

Clinical Research

Development and Validation of an Acute Heart Failure-Specific Mortality Predictive Model Based on Administrative Data

Noriko Sasaki, MD, Jason Lee, PhD, Sungchul Park, BA, Takeshi Umegaki, MD, PhD, Susumu Kunisawa, MD, Tetsuya Otsubo, PhD, Hiroshi Ikai, MD, PhD, and Yuichi Imanaka, MD, PhD

Department of Healthcare Economics and Quality Management, Kyoto University Graduate School of Medicine, Kyoto, Japan

See editorial by Tu, pages 1024-1026 of this issue.

ABSTRACT

Background: Acute heart failure (AHF) with its high in-hospital mortality is an increasing burden on healthcare systems worldwide, and comparing hospital performance is required for improving hospital management efficiency. However, it is difficult to distinguish patient severity from individual hospital care effects. The aim of this study was to develop a risk adjustment model to predict in-hospital mortality for AHF using routinely available administrative data.

Methods: Administrative data were extracted from 86 acute care hospitals in Japan. We identified 8620 hospitalized patients with AHF from April 2010 to March 2011. Multivariable logistic regression analyses were conducted to analyze various patient factors that might affect mortality. Two predictive models (models 1 and 2; without and with New York Heart Association functional class, respectively) were

Acute heart failure (AHF) requiring hospitalization is associated with high rates of morbidity and mortality.¹⁻³ Several recent AHF registries and surveys have reported in-hospital mortality rates in AHF patients ranging from 3.8% to 7.7%.⁴⁻⁷ Aging of the population, progression of therapeutic intervention, and effective secondary prevention have all led to an increasing burden on heart failure and AHF on health care systems worldwide.^{8,9} The comparison of hospital performance and quality of care is an initial step to evaluate, benchmark, and improve hospital management under the growing health care costs associated with AHF. However, it is difficult to distinguish between

RÉSUMÉ

Introduction : En raison de sa mortalité hospitalière élevée, l'insuffisance cardiaque aiguë (ICA) est un fardeau de plus en plus lourd pour les systèmes de soins de santé à l'échelle mondiale. Ainsi, la comparaison de la performance hospitalière est nécessaire pour améliorer l'efficacité de la logistique hospitalière. Toutefois, il est difficile de distinguer la gravité de l'état de santé du patient des effets des soins hospitaliers individuels. Le but de cette étude était de développer un modèle d'ajustement au risque pour prédire la mortalité hospitalière par ICA en utilisant les données administratives couramment disponibles.

Méthodes : Les données administratives ont été extraites de 86 hôpitaux de soins de courte durée du Japon. Nous avons sélectionné 8620 patients hospitalisés ayant une ICA d'avril 2010 à mars 2011.

the influences of patient disease severity from individual hospital care effects, thereby impeding adequate comparison of hospitals.

Because some hospitals treat sicker patients than others, patient severity should be taken into consideration when comparing hospitals. The comparison of crude mortality rates between facilities would bias evaluations against hospitals with a greater proportion of high risk patients, and risk-adjusted mortality rates can make hospital-level comparisons more meaningful.¹⁰ Risk adjustment accounts for the differences in intrinsic patient health risks at admission. To this end, administrative data are appealing because of its ability to derive numerous variables from a routine work flow, and the relatively large quantity of data available which allow inter-hospital comparisons.

However, because the real-world diagnosis of AHF is highly complex² and administrative data have limitations in acquiring clinical variables that influence patient outcomes, the usage of administrative data for risk adjustment among AHF patient groups has been restricted and appears to be challenging thus far.

Received for publication September 22, 2012. Accepted November 21, 2012.

Corresponding author: Dr Yuichi Imanaka, Department of Healthcare Economics and Quality Management, Kyoto University Graduate School of Medicine, Yoshida Konoe-cho, Sakyo-ku, Kyoto 606-8501, Japan. Tel.: +81-75-753-4454; fax: +81-75-753-4455.

E-mail: imanaka-y@umin.net

See page 1060 for disclosure information.

developed and bootstrapping was used for internal validation. Expected mortality rates were then calculated for each hospital by applying model 2.

