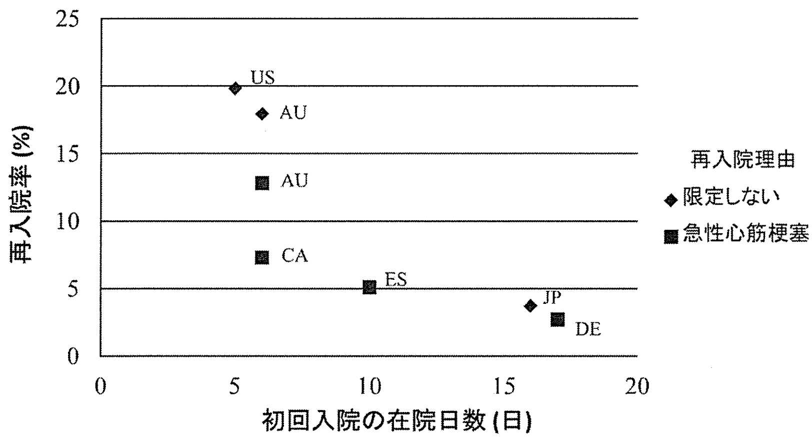

国名コード	国名	再入院理由	参照年度	再入院率の引用元*
US	アメリカ	限定しない	2009	U.S. Department of Health and Human Services (9)
AU	オーストラリア	限定しない	1999-2000	Scott I et al. (10)
AU	オーストラリア	急性心筋梗塞	1999-2000	Scott I et al. (10)
CA	カナダ	急性心筋梗塞	1998	Canadian Institute for Health Information (11)
ES	スペイン	急性心筋梗塞	1992-1994	Lupón J et al. (12)
DE	ドイツ	急性心筋梗塞	2000-2006	Schreyögg J et al. (13)
JP	日本	限定しない	2009	Present study

*: 在院日数は、日本を除くいずれの国においてもKaul P et al. (8) を参照した。

図3　初回入院における在院日数と再入院率の国際比較

考　　察

急性心筋梗塞の再入院率は，米国の11.3%(14) から28.1%(15)，オーストラリアの17.9%(10) などの報告に比して，3.7%と非常に低いことが明らかとなった。また，初回入院の在院日数については，米国の5日 (8)，オーストラリアの6日 (10) に対して，本研究の結果は16.3日と長い。国際比較の結果，図3にみられるように，在院日数が短い国はより再入院率が高い傾向が確認された。これまでわが国の在院日数は，病院完結型の医療システムであったが故に諸外国と比して，長いことが指摘されてきた (16)。しかしながら，急性心筋梗塞の再入院率は，欧米諸国と比しても低いため，医療の質の確保を主眼とした効率を維持向上する医療システムとして機能してきたことを裏付けるものである。ただし，経年的な在院日数の短縮と再入院率の変化においては，有意な関連がみられなかったという報告が米国を中心になされており (17)，わが国においても機能分化・連携型の医療システムへと変革を遂げる中で，検討すべき事項の一つといえよう。

わが国における医療システム評価における再入院率の利用可能性について考察する。再入院率は，病院における医療の質の評価のみならず，地域医療システムの評価においてもプロセスの連続性の観点から適用可能である。しかし，再入院の定義は一意ではない。すなわち，どのようなシステムについて，どのような精度，粒度で医療の質に関する課題を発見したいかによって，退院後から再入院までの期間，再入院の原因の特定やリスク調整の必要性について指標の定義を行なう必要がある。本研究結果においても，再入院の原因は心疾患によるものが主であったが，その他の多様な原因も存在することが確認された。再入院までの期間を延ばした場合，より多様な疾患によって再入院が生じることが観察されるであろう。また，アウトカムの評価において，死亡率と再入院率を包括した，退院後30日以内死亡または再入院率を評価指標とすることも提案されており (18)，医療システム評価の目的に合わせて指標を組み合わせることも有効であると考える。

