

An outcome prediction model for adult intensive care

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Concerns about quality of care and patient safety have increased the importance of monitoring of intensive care units in health care organisations. Performance measures for intensive care have been developed in response to increased demands to improve the quality of care.¹⁻³ Most studies have included mortality as an indicator of outcome, but mortality has varied between ICUs because of differences in the nature and severity of illness.⁴⁻⁶ Several ICU risk-adjustment models¹ have been developed to compare mortality between institutions, including the Acute Physiology and Chronic Health Evaluation (APACHE) score, the Mortality Prediction Model (MPM), and the Simplified Acute Physiology Score (SAPS). Render and colleagues have proposed an automated ICU risk-adjustment tool.⁷

Severity scores have been constructed from demographics, physiological data and clinical diagnosis, and their validity has been confirmed in large-scale studies.⁸⁻¹⁰ However, it is difficult to compare mortality rates between different ICUs based on the data available. Recently, the Critical Care Outcome Prediction Equation (COPE) model was proposed as a hospital mortality prediction model using administrative data. This model was constructed using five variables (age, unplanned admission, mechanical ventilation, hospital category and primary diagnosis). It showed that mortality could be well predicted from this model (area under the Receiver Operating Characteristic curve [AUROC] = 0.83–0.84).¹¹ Administrative data have the advantage of being available in a standardised format, which facilitates data collection from a large population and enables large-scale studies.

The Diagnosis Procedure Combination (DPC) system in Japan was introduced in 2004 and has become the standard method used in the health care financial system. Administrative data in this system include records of patient information and daily medical care. From these data, the types of all tests, medications and procedures and the use of intensive or special care and nursing services can be itemised on a daily basis. Procedures such as mechanical ventilation, renal replacement therapy and the use of vasoactive drugs are closely associated with mortality,¹¹⁻¹⁶ and their use varies somewhat among intensivists. Therefore, data on these interventions may help to predict mortality.

We used administrative data to develop three 28-day mortality prediction models based on:

ABSTRACT

Objective: To develop a prediction model of 28-day mortality in adult intensive care units using administrative data.

Design, setting and participants: We obtained data from 33 ICUs in Japan on all adult patients discharged from ICUs in 2007. Three predictive models were developed using (i) the five variables of the Critical Care Outcome Prediction Equation (COPE) model (age, unplanned admission, mechanical ventilation, hospital category and primary diagnosis) (the C model); (ii) 11 variables, including the COPE variables and six additional variables (sex, reason for ICU entry, time between hospital admission and ICU entry, use of fresh frozen plasma or a platelet preparation, dialysis, and use of pressors/vasoconstrictors (the P⁺ model); and (iii) ten of the 11 variables, excluding primary diagnosis (the P⁻ model). Data for 6758 patients were stratified at the hospital level and randomly divided into test and validation datasets. Using the test dataset, five, 10 or nine variables were subjected to multiple logistic regression analysis (sex was excluded [$P > 0.05$]).

Main outcome measure: Mortality at 28 days after the first ICU day.

Results: Areas under the Receiver Operating Characteristic curve (AUROCs) for the test dataset in the C, P⁺ and P⁻ models were 0.84, 0.89 and 0.87, respectively. Predicted mortality for the validation dataset gave Hosmer–Lemeshow χ^2 values of 12.91 ($P = 0.12$), 10.76 ($P = 0.22$) and 13.52 ($P = 0.1$), respectively, and AUROCs of 0.84, 0.89 and 0.90, respectively.

Conclusions: Our P⁻ model is robust and does not depend on disease identification. This is an advantage, as errors can arise in coding of primary diagnoses. Our model may facilitate mortality prediction based on administrative data collected on ICU patients.