Results: The overall in-hospital mortality rate was 7.1%. Factors independently associated with higher in-hospital mortality included advanced age, New York Heart Association class, and severe respiratory failure. In contrast, comorbid hypertension, ischemic heart disease, and atrial fibrillation/flutter were found to be associated with lower in-hospital mortality. Both model 1 and model 2 demonstrated good discrimination with c-statistics of 0.76 (95% confidence interval, 0.74-0.78) and 0.80 (95% confidence interval, 0.78-0.82), respectively, and good calibration after bootstrap correction, with better results in model 2.

Conclusions: Factors identifiable from administrative data were able to accurately predict in-hospital mortality. Application of our model might facilitate risk adjustment for AHF and can contribute to hospital evaluations.

The aim of our study was to develop an accurate, practical, and reproducible risk adjustment model to predict AHF in-hospital mortality using factors identifiable from administrative data, and to apply this model to an interhospital comparison.

Methods

Data source

All data were extracted from the Quality Indicator/Improvement Project (QIP), a project that involves the collection of administrative data from voluntarily participating acute care hospitals, and subsequent analysis of healthcare processes, patient outcomes, and disease management in Japan.^{11,12} Participating hospitals vary widely in patient volume, bed numbers, region, and type (publicly- or privately-owned; teaching or nonteaching). Moreover, QIP hospitals provide administrative data based on the Japanese case-mix classification system, known as the Diagnosis Procedure Combination (DPC).¹² The DPC-based hospital reimbursement system was introduced in 2003, and has been adopted by more than 1400 hospitals by 2011, accounting for more than half of the total 910,000 hospital beds nationwide. This payment scheme is based on per diem charges. The DPC system database includes information on hospital codes, patient demographic characteristics, admission and discharge dates, admission routes, outcomes, primary and secondary diagnoses, comorbidities at admission, complications, surgeries performed, and high cost procedures such as mechanical ventilation, hemodialysis, and cardiopulmonary support device use. Diagnoses including comorbidities and complications are coded by physicians based on International Classification of Diseases, 10th revision (ICD-10) codes. Furthermore, AHF was specifically identified using the 'acute exacerbation' code available in DPC data, which has been

Des analyses multivariées de régression logistique ont été menées pour analyser les divers facteurs liés aux patients qui pourraient influencer la mortalité. Deux modèles prédictifs (modèles 1 et 2; sans et avec la classification fonctionnelle de la *New York Heart Association*, respectivement) ont été élaborés, et la méthode d'autoamorçage a été utilisée pour la validation interne. Les taux de mortalité attendus ont ensuite été calculés pour chaque hôpital par l'application du modèle 2.

Résultats : Le taux global de mortalité hospitalière a été de 7,1 %. Les facteurs indépendamment associés à la mortalité hospitalière élevée ont inclus l'âge avancé, la classification de la *New York Heart Association* et l'insuffisance respiratoire grave. En revanche, l'hypertension associée à une maladie, la cardiopathie ischémique, et la fibrillation et le flutter auriculaires ont été associés à une plus faible mortalité hospitalière. Les modèles 1 et 2 ont démontré par les statistiques C une bonne discrimination de 0,76 (intervalle de confiance à 95 %, 0,74-0,78) et de 0,80 (intervalle de confiance à 95 %, 0,78-0,82), respectivement, et une bonne calibration après la correction par méthode d'autoamorçage par de meilleurs résultats au modèle 2.

Conclusions : Les facteurs identifiables des données administratives ont été en mesure de prédire avec précision la mortalité hospitalière. L'application de notre modèle pourrait faciliter l'ajustement au risque pour l'ICA et peut contribuer aux évaluations hospitalières.

determined by the attending physician at admission. Similarly, the reporting of the New York Heart Association (NYHA) functional class at admission by physicians is mandatory within the DPC system.