再入院率を病院単位での評価に用いる場合，院内医療情報システム，DPCデータまたはレセプトデータの活用が考えられる。一方，本研究結果から，他医療機関への再入院は2割程度発生しており，同一病院に限った再入院率は医療プロセスの質として信頼性に乏しいというNasir et al.(19) の指摘は，わが国においても一定程度当てはまるため，レセプトデータによる再入院率の算出は意義がある。本研究では，レセプトデータを用いて，個人追跡の実施可能性を重視した指標算出を行なったが，より臨床的な概念から指標を定義する際には，DPCデータや院内医療情報システムにおけるデータによる算出が望まれる。この様に，指標の定義，データ構造により結果の値そのものが変わり得ることから，各種データを取扱える環境にある場合，各データの特徴を生かした再入院率を算出して，結果の信頼性と妥当性を評価することが望まれる。

再入院率を地域単位での評価に用いる場合，標本数の確保が課題となろう。京都府下の市町村国民健康保険及び後期高齢者医療制度の被保険者数約100万人について1年間にわたって入院歴を参照した結果，急性心筋梗塞を対象とした再入院事象は87件と少なかった。このため，市町村や二次医療圏単位での評価を行なう際，より長期間のデータを参照する必要があろう。ただし，参照期間が中長期にわたる場合，地域医療システムの変遷を包含した評価指標となるため，解釈に留意する必要がある。

本研究では，同一患者における複数回の再入院事象の発生も懸念される中，初回退院後から30日以内の直近の再入院の有無についてのみ分析対象とした。今後，再々入院以降の入院についても患者レベルでの医療機関間連携を踏まえた医療プロセスを把握し，要した資源量を測定することで，医療機関単独としてではなく，より包括的な医療システムとしての効率性の評価が可能となる。

結　論

わが国において，急性心筋梗塞の在院日数は諸外国と比して長いが，再入院率は極めて低い。しかしながら，在院日数短縮による再入院の発生が危惧されるため，退院時の患者の状態や退院後の医療プロセスについて今後検討する必要がある。再入院率は，ヘルスケアシステムにおける，機能の分化と連携および，それらに伴う在院日数短縮の潮流が強まる中，医療の質と効率性を確保するために把握すべき評価指標としてますます重要となるだろう。

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Clinical Research

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

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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

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

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 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 interhospital comparisons.

However, because the real-world diagnosis of AHF is highly complex[2] 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.

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

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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 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.

l'efficience 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. 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 l'autoamorçage (*bootstrapping*) a été utilisé 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 l'autoamorçage par des 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.

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 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 Institutional Review Board of the Faculty of Medicine at the Graduate School of Medicine of Kyoto University, 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.

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).

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.

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.

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

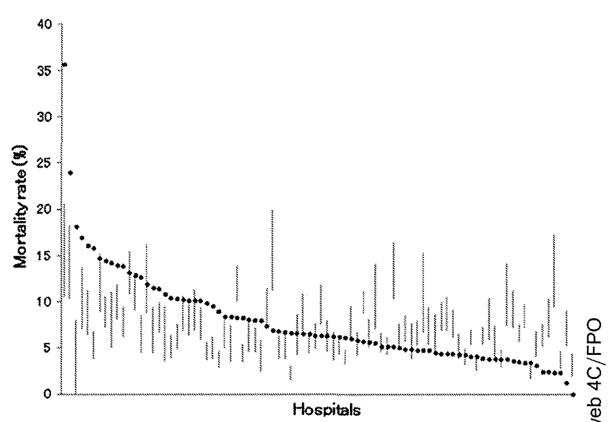

Figure 1. The **dots** represent observed in-hospital mortality rates of acute heart failure in individual hospitals. The **lines** represent 95% confidence intervals of the expected mortality rate in individual hospitals. Model 2 (with NYHA functional class) was adopted for risk adjustment in the figure.

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 (7.1)
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.

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 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.

Table 3. Multivariable predictors of in-hospital mortality

	Adjusted odds ratio (95% CI)	
Variables	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.

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 in another report,[20] the result might require future examination.