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- the five variables used in the COPE model (the C model);
- 11 variables: the five COPE model variables and six additional variables (sex, reason for ICU entry, time between hospital admission and ICU entry, use of fresh frozen plasma or a platelet preparation, dialysis, and use of pressors/vasoconstrictors) (the P⁺ model); and

Table 1. Candidate variables used to develop the 28-day mortality prediction model

Type	Candidate variables	Category
Demographics	(1) Sex	Male; female
	(2) Age (years)	Continuous variable
Clinical factors	(3) Hospital admission	Scheduled;* emergency
	(4) Hospital category [†]	Metropolitan = 1; tertiary or regional = 0
	(5) Reason for entering ICU	After scheduled surgery;* after emergency surgery; internal medical disease
Any time during ICU admission	(6) Primary diagnosis on admission	(See Table 2)
	(7) Time between admission and ICU entry (days)	Direct; after 1 day; after 2–4 days;* after > 4 days
	(8) Use of fresh frozen plasma or platelet preparation	Yes = 1; No = 0
	(9) Mechanical ventilation	Used ≥ 5 hours; used < 5 hours; not used*
	(10) Dialysis	Yes = 1, No = 0
	(11) Pressor/vasoconstrictor	Yes = 1, No = 0

ICU = intensive care unit. * Reference value. † Hospital category for the present study was assumed to be metropolitan.

- ten of the 11 variables (excluding primary diagnosis) (the P⁻ model).

The aim of our study was to compare the predictive value of the P⁻ model with that of the models that included primary diagnosis as a variable.

Methods

Data sources and case selection criteria

All data for the study were extracted from the Quality Indicator/Improvement Project (QIP), which collects administrative data and analyses numerical indices of health care process outcomes in Japan. Of the hospitals that voluntarily participate in the QIP, we included 33 acute-care hospitals with ICUs, including surgical ICUs, medical ICUs, and surgical-medical ICUs. These hospitals were relatively large urban teaching hospitals, functioning in a similar manner in provision of cardiac surgery and neurosurgery. The database used in the analysis included all patients aged 20 years or over treated in an ICU at one of the 33 hospitals and discharged between 1 January and 31 December 2007. We were able to identify the time of ICU entry and the dates for the ICU stay based on specific codes in the administrative data. Patients with cardiovascular disease as a primary diagnosis (regardless of internal medical disease) and those who had undergone cardiovascular surgery were excluded from the study, as they were cared for primarily in cardiovascular care units. The data did not indicate whether a patient had been previously hospitalised in another ICU. However, as critical care patients are rarely transferred from one centre to another in Japan, we assumed that patients entering the ICU had not been transferred from another ICU.

Development of the prediction model and potential risk factors

Data for 6758 patients were stratified at the hospital level and randomly divided into test and validation datasets. Using the test dataset, five, 10 or nine variables were subjected to multiple logistic regression analysis (sex was excluded, as it was not significantly associated with mortality in the univariate analysis). Hospitals were stratified based on the number of beds, and hospitals were paired based on a similar number of beds. Test and validation datasets were established that contained similar numbers of hospitals, hospitals of similar sizes, and similar numbers of patients. The primary measure was defined as outcome 28 days after the first ICU day. A survivor who was discharged from hospital within 28 days was defined as a survivor at 28 days after the first ICU day. The mortality prediction model was constructed using the test dataset and evaluated using the validation dataset. Coefficients obtained from the test dataset were applied to cases in the validation dataset to calculate the predicted mortality.

Model development was based on up to 10 variables (Table 1), including the five variables in the COPE model.¹¹ Age was defined as a continuous variable. In defining the reason for ICU entry, patients who underwent surgery on the first ICU day or earlier were considered to be surgical patients. Among surgical patients, those who underwent surgery on the day of hospital admission or the following day were defined as “emergency” surgery cases, and those who did not have emergency surgery were defined as “scheduled” surgery cases. All other patients were considered to be internal medical patients. To define admission categories, items in the administrative data pertaining to the course of admission were used. The “emergency”

admission category indicates hospital admission after transport by ambulance or an unexpected admission. For the time between admission and ICU entry (in days), we referred to the Project IMPACT study.⁷ As Japan is a comparatively small country and development of access to hospitals has occurred through medical care policy, the hospital category (as defined in the COPE model) was assumed to be metropolitan. As International classification of diseases, 10th revision (ICD-10) codes rather than ICD-10-AM (Australian modification) codes are used in Japan, we translated ICD-10-AM codes into their nearest equivalent ICD-10 codes (Table 2).

