Present-at-admission diagnoses improved mortality risk adjustment among acute myocardial infarction patients

George J. Stukenborg, Douglas P. Wagner, Frank E. Harrell Jr, M. Norman Oliver, Steven W. Heim, Amy L. Price, Caroline Kim Han, Andrew M.D. Wolf, Alfred F. Connors Jr

University of Virginia School of Medicine, Department of Public Health Sciences, Charlottesville, VA, USA
Vanderbilt University, School of Medicine, Department of Biostatistics, Nashville, TN, USA
University of Virginia, School of Medicine, Department of Family Medicine, Charlottesville, VA, USA
Eastern Virginia Medical School, Department of Family and Community Medicine, Norfolk, VA, USA
Charlottesville Wellness Center, Charlottesville, VA, USA
University of Virginia, School of Medicine, Department of Internal Medicine, Charlottesville, VA, USA
Case Western Reserve University, School of Medicine, Department of Medicine at MetroHealth Medical Center, Cleveland, OH, USA

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Abstract

Objective: Hospital mortality outcomes for acute myocardial infarction (AMI) patients are a focus of quality improvement programs conducted by government agencies. AMI mortality risk-adjustment models using administrative data typically adjust for baseline differences in mortality risk with a limited set of common and definite comorbidities. In this study, we present an AMI mortality risk-adjustment model that adjusts for comorbid disease and for AMI severity using information from secondary diagnoses reported as present at admission for California hospital patients.

Study Design and Setting: AMI patients were selected from California hospital administrative data for 1996 through 1999 according to criteria used by the California Hospital Outcomes Project Report on Heart Attack Outcomes, a state-mandated public report that compares hospital mortality outcomes. We compared results for the new model to two mortality risk-adjustment models used to assess hospital AMI mortality outcomes by the state of California, and to two other models used in prior research.

Results: The model using present-at-admission diagnoses obtained substantially better discrimination between predicted survival and inpatient death than the other models we considered.

Conclusion: AMI mortality risk-adjustment methods can be meaningfully improved using present-at-admission diagnoses to identify comorbid disease and conditions related closely to AMI.

Keywords: Myocardial infarction; Mortality; Risk factors; Logistic regression; Risk adjustment; Comorbidity

1. Introduction

Hospital mortality outcomes for acute myocardial infarction (AMI) patients are a focus of quality improvement programs conducted by state and federal government agencies. Public reports comparing AMI mortality outcomes across hospitals are available from state agency–operated Internet Web sites in California [1], New York [2], and Pennsylvania [3]. Comparisons of hospital mortality outcomes for Medicare patients with AMI are also available [4].

Public reporting of hospital AMI mortality is intended to improve health care quality by directing patients toward hospitals with lower than expected mortality, although there is little evidence that public reports reduce patient volume at hospitals with higher than expected mortality [5] or reduce overall hospital mortality [6]. Financial incentives based on hospital AMI mortality outcomes are also being used to encourage improvements in the quality of care. The Centers for Medicare and Medicaid Services use AMI inpatient mortality as a key component of a pay-for-performance demonstration reimbursement system that provides financial incentives for hospitals based on Medicare patient outcomes [7].

Comparisons of hospital AMI mortality typically use hospital administrative data, because of the expense of...
abstracting additional clinical data for large populations [8]. Several studies indicate that statistical models that adjust for differences in AMI mortality risk using administrative data can perform nearly as well as models that use additional clinical information about vital signs, laboratory data, and other details abstracted from medical records [9,10].

AMI mortality risk-adjustment models that use administrative data typically adjust for baseline differences in mortality risk among patients with a limited set of common and definite comorbidities of AMI, such as diabetes mellitus and cerebrovascular disease. Rare comorbidities and conditions assumed to have insignificant effects on mortality risk are typically excluded from the adjustments. Most administrative data do not explicitly distinguish conditions that were present at admission from those that occurred after admission. As a result, AMI mortality risk-adjustment models using administrative data typically include only comorbidities measured by diagnoses that represent chronic conditions or other conditions that are unlikely to have occurred during the hospitalization. Conditions that can represent complications of care for some patients, such as stroke and shock, are excluded.

Since 1996, California hospitals have specified whether or not a secondary diagnosis reported for a patient was present when the patient was admitted to the hospital. Prior studies of aspiration pneumonia patients [11] and of lung cancer surgery patients [12] in California hospitals indicate that adjustments for present-at-admission diagnoses can yield substantial improvements in the performance of mortality risk-adjustment models. Present-at-admission diagnoses have also improved AMI mortality risk-adjustment models developed using administrative data for patients in Canada [13].