In addition, IHD and atrial fibrillation/flutter were also found to be associated with lower in-hospitality 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 BNP level or other factors that are considered to be Q1 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.

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Q2

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Q3

Disclosures

The authors have no conflicts of interest to disclose.

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SUMMARY

We developed feasible and accurate risk adjustment models of in-hospital mortality in acute heart failure (AHF) patients using only administrative data. The accuracy of our models was excellent, especially when adjusted for New York Heart Association class. Our model facilitates risk adjustment of AHF patients and might contribute to evaluating quality of care among multiple hospitals related to AHF.

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題名：急性心不全患者の院内死亡予測モデル開発とリスク調整死亡率の病院間比較

佐々木典子、Jason Lee、國澤進、大坪徹也、猪飼宏、今中雄一

【背景】急性心不全は死亡率・再入院率とも高く、高齢化に伴いますます患者が増加すると予測され、医療費増加の大きな一因と考えられている。しかしながら、急性心不全の病態は多彩であり、これまでDPCデータのみから対象患者を同定することは困難で、病院間の医療提供内容やアウトカム指標を比較検討することは不可能だった。【目的】新規に導入された病名付加コードから急性心不全患者を同定し、大規模施設を中心とした29病院が参加する急性心不全の臨床的な多施設症例登録 ATTEND レジストリー結果(2010 年報告)と比較して、対象集団の疫学的位置づけを確認する。その後、多数の病院の医療提供内容・質につき妥当な比較を行うために、院内死亡率をアウトカムとして、重症度など患者因子でリスク調整を行うモデルを作成し、モデルの妥当性につき検討する。また、同モデルを用いたリスク調整死亡率の病院間比較を行う。

【方法】「医療資源を最も投入した傷病名」が「心不全」(DPC コード 050130)で、病勢を表す病名付加コード(急性：30101、慢性の急性増悪：30102)があり、2010 年 4 月 1 日から 2011 年 3 月 31 日の 12 ヶ月間データのある Quality Indicator/Improvement Project (QIP;自発的参加のベンチマーキング事業)登録 90 急性期病院より、同期間内に退院した 9557 件の患者レコードを抽出した。尚、「主傷病名」「入院時併存症」に来院時心肺停止、成人呼吸促迫症候群、重症肺炎、胸膜炎、末期腎不全がある症例、手術病名に透析導入関連手術のある症例、在院日数が極端に長い症例、データ不整合症例、NYHA 分類欠損症例及び 20 歳以下の症例は除外した。また 20 症例以下の施設および急性期に人工呼吸器使用歴のない施設は除外した。まず、90 施設を病床規模で対応させてランダムに 2 群に分け、全 9557 症例を test dataset (n=4861)と validation dataset (n=4696) に分割した。年齢、性別のほか、入院時の重症度を反映すると考えられる NYHA 分類、救急搬送の有無、48 時間以内人工呼吸器使用の有無、各種併存症など DPC データで得られる変数から、ロジスティック回帰分析(ステップワイズ法)を用いて前者で院内死亡予測モデルを作成し、後者で妥当性を検証した。全病院の粗死亡率とリスク調整死亡率を算出し、病院間比較を行った。【結果】全集団における院内粗死亡率は 7.0%で、基礎疾患の約 3 割を占める虚血性心疾患(急性心筋梗塞は除く)割合とともに、ATTEND レジストリーと類似の結果となった。今回のデータでは大学病院は含まれなかったが、ATTEND 参加病院よりも多数、病院規模も多様で、構成患者はより高齢で、性差が少なく、よ

り軽症な患者が多かった。test dataset, validation dataset の院内死亡予測モデルの C-statistics は各々0.82,0.80 で、Hosmer-Lemeshow χ^2 検定で 1.07 (P = 0.96)を示し、適合度は良好だった。病院間比較結果は供覧する。【考察】「急性」を示す病名付加コードにより、従来困難だった急性心不全を同定することができた。対象集団の疫学的位置づけは、比較した ATTEND レジストリーが大学病院など積極的に加療する施設を主とした集団であり、解釈に注意を要する。本研究で開発した院内死亡予測モデルの予測力は高く、今後の応用が期待できる。QIP 参加病院は医療の質改善に積極的な傾向があるなどの交絡については留意が必要である。【結論】本研究で開発した急性心不全患者の院内死亡予測モデルの予測力は高く、高額医療につながる急性心不全医療の質について病院間比較を行う際、今後も広く利用できると考えられる。(1594)