In addition to mechanical ventilation, which is included in the COPE model, dialysis, pressors/vasoconstrictors, and use of fresh frozen plasma or a platelet preparation were considered as life-support interventions. These factors have been found to be significantly associated with prognosis in ICU patients.^{12–16} Patients having mechanical ventilation were defined as those requiring the procedure for 5 or more hours after ICU entry. These patients were identified from the corresponding codes. Because the data distinguished between continuous (≥ 5 hours) and temporary (< 5 hours) mechanical ventilation, the patients were divided into two categories. Non-invasive positive pressure ventilation was excluded. Dialysis included continuous renal replacement therapy, intermittent renal replacement therapy, plasma absorption, and plasma exchange, but excluded peritoneal dialysis, as this is rarely used for ICU patients. Pressors/vasoconstrictors included dopamine, dobutamine, noradrenaline (norepinephrine), adrenaline (epinephrine) and vasopressin, but the use of adrenaline in cardiopulmonary resuscitation was excluded. We were unable to identify whether dopamine was given as a renal dose or for cardiovascular support, but as we found no evidence that low-dose (renal-dose) dopamine was used,¹⁷ we assumed that dopamine was used for cardiopulmonary support.

Relationships between individual variables and 28-day mortality were analysed by a χ^2 test using the test dataset. After exclusion of variables with $P > 0.25$, the remaining variables were subjected to multiple logistic regression analyses (stepwise backward selection method). The model was constructed using variables with $P < 0.05$, and the AUROC was calculated.

Prediction model performance

Calibration of the model was evaluated using the Hosmer–Lemeshow χ^2 test. A well calibrated model has a low χ^2 value (< 15.5 ; $df = 8$) and a high P value (> 0.05). The discrimination of the model was assessed by the AUROC, for which a value of > 0.80 is favourable.

Table 2. Translation of ICD-10-AM codes to ICD-10 codes in our study

Diagnostic category	ICD-10-AM codes	ICD-10 codes
Anaemia	D5	D5
Aplastic anaemia	D6	D60–61
Bacterial sepsis	A4	A4
Breast cancer	C5	C5
Cardiac arrest	I46	I46
Cardiac arrhythmias	I49	I47–49
Cardiac failure	I22–25	I50
CNS malignancy	C69–72	C69–72
COPD	J40–44	J40–44
Drug poisoning	T36–50	T36–50
Enteritis or colitis	K50–52	K50–52
Environmental disease	T66–79	T66–78
Epilepsy	G4	G40
Fluid and electrolyte disorders	E86–88	E86–88
Fungal sepsis	B30–49	B35–49
GIT investigation	R1	R1
Haemopoietic malignancy	C80–99	C81–96
Haemorrhagic shock	R57–58	R57–58
Head injury	S0	S0
Interstitial lung disease	J8	J8
Intracranial haemorrhage	I60–62	I60–62
Ischaemic bowel	K55	K55
Liver disease	K7	K7
Lower limb trauma	S7	S7
Lung malignancy	C3	C3
Malabsorption	K9	K90
Malignancy – other	D37–49	D37–48
Myocardial ischaemia	I20	I20–25
Other cerebrovascular disease	I65–69	I65–69
Other CNS disease	G9	G9
Other intestinal disease	K63	K63
Pancreatic cancer	C22–26	C25
Penetrating trauma	T15–19	T15–19
Pneumoconiosis	J60–79	J60–70
Pneumonia	J1	J12–18
Protozoal sepsis	B50–64	B50–64
Pulmonary vascular disease	I26–28	I26–28
Renal failure	N1	N17–19
Respiratory failure	J95–99	J96
Secondary malignancy	C76–79	C76–80
Stroke or CVA	I63–64	I63–64
Type 2 diabetes	E11	E11

CNS = central nervous system. COPD = chronic obstructive pulmonary disease. CVA = cerebrovascular accident. GIT = gastrointestinal. ICD-10 = International classification of diseases, 10th revision. ICD-10-AM = ICD-10 (Australian modification).