Study population

Data were collected from 19,792 patients across 139 hospitals with a primary diagnosis of heart failure (ICD-10 code I50.x). Patients were included in the study if they had been discharged between April 1, 2010 and March 31, 2011; and had been admitted to hospitals that had continuously provided data during the 12-month study period. The following selection criteria were also used: (1) patients who had both an 'acute exacerbation' of heart failure code and NYHA functional class II or higher, which were available within the DPC system and (2) patients who were at least 20 years of age at admission. The selection yielded 11,503 patients from 134 hospitals. Patients were excluded from the analysis if they simultaneously had acute myocardial infarction or if they had other conditions indistinguishable from AHF (n = 2211), including cardiopulmonary arrest (ICD-10 codes: I46.1, I46.9, R96), acute respiratory distress syndrome (ICD-10 code: J80), severe pneumonia (ICD-10 codes: J10.0, J11.0, J12-J18, J69), pleuritis (ICD-10 codes: A15.6, A16.5, R09.1, J90, J91, J94.x), and severe renal failure (ICD-10 code: N18.0) with or without dialysis at admission. Patients with a length of stay longer than 3 standard deviations from the mean (n = 169) and an invalid mortality record (n = 1) were also excluded from the analysis.

Because of wide variations in hospital volume and available emergency care, hospitals with fewer than 20 registered cases and those with no recorded utilization of acute mechanical ventilation during the study year were also excluded (46 hospitals with 545 patients). This resulted in a final sample size of 8620 patients from 86 hospitals ranging from 21 patients to 317 patients at the hospital level.

This study was approved by the Kyoto University Graduate School and Faculty of Medicine Ethics Committee, Japan.

Statistical analysis

In-hospital mortality rate was used as the primary outcome measure. Two types of mortality prediction models (model 1 and model 2; using identical predictors without and with NYHA functional class, respectively) were constructed with multivariable logistic regression using the original dataset (training set). Discrimination of the logistic regression models was assessed using the *c*-statistic.¹³ Bootstrapping was used to assess the internal validation of the model. We used 1000 bootstrap resamples to evaluate the reliability of the regression coefficients and the *c*-statistics.¹⁴ To validate the prediction model, a model in the bootstrap sample dataset (*n* = 8620) was derived and Hosmer-Lemeshow test was performed to evaluate model calibration (*P* > 0.05 is considered favourable).¹⁵

During model construction, we explored clinically and potentially important predictors available in the database as candidate explanatory variables (Table 1). These variables were categorized into 3 fields of measurement: demographic characteristics, clinical factors associated with patient severity, and comorbidities at admission. Multivariable logistic regression was used to estimate the predictors of in-hospital mortality of the original full dataset. We retained all covariates in the final model.

Table 1. Candidate variables used to develop the in-hospital mortality prediction model

Candidate variables	Category
Demographic characteristics	
Sex	Male*, female
Age (y)	20-59* 60-69 70-79 80-89 ≥90
Hospital admission route	1. Emergency with ambulance 2. Emergency without ambulance 3. Scheduled*
Clinical factors	
NYHA functional class	II*; III; IV
Severe respiratory failure because of AHF	0, Absent; 1, present
Comorbidities	
Ischemic heart disease (ICD-10 codes: I201, I208, I209, I25)	0, Absent; 1, present
Hypertension (including HHD; ICD-10 codes: I10-I15)	
Atrial fibrillation/flutter (ICD-10 code: I48)	
Life-threatening arrhythmia (ICD-10 codes: I490, I442, I46)	
Chronic renal failure (mild to moderate; ICD-10 codes: N188, N189, N19)	
Shock (including cardiogenic shock; ICD-10 codes: R570, R571, R578, R579, A419)	

AHF, acute heart failure; HHD, hypertensive heart disease; ICD-10, *International Classification of Diseases, 10th revision*; NYHA, New York Heart Association.

* Reference value.

Clinical factors related to patient severity were defined as follows: admission route was identified using an “emergency” admission code, which allowed for the identification of unplanned admissions with or without ambulance use. Severe respiratory failure because of AHF was identified with procedure codes reflecting acute mechanical ventilation use within 48 hours postadmission. Potential comorbidities were selected from the previous published literature as risk factors for mortality.^{1,3,4} However, available diagnoses of comorbidities in each patient were restricted to 4 coding slots. Comorbidities with a prevalence of less than 0.7% were excluded because of possible undercoding.¹⁰

Finally, the predicted mortality was calculated using the coefficients derived from the average of the bootstrapping datasets. All statistical analyses were conducted using SPSS software, version 19.0J (SPSS Inc, Chicago, IL) and STATA 12 statistical software (StataCorp, College Station, TX).