【キーワード】アウトカム指標、リスク調整死亡率、急性心不全

Possible categories (2 つ) : 01)医療政策 02)地域医療 03)医療経済 04)看護管理 05)医療安全 06)質管理・ガイドライン 07)医療情報管理 08)薬剤・資材管理 09)病院経営 10)人材育成・管理 11)在宅介護・ケアマネジメント 12)診療報酬 13)患者参加・患者支援 14)国際貢献 15)その他

急性心不全患者の院内死亡予測モデル開発とリスク調整死亡率の病院間比較

京都大学大学院　医学研究科　社会健康医学系専攻
医療経済学分野

佐々木　典子、國澤　進、大坪　徹也、猪飼　宏、今中　雄一

1

背景

- 急性心不全は死亡率・再入院率とも高く、高齢化による患者数増加は医療費圧迫の大きな一因となることが世界的に懸念されている。　(Dickstein K et al, Eur J Heart Failure 2008;10:933)
- 多彩な病態を呈する急性心不全患者をこれまでDPCデータで同定することは困難で、病院間の医療提供内容やアウトカム指標を比較検討することは不可能だった。
- 急性心不全の国内疫学データは乏しく、急性心不全の臨床的な多施設症例登録 The acute decompensated heart failure syndromes (ATTEND) レジストリー結果が参考になる。しかし、この研究は大規模施設を中心とした29病院の限られたデータである(2007年4月～ 2009年5月の中間報告) ことを考慮する必要がある。(Sato N et al, Am Heart J 2010;159:949)

2

目的

- 新規に導入された病名付加コードから急性心不全患者を同定し、ATTENDレジストリーと比較して対象集団の疫学的位置づけを確認する。
- 院内死亡をアウトカムとして、病院の医療提供内容の妥当な比較を行うため、重症度など患者因子でリスク調整を行うモデルを作成し、そのモデルの妥当性を検討する。
- 同モデルを用いて、観察死亡率とリスク調整予測死亡率につき病院間比較を行う。

方法 (1)

- 研究デザイン: 観察横断研究

- 本研究で使用したデータは、当教室で主催する Quality Indicator/Improvement Project (QIP) のデータベースである。QIPは全国の急性期病院から自発的に提供されたDPCデータの分析・比較を通して、医療の質・効率性・経済性について検討し、解析結果を参加病院にフィードバックするプロジェクトである。
  施設の種類は、教育病院/非教育病院、国公立病院/公的病院/ 民間病院からなる。