In this study, we present an AMI mortality risk-adjustment model that adjusts for comorbid disease and for AMI severity using information from secondary diagnoses reported as present at admission for California hospital patients. We compare the statistical performance of this new model to that of models used by the state of California to compare hospital AMI outcomes, and to that of models that adjust for comorbid disease measured by methods developed in other studies.

2. Methods

2.1. Study population

Discharge abstract records for patients with AMI discharged from nonfederal hospitals in California between January 1996 and December 1999 [14] were used in this study. Patients were selected according to the inclusion and exclusion criteria developed for the California Hospital Outcomes Project Report on Heart Attack Outcomes, which is a state-mandated public report that compares hospital mortality outcomes for AMI patients [15,16]. We identified all discharges reported by California hospitals for patients with an International Classification of Disease—9th revision—Clinical Modification (ICD-9-CM) principal diagnosis code of AMI, initial or unspecified episode of care (410.x0 or 410.x1), or a presumed AMI complication with a secondary diagnosis of AMI, initial or unspecified episode of care (427.1, 427.41, 427.42, 427.5, 429.5, 429.6, 429.71, 429.79, 429.81, 518.4, 780.2, and 785.51).

Patients under 18 years of age were excluded, as in the original California Hospital Outcomes Project [15,16], which eliminated these patients in order to exclude cases potentially related to congenital heart disease. We excluded patients who were admitted from long-term care, acute in-patient hospital care, or from newborn care and excluded patients whose initial hospitalization length of stay was less than 2 days if the record included a discharge disposition other than transfer to another acute care hospital, discharge against medical advice, or death. We also excluded initial hospitalizations that listed external cause of injury (E codes) indicating motor vehicle and related transport accidents (E800.x–E848) from index record or any subsequent record. These criteria from the original California study are intended to exclude patients with steering column impact chest trauma that can cause the release of the heart enzymes used to test for myocardial injury.

Several data elements used in the original California Hospital Outcomes Project, including Social Security number, days of the month of admission and discharge, and mortality status at 30 days, are not available for public use. Our reproduction of the original study population was limited by these missing elements. Unique encrypted patient identifiers are reported in the public use data. We found that these were missing for 3.7% of the 239,618 California hospital discharges in the 1996 through 1999 calendar year data files for patients aged 18 or older with AMI as a principal diagnosis or with presumed AMI complication with AMI as a secondary diagnosis. In the original California study, transfer hospitalization records for patients were identified using Social Security numbers and actual dates of admission. We identified patients with more than one hospital discharge during the study period by examining discharge records with the same encrypted unique patient identifier, sorted according to the earliest month of admission. The initial hospitalization record was selected using the discharge with the earliest month of admission and earliest month of discharge. Among patients with multiple hospitalizations, 81.7% of the subsequent admissions were within 1 month of the earliest hospital discharge. If a patient had two or more hospitalizations within the same earliest month of admission and the same month of discharge, we used the source of admission information to distinguish the initial from the transfer hospitalization record.

Mortality outcomes were identified by determining the patient’s status at discharge from the initial hospitalization, except for patients whose initial hospitalization length of stay was less than 30 days who had been transferred from
that initial hospitalization to another acute care hospital. Mortality for these transferred patients was determined by their status at discharge from the hospital to which they were transferred.

The reproduced inclusion and exclusion criteria from the California Hospital Outcomes Project Report were used to identify 120,706 patients who were discharged during the period from January 1996 through November 1998. This total is slightly smaller than the 128,509 patients with AMI identified in the original study of patients who had been discharged during this period. There were 12,178 in-hospital deaths in the reproduced study population (10.1%), compared to the 12,799 identified in the original study (10.0%).

The same process as that used to develop the final study population was used to develop an independent validation population for all discharges reported by California hospitals from December 1998 through November 1999. The validation population includes 42,678 AMI patients and 4,279 (10.0%) in-hospital deaths. We were unable to include patients discharged after November 1999, because California hospital data files available for the year 2000 and later do not include information about the patient’s month of admission and do not include unique encrypted patient identifiers.

