A Comparison of MICU Survival Prediction Using the Logistic Regression Model and Artificial Neural Network Model

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ABSTRACT: Under the policy of restraint in medical expenditure and with the dual pressures of medical technology development and population aging, the critical care services will exert even greater pressure on the limited medical resources. Therefore, the objective of this study is to compare the abilities of two models, the Logistic Regression Model and the Neural Network Model, to predict the survival of critical care patients, in order to provide a more ethical and objective survival prediction system, as well as to promote more effective management of the resources of the medical intensive care unit (MICU). The two models use the Acute Physiology and Chronic Health Evaluation-II (APACHE-II) and Glasgow Coma Scale (GCS) scores of 1,496 patients stayed who in the MICU of a Taiwan medical center during January 2002–January 2004 to conduct the survival prediction. The study results show that the Neural Network Model has a better predictive ability than the Logistic Regression Model both with regard to the survivors (86.7%, *n* = 361) and with regard to the entire population of patients studied (74.7%, *n* = 498).

Key Words: survival rate, medical intensive care unit (MICU), Artificial Neural Network Model, Logistic Regression Model.

Introduction

Continually rising medical expenditures are a problem for most countries all over the world. They try to control the upward trend in medical expenses and to fully and effectively employ medical resources. Recently, developments in medical technology and the sharp increase in the aged population have caused the demand for the intensive care unit (ICU) treatment to grow continuously, further adding to the difficulties of the medical expense control. According to Sznajder et al. (2001), ICU wards accounted for 10% of total US hospital beds, but their expenditures represented 34% of the total. The average expenditure was US$14,130 daily, or about US$6.4 billion yearly, which was over 1% of the American Gross Domestic Product (GDP). Additionally, patients over age 65 were about 38% of patients in American ICUs but accounted for 50% of the total expenditures of the ICUs. Nowadays, Taiwan's National Health Insurance scheme is under the dual pressures of the policy of restraint on medical expenditure and an aging population with 9.48% aged over 65 in 2004 (Department of Health, Executive Yuan, 2005b). It can be expected that critical care services will cause huge and growing pressure on limited medical resources and that ICUs will be unable to meet the demand.

According to statistics issued by Department of Health, the number of ICU beds increased from 1,744 to 6,955 between 1989 and 2004 (Department of Health, Executive Yuan, 2004, 2005a). The growth rate was 298.8% in 16 years. Tong (1998) mentioned that patients in the ICU must receive strict monitoring and care because most of them have life threatening and severe illnesses. Therefore, the most expensive and advanced medical facilities, and specially trained medical personnel are highly needed. This

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increases the expenditures of the ICU and accounts for about 20% of the total medical expenditures. Therefore, giving proper attention to both medical service quality and the allocation of limited medical resources, how to establish an objective prediction system to assist ICU clinical care to be more effectively operated is an important issue.

For medical personnel, patients and their families, the most important thing is to increase the patient's likelihood of survival. Therefore, if patients can know the situations that they are going to face as soon as possible, it may help related personnel to make effective and proper decisions. It will help them to make psychological adjustments and preparation. On the other hand, for the medical institutions, they can better organize the deployment of beds and make more effective utilization of the limited ICU beds. For the medical personnel, they can make early arrangements for assignments and medical support, and offer patients careful and proper care. Early prediction helps medical personnel to make arrangements and treatment plans, and to take the initiative in treatments. In addition, at present, when every medical organization faces an unfair global budget allocation, as well as conflicts and disputes in the health insurance itemized payment schedule, it is very important to establish an objective predictive system to effectively assist the allocation of limited medical resources to ICUs and to offer a better medical service.

In the clinic, the medical personnel take survival as an indicator of successful treatment. It is especially important for critical patients because if patients know their condition earlier, then they may take the treatment enthusiastically to prevent their condition from worsening, reducing unnecessary medical care, shortening the length of stay and saving medical costs and resources. Thus, early prediction has great importance and significance for ICU patients. This study conducts an empirical result comparison by data analysis method. Data came from the measurement of patients' degree of severity of illness and the mortality rate in a medical intensive care unit (MICU) by two widely used measuring tools, Acute Physiology and Chronic Health Evaluation-II (APACHE-II) and Glasgow Coma Scale (GSC), presently used in MICUs in Taiwan. In addition, the research refers to Goss and Ramchandani (1998), who used patients in an adult ICU in the USA, and compare the effectiveness of the Binary Logit Regression Model and Neural Networks Model to establish a simple, trustworthy, objective, and appropriate survival predictive model for patients in Taiwanese MICUs. The result of the comparison will assist medical personnel in providing relevant suggestions and making appropriate medical decisions, and to allocate limited medical resources in promoting effectiveness.