Evaluation of hospitals

We identified hospitals as having a better or worse observed mortality rate than their expected mortality rate based on 95% confidence interval (CI). The expected mortality rate of each hospital was calculated using model 2 by adding the predicted mortality risk of each patient within an individual hospital and dividing the sum by the number of patients (Fig. 1).

Results

Hospital characteristics and patient clinical baseline characteristics are shown in Table 2. Overall observed in-hospital mortality rate was 7.1%, which was within the range reported in recent AHF registries.⁴⁻⁷ The mean age was 78 years, with minimal differences in sex. The prevalence of hypertension (including hypertensive heart disease) was approximately 57%, and that of ischemic heart disease (IHD) and atrial fibrillation/flutter were approximately 34% and 29%, respectively.

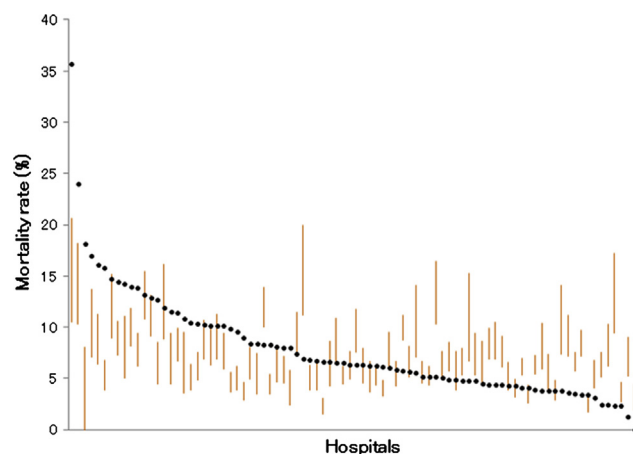


Figure 1. The dots represent observed in-hospital mortality rates of acute heart failure in individual hospitals. The lines represent 95% confidence intervals of the expected mortality rate in individual hospitals. Model 2 (with NYHA functional class) was adopted for risk adjustment in the figure.

Table 2. Demographic characteristics of the original dataset

	Original dataset
Facility level characteristics	
Number of hospitals	86
Teaching, n (%)	73 (84.9)
Larger beds (>380), n (%)	43 (50.0)
Patient level characteristics	
Number of patients	8620
Female, n (%)	4318 (50.1)
Age (y, mean ± SD)	78.5 ± 12.0
Admission route, n (%)	
Emergency with ambulance	2598 (30.1)
Emergency without ambulance	4396 (51.0)
Scheduled	1626 (18.9)
NYHA functional class, n (%)	
II	2482 (28.8)
III	3298 (38.3)
IV	2840 (32.9)
Severe respiratory failure because of AHF	
	601 (7.0)
Comorbidities, n (%)	
Ischemic heart disease	2929 (34.0)
Hypertension (including HHD)	4933 (57.2)
Atrial fibrillation/flutter	2534 (29.4)
Life-threatening arrhythmia	193 (2.2)
Chronic renal failure (mild to moderate)	956 (11.1)
Shock (including cardiogenic shock)	97 (1.1)
Clinical outcome	
In-hospital mortality, n (%)	611 (7.1)

AHF, acute heart failure; HHD, hypertensive heart disease; NYHA, New York Heart Association.

Predictive model of in-hospital mortality in patients with AHF

Table 3 shows the logistic regression coefficients and adjusted odds ratio with corresponding 95% CI for the final equation of the validation dataset. Factors that were independently associated with higher in-hospital mortality included advanced age, NYHA functional class, severe respiratory failure because of AHF, shock, life-threatening arrhythmia including ventricular fibrillation/flutter or sinus arrest, and mild to moderate chronic renal failure. In contrast, hypertension, IHD, and atrial fibrillation/flutter were associated with lower in-hospital mortality.