2.2. California Hospital Outcomes Project mortality risk-adjustment models

We reproduced two mortality risk-adjustment models, California Model A and California Model B, which were used to assess hospital AMI mortality outcomes in the California Hospital Outcomes Project Report on Heart Attack Outcomes [15,16]. Both models were originally developed through consultation with a clinical advisory panel of cardiologists and research professionals, who selected covariates and covariate interactions for the models that were appropriate predictors of baseline risk. Both models were reproduced using the exact definitions for each of the covariates listed in the California Hospital Outcomes Project reports.

California Model A includes adjustments for demographic characteristics, descriptions of the infarct location, and selected covariates considered likely to be present at admission for patients with AMI. California Model B includes covariates from Model A and additional covariates for conditions that may have developed after admission for some patients. The additional covariates in Model B include shock, hypertension, pulmonary edema, complete atrioventricular block, pleural effusion, urinary tract infection, syncope, acidosis, alkalosis, sepsis, paroxysmal ventricular tachycardia, hyponatremia or hyposmolality, hypernatremia or hyperosmolality, gastrointestinal hemorrhage, pneumonia, aspiration pneumonitis, and unstable angina. In the California Hospital Outcomes Project reports, Model A is described as a conservative adjustment for baseline characteristics, because the adjustments included in Model B may represent complications of care instead of conditions present at admission for some patients.

The California Hospital Outcomes Project developed two versions of Model A and two versions of Model B. One version was developed for patients without prior admissions, and the other for patients who had at least one prior admission up to 6 months before the index AMI admission. These versions were created to obtain additional information about comorbid disease from prior hospitalization records when it was available. We reproduced only the versions of the California Models A and B developed for patients without prior admissions. Prior studies of in-hospital mortality risk for patients with AMI and for other disease populations indicate that supplementing the measurement of comorbid disease in this manner produces little or no improvement in statistical performance [17–19].

Multivariable logistic regression was used to estimate the adjusted risk of inpatient death using California Models A and B. Both models were developed using the maximum likelihood method using records for AMI patients discharged during the period from January 1996 through November 1998.

The predictive accuracy of each model was quantified using the C statistic, which is an estimate of the model’s ability to discriminate between observed in-hospital death and survival [20,21]. The C statistic achieves its maximum value of 1.0 when all of the model’s predicted risks for patients who died are higher than all of the predicted risks for patients who survived. The C statistic equals 0.5 when the model has no ability to discriminate. We also measured the explanatory power of each model using the maximum rescaled $R^2$ statistic, which is a log-likelihood ratio chi-square–based measure analogous to the $R^2$ statistic in ordinary multiple regression [22–24]. Finally, we applied each of the developed model equations with fixed coefficients to the validation population to obtain validated C statistics and maximum rescaled $R^2$ statistics for these models in an independent study population. Model calibration was assessed by sorting the validation population into ascending order by estimated mortality risk, segmenting the sorted population into 100 equally sized quantiles with similar estimated mortality risk, calculating the observed probability of death and predicted probability of death for patients in each quantile, and then plotting the relationship between the observed and predicted number of deaths for each quantile compared to a 45° line [25].

2.3. Mortality risk adjustment using ICD-9-CM diagnoses reported as present at admission

Since January 1996, California hospitals have been required to indicate whether each secondary diagnosis reported for a discharged patient was present when the patient was admitted to the hospital. This information was not available at the time that California Models A
Among AMI patients discharged from January 1996 through November 1998, 90% of all secondary diagnoses were reported as present at admission. To test the quality of the data, we used definitions from prior research [26] to identify secondary diagnoses for surgical complications and iatrogenic events and then calculated the percent reported as present at admission. We reasoned that the quality of the data could be indirectly assessed by determining whether secondary diagnoses for complications and iatrogenic events were reported rarely as present at admission. We found that 14% of all secondary diagnoses for surgical complications and iatrogenic events were reported as present at admission.

Thousands of individual ICD-9-CM diagnosis codes were reported as present at admission in the study population. We summarized the collection of individual ICD-9-CM codes by grouping them into categories using the structure of the Clinical Classification System (CCS), which sorts the ICD-9-CM diagnosis code taxonomy into 260 clinically coherent and mutually exclusive categories of disease [27,28]. Mortality risk-adjustment models using CCS categories as measures of risk demonstrated superior statistical performance in a prior study of mortality at 1 year among Medicare hospital patients with AMI [29].

