation	Inpatient mortality	Mortality-specific CCI	0.901 (0.894–0.908)
		CCI	0.806 (0.794–0.817)
		AACCI	0.837 (0.827–0.847)
	Cardiac morbidity	Cardiac-specific CCI	0.841 (0.832–0.849)
		CCI	0.749 (0.737–0.761)
		AACCI	0.807 (0.798–0.816)
	Renal morbidity	Renal-specific CCI	0.812 (0.805–0.818)
		CCI	0.758 (0.751–0.766)
		AACCI	0.778 (0.771–0.785)

AACCI indicates age-adjusted Charlson Comorbidity Index; CCI, Charlson Comorbidity Index; CI, confidence interval.

respectively (Table 3). Optimal and diagnostic cut-points obtained from the ROC curve analysis for the mortality-specific CCI were used to categorize patients as low risk (cumulative point score $\leq$32), intermediate risk (cumulative points score between 33 and 45), and high-risk (cumulative points score >45).

Posttest probabilities for the high-risk category indicate that 25% of patients with cumulative point scores that fall within this category are likely to suffer postoperative mortality, whereas only <2% of patients who do not fall within the high-risk category die in-hospital following their procedure (Table 4).

Cardiac-specific CCI

Only 7 of the 17 CCI comorbidities were independently associated with cardiac morbidity following noncardiac surgery (Table 2). Of these, 3 retained their original CCI weighting (uncomplicated diabetes, hemiplegia, and renal disease), 3 increased in points weighting (congestive heart failure, peripheral vascular disease, and chronic obstructive pulmonary disease), and 1 decreased in points weighting (complicated diabetes). Male sex, emergent admission, and high-risk surgical procedures were independently associated with a higher risk of cardiac morbidity, whereas nonwhite race was not an independent predictor of poor cardiac outcomes in this study. The results of the Hosmer-Lemeshow test for the cardiac morbidity model indicated appropriate model fit (P=0.821). Although age contributed an increased cumulative cardiac-specific point score, the weighting of each age category was lower than that used in the AACCI. The maximum cumulative point score for the cardiac-specific CCI which could theoretically be obtained for an individual patient was 49 points (Table 2).

The AUC values obtained from the subsequent ROC curve analysis for the cardiac-specific CCI, CCI, and AACCI were 0.837, 0.739, and 0.799, respectively (Table 3). As with the mortality-specific CCI, the results of the ROC curve analysis were used to categorize patients as low risk (cumulative point score $\leq$17), intermediate risk (cumulative points score between 18 and 24), and high risk (cumulative points score >24) for cardiac morbidity.

Posttest probabilities for the high-risk category indicate that 17% of patients with cumulative point scores that fall within this category are likely to suffer postoperative cardiac morbidity, whereas only <2% of patients who do not fall within the high-risk category will suffer cardiac morbidity following their procedure (Table 4).

Renal-specific CCI

Eleven of the 17 CCI comorbidities were independently associated with a higher risk of acute kidney injury following noncardiac surgery (Table 2). Associations between the remaining 6 comorbidities and poor renal outcomes were unclear. Only 1 of the 11 independently associated comorbidities retained the same CCI weighting (complicated diabetes), whereas there was an increase in point score weighting for 9 comorbidities (congestive heart failure, peripheral vascular disease, chronic obstructive pulmonary disease, peptic ulcer disease, mild liver disease, uncomplicated diabetes, hemiplegia, renal disease, and moderate or severe liver disease), and a reduction in point score weighting for 1 comorbidity (metastatic malignancy). Male sex, emergent hospital admission, and high-risk procedures were also independently associated with a higher risk of poor renal outcomes, whereas nonwhite race did not seem to contribute to risk (Table 2). The results of the Hosmer-Lemeshow test for the renal morbidity model indicated appropriate model fit (P=0.560). All age categories in the renal-specific CCI carried a higher point score weighting than the same age categories used in the AACCI (Table 2). The maximum cumulative point score for the renal-specific CCI which could theoretically be obtained for an individual patient was 222 points (Table 2).

The AUC values obtained from the subsequent ROC curve analysis for the renal-specific CCI, CCI, and AACCI were 0.818, 0.766, and 0.780, respectively (Table 3). The results of the ROC curve analysis were used to categorize patients as low risk (cumulative point score $\leq$56), intermediate risk (cumulative point score between 57 and 92), and high risk (cumulative point score >92) for renal morbidity.

Posttest probabilities for the high-risk category indicate that 30% of patients with cumulative point scores that fall within this category are likely to suffer postoperative renal morbidity, whereas only <5% of patients who do not fall within the high-risk category will suffer renal morbidity following their procedure (Table 4).