The c-statistics for the training models of model 1 and model 2 were 0.77 (95% CI, 0.75-0.79) and 0.81 (95% CI, 0.79-0.82), respectively. In the sample dataset, the discriminative ability of the model was maintained with the c-statistics at 0.76 (95% CI, 0.74-0.78) and 0.80 (95% CI, 0.78-0.82), respectively, after bootstrap correction. The Hosmer-Lemeshow test showed no significance ($P = 0.44$ and $P = 0.88$, respectively), indicating good calibration.

Comparing hospital performance

The observed mortality rates ranged from 0.0% to 35.7% for all 86 hospitals. Figure 1 shows the observed mortality rates for each hospital in descending order. Graph lines represent the 95% CI of the expected mortality rates calculated using the logistic regression model. Model 2 with NYHA functional class was adopted to calculate the expected mortality rate because of its better predictivity. Hospital

Table 3. Multivariable predictors of in-hospital mortality

Variables	Adjusted odds ratio (95% CI)	
	Model 1	Model 2
Female	0.96 (0.80-1.15)	0.96 (0.80-1.15)
Age (reference, 20-59 y)		
60-69	1.32 (0.72-2.41)	1.32 (0.71-2.44)
70-79	2.21 (1.29-3.79)*	2.24 (1.30-3.86)*
80-89	4.10 (2.44-6.87)†	4.15 (2.46-6.99)†
≥90	7.53 (4.42-12.82)‡	7.47 (4.36-12.79)‡
Admission route (reference, scheduled)		
Emergency with ambulance	1.39 (1.06-1.84)‡	1.09 (0.82-1.45)
Emergency without ambulance	1.11 (0.85-1.44)	1.00 (0.76-1.31)
NYHA functional class at admission§		
III	—	2.28 (1.66-3.12)†
IV	—	5.67 (4.20-7.65)†
Severe respiratory failure because of AHF	3.09 (2.40-3.98)†	2.49 (1.91-3.24)†
Ischemic heart disease	0.58 (0.47-0.71)†	0.57 (0.47-0.70)†
Hypertension	0.28 (0.23-0.34)†	0.29 (0.24-0.36)†
Atrial fibrillation/flutter	0.61 (0.49-0.76)†	0.64 (0.52-0.79)†
Life-threatening arrhythmia	2.04 (1.34-3.10)*	1.93 (1.26-2.95)*
Chronic renal failure (mild to moderate)	1.59 (1.25-2.01)†	1.53 (1.20-1.95)*
Shock	3.36 (2.08-5.40)†	2.86 (1.71-4.76)†
C-statistics (95% CI)	0.76 (0.74-0.78)	0.80 (0.78-0.82)

Model 1 does not include NYHA class; model 2 includes NYHA class. AHF, acute heart failure; CI, confidence interval; NYHA, New York Heart Association.

* $P < 0.01$.

† $P < 0.001$.

‡ $P < 0.05$.

§ Reference: NYHA II.

performance was evaluated based on whether the observed mortality rate was within, higher, or lower than the 95% CI range of the expected mortality rate.

Generally speaking, measured outcome has 4 basic components: (1) intrinsic patient specific risk, (2) quality of care provided, (3) random variation, and (4) bias introduced by systematic errors in measurement.¹⁶ Because our model showed high predictivity based on intrinsic patient risk, random variation is considered to be minimized. Systematic error in measurement was assumed to be negligible when comparing hospital performance. Consequently, a difference observed outside the 95% CI range of the expected outcomes measured for a single organization is considered to reflect the real differences between the organization and the reference standard in the quality of care provided. In other words, unexplained differences between expected outcomes and observed outcomes might reveal unwarranted institutional variations.

Discussion

Predictive model based on routinely available administrative data

In the present study, a risk adjustment model for AHF in-hospital mortality was developed using DPC administrative data in Japan. Our model was designed to account for differences in intrinsic patient health risks for assessing clinical performance of acute care hospitals.

A number of risk stratification models or scores for AHF using clinical data have been reported, mainly as beneficial tools for supporting clinical decision-making including initial triage or effective treatment.^{1,4,17-19} However, there is a lack of clinically plausible and feasible risk adjustment methods in the interest of evaluating and comparing multiple hospital performance in this field, particularly when using administrative databases.