Most secondary diagnoses that are present at admission are comorbid diseases. However, some secondary diagnoses that are present at admission are related too closely to AMI to be considered comorbidities, and are instead characteristics of AMI severity. In order to isolate the effects of conditions related closely to AMI, all of the ICD-9-CM diagnosis codes reported as present at admission were separated into comorbid diseases and conditions related closely to AMI.

The codes were separated by a multidisciplinary panel of five physicians who were specialists in family or internal medicine using the Delphi method [30,31]. Panelists used computer software to score each ICD-9-CM code as closely related, equivocal, or not closely related to AMI. “Closely related” was defined as including only ICD-9-CM codes for conditions likely to be caused directly by AMI or closely related to the immediate cause of AMI. Long-term risk factors for AMI were not considered to be closely related.

Each panelist reviewed and scored the ICD-9-CM codes independently. The codes were grouped by CCS categories, and presented along with detailed text descriptions for each individual ICD-9-CM code. The software allowed panelists to move through the lists of codes by category, and panelists could score ICD-9-CM codes within the same category globally whenever appropriate.

ICD-9-CM codes scored as closely related by at least one but not all of the panelists were reviewed and rescored by the panel. Before reviewing these codes again, the panelists met to discuss their clinical reasoning concerning the relatedness of these ICD-9-CM diagnosis codes and of groups of codes within CCS categories. After the meeting, each panelist rescored these ICD-9-CM codes using computer software that listed the panelist’s original score and the series of anonymous original scores from all panel members.

All of the ICD-9-CM codes that a majority of the panel considered to be related closely to AMI were grouped by CCS category. All of the remaining ICD-9-CM codes were separately grouped by CCS category and distinguished as comorbid disease. Some of the CCS categories included ICD-9-CM codes that were heterogeneous in their relationship to AMI. These categories were split into a category of comorbid disease and a separate category of closely related conditions.

The new AMI mortality risk-adjustment model includes adjustments for each category of comorbid disease and for each category of conditions related closely to AMI that occurred at least once among patients in the study population. The new model also includes adjustments for the following categories of infarct location distinguished by the ICD-9-CM diagnosis code for AMI (410.x1): anterolateral wall, other anterolateral wall with contiguous portion of intraventricular septum, inferolateral wall, inferoposterior wall, other inferior wall with contiguous portion of intraventricular septum, other lateral wall high lateral posterolateral, true posterior wall infarction, subendocardial infarction, other specified site including ruptured septum, and unspecified site. The model also includes adjustments for patient race (white, African American, Asian, Native-American, other, and unknown), Hispanic ethnicity, gender, type of insurance (private, Medicare, Medicaid, other government, workers comp, charity, uninsured, and insurance status unknown), whether the hospitalization was an emergency admission, whether the patient had been transferred from another acute care hospital, and the patient’s age in years.

Multivariable logistic regression was used to estimate the adjusted risk of inpatient death using the new model for patients in the study population. We retained all covariates in the final model, including nonsignificant predictors. No interaction terms were included in the new model, because the large number of potential interactions prohibited including them all, and we did not have a theoretic basis for specifying a subset prior to estimating the model. We validated the statistical performance of the new model in the same manner as that previously described for California Models A and B.

We measured the contribution of conditions related closely to AMI to the total model’s predictive performance using the likelihood ratio test method, with penalties for the number of parameters being estimated [32,33]. Their proportional contribution was measured as the ratio of the log-likelihood achieved by a submodel including only these covariates to the log-likelihood achieved by the full model.
2.4. Mortality risk adjustment using other measures of comorbid disease

Prior studies of AMI mortality outcomes in other study populations have included adjustments for comorbid disease measured using adaptations of the Charlson index [34] or other similar methods. To compare results from the new model to prior research using adaptations of the Charlson index, we identified each occurrence of the 17 categories of comorbid disease included by the Deyo et al. adaptation of the Charlson index [35] among patients in the study population. We also identified each occurrence of the 30 categories of comorbid disease included by the method of Elixhauser et al. [36,37] for each patient, which has been demonstrated to have better statistical performance than the Deyo et al. adaptation of the Charlson index in several prior studies of AMI patients and in other study populations [17,38].

We developed multivariable logistic regression models that included adjustments for categories of comorbid disease measured by the Deyo et al. adaptation of the Charlson index and by the method of Elixhauser et al. Both of these models included adjustments for infarct location, demographic variables, and hospitalization characteristics identical to those included in the new model. Both of these models were estimated and validated in the same manner as that previously described for the new model and for California Models A and B.

