5） 考 察

考 察

1） DPC導入が、がん診療に与える影響

1. がん診療の解析の精度を追求するのに、DPCデータへの初発・再発、病期分類などの臨床情報は必要不可欠であるが、実際の記入率は高いとは言えず、データは限定的である。

2. 年次別変化における、病期および併存症の軽症化の要因として、DPC導入によるインセンティブが働いたためか、乳がん検診の普及による早期発見例が増加したためかは、比較対象の評価を欠いており、判断するのは難しい。

3. DPC対象にならない、乳腺専門の有床診療所などの近年の増加の影響が未知数である。

考　察

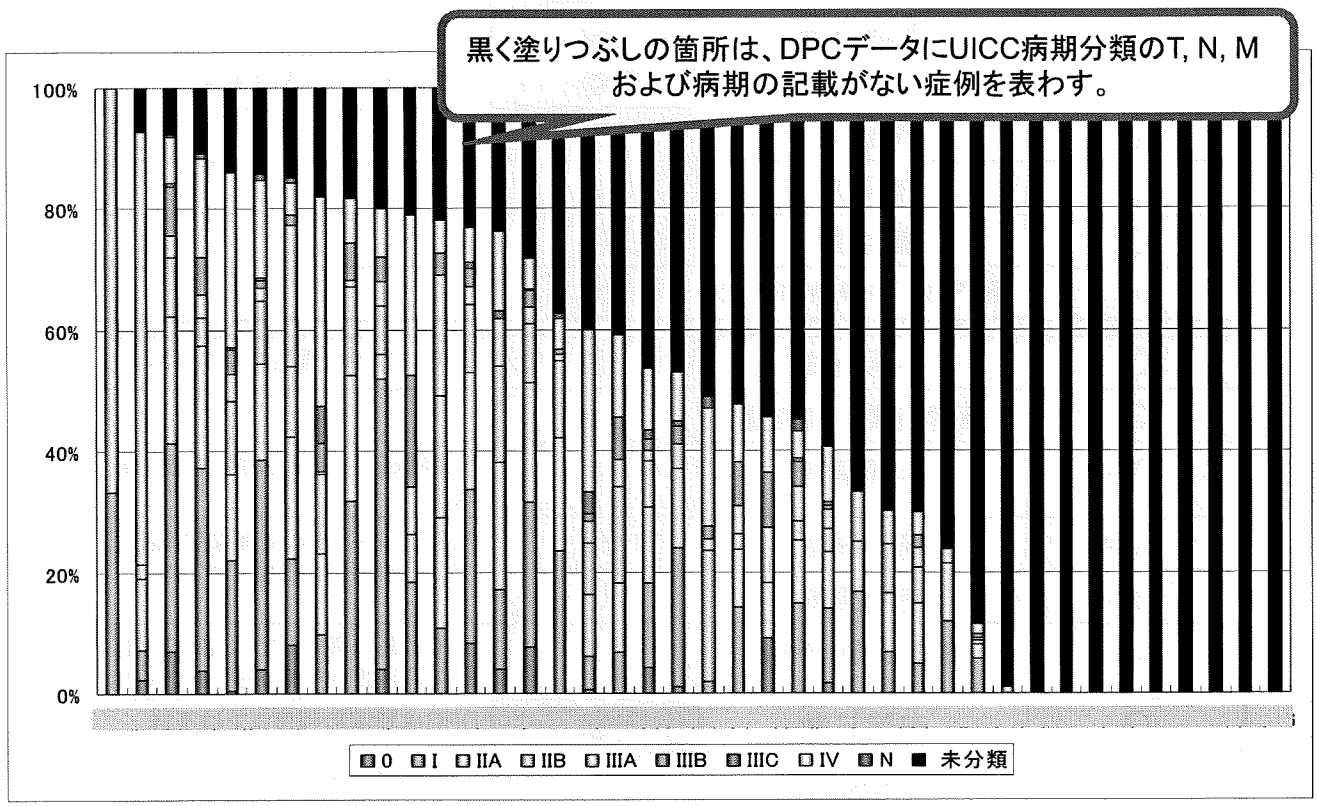
2）がん診療解析におけるDPCデータの問題点

1. がん診療の解析の精度を追求するのに、DPCデータへの初発・再発、病期分類などの臨床情報は必要不可欠であるが、実際の記入率は高いとは言えず、データは限定的である。

2. 年次別変化における、病期および併存症の軽症化の要因として、DPC導入によるインセンティブが働いたためか、乳がん検診の普及による早期発見例が増加したためかは、比較対象の評価を欠いており、判断するのは難しい。