With the nationwide spread of the DPC administrative data system in Japan, disease-specific risk adjustment methods will become more useful and practical for hospital management intending to improve quality of care. It would be labourious, costly, and time-consuming for physicians, researchers, insurers, and policymakers to collect laboratory data or other clinical findings in addition to administrative data. Although we had only used data available from the administrative database in this study, our model was shown to reliably predict in-hospital mortality in AHF patients.

There are several previous studies in which in-hospital mortality of acute myocardial infarction patients or patients with other disease was accurately predicted by complementing administrative data with present on admission (POA) modifiers for secondary diagnosis.¹⁸ The high predictivity of our model was assumed to be partly because of the fact that this POA information is contained and routinely available in the DPC data system.

Furthermore, in-hospital mortality predictors detected in the current study were partially consistent with previous clinical reports. Advanced patient age and mild to moderate chronic renal failure were found to be associated with increased risk of in-hospital mortality in both this study and in previous studies.^{1,4,5} Advanced NYHA class at admission and shock were also reported to be associated with higher mortality.^{3,19}

Our model differs from other models used to predict AHF mortality in a number of important ways. A unique difference is that essential predictors of patient severity such as NYHA functional class and severe respiratory failure because of AHF on admission were included as independent variables despite using only administrative data, as the DPC system provides POA information as part of the database. Mechanical ventilation use within the first 48 hours of admission could reflect, in part, care provided in the hospital, and the inclusion of this variable might be debatable. However, we assumed that the clinical decision to intubate might not be extremely different among physicians facing critically ill patients. Considering the inevitable limitations in specifying the exact severity only from diagnoses, we used this variable included in administrative data as a surrogate for severe respiratory failure because of AHF. Moreover, the variables can be easily obtained, because they are continuously generated through a routine work flow.

A second unique characteristic is that despite the lack of precise clinical data and the possibility of undercoding, the model was able to reveal that hypertension was highly associated with a lower risk of in-hospital mortality. Hypertension is usually considered to be 1 of the most common precursors and the most frequent underlying disease in patients with AHF. Although elevated blood pressure (BP) is an increased risk of developing heart failure in the general population, recent studies have shown that higher BP on admission is associated with lower risk of dying.^{1,4,20,21} Indeed, high BP on

admission does not always imply antecedent hypertension, and considering that previous hypertension had no independent influence on in-hospital mortality,²⁰ the result might require future examination.

In addition, IHD and atrial fibrillation/flutter were also found to be associated with lower in-hospital mortality in this study. This might be because of the following reasons. In the case of IHD, there are previous reports consistent with our study, indicating coronary revascularization status might be associated with improved early survival.²² Next, although new-onset atrial fibrillation has been reported to increase in-hospital mortality,²³ there is no compelling evidence to show the prognostic value of previous atrial fibrillation in patients with AHF. It would be debatable to interpret these factors as solely having protective effects, because the results might also reflect undercoding of patients who died in hospitals.²⁴ However, hypertension and history of coronary angioplasty have shown possible protective effects in administrative claims and chart-based models,²⁵ which might partly support our results. Because our sample has limitations in obtaining precise clinical information, further studies are also required to evaluate this issue.

Finally, despite the relatively small number of variables used in the present study, the model performance was noteworthy. The c-statistics of our model was approximately 0.8 after bootstrap correction. The value was at least equal or superior to previous studies using variables derived from chart reviews including comorbidities and clinically-extracted data such as symptoms, vital signs, physical examination findings, laboratory test results and multiple therapies.^{1,3,4,17,25} The c-statistics of these studies based on chart reviews ranged from 0.71 to 0.84. The results from this study might imply possible applications of our model in the risk adjustment of wider AHF populations in the future.

Implications of hospital performance evaluation using the predictive model

The accurate prediction of hospital mortality rates for AHF using routinely available administrative data would lead to increased use of risk-adjusted outcome as a quality indicator. The staff of individual hospitals can assess their quality of care by analyzing the disparity between the 95% CI of expected mortality rates and observed mortality rates, or by comparing their outcomes with other hospitals. Periodical and continual measurement will help hospitals self-monitor their quality of care. If a facility's performance is consistently an outlier when compared with other hospitals, that facility would require greater scrutiny.