2.5. Sensitivity of models to diagnoses not reported as present at admission

The new mortality risk-adjustment model only includes information from secondary diagnoses reported as present at admission for each discharged patient. In each of the other models, comorbidities are measured using selected sets of ICD-9-CM codes for conditions considered likely to be present at admission. Each model includes a different set of select ICD-9-CM codes. The main difference between California Models A and B is that California Model A includes fewer categories of comorbid disease and fewer ICD-9-CM diagnosis codes. California Model A is described in the California Hospital Outcomes Project report as a more conservative adjustment model than Model B, because it is less likely to include adjustments for conditions that are complications occurring during the hospitalization for some patients.

We repeated the complete development and validation process for each model (except for the CCS model) using only ICD-9-CM diagnosis codes reported as present at admission for each patient. We then compared the validated statistical performance achieved by each model using all available ICD-9-CM codes to that using only ICD-9-CM codes reported as present at admission. This pairwise comparison measures the amount of the contribution made to each model’s statistical performance by diagnoses not present at admission.

3. Results

Validated C statistics, which measure each model’s ability to discriminate between patients who were discharged alive and those who were discharged deceased in the validation data set, are presented in Table 1. The CCS model and California Model B both achieved a validated C statistic of 0.86. California Model A achieved a C statistic of 0.77. The C statistics obtained for California Models A and B are identical to the C statistics reported for each model in the California Hospital Outcomes Project Report on Heart Attack Outcomes [15]. The model that adjusted for comorbid disease using the Elixhauser et al. method obtained a C statistic of 0.80. The model using the Deyo et al. adaptation of the Charlson index obtained a C statistic of 0.74, which was the lowest C statistic obtained among the five models applied to the study population. Validated maximum rescaled $R^2$ statistics, which measure the predictive strength of each model, are also presented in Table 1. The CCS model and California Model B achieved the best explanatory power.

Table 1
Mortality risk-adjustment model statistical performance in validation population

<table>
<thead>
<tr>
<th>Mortality risk-adjustment model</th>
<th>DF</th>
<th>Present-at-admission ICD-9-CM diagnoses only</th>
<th>All specified ICD-9-CM diagnoses</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>C statistic</td>
<td>Maximum rescaled $R^2$</td>
</tr>
<tr>
<td>CCS categories of present-at-admission diagnoses</td>
<td>265</td>
<td>0.86</td>
<td>0.30</td>
</tr>
<tr>
<td>California Hospital Outcomes Project, Model A</td>
<td>25</td>
<td>0.76</td>
<td>0.13</td>
</tr>
<tr>
<td>California Hospital Outcomes Project, Model B</td>
<td>63</td>
<td>0.82</td>
<td>0.22</td>
</tr>
<tr>
<td>Deyo et al. adaptation of the Charlson index comorbidities</td>
<td>40</td>
<td>0.74</td>
<td>0.11</td>
</tr>
<tr>
<td>Elixhauser et al. method comorbidities</td>
<td>57</td>
<td>0.79</td>
<td>0.17</td>
</tr>
</tbody>
</table>

Note: The models with CCS categories, the Deyo et al. adaptation of the Charlson index, and the Elixhauser et al. method include identical adjustments for infarct location, demographic variables, and hospitalization characteristics.

Abbreviation: DF = total model degrees of freedom.
Information from ICD-9-CM diagnoses not reported as present at admission contributed substantially to the statistical performance achieved by California Model B. The C statistic for California Model B declined from 0.86 to 0.82 and the $R^2$ statistic declined from 0.30 to 0.22 when we repeated the development and validation process using only ICD-9-CM diagnosis codes reported as present at admission for each patient. Statistical performance declined only slightly or remained the same when we repeated the development and validation process for the other models.

Figures 1–5 are plots of Wald chi-square statistics obtained for individual covariates in each model. These figures depict the statistical significance and relative contribution to statistical performance made by each model covariate. Results for all covariates are listed for each model, except for the new model, which includes adjustments for 244 covariates. Fig. 1 lists results for the 92 covariates in the new model that had a $P$-value less than 0.05 for the Wald chi-square statistic. Complete results for each model are available from the corresponding author on request.

The comorbid condition “shock” had the single largest contribution to the statistical performance of the new model. California Model B includes “shock” as an individual covariate and as a component of nine interaction terms in the model, and each of these covariates were statistically significant ($P < 0.05$). California Model A, the model using the Deyo et al. adaptation of the Charlson index, and the model using the Elixhauser et al. method do not include “shock” as a covariate.