Table 3. Demographic data and primary diagnosis for the test and validation datasets

	Test dataset (n = 3505)	Validation dataset (n = 253)	P
Number of hospitals	16	17	
Type of hospital			
Teaching hospital	16	17	
University hospital	0	0	
Non-teaching hospital	0	0	
Hospital with provision of cardiac surgery	15	16	0.742
Hospital with provision of neurosurgery	15	16	0.742
Mean number of beds	541.7 (SD, 189.3)	566.7 (SD, 258.4)	0.768
Mean number of ICU beds	7.4 (SD, 4.5)	7.8 (SD, 2.7)	0.802
Mean number of admissions (per year)*	10 767.9 (SD, 5199.7)	118 16.0 (SD, 6937.5)	0.688
Mean number of ICU admissions (per year)*	512.3 (SD, 317.6)	543.2 (SD, 279.6)	0.807
Mean length of stay (days)	13.6 (SD, 1.8)	13.9 (SD, 1.8)	0.721
Mean length of ICU stay (days)	3.6 (SD, 4.8)	4.4 (SD, 7.4)	<0.001
Hospital mortality (%)	9.6%	13.7%	<0.001
28-day mortality (%)	7.4%	9.7%	<0.001
Primary diagnosis on admission	Frequency (%)	Frequency (%)	<0.001
Infection	6.4%	6.6%	
Toxin	1.2%	0.9%	
Neoplastic [†]	2.2%	4.2%	
Metabolic [†]	1.2%	0.6%	
Haematological and immunological	0.8%	0.8%	
Gastrointestinal [†]	2.9%	2.2%	
Renal	1.5%	1.4%	
Respiratory [†]	5.9%	6.4%	
Neuromuscular [†]	1.1%	2.8%	
Other internal medical disease	1.0%	1.1%	
Cerebral surgery [†]	11.6%	16.7%	
Abdominal surgery [†]	38.4%	30.6%	
Lung or mediastinal surgery [†]	9.2%	12.0%	
Orthopaedic surgery [†]	7.4%	5.2%	
Other surgery [†]	9.1%	8.5%	

ICU = intensive care unit. * Estimated values (per year) are shown because the information that the Quality Indicator/Improvement Project received from each facility covered the period from 1 January to 31 December or until 30 June. † Significant difference between the two datasets by χ^2 test.

Prediction model validation

The three models were validated as follows. Cross-validation was performed using the validation dataset to demonstrate that the prediction equation obtained from multiple logistic regression analyses of the test dataset had predictive validity. Predicted mortality for the validation dataset was calculated using the coefficients we had derived from the test dataset. The performance of the equation was tested using the Hosmer–Lemeshow χ^2 statistic and the AUROC (95% CI). In the P⁻ model, a contingency table for different cut-off points was obtained for the validation dataset. Predicted mortality for internal medical disease, emergency

surgery, scheduled surgery and sepsis was also examined. All statistical analyses were performed using SPSS software, version 11.0J (SPSS Inc., Chicago, IL, USA).

Comparisons among the three models

The C, P⁺ and P⁻ models were compared using the Hosmer–Lemeshow χ^2 test and the AUROC (95% CI).

Results

Demographic data are summarised in Table 3. Explanatory variables did not differ significantly between the two

Table 4. Frequency and mortality based on individual variables in the test dataset (univariate analysis) (n = 3505)

Variable	Frequency (%)	28-day mortality (%)	P*
(1) Sex			0.489
Male	56.3	8.2	
Female	43.7	7.2	
(2) Age (years)			< 0.001
20–44	9.8	3.1	
45–54	9.0	4.1	
55–64	18.8	5	
65–74	26.0	7	
≥ 75	36.3	10.8	
(3) Admission category			< 0.001
Scheduled	48.8	1.5	
Emergency	51.2	12.9	
(5) Reason for entering ICU			< 0.001
After scheduled surgery	46.4	4.1	
After emergency surgery	29.4	5.9	
Medical disease	24.3	15.4	
(7) Time from admission to ICU entry			< 0.001
Direct	30.5	12.7	
After 1 day	18.2	3.4	
After 2–4 days	25.3	2.8	
After > 4 days	25.9	8.3	
(8) Use of fresh frozen plasma or platelet preparation			< 0.001
Yes	9.2	14.5	
No	90.8	6.6	
(9) Mechanical ventilation			< 0.001
Used ≥ 5 hours	14.4	25.6	
Used < 5 hours	19.8	5.6	
Not used	65.8	3.0	
(10) Dialysis			< 0.001
Yes	3.7	32.8	
No	96.3	6.4	
(11) Pressors/vasoconstrictors			< 0.001
Yes	41.3	13.3	
No	58.7	3.2	