Literature Review

In the past, the methods adopted in predictive research on survival in the ICU were mainly of two kinds: one was the Logistic Regression Model using parametric method and the other was the Artificial Neural Network Model using nonparametric method. Therefore, the purpose of this study is to utilize the APACHE-II and GCS commonly used in the Taiwanese MICU to further compare the accuracy of predicted patient survival between the two models, the Logistic Regression Model and Artificial Neural Network Model.

Logistic Regression Model

The Logistic Regression Model mainly uses Dichotomous Dependent Variables, such as "survival" or "death". The nature of Logistic Regression is similar to traditional regression analysis, but Logistic Regression is used to deal with problems of categorical data. Because categorical data is discrete, we must transfer the data to a continuous data pattern with data between 0 and 1, and then conduct regression using the transferred continuous data. The purpose is to look for the relationship between response variables and a series of explained variables in the categorical pattern. Therefore, the greatest difference between Logistic Regression and generalized regression analysis is the varying response variables. The utilization of Logistic Regression needs to meet with the generalized hypothesis of traditional regression analysis. That avoids the collinear problem among the explained variables, allowing for statistic basis hypotheses of residuals and auto-correlation and in accordance with normal distribution. Thus, Logistic Regression can only establish a linear model but cannot explain the relationship among independent variables.

Artificial Neural Network Model

An Artificial Neural Network is a kind of information processing system imitating the biological nerve network. The precise definition is: "An Artificial Neural Network is a calculation system, including software and hardware. It utilizes a large number of simple connected artificial neurons to imitate the capabilities of a biological nerve network. An artificial neuron is a simple simulation of a biological neuron. It obtains data from the outside environment or other artificial neurons, performs a very simple calculation, and outputs the outcome to the outside environment or other artificial neurons." (Chiu, 2002).

The structure of the Artificial Neural Network contains three layers: the input layer, the output layer and the hidden layer; each layer is formed by nodes (neurons) and links. The links of each layer represent the weight of information transmission, and the weight value responds to the degree of influence between the neurons of different layers. The nodes of the input layer are the predicted variables; the nodes of output layer are the outcome variables. Of the various Artificial Neural Network Models, the Back-Propagation Network (BPN) is the simplest and easiest to understand. Therefore, it is the most commonly used model at present. Its structure is shown below in Figure 1.

When using the Artificial Neural Network Model it is not necessary to hypothesize the data input and output relationship, and the model has the advantages of establishing non-linear models, expressing correlations between input variables and accepting logical, numerical and categorical variables as inputs, a high degree of accuracy, and strong adaptability. Therefore, the Artificial Neural Network Model has been widely used in many fields in recent years. Recently, Goss and Ramchandani (1998), and Wong and Young (1999) used the Artificial Neural Network Model to predict the ICU patient's survival.

Comparison of Logistic Regression Model and Artificial Neural Network Model

Both the Logistic Regression Model and Artificial Neural Network Model establish models by data and have adjustable parameters, such as the regressive coefficient of the Logistic Regression Model and the network-connected weighting value and threshold value of the Artificial Neural Network Model.

The differences between the alternative Logistic Regression Model and the Artificial Neural Network Model are that the Logistic Regression Model is a linear model but the Artificial Neural Network Model is both linear and non-linear; the Logistic Regression Model cannot show the correlation among input variables, but the Artificial Neural Network Model can; the numbers of adjusted variables in the Logistic Regression Model are fixed, but the numbers are variable in the Artificial Neural Network Model and often more than in the Logistic Regression Model; the regressive coefficient of the Logistic Regression Model has a unique solution, but the network-connected weighting value and threshold value of the Artificial Neural Network Model have non-unique solutions and it is also hard to prove which answer is the best solution.

Methods

Material Description

This study utilizes 1,496 admissions of an MICU at a Medical Center in Taiwan during 1 January, 2002 to 31 January, 2004. Six nurses trained in APACHE-II and GCS appraisal in skills were responsible for collecting patients' APACHE-II scores, GCS scores, sex, survival or not, and age in the first 24 hours after admission to the ICU. Table 1 and Table 2 show detailed data of patient characteristics. The age distribution is from 14 to 104 and the average is 66.5. At 24 hours after admission, the measured average APACHE-II score was 15.8 (the standard deviation, *SD* was 9.36) with an average GCS score of 11.1 (the *SD* was 4.51). After ICU treatment, there were 72.79% survivals