The model includes adjustments for 233 categories of comorbidity, each measured by ICD-9-CM codes reported as present at admission. Besides “shock,” the categories of comorbid disease that contributed most to the statistical performance of the model were “coma, stupor, and brain damage,” “acute and unspecified renal disease,” “respiratory failure, insufficiency, arrest,” and “acute cerebrovascular disease.”

Infarct location contributed substantially to statistical performance in all of the models we developed. Infarct location was represented by a single polychotomous covariate in the new model, in the model using the Deyo et al. adaptation of the Charlson index, and in the model using the Elixhauser et al. method. Information related to infarct location was represented in 8 of the 25 covariates in California Model A, and in 9 of the 63 covariates in California Model B. Infarct location was a statistically significant covariate ($P < 0.0001$) in each model.

In addition to infarct location, the new model included four other covariates that adjusted for the effects of conditions related closely to AMI that were present at admission. These conditions were “cardiac arrest and ventricular fibrillation,” “heart disease related closely to AMI,” “coronary atherosclerosis and other related heart disease,” and “cardiac dysrhythmias.” Each of these covariates was statistically significant ($P$-value $< 0.05$). The global model log-likelihood ratio test demonstrated that the combined effect of the five covariates for conditions related closely to AMI was equivalent to 39% of the total log-likelihood achieved by the new model.

Fig. 6 presents calibration charts for the CCS model and for the four comparison models. Each of the five models were well calibrated in the validation population, with generally similar numbers of observed and predicted deaths across 100 quantiles of estimated risk. The CCS model and California Model B identified more patients with the highest risks of death. The model using the Elixhauser et al. method identified more high-risk patients than California Model A or the model using the Deyo et al. adaptation of the Charlson index. Each of the five models tended to overestimate mortality risk for the top 2% of patients at highest risk.

4. Discussion

AMI mortality risk-adjustment methods can be meaningfully improved by using present-at-admission diagnoses to identify comorbid disease and conditions related closely to AMI. The CCS model using present-at-admission diagnoses obtained better discrimination between predicted survival and inpatient death, measured a wider range of mortality risk, and had more explanatory power than the other models we considered. More complete and better-calibrated AMI mortality risk-adjustment methods can be used to obtain more accurate comparisons of quality-of-care differences among hospitals.

The higher explanatory power achieved by the CCS model is not the result of overfitting the data with the large number of variables included in the model. The statistical performance of each model we considered was calculated based on the validation data only, using models with fixed coefficients estimated in the development data to forecast a risk of death for each individual patient in the validation data. These results indicate that additional predictive value is obtained by including adjustments for a large number of conditions present at admission, including conditions with small effects on in-hospital mortality and conditions that occur infrequently.

Increased statistical performance should not be obtained at the expense of decreased accuracy in adjustments for baseline differences among patients, especially when the objective of the analysis is to compare hospital mortality outcomes. The adequacy and accuracy of these adjustments is an enduring issue for studies that rely on administrative data, because it is difficult to distinguish the timing of some events. All Patient Refined Diagnosis Related Groups (APR-DRGs) have been used for AMI mortality risk adjustment in several state reports that compare hospitals, although prior studies suggest that this method misadjusts because complications of care are included in the adjustments [39]. When complications are included in mortality risk adjustments, hospitals with high complication rates...
Fig. 1. Plot of Wald chi-square statistics for variables in the model with CCS categories of present-at-admission diagnoses. The plot lists results for variables in the model that were statistically significant (p < 0.05), presented in descending order according to their relative contribution to the statistical performance of the model.
appear to have lower than expected mortality compared to otherwise similar hospitals whose patients have few complications.

The trade-off between increased statistical performance and decreased accuracy was accommodated in the California Hospital Outcomes Project by including results for both the conservative Model A and for Model B, which includes covariates for conditions that may have developed after admission. This study demonstrates that a large portion of the increase in statistical performance achieved by Model B is attributable to conditions not identified as present at admission. These results are consistent with an earlier study that examined diagnosis codes abstracted from the medical records of 974 California hospital patients with AMI, conducted before California hospitals began to identify which diagnoses were present at admission [40]. The prior study found that the C statistic achieved by California Model A using all available data declined from 0.81 to 0.79 when the model was recalculated using only conditions documented in physician notes recorded at the time of admission or in notes made prior to admission during the time the patient was in the emergency room. In comparison, the C statistic for California Model B declined from 0.88 to 0.82, indicating that the additional covariates included in California Model B were more likely to represent conditions occurring after admission than those included in California Model A.