3. DPC対象にならない、乳腺専門の有床診療所などの近年の増加の影響が未知数である。

補）施設別の病期の記載状況



補） DPCデータで入手可能な、がん診療データ

DPC	患者側要因	がん登録	注記
◎	年齢・性別	◎	
△	部位・局在	◎	一部のDPCソフトは記載可能。
◎	初発・再発	◎	ただしDPCへの入力率は低い。
×	家族歴	◎	
◎	P S	×	ただしDPCへの入力率は低い。
○	併存症	×	全て網羅されているとは限らない。 “保険病名”の存在もある。
×	発見状況	◎	DPCでは“入院経路”の項目はある。
×	腫瘤サイズ	◎	
×	組織型・ﾚｾﾌﾟﾀｰ etc	◎	
○	TNM病期分類	◎	DPCへの入力率は低い。また、癌取り扱い規約の改正には適宜修正が必要。

DPC	医療側要因	がん登録	注記
◎	施設	◎	
◎	都道府県	◎	一部のDPCソフトは記載可能。
◎	医療圏	◎	ただしDPCへの入力率は低い。
◎	開設者	◎	
○	機能別	△	
○	病床数	○	
×	専門医・ｽﾀｯﾌ勤務状況	×	
○	手術術式	◎	DPCは郭清の程度までは不詳。
○	麻酔時間、輸血量	×	
○注	有害事象	×	“保険病名”もあり正確な実態を反映？
△注	補助療法	◎	外来EFファイルに詳細な記録あり。ただし転院治療は把握できない。
◎注	使用薬剤	○	
×注	治療成績・予後	△	DPCは再入院やICU入室は記載。 個々の施設や学会の努力に依存。
○	在院日数	◎	DPCは郭清の程度までは不詳。
◎	医療費	×	DPCは再入院やICU入室は記載。 個々の施設や学会の努力に依存。

結　論

DPC導入病院の乳癌治療を様々な角度から検証し、在院日数の短縮、補助療法の施行率の低下などの経時的な変化を認めた。

補）乳房手術と保険収載およびKコード,診療報酬の変更

平成16年度(2004.4～)			平成18年度(2006.4～)		
K474-2	乳腺腺葉区域切除術	9880	K474-2	乳腺腺葉区域切除術	9880
K474-3	乳腺腫瘍画像ガイド下吸引術(一連につき)	3400	K474-3	乳腺腫瘍画像ガイド下吸引術(一連につき)	3400
K4741	乳腺腫瘍摘出術5cm未満	2660	K4741	乳腺腫瘍摘出術5cm未満	2660
K4742	乳腺腫瘍摘出術5cm以上	5180	K4742	乳腺腫瘍摘出術5cm以上	5180
K475	乳房切除術	6040	K475	乳房切除術	6040
	乳癌冷凍凝固摘出術	6040	K475-2	乳癌冷凍凝固摘出術	6040
K476-2	陥没乳頭形成術、再建乳房乳頭形成術	7350	K476-2	陥没乳頭形成術、再建乳房乳頭形成術	7350
	乳房再建術は保険収載なし		K476-31	乳房再建術　1期的に行うもの	21900
			K476-32	乳房再建術　2期的に行うもの	30000
K476	**乳腺悪性腫瘍手術**		**K476**	**乳腺悪性腫瘍手術**	
K4761	単純乳房切除術(乳腺全摘術)	10400	K4761	単純乳房切除術(乳腺全摘術)	10400
K4762	乳房部分切除術(腋窩郭清を伴わないもの)	**20000**	K4762	乳房部分切除術(腋窩郭清を伴わないもの)	**16000**
			K4763	乳房切除術(腋窩郭清を伴わないもの)	**19000**
K4763	乳房部分切除術(腋窩郭清を伴うもの)	26600	K4764	乳房部分切除術(腋窩郭清を伴うもの)	26600
K4764	乳房切除術(腋窩鎖骨下部郭清を伴う)胸筋切除を併施しない	27100	K4765	乳房切除術(腋窩鎖骨下部郭清を伴う)胸筋切除を併施しない	27100
K4765	乳房切除術(腋窩鎖骨下部郭清を伴う)胸筋切除を併施するもの	22100	K4766	乳房切除術(腋窩鎖骨下部郭清を伴う)胸筋切除を併施するもの	22100
K4766	拡大乳房切除術	33000	K4767	拡大乳房切除術	33000

Physician Staffing Patterns and Costs for Septic Patients in Intensive Care Units

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Background

- Sepsis is a serious disease from both clinical and economical perspectives.
- Patients with sepsis still have high mortality, with approximately 7.3 deaths per 100,000 population in Japan in 2007.