The mortality prediction model in this study might provide a feasible and low-cost alternative to the labour-intensive chart review approach for the evaluation of multiple hospital performance, especially in the management of patients with AHF.

Limitations

There are several limitations in the present study. First, AHF has been referred to as "heterogeneous syndromes,"² varying in case identification with multiple types of data sources, leading to difficulties in straightforward comparisons with previous studies. There are also several detailed aspects of

AHF identification that remain unclear because we could not collect clinical data such as left ventricular systolic function, serum brain natriuretic peptide levels or other factors that are considered to be critical to the heart failure prognosis.³

Second, the designation of NYHA functional class at admission by the attending doctors might not be completely reliable in all cases, because these attending doctors might include noncardiologists. However, because NYHA class is rarely available in administrative data in other countries, the effect and applications of NYHA class shown here might be informative for people involved in the development and analyses of these databases.

Third, the study population was restricted to AHF patients from acute care hospitals voluntarily participating in the QIP. A selection bias might have occurred by only comparing hospitals willing to participate in this program. However, the large number and diverse characteristics of QIP participant hospitals might reduce the effect of this bias.

Fourth, the coding slots for comorbidities are limited to only 4 slots in the DPC system, which might result in possible undercoding. Refinement of the coding system will be required in order to further improve subsequent research quality.

Finally, there are still concerns with using administrative data as the sole data source, as opposed to including any kind of clinical data. The inability to obtain and describe in detail the specific clinical conditions of each individual patient is a fundamental limitation of administrative data. Therefore, the validity of risk adjustment using administrative data alone has been repeatedly challenged, and the results of several model comparisons have been reported.^{25,26} Although these reports have advocated the addition of clinical data to administrative data-based analyses, it has also been shown that difficult-to-obtain key clinical findings add little to predictive power or risk-adjustment equations.¹⁸ In the present study, POA information that is already included in the DPC administrative database proved to be a useful alternative source of clinical data.

Conclusions

Despite the relatively small number of variables used in the current models, the factors identifiable from routinely-available administrative data were able to predict in-hospital mortality for AHF with a high level of discrimination. Our models facilitate risk adjustment of AHF patients and might contribute to evaluating quality of care among multiple hospitals related to AHF.

Acknowledgements

The authors thank Dr Yoshio Yasumura (Division of Cardiology, National Hospital Organization Osaka National Hospital) for his valuable contributions to this study. We also thank the participating hospitals of QIP.

Funding Sources

The research reported here was supported in part by a Health Sciences Research Grant from the Ministry of Health, Labour and Welfare of Japan, and a Grant-in-Aid for

Scientific Research from the Japan Society for the Promotion of Science.

Disclosures

The authors have no conflicts of interest to disclose.