Models with measures of comorbid disease developed for general use with administrative data can achieve better performance than disease-specific models. We found that a model using the Elixhauser et al. generalized measure of comorbid disease performed better than California Model A, and that both models had similar decrements in performance when calculated using only ICD-9-CM diagnoses reported as present at admission. The California models include measures of patient demographic characteristics and infarct location that are different from those used in the model using CCS categories. Part of the difference in statistical performance between the models may be attributable to differences in these variables, rather than to the differences in how comorbid disease is measured. On the other hand, no interaction terms were included in the model using CCS categories, while the California models include many interaction terms as covariates. The amount of statistical performance improvement obtainable from the CCS categories may have been underestimated because of the failure to include interaction terms in the model.

All mortality risk-adjustment methods using administrative data are limited by the potential for imprecision and inaccuracy in the data [41–43] and by the potential for bias in how secondary diagnoses are recorded for different patients by different hospitals [44]. These limitations accompany our results along with a limitation unique to this study. The validity of the results for the CCS model depends on the quality of the present-at-admission indicator. We found that ICD-9-CM codes independently selected as reliable indicators of comorbid disease in the California Model A, in the Deyo et al. adaptation of the Charlson index model, and in the Elixhauser et al. model were overwhelmingly reported as present at admission in the California data. There was little or no difference in the statistical performance of these models calculated using all available data compared to their performance when calculated using only diagnoses reported as present at admission. More rigorous evidence of the validity of the present-at-admission data was not available for our study.
The CCS model achieved improvements in statistical performance by including more comprehensive adjustments for comorbid diseases and conditions related closely to AMI. Adjustments for comorbid diseases and AMI severity in the CCS model and in the other models examined are limited to the information available from ICD-9-CM codes. Differences in comorbid disease and AMI severity could be even more comprehensively measured using more detailed clinical data obtained by abstracting additional data from patient medical records. However, prior research suggests that AMI mortality risk-adjustment models using such data might not obtain the level of statistical performance demonstrated by the CCS model.

A prior study compared California Models A and B to several AMI mortality risk-adjustment models that included data abstracted from patient medical records, including models from the Cooperative Cardiovascular Project (CCP), the Global Utilization of Streptokinase and Tissue

Fig. 3. Plot of Wald chi-square statistics for variables in California Model B. The plot lists results for all variables included in the model, presented in descending order according to their relative contribution to the statistical performance of the model. Some variables in California Model B are represented individually and as part of interaction terms that allow their effect on mortality to be modified by the value of another variable. Interactions are represented in the plot as two variables separated by the “*” symbol.
Plasminogen Activator for Occluded Coronary Arteries Trial (GUSTO-I), and the Medicare Mortality Predictor System (MMPS) [9]. These comparison models included covariates such as systolic and diastolic blood pressure, heart rate, blood urea nitrogen, creatinine, and white blood cell count. This prior study applied each model to the same study population of Medicare patients and obtained validated $C$ statistics of 0.71 for California Model A, 0.74 for GUSTO-I, 0.78 for the CCP model, 0.78 for the MMPS model, and 0.78 for California Model B. In our study, we
obtained a validated C statistic of 0.77 for California Model A and 0.86 for the CCS model using conditions present at admission. The scale of the increase in statistical performance obtained using present-at-admission diagnoses in our study exceeds that obtained by models using clinical data abstracted from patient medical records in this prior study.

Accurate and comprehensive mortality risk adjustment is essential for obtaining valid comparisons of AMI mortality outcomes among hospitals. This study suggests that knowing which secondary diagnoses were present at admission for each patient provides a substantial advantage for AMI mortality risk adjustment in studies using

![Fig. 6. Calibration charts for each of the five models. Each plot contains 100 points (circles) representing 100 quantile groups with similar levels of mortality risk estimated using each model in the validation population. Each point represents the ratio of the actual observed proportion of deaths in each group to the average mortality risk estimated by the model. Observed and predicted death rates are equivalent for points along the superimposed 45° line.](image-url)
administrative data. We plan to conduct further analysis of differences in these models to assess how improvements in statistical performance influence the identification of hospitals with higher or lower than expected AMI mortality.

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