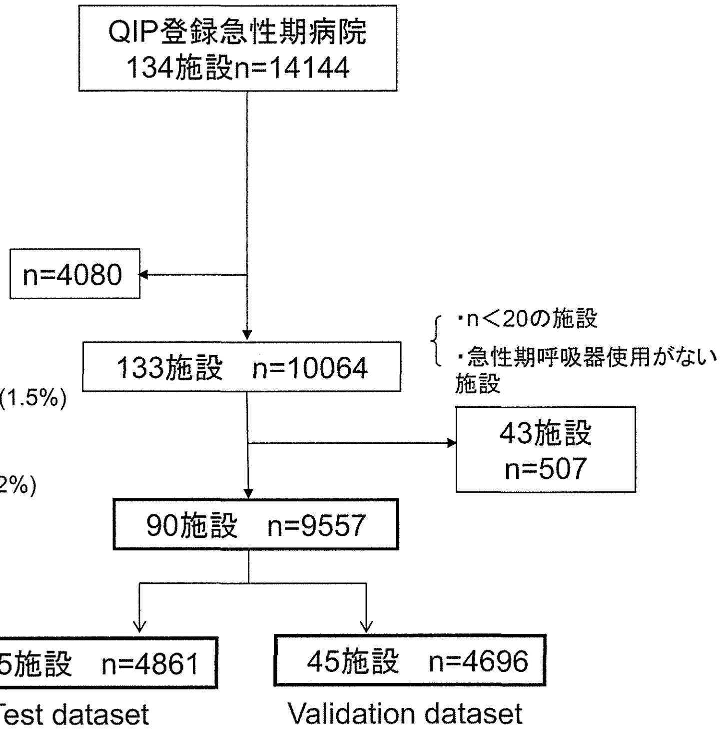
方法（2）～Selection process of patients～

<選択基準>

- **・2010年4月～2011年3月（12ヶ月分データ提出病院）**
- **・「医療資源を最も投入した傷病名」が「心不全」DPCコード 050130**
- **・急性増悪コード 30101 / 30102　あり**
- **・年齢≧20才**

<除外基準>

- ・来院時に心肺停 止、末期腎不全、ARDS、胸膜炎、肺炎併存症例 n=2421(17.1%)
- ・在院日数が極　端に長い症例 n=216(1.5%)
- ・データ不整合症例 n=1 (0.01%)
- ・入院時NYHA欠損症例　n=1862 (13.2%)



方法 (3)

■ **モデル作成方法**

・対象90**施設を病床規模で対応させてランダムに**2**群に分け**(Split Sample法), **一方を**test dataset　(n=4861), **もう一方を**validation dataset (n=4696)**とした。**

・年齢、性別のほか、入院時に重症度を反映すると考えられる変数(次表)を用いてロジスティック回帰分析(ステップワイズ法)を行い、院内死亡予測モデルを作成した。予測精度としてC-statistics**を算出した。**

■ **モデル妥当性検証方法**

test dataset**で作成した院内死亡予測モデルの回帰係数を用いて**validation dataset**で予測死亡率を計算した。**Validation dataset**における**C-statistics**を求め、その後モデル適合度判定のため**Hosmer-Lemeshow χ^2**検定（p>0.05で適合度良好）を行った。**

■ **病院間比較**

全病院の粗死亡率（観察死亡率）とリスク調整予測死亡率(95%信頼区間)を算出し、病院間比較を行った。

モデル説明変数候補

Type	Candidate Variables	Category
Demographics	Gender	Male*, Female
	Age (years)	20-59years* 60-69years 70-79years 80-89years ≥ 90years
Clinical Factors	Hospital admission route	1 Emergency with ambulance 2 Emergency without ambulance 3 Scheduled*
	NYHA functional class	I or II*; III; IV
	Severe respiratory failure due to acute heart failure	0 Absent, 1 present
Comorbidities	Ischemic heart disease DCM Hypertension (including HHD) Other cardiomyopathy Atrial fibrillation/flutter Life-threatening arrhythmia Chronic renal failure (mild to moderate) COPD Previous stroke Anemia DM Dyslipidemia Cancer Shock (including cardiogenic shock)	0 Absent, 1 present

*Reference value. NYHA, New York Heart Association; DCM, dilated cardiomyopathy; HHD, hypertensive heart disease; COPD, chronic obstructive pulmonary disease; DM, diabetes mellitus.

結果

Baseline characteristics　～ATTENDレジストリーとの比較～

	QIP*	ATTEND	P
No. of patients	**9557**	1110	
No. of hospitals	**90**	29	
Facility Level			
Hospital beds: median (range)	**381 (95-979)**	503 (42-1358)	
University hospitals　n (%)	**0 (0)**	13 (41)	<.0001
Teaching hospitals　n (%)	**76 (84)**	25 (78)	0.82
Patient Level			
Age, years　**mean (SD)**	**78 (12)**	73 (14)	<.0001
Male　%	**50**	59	<.0001
NYHA functional class n (%)		n=1100	<.0001
I	**588 (6.2)**	8 (0.7)	
II	**2585 (27.0)**	134 (12.1)	
III	**3400 (35.6)**	434 (39.1)	
IV	**2984 (31.2)**	524 (47.2)	