- Healthcare costs vary between hospitals

- We used patient classification data to evaluate the relationship between ICU physician staffing patterns and healthcare costs for patients with sepsis in Japan.

Design

- Observational cross-sectional study

- From January 1, 2007 to December 31, 2008

- Forty-nine ICUs in 49 acute-care hospitals

- Data were obtained from the Quality Indicator/Improvement Project.

- Inclusion criteria

  coding for bacterial, fungal, viral, and obstetric sepsis in the ICD-10.

- Exclusion criteria

  aged less than 20 years old.

Condition	Code
Salmonella septicaemia	A02.1
Septicaemic plague	A20.7
Anthrax septicaemia	A22.7
Erysipelothrix septicaemia	A26.7
Listerial septicaemia	A32.7
Streptococcal septicaemia	A40
Other septicaemia	A41
Actinomycotic septicaemia	A42.7

Condition	Code
Disseminated herpesviral disease	B00.7
Candidal septicaemia	B37.7
Disseminated coccidioidomycosis	B38.7
Disseminated histoplasmosis capsulati	B39.3
Disseminated blastomycosis	B40.7
Disseminated paracoccidioidomycosis	B41.7
Disseminated sporotrichosis	B42.7
Disseminated aspergillosis	B44.7
Disseminated cryptococcosis	B45.7
Disseminated mucormycosis	B46.4
Puerperal sepsis	O85

- The ICUs were classified into high-intensity ICUs and low-intensity ICUs.

- Healthcare costs during ICU stays (total ICU costs) were calculated from the day of ICU admission to the day of ICU discharge.
- Daily ICU costs were calculated by dividing the all healthcare costs during the ICU stay by the length of ICU stay (in days).

- All costs were converted to US dollars at the 2008 exchange rate (¥102=US $1).

Statistical Analysis

- A Student *t* test or Mann-Whitney test was used for continuous variables, and a chi-square test or Fisher exact test was used for categorical variables.

- $P < 0.05$ was considered to be significant.

Results

- A total of 797 patients were included in the analysis.
- The 49 ICUs were classified into high-intensity ICUs (n=18; 303 cases), and low-intensity ICUs (n=31; 494 cases).

	High-intensity ICU (n = 303)	Low-intensity ICU (n = 494)	*P* value
Age (years)	70.7±13.0	71.7±13.0	0.271
Sex (male) (%)	60.4	61.3	0.792
Predicted mortality rate (%)	21.3±19.5	20.0±17.9	0.322
Mortality rate (%)	46.9	46.8	0.9
Reason for ICU admission† (%)			
Internal medical disease	53.5	46.0	
Emergency surgery	20.5	22.7	0.074
Scheduled surgery	26.1	31.4	

	High intensity ICU (n = 303)	Low intensity ICU (n = 494)	*P* value
Total ICU costs ($)	10,264 (1,057-234,818)	9,937 (916-115,698)	0.987
Daily ICU costs ($)	1,688 (301-18,063)	1,761 (312-34,010)	0.461

	optional consultation group (n = 475)	no-CCP group (n = 19)	*P* value
Total ICU costs ($)	9,853	35,730	< 0.05
Daily ICU costs ($)	1,750	3,970	< 0.01

Discussion

- The association between ICU physician staffing models and ICU costs is unknown.
- There were no significant differences in total and daily ICU costs between the low- and high-intensity ICU models.

- The septic patients that incurred extremely large ICU costs had a low severity of illness.
- Most of these patients were in the no-CCP group.

Conclusion

- There was no difference in healthcare costs between staffing patterns for critically ill patients with sepsis.
- However, the finding that almost all patients with extremely high ICU costs were treated in a no-CCP ICU
- CCPs have an important role in reducing healthcare costs for septic patients in critical care.

An Outcome Prediction Model for Adult Intensive Care

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ABSTRACT

Purpose: Many models are used for severity evaluation and mortality prediction in adult intensive care, but most do not use administrative data. These data can be collected routinely and constructed from patients' records, and are useful for comparison of performance among intensive care units (ICUs). Administrative data in Japan includes information on daily medical care and daily costs from admission to discharge, but not for severity of critical care patients. Identification of the disease itself in ICU patients is difficult using administrative data due to the typically multifactorial nature of the condition. Therefore, we aimed to construct a mortality prediction model based on administrative data without using International Statistical Classification of Diseases and Related Health Problems (ICD) coding.