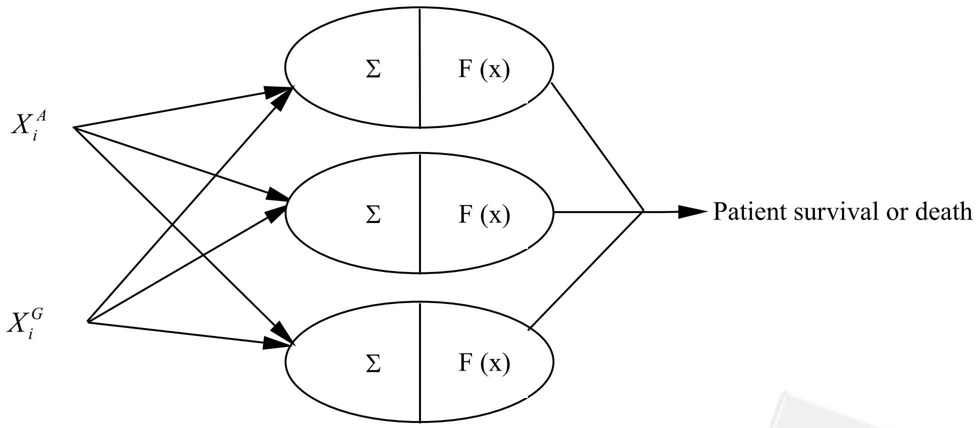

Figure 1. Structure of Back-Propagation Network.

Table 1.
Characteristics of Patients and Outcomes

	Total patients (n = 1,496)			Survival (n = 1,089, 72.79%)			Death (n = 407, 27.21%)		
Items	***M***	***SD***	**Range**	***M***	***SD***	**Range**	***M***	***SD***	**Range**
Age	66.5	16.17	14–104	66.8	16.44	14–104	65.8	15.43	19– 93
LOS	7.5	8.02	0–114	7.9	8.56	0– 51	6.32	9.01	0–114
APACHE-II	15.8	9.36	0– 59	13.9	7.99	0– 41	21.0	10.70	0– 59
GCS	11.1	4.51	3– 15	11.9	4.04	3– 15	8.87	4.93	3– 15

Note. LOS = Length of Stay; APACHE-II = Acute Physiology and Chronic Health Evaluation-II; GCS = Glasgow Coma Scale.

Table 2.
Gender and Characteristics of Patients

	Male (n = 866, 57.89%)			Female (n = 630, 42.11%)		
Items	***M***	***SD***	**Range**	***M***	***SD***	**Range**
Age	66.5	15.82	19–104	66.4	16.65	14–104
LOS	7.44	8.24	0–114	7.6	7.71	0– 51
APACHE-II	16.05	9.24	0– 59	15.5	9.53	0– 59
GCS	11.06	4.52	3– 15	11.1	4.51	3– 15

Note. LOS = length of stay; APACHE-II = Acute Physiology and Chronic Health Evaluation-II; GCS = Glasgow Coma Scale.

and 27.21% deaths. The average APACHE-II score of the 1,089 survivors was 13.9 (the *SD* was 7.99) and the average GCS score was 11.9 (the *SD* was 4.04). In the 407 deaths, the average APACHE-II score was 21.0 (the *SD* was 10.7) with an average GCS score of 8.87 (the *SD* was 4.93). We found that the deaths had a higher APACHE-II score and a lower GCS score. In this study, male patients accounted for 57.89% of the sample and female patients for 42.11%.

Instruments

Logistic Regression Model

As the Logical Regression Model is a parametric statistical method, it needs to hypothesize a predictive variable with a specific rule. Therefore, firstly, the study hypothesizes that the survival rate of the ith patient is given by $p_i = P(Y_i = 1 \mid X_i^A, X_i^G)$, where $Y_i = 1$ represents the ith patient's survival, $Y_i = 0$ is the ith patient's death, X_i^A means the APACHE-II value measured when the ith patient in the first 24 hours after admission to the ICU, and X_i^G is the GCS value measured when the ith patient in the first 24 hours after admission to the ICU. The survival rate according to the Logical Regression Model is given by

$$\ln \frac{p_i}{1-p_i} = \alpha + \beta_1 X_i^A + \beta_2 X_i^G \text{..................................} (1)$$

We calculate the equation (1) by the maximum likelihood method to get α, β_1 and β_2, then get the optimal GFI index value and the survival rate accuracy, $t_0 = \hat{n}_l/n$, by APACHE-II and GCS, where $\hat{n}_l$ stands for the number of correctly predicted patient survivals and deaths and n is the total patients.