References

1. Lee DS, Austin PC, Rouleau JL, Liu PP, Naimark D, Tu JV. Predicting mortality among patients hospitalized for heart failure: derivation and validation of a clinical model. *JAMA* 2003;290:2581-7.
2. Weintraub N, Collins S, Pang P, et al. Acute heart failure syndromes. *Circulation* 2010;122:1975-96.
3. Fonarow GC. Epidemiology and risk stratification in acute heart failure. *Am Heart J* 2008;155:200-7.
4. Abraham WT, Fonarow GC, Albert NM, et al. Predictors of in-hospital mortality in patients hospitalized for heart failure: insights from the Organized Program to Initiate Lifesaving Treatment in Hospitalized Patients with Heart Failure (OPTIMIZE-HF). *J Am Coll Cardiol* 2008;52:347-56.
5. Adams KF, Fonarow GC, Emerman CL, et al. Characteristics and outcomes of patients hospitalized for heart failure in the United States: rationale, design, and preliminary observations from the first 100,000 cases in the Acute Decompensated Heart Failure National Registry (ADHERE). *Am Heart J* 2005;149:209-16.
6. Nieminen MS, Brutsaert D, Dickstein K, et al. EuroHeart Failure Survey II (EHFS II): a survey on hospitalized acute heart failure patients: description of population. *Eur Heart J* 2006;27:2725-36.
7. Sato N, Kajimoto K, Asai K, et al. Acute decompensated heart failure syndromes (ATTEND) registry. A prospective observational multicenter cohort study: rationale, design, and preliminary data. *Am Heart J* 2010;159:949-955.e1.
8. Dickstein K, Cohen-Solal A, Filippatos G, et al. ESC guidelines for the diagnosis and treatment of acute and chronic heart failure 2008. *Eur J Heart Fail* 2008;10:933-89.
9. Dai S, Walsh P, Wielgosz A, Gurevich Y, Bancej C, Morrison H. Comorbidities and mortality associated with hospitalized heart failure in Canada. *Can J Cardiol* 2012;28:74-9.
10. Iezzoni L. Risk Adjustment for Measuring Health Care Outcomes. 4th Ed. Chicago: Health Administration Press, 2003.
11. Hayashida K, Imanaka Y, Sekimoto M, Kobuse H, Fukuda H. Evaluation of acute myocardial infarction in-hospital mortality using a risk-adjustment model based on Japanese administrative data. *J Int Med Res* 2007;35:590-6.
12. Hamada H, Sekimoto M, Imanaka Y. Effects of the per diem prospective payment system with DRG-like grouping system (DPC/PDPS) on resource usage and healthcare quality in Japan. *Health Policy* 2012;107:194-201.
13. Harrell FE, Lee KL, Mark DB. Multivariable prognostic models: issues in developing models, evaluating assumptions and adequacy, and measuring and reducing errors. *Stat Med* 1996;15:361-87.
14. Steyerberg EW. *Clinical Prediction Models*. Lexington: Springer, 2012.
15. Lemeshow S, Hosmer DW. A review of goodness of fit statistics for use in the development of logistic regression models. *Am J Epidemiol* 1982;115:92-106.

16. Pine M. Measuring and managing clinical outcomes. In: Kongstvedt PR, ed. *The Managed Healthcare Handbook*. Maryland: Aspen Publishers, 2001:556-78.
17. Rohde LE, Goldraich L, Polanczyk CA, et al. A simple clinically based predictive rule for heart failure in-hospital mortality. *J Card Fail* 2006;12:587-93.
18. Pine M, Jordan HS, Elixhauser A, et al. Enhancement of claims data to improve risk adjustment of hospital mortality. *JAMA* 2007;297:71-6.
19. Senni M, Parrella P, De Maria R, et al. Predicting heart failure outcome from cardiac and comorbid conditions: the 3C-HF score. *Int J Cardiol* 2013;163:206-11.
20. Felšöci M, Pařenica J, Spinar J, et al. Does previous hypertension affect outcome in acute heart failure? *Eur J Intern Med* 2011;22:591-6.
21. Gheorghide M, Abraham WT, Albert NM, et al. Systolic blood pressure at admission, clinical characteristics, and outcomes in patients hospitalized with acute heart failure. *JAMA* 2006;296:2217-26.
22. Rossi JS, Flaherty JD, Fonarow GC, et al. Influence of coronary artery disease and coronary revascularization status on outcomes in patients with acute heart failure syndromes: a report from OPTIMIZE-HF. *Eur J Heart Fail* 2008;10:1215-23.
23. Rivero-Ayerza M, Scholte Op Reimer W, Lenzen M, et al. New-onset atrial fibrillation is an independent predictor of in-hospital mortality in hospitalized heart failure patients: results of the EuroHeart Failure Survey. *Eur Heart J* 2008;29:1618-24.
24. Holstein J, Taright N, Lepage E, et al. Quality of medical database to valorize the DRG model by ISA cost indicators [in French]. *Rev Epidemiol Sante Publique* 2002;50:593-603.
25. Krumholz HM, Wang Y, Mattera JA, et al. An administrative claims model suitable for profiling hospital performance based on 30-day mortality rates among patients with heart failure. *Circulation* 2006;113:1693-701.
26. Tabak YP, Johannes RS, Silber JH. Using automated clinical data for risk adjustment: development and validation of six disease-specific mortality predictive models for pay-for-performance. *Med Care* 2007;45:789-805.