TABLE 4. Posttest Probabilities for Each Outcome-specific Index Expressed as a Percentage

Cohort	Outcome-specific CCI	Low-risk Category		Intermediate-risk Category		High-risk Category	
		Positive Posttest Probability	Negative Posttest Probability	Positive Posttest Probability	Negative Posttest Probability	Positive Posttest Probability	Negative Posttest Probability
Derivation	Mortality-specific CCI	0.9	<0.1	9.0	<0.1	25.0	1.8
	Cardiac-specific CCI	0.9	<0.1	6.0	0.7	17.0	1.9
	Renal-specific CCI	2.3	0.3	12.0	1.6	30.0	4.5
Validation	Mortality-specific CCI	0.9	<0.1	8.0	0.3	26.0	1.6
	Cardiac-specific CCI	0.9	0.1	6.0	0.6	18.0	1.9
	Renal-specific CCI	2.1	0.3	13.0	1.6	29.0	4.0

CCI indicates Charlson Comorbidity Index.

Validation of Outcome-specific CCIs

Mortality-specific CCI

The AUCs obtained for the mortality-specific CCI, CCI, and AACCI when applied to the validation cohort were 0.901, 0.806, and 0.837, respectively (Table 3). When the mortality-specific CCI was applied to the validation cohort, posttest probabilities for positive and negative test results in the high-risk category were similar to those obtained for the derivation cohort (Table 4).

Cardiac-specific CCI

AUC values for the cardiac-specific CCI, CCI, and AACCI were 0.841, 0.749, and 0.807, respectively (Table 3). The results of the ROC curve analysis suggest that the prognostic accuracy of the cardiac-specific CCI was similar in both derivation and validation cohorts. Posttest probabilities obtained for the cardiac-specific CCI in high-risk patients were similar in the derivation and validation cohorts (Table 4).

Renal-specific CCI

Similar to the results for the ROC curve analyses for the mortality-specific and cardiac-specific CCIs, the AUC values obtained for the renal-specific CCI were higher than those obtained for the CCI and the AACCI, with similar levels of prognostic accuracy and posttest probabilities for the renal-specific CCI being retained between the derivation and validation cohorts (Table 4).

DISCUSSION

This study successfully developed and validated 3 outcome-specific CCIs for use with hospital administrative data in a noncardiac surgery setting. In most instances the weighting of point scores for comorbidities and age in the outcome-specific CCIs was different from that specified for the original CCI and the AACCI. Furthermore, the weighting of point scores for comorbid conditions and age also varied among the different outcome-specific CCIs. There are several possible explanations for these findings.

Firstly, the original CCI and AACCI were based on prediction of longer-term poor patient outcomes.[3,4] It is possible that whereas several comorbidities might be associated with increased long-term mortality, these same comorbidities may have little impact on the incidence of poor short-term outcomes such as those investigated in our study. Secondly, the treatment of some comorbid conditions comprising the CCI has improved significantly since the development of the CCI. For instance, there has been a marked reduction in mortality in patients with HIV infection since the introduction of antiretroviral therapy in the mid 1990s.[20] This might explain why HIV infection was not associated with poor patient outcomes in our study. Lastly, the CCI is considered a generic perioperative risk stratification method.[21]

Our findings clearly indicate that the clinical importance of comorbid disease and age differs among postoperative outcomes such as mortality, and cardiac or renal morbidity. These findings are important, as it demonstrates the caveats of applying generic comorbidity indices for risk stratification for specific outcomes.

When compared with the CCI and the AACCI, the outcome-specific CCIs demonstrated better performance as a prognostic tool. Considering the discreetness of the confidence intervals obtained for the prognostic accuracies of each index, it can be concluded that all outcome-specific CCIs performed significantly better than the CCI and AACCI. It is interesting that all outcome-specific CCIs showed good overall prognostic performance considering that the indices were comprised entirely of preoperative data collected on admission for medical billing purposes (through ICD-9 codes) and there were no intraoperative variables included.

Categorization of risk within each outcome-specific CCI can also provide probability values that are clinically meaningful and could assist with the subsequent management of patients. With current medical informatics technologies, outcome-specific CCIs have the potential to be automatically calculated before a patient's planned surgery, such that patient risk can be determined. Appropriate patient

management decisions can then be made by doctors treating the patient, such as whether to proceed with the planned surgical procedure, opt for a more conservative intervention, or whether patients should be transferred to high care wards for more stringent postoperative observation should there be no other option but to proceed with surgery. Additional approaches to guided management in the noncardiac surgery population would no doubt reduce inpatient mortality and morbidity. Further validation of the outcome-specific CCIs described in this study is warranted.

This study had several limitations. Firstly, this study utilized data collected from a single US state. However, the dataset obtained still provided a large cohort of patients, which allowed us to derive and validate the outcome-specific CCIs. The American Society of Anesthesiologists physical status and data related to medication use was not collected as part of the SID, and we were unable to investigate the impact of these variables on patient outcome in this study. Preoperative laboratory data were also not included during data collection for the SID. Potential inaccuracies in the medical coding of "Present on Admission" diagnoses has been reported in the SID,[22] therefore necessitating the external validation of our study findings. Finally, this study developed and validated risk stratification indices for in-hospital events only, and therefore the applicability of the outcome-specific CCIs with regard to postdischarge events is unknown.

In summary, we adapted and validated 3 preoperatively administered outcome-specific CCIs based on ICD-9 and hospital admission data. All outcome-specific CCIs exhibited good prognostic performance in our study and predicted inpatient outcomes better than the CCI and AACCI. Further external validation of the outcome-specific CCIs developed in this study is warranted.

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