ICU = intensive care unit. * P value for 28-day mortality.

datasets, except for length of ICU stay and primary diagnosis. Abdominal surgery was the most common type of surgery among surgical patients in both datasets. In patients with medical conditions, the most common reason for hospitalisation was infection. Among surgical patients, rates of cerebral, abdominal, lung, mediastinal and ortho-

paedic surgery differed significantly between datasets, and similarly, among medical patients, rates of neoplastic, metabolic, gastrointestinal, respiratory and neuromuscular disease differed significantly.

The overall 28-day mortality was 8.5%. In the univariate analysis (Table 4), the strongest association with mortality was found for dialysis (32.8%), followed by mechanical ventilation (≥ 5 hours) (25.6%). Sex was not significantly associated with mortality ($P=0.489$). Variables other than sex were subjected to multiple logistic regression analysis.

Coefficients of the variables, odds ratios (ORs), and the final equation for the validation dataset are shown in Table 5. Factors associated with a high risk of death in the C, P⁺ and P⁻ models were haemopoietic malignancy (OR, 23.07 [95% CI, 4.91–108.44]); stroke or cerebrovascular accident (OR, 20.34 [95% CI, 2.34–176.77]); and use of pressors/vasoconstrictors (OR, 7.12 [95% CI, 5.11–9.91]). Hosmer–Lemeshow χ^2 values, P values, and 95% confidence intervals for AUROC values are shown in Table 6. The P⁻ model showed good calibration for three of four diagnostic groups (being best for internal medical disease [$\chi^2=4.00$] and worst for sepsis [$\chi^2=17.38$]). We also identified different levels of probability in the validation dataset (Table 7). The discrimination ratio was 91.8% for 50% probability, and the AUROC was 0.87 for the test dataset and 0.90 for the validation dataset.

Discussion

The APACHE score, MPM and SAPS are widely used in intensive care medicine.^{18–29} These approaches depend primarily on organ scores that require physiological data. Ohno-Machado and colleagues found that AUROCs for APACHE II, APACHE III, MPM₀ (MPM at admission), MPM₂₄ (MPM at 24 hours), MPM II₀, MPM II₂₄, SAPS and SAPS II were all ≥ 0.80 except for SAPS.¹⁸

In contrast to these models, Duke and colleagues¹¹ derived the COPE model using administrative data. This model is favoured because it can predict mortality with relatively few variables, and is currently the only model based on administrative data alone. The COPE model includes mechanical ventilation as intensive-care therapy but does not include other life-support interventions such as dialysis and pressors/vasoconstrictors. However, the Hosmer–Lemeshow χ^2 statistic suggested that calibration of the COPE model was no better than that of APACHE III.

Compared with the COPE model, the P⁻ model developed in our study is based on prediction of 28-day mortality, rather than hospital mortality, and may serve as a new tool for ICU evaluation based on administrative data. The P⁻ model also has several other advantages over existing models. First, the variables depend on information that can

Table 5. Coefficients in the C, P⁺, P⁻ models developed using the test dataset (multivariate analysis) (n = 3505)*