*** DPC administrative data**

アウトカムと入院時併存症　～ATTENDレジストリーとの比較～

	QIP* n=9557	ATTEND n=1110	P
Outcomes			
Length of stay (median,d)	17	21	
Length of stay (mean,d)	21	31	
In-hospital mortality (%)	7.0	7.7	0.43
Underlying disease (%)			
Ischemic heart disease (without AMI**)	33.8	33†	0.58
Atrial fibrillation/ flutter	29.0	40	<.0001
Hypertension	57.1	71	<.0001
Diabetes mellitus	27.9	34	<.0001
Previous stroke	6.8	12	<.0001
COPD***	6.5	9	.001

*** DPC administrative data**
†:without acute coronary syndromes (ACS)
****AMI: acute myocardial infarction**
*****COPD: chronic obstructive pulmonary disease**

Baseline characteristics ～Test / Validation dataset 比較 1～

	Test Dataset	Validation Dataset	*P*- value
Facility level characteristics			
Number of hospitals	45	45	
Teaching, n (%)	40 (88.9)	36 (80.0)	0.2447
Larger beds (＞380), n (%)	22 (48.8)	23 (51.1)	0.6086
Patient level characteristics			
Number of patients	4861	4696	
Female, n (%)	2397 (49.3)	2349 (50.0)	0.487
Age (years, mean ± SD)	78.0 ± 12.4	78.7 ± 11.7	0.007
Admission route, n (%)			
Emergency with ambulance	1447 (29.8)	1467 (31.2)	0.118
Emergency without ambulance	2661 (54.7)	2185 (46.5)	<0.0001
Scheduled	753 (15.5)	1044 (22.2)	<0.0001
NYHA functional class, n (%)			
I or II	1658 (34.1)	1515(32.3)	0.055
III	1746 (35.9)	1654 (35.2)	0.477
IV	1457 (30.0)	1527 (32.5)	0.007
Severe respiratory failure due to acute heart failure	306 (6.2)	397 (8.5)	<0.0001
In-hospital mortality, n (%)	326 (6.7)	344 (7.7)	0.236

Baseline characteristics ～Test / Validation dataset 比較 2～

	Test Dataset	Validation Dataset	*P*- value
Patient level characteristics			
Comorbidities, n (%)			
Ischemic heart disease	1593 (32.8)	1637 (34.9)	0.031
DCM	184 (3.8)	249 (5.3)	<0.0001
Hypertension (including HHD)	2798 (57.6)	2657 (56.6)	0.333
Other cardiomyopathy	89 (1.8)	97 (2.1)	0.406
Atrial fibrillation/flutter	1374 (28.3)	1400 (29.8)	0.096
Life threatening arrhythmia	103 (2.1)	110 (2.3)	0.459
Chronic renal failure (mild to moderate)	509 (10.5)	528 (11.2)	0.225
COPD	293 (6.0)	326 (6.9)	0.069
Previous stroke	337 (6.9)	309 (6.6)	0.492
Anemia	391 (8.0)	366 (7.8)	0.651
DM	1393 (28.7)	1274 (27.1)	0.096
Dyslipidemia	993 (20.4)	745 (15.9)	<0.0001
Cancer	247 (5.1)	226 (4.8)	0.545
Shock (including cardiogenic shock)	51 (1.0)	78 (1.7)	0.010

DCM, dilated cardiomyopathy; HHD, hypertensive heart disease; COPD, chronic obstructive pulmonary disease; DM, diabetes mellitus.