Methods: The prediction model was developed from administrative datasets for ICUs in 33 acute-care hospitals in Japan. The subjects were patients aged ≥ 20 years old who were treated in the general ICU and discharged between January 1, 2007 and December 31, 2007. We excluded patients with coding for a primary diagnosis of cardiovascular disease such as heart failure or cardiac surgery since they were usually treated in a cardiovascular care unit (CCU).

Results: Using administrative data, a total of 6,758 patients were identified who met the criteria. The data were stratified at the hospital level and randomly divided into test and validation datasets. Using the test dataset, 8 variables were subjected to multiple logistic analysis with the probability of mortality in the ICU after hospital admission as the conditional variable, and a hospital mortality prediction model was constructed. The C statistic for the test dataset was 0.86. The model was used to evaluate the predicted mortality rate for the validation dataset, for which the Hosmer-Lemeshow χ-square value was 3.08 ($p = 0.93$) and the C statistic was 0.88, indicating good calibration and discrimination.

Conclusions: Administrative data were used to construct a robust hospital mortality prediction

model without identification of the disease itself. This model may facilitate evaluation of predicted mortality for intensive care cases in future studies using administrative data.

Key Words: outcome prediction model; adult intensive care; hospital mortality; administrative data

INTRODUCTION

The Diagnosis Procedure Combination (DPC) system in Japan was introduced in 1998 and has become a standard of the health care financial system. Administrative data are the basis of the DPC system and include records of patient information, detailed costs, and daily medical care. These data are a potential tool for evaluation of clinical, epidemiological and economic performance. In addition, administrative data include medical records of all discharged patients in hospitals in Japan, which facilitates collection of information for a large population in a short period. Therefore, the number of studies using administrative data is gradually increasing in Japan.

In ICU patients, it is important to consider the severity of illness for risk adjustment. This severity can be evaluated using scoring systems such as the Acute Physiology and Chronic Health Evaluation (APACHE) versions I - IV, the Mortality Prediction Model (MPM) versions I-II, and the Simplified Acute Physiology Score (SAPS) versions I-III. Render et al. have described an automated ICU risk adjustment tool developed using a large population dataset and variables including APACHE-III [1]. However, physiological data and severity scores are not included in administrative data. Since identification of the severity of illness (mortality) from administrative data would contribute to studies in critical care, we chose to construct a model for this purpose using DPC data.

The Critical care Outcome Prediction Equation (COPE) model uses administrative data and is independent of therapy except for mechanical ventilation [2]. However, coding with ICD-10 for primary diagnosis, one of the variables in the COPE model, is the basis of reimbursement in the healthcare system. This presents a potential problem regarding data coding errors in primary diagnosis, especially in ICU patients. If the COPE model is used to evaluate severity, it is difficult to avoid the problem of coding errors in ICU patients. Therefore, we attempted to construct a mortality prediction model in ICU patients using administrative data without the primary diagnosis.

This diagnosis might be an important factor in determining the severity of illness, but the current model is designed for use of administrative data without a requirement for further information.

METHODS

Data sources and case selection criteria

The aim of the Quality Indicator/Improvement Project (QIP) is to improve the quality of hospitals from medical and economic perspectives through collection of yearly data. Of the hospitals participating in this project, we included 33 acute-care hospitals with general ICUs including surgical ICUs, medical ICUs, and surgical-medical ICUs. The database used in our analysis included all patients aged ≥20 years old who were treated in an ICU at one of these hospitals and discharged between January 1, 2007 and December 31, 2007. We were able to identify entry into the ICU and 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 that underwent cardiovascular surgery were mainly managed in cardiovascular care units (CCUs) and were excluded from the study. The data did not provide records of pre-hospitalization in another ICU, but in Japan it is rare for patients in critical care to be transferred from one center to another. Therefore, we assumed that patients entering the ICU had not transferred from another ICU.

Development of the prediction model and potential risk factors

We divided the hospitals into two groups to construct and validate the model. The hospitals were stratified based on the number of beds, and test and validation datasets were established with each set containing similar numbers of hospitals, hospitals of similar sizes, and patients. The hospital mortality prediction model was constructed using the test dataset (3,505 cases) and

evaluated using the validation dataset (3,253 cases). Coefficients obtained from the test dataset were applied to cases in the validation dataset to calculate the predicted mortality rate.