Variable	C model		P ⁺ model		P ⁻ model	
	B	OR (95% CI)	B	OR (95% CI)	B	OR (95% CI)
(2) Age	0.03	1.03 (1.02–1.04)	0.04	1.04 (1.02–1.05)	0.03	1.03 (1.02–1.04)
(3) Admission category (emergency)	1.83	6.26 (4.05–9.67)	1.91	6.74 (4.11–11.08)	1.85	6.38 (3.96–10.30)
(5) Reason for ICU entry						
(i) After emergency surgery			1.02	2.78 (1.37–5.62)	1.06	2.90 (1.47–5.73)
(ii) Medical disease			1.25	3.51 (1.97–6.25)	1.20	3.31 (1.89–5.79)
(7) Time from admission to ICU entry						
(i) Direct			-1.34	0.26 (0.15–0.46)	-1.17	0.31 (0.18–0.54)
(ii) After 1 day			-1.59	0.20 (0.10–0.44)	-1.49	0.22 (0.11–0.47)
(8) Use of fresh frozen plasma or platelet preparation			0.47	1.60 (1.03–2.50)		
(9) Mechanical ventilation (≥ 5 hours)	1.66	5.28 (3.97–7.03)	1.53	4.61 (3.33–6.37)	1.56	4.77 (3.51–6.50)
(10) Dialysis			1.33	3.78 (2.31–6.17)	1.47	4.35 (2.72–6.95)
(11) Pressors/vasoconstrictors			2.07	7.91 (5.62–11.15)	1.96	7.12 (5.11–9.91)
(6) Primary diagnosis on admission						
Haemopoietic malignancy	3.14	23.07 (4.91–108.44)	3.00	20.14 (3.42–118.76)		
Other CNS disease	1.41	4.11 (0.95–17.87)	1.85	6.37 (1.33–30.43)		
Haemorrhagic shock			1.39	4.03 (1.47–11.05)		
Stroke or CVA	1.21	3.37 (1.30–8.73)	3.01	20.34 (2.34–176.78)		
Liver disease	2.01	7.46 (2.72–20.43)	2.08	8.00 (2.52–25.16)		
Intracranial haemorrhage			1.36	3.90 (1.73–8.79)		
Environmental disease	1.70	5.49 (1.33–22.60)	1.60	4.93 (1.13–21.48)		
Lower limb trauma	-2.29	0.10 (0.01–0.74)	-2.28	0.10 (0.01–0.78)		
Renal failure	0.73	2.07 (1.01–4.26)				
Pneumonia	0.64	1.90 (1.05–3.43)				
Constant	-6.14		-8.23		-7.67	

B = β coefficient. CNS = central nervous system. CVA = cerebrovascular accident. ICU = intensive care unit. OR = odds ratio.

* Predicted mortality risk = $e^y / (e^y + 1)$, where $y = [B_{(2)} \times (2)] + [B_{(3)} \times (3)] + [B_{(5-i)} \times (5-i)] + [B_{(5-ii)} \times (5-ii)] + [B_{(7-i)} \times (7-i)] + [B_{(7-ii)} \times (7-ii)] + [B_{(8)} \times (8)] + [B_{(9)} \times (9)] + [B_{(10)} \times (10)] + [B_{(11)} \times (11)] + [B_{(6)} \times (6)] + \text{constant}$. Each of the values (3), (5-i), (5-ii), (7-i), (7-ii), (8), (9), (10), (11) and (6) is equal to 1 if the variable is applicable or 0 if the variable is not applicable.

Table 6. Validation of the prediction model

Dataset	Model	No. of patients	28-day mortality	Hosmer–Lemeshow χ^2	P	AUROC (95% CI)
Test	P ⁻	3505	7.4	14.49	0.07	0.87 (0.85–0.90)
Test	P ⁺	3505	7.4	5.36	0.72	0.89 (0.87–0.91)
Test	C	3505	7.4	20.41	0.01	0.84 (0.82–0.87)
Validation	P ⁻	3253	9.7	13.52	0.10	0.90 (0.88–0.92)
Validation	P ⁺	3253	9.7	10.76	0.22	0.89 (0.87–0.90)
Validation	C	3253	9.7	12.91	0.12	0.84 (0.82–0.86)
(Subgroup of validation dataset)						
Internal medical disease	P ⁻	877	21.7	4.00	0.86	0.85 (0.82–0.88)
Emergency surgery	P ⁻	854	7.6	14.95	0.06	0.91 (0.88–0.94)
Scheduled surgery	P ⁻	1522	4.1	11.55	0.17	0.85 (0.81–0.90)
Sepsis	P ⁻	264	36.0	17.38	0.03	0.82 (0.77–0.89)