院内死亡予測モデルに使用した最終説明変数

(Test dataset n=4861)

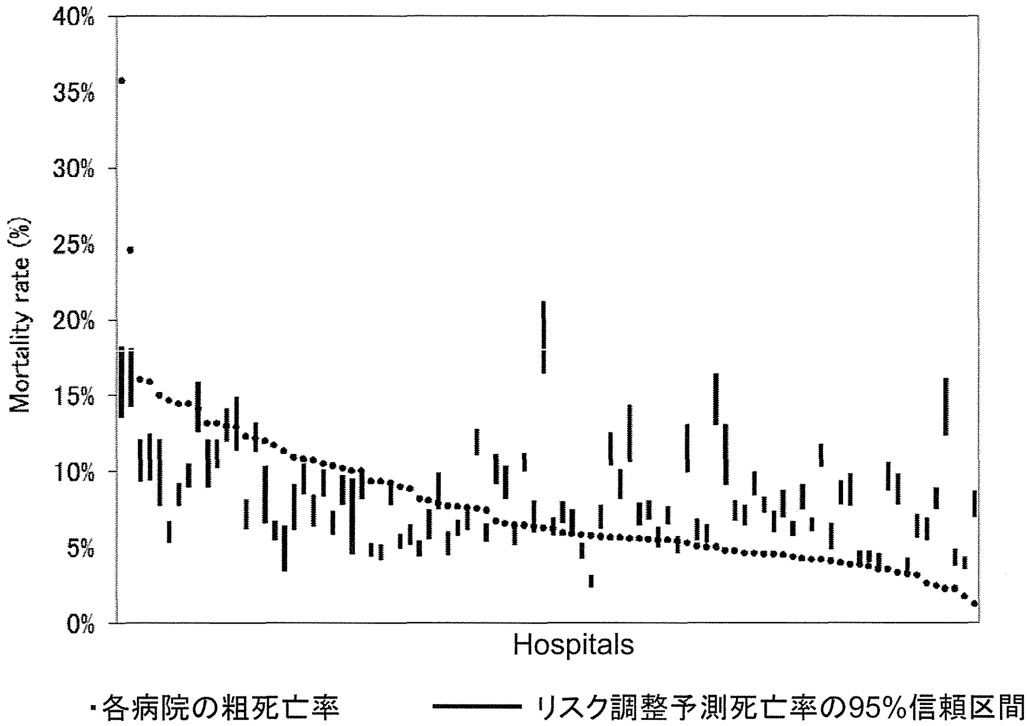
Variables	Standardized coefficient	Adjusted odds ratio (95% CI)	*P*-value
Female	0.137	1.15(0.89-1.48)	0.288
Age (reference; 20-59 years)			
60-69	0.290	1.34(0.61-2.94)	0.472
70-79	0.580	1.79(0.88-3.62)	0.107
80-89	1.330	3.78(1.93-7.39)	<0.001
≥ 90	2.051	7.78(3.90-15.51)	<0.001
*NYHA functional class at admission**			
III	0.659	1.93(1.30-2.87)	0.001
IV	1.659	5.25(3.66-7.54)	<0.001
Severe respiratory failure due to acute heart failure	1.251	3.49(2.47-4.93)	<0.001
Hypertension	-1.069	0.34(0.27-0.44)	<0.001
Life-threatening arrhythmia	0.961	2.61(1.48-4.62)	0.001
Chronic renal failure (mild to moderate)	0.566	1.76(1.27-2.44)	0.001
Shock	0.808	2.24(1.03-4.91)	0.043
Intercept	-4.584		

CI, confidence interval; NYHA, New York Heart Association. *Reference: NYHA I or II.

院内死亡予測モデルの予測力と妥当性検証

	n	C-statistics	Hosmer-Lemeshow 検定	P
Test dataset	4861	0.82	5.01	0.76
Validation dataset	4696	0.79	1.07	0.96

急性心不全院内粗死亡率および予測死亡率の病院間比較



考察

- 「急性」を示す病名付加コードにより、従来同定困難だった急性心不全を、臨床像とかけ離れない形で同定することが可能だといえる。

- 本研究で開発した院内死亡予測モデルの予測力は高く、今後の応用が期待できる。

- 開発したモデルを用いて、各病院の粗死亡率(観察死亡率)とリスク調整予測死亡率との違いを示すことができる。あまりにも観察死亡率が悪い場合は、提供医療の質を検討する契機とすることが可能である。