The survival rate accuracy in (1) is explained by APACHE-II and GCS from collected data, and not predictive survival rate accuracy. We can get the predictive survival rate accuracy by Cross Verification, as follows. Group all patients in two groups randomly. The first group comprising 2/3 of the patients is called the predictive sample, and the second one comprising 1/3 of the patient is called the test sample. Then, we calculate the predictive model of (1) using the predictive sample, and then introduce the test sample into (1) to get the predictive accuracy, $t_1 = 3\hat{n}_{lt} / n$, where $\hat{n}_{lt}$ is the number of correctly predicted patient survivals and deaths in the test sample and n is the total patients.

Artificial Neural Network Model

The analysis steps of the Artificial Neural Network in the study were as follows.

Step 1. Set the training sample as the analyzed data; X_i^A (APACHE-II) and X_i^G (GCS) are the input layer; and the patient survival rate is the output layer.

Step 2. Place (x_i^A, x_i^G) on the input layer and calculate the weight value from the input layer to the hidden layer, $z_j^{in} = x_i^A v_{1j} + x_i^G v_{2j}$, where j = 1, 2, …, p, p is the number of nodes in the hidden layer, and v_{ij} is the linked weight from the input layer to the hidden layer. Convert $z_j^{in} = x_i^A v_{1j} + x_i^G v_{2j}$ by Sigmoid function (2), where the range is between 0 and 1.

$$f(z_j^{in}) = \frac{1}{1+e^{-z_j^{in}}} \quad \text{...(2)}$$

Then, we calculate the weight value, $y^{in} = \sum_{j=1}^{p} z_j w_j$ transmitted from the hidden layer to the output layer, with the hidden layer value $z_j = f(z_j^{in})$, where w_{jk} is the linked weight from the hidden layer to the output layer, and the output layer value is $y = f(y^{in})$.

Step 3. Compute the deviation of the weight adjustment from the hidden layer to the output layer, i.e. $\Delta w_j = \alpha\delta_i z_j$, to do the back-propagation, where $\delta_i = (t_i - y_i) f'(y_i^{in})$ and α is the learning rate; then, calculate the deviation of the weight adjustment from the input layer to the hidden layer, i.e. $\Delta v_{1j} = \alpha\delta_j^* x_i^A$ and $\Delta v_{2j} = \alpha\delta_j^* x_i^G$, where $\delta_j = \delta_j^{in} f'(z_j^{in})$ and $\delta_j^{in} \sum_{k=1}^{m} \delta_k w_{jk}$. The purpose is to minimize the error of the estimated value y_i and the true value t_i in the back-propagation. Hence we set the error function as $E_l = \frac{1}{2}\sum_{i=1}^{\frac{2}{3}n} [y_i - t_i]^2$, where l represents the training time, if $E_l - E_{l+1} \le \varepsilon$, where ε means the designed minimum with training completed. Otherwise, the weight of each layer needs to be adjusted till $E_l - E_{l+1} \le \varepsilon$. Finally, modify the weight from the hidden layer to the output layer with w_{jk} (*new*) = w_{jk} (*old*) + Δw_{jk} and the weight from the hidden layer to the input layer with v_{ij} (*new*) = v_{ij} (*old*) + Δv_{ij}.

Step 4. Introduce the test sample into the training sample model shown above and calculate the predictive accuracy as $t_2 = 3\hat{n}_{nnt} / n$, where $\hat{n}_{nnt}$ is the number of correctly predicted patient survivals and deaths in the test sample, and n is the total patients.

Based on the above, the ICU patient survival rate is estimated using both the Logistic Regression Model and the Artificial Neural Network Model. According to the statistical data, the survival rate is 0.72; therefore, we set this as the cutoff value of the survival rate. That is, if the estimated survival rate in both models is greater than 0.72, then we predict the patient's survival; otherwise we predict death.

Results and Discussion

Based on the previously established Logistic Regression Model and the Back-Propagation Neural Network Model, this study analyzes on the predictive outcome of patient survival rate in the MICU and compares the effectiveness of prediction by the two models, as detailed below.

Logistic Regression Model

The collected data from 1,496 patients were introduced into the Logistic Regression Model. The results are detailed in Table 3.

The significant survival rate by the Logistic Regression Model can be determined because G^2 = 1570.73 in this model and APACHE-II (χ^2 = 46.86, p = .00), GCS (χ^2 = 10.95, p = .001) and the constant (χ^2 = 19.80, p = .00) of each independent variable coefficient all have a significant level. We can obtain a Logistic Regression Model, $\ln(\frac{