Limited information was available from the administrative data due to the absence of physiological data. Development of the model was based on 9 candidate variables (Table 1), included novel variables and those previously reported [2]. Our age variable was defined as a continuous variable. To define the reason for ICU entry, we considered patients who underwent surgery on the day of entry into the ICU or earlier as scheduled or emergency cases: patients with a period from hospital admission to ICU entry of ≥3 days were defined as scheduled surgery cases, and those who underwent surgery on the day of hospital admission or the day following admission were defined as emergency surgery cases. All others were considered to be internal medical cases. To define the admission category, we used the applicable item for the admission course in the administrative data. The emergency admission category indicates admission to the hospital after transport by ambulance or an unexpected admission. Concerning the time between admission and ICU entry (days), we referred to the Project IMPACT study [1]. Positive use of fresh frozen plasma or a platelet preparation required use of more than 1 unit. Mechanical ventilation was defined as cases requiring ≥5 hours after ICU entry and was identified from the corresponding code in the administrative data. Non-invasive positive pressure ventilation was excluded. Dialysis included continuous renal replacement therapy (CRRT), intermittent renal replacement therapy (IRRT), plasma absorption (PA), and plasma exchange, but excluded peritoneal dialysis since this is rarely used for ICU patients. Pressors/vasoconstrictors included dopamine, dobutamine, norepinephrine, and vasopressin, but excluded epinephrine due to its common use in cardiopulmonary resuscitation.

Relationships between individual variables and hospital mortality were analyzed by a χ-square test using the test dataset. After exclusion of variables with $p > 0.25$, the remaining variables were subjected to multiple logistic analyses (stepwise backward selection method). The model was

constructed using variables with p <0.05 and the C statistic was calculated.

Prediction model performance

The calibration of the model was evaluated using the Hosmer-Lemeshow χ-square statistic. A well-calibrated model has a low χ-square value (< 15.5; df = 8) and a high P value (<0.05). The accuracy was confirmed by Bland-Altman analysis between the COPE model and our model. The discrimination of the model was assessed with the C statistic, for which a value >0.80 is favorable.

Prediction model validation

The prediction model was validated by two methods. First, cross-validation was performed using the validation dataset to demonstrate that the prediction equation obtained from multiple logistic regression analysis in the test dataset has predictive validity. The predicted mortality rate for the validation dataset was calculated using the coefficients derived from the test dataset. The performance of the prediction equation was tested using the Hosmer-Lemeshow χ-square statistic and the area under the ROC curve (95% confidence interval; CI). Hosmer-Lemeshow contingency tables and contingency tables for different levels of probability (20%, 50% and 70%) were also obtained for the validation dataset. Secondly, the predicted mortality with the COPE model for the internal medical disease, emergency surgery, and scheduled surgery cases in the validation dataset were similarly examined. All statistical analyses were performed using Dr. SPSS II (Windows Inc.).

RESULTS

Demographic data for the test and validation datasets are shown in Table 2. There were no significant differences in the explanatory variables between the two datasets, except for the length of ICU stay and the primary diagnosis. In the test and validation datasets, abdominal surgery was

most frequent among the surgery cases (38.4% and 30.6 %, respectively) and infection was most frequent in the internal medical disease cases. There were significant differences in the rates of neoplastic, metabolic, gastrointestinal, respiratory and neuromuscular disease in the internal medical disease cases and in cerebral surgery, abdominal surgery, lung or mediastinal surgery, and orthopedic surgery in the patients who underwent surgery. The results of univariate analysis are shown in Table 3. The overall mortality rate was 9.8%. The strongest association with mortality was found for use of dialysis (45.3%), followed by mechanical ventilation (32.9 %). Gender was not a significant factor ($p = 0.489$) ($p > 0.25$). Excluding gender, the remaining 8 variables were subjected to multiple logistic analysis (stepwise backward selection method) to construct the model.

In the validation data set, coefficients of the prediction model variables, odds ratios, 95% confidence intervals, and the final equation are shown in Table 4. The most influential factor was use of dialysis (OR = 4.85, 95 % CI = 3013-7.5). A Hosmer-Lemeshow contingency table for the validation dataset is presented in Table 5. For validation of the prediction model, the Hosmer-Lemeshow χ-square, p value, and the area under the ROC curve (95% CI) are shown in Table 6. The Hosmer-Lemeshow statistic (a measure of the discrepancy between the observed and predicted risk) was 13.45 ($p = 0.1$) and 3.08 ($p = 0.93$) in the test and validation datasets, respectively, indicating good calibration of the model. The calibration was also shown to be better than that of the COPE model. Cases in the internal medical disease, emergency surgery, and scheduled surgery categories also showed good Hosmer-Lemeshow χ-square values indicating good calibration (7.61, 8.54, and 7.53, respectively). The different levels of probability in the validation dataset are shown in Table 7. The discrimination ratio was 88.7% for 50% probability. The C statistic for the test dataset was 0.86 (Figure 1) and that for the validation dataset was 0.88 (Figure 2), indicating good discrimination.