Table 7. Contingency table for different levels of cut-off points in the validation dataset in the P⁻ model

Cut-off points	Observed	Survivor	Expected		DR
			Survivors	Non-survivors	
20%		Survivor	2699	237	89.6%
		Non-survivor	100	217	
50%		Survivor	2874	62	91.8%
		Non-survivor	205	112	
70%		Survivor	2926	10	91.4%
		Non-survivor	269	48	

DR = discrimination ratio.

be obtained from administrative data. These variables can be input by doctors and nurses in a timely manner, rather than at or after discharge, which improves the reliability of the data. Moreover, the model uses only eight variables, which facilitates its generalisation and application. Second, the model is independent of the primary diagnosis, which avoids the difficulty of disease identification in critical care patients. Also, coding for primary diagnosis is the basis for reimbursement in the health care system, and this diagnosis may be important for determining illness severity. A disadvantage of this approach is the potential for coding errors, especially in ICU patients.¹¹

The 2007 Project IMPACT study³⁰ used a combination of MPM II₀ to assess clinical performance and a new Weighted Hospital Days scale to assess resource utilisation for ICU benchmarking. Our QIP study and the Project IMPACT study had a similar element of uncertainty regarding the clinical course after discharge, as data collection is difficult after discharge.³¹ Thus, although 90-day mortality rate may be a better measure of outcome than 28-day mortality, the latter measure is more accurate because patients are usually discharged after less than 90 days. The COPE model is also a good predictor of hospital mortality. For these reasons, we used 28-day mortality as the endpoint.

There are several limitations to our study. First, we did not compare our model with scoring systems using physiological data, as our data did not include severity scores. Thus we cannot determine whether the accuracy of the model is high or low compared with other systems. Second, the administrative data include information on a calendar-day basis rather than an hourly basis, and thus the first ICU day was defined by a calendar day. This meant we were unable to distinguish between the use of dialysis and pressors/vasoconstrictors before or after ICU entry on the first ICU day. However, these resources are mostly used under monitoring in the ICU. Third, the indications for mechanical

ventilation, dialysis and pressors/vasoconstrictors varied among hospitals, which may have produced therapeutic bias. Fourth, the administrative data do not indicate whether renal replacement therapy was given for chronic or acute renal failure or for a non-renal indication; whether mechanical ventilation was used for acute respiratory failure or during the postoperative course; or whether pressors/vasoconstrictors were used to treat hypovolaemic or septic shock. Finally, different admission criteria among ICUs could have produced a selection bias that affected mortality. Our model has a therapeutic bias similar to that of the COPE model, including the use of mechanical ventilation, dialysis, pressors/vasoconstrictors, and the use of fresh frozen plasma or a platelet preparation. However, it is likely that there would have been appropriate selection of these therapies because of common knowledge of guidelines.

Among the variables, sex was not significantly associated with outcome, which is consistent with other scoring systems. Age is an important variable for all scoring systems, and the predictive value of the model can be increased by adding other variables.³¹ The COPE model¹¹ has high discrimination, suggesting that the predictive ability of a model constructed from administrative data is high. The absence of physiological data in administrative data is a disadvantage, as diagnosis is not included in the P⁻ model, but our model has the advantage of using administrative data that is routinely collected on all patients. Comparison of the performance of ICUs is currently being attempted using administrative data, and our model establishes a method for evaluation of illness severity. However, as our study included 9% of hospitals that use the DPC system and did not include university hospitals and non-teaching hospitals, further verification and modification of the model is required in a larger sample of patients and ICUs.

Conclusion

The 28-day mortality prediction model for intensive care (the P⁻ model) proposed in our study is based solely on administrative data, is independent of primary diagnosis, and uses a relatively small number of variables that are easily collected. In addition to the COPE model, this model can be used to evaluate illness severity based on administrative data and may be applicable to critical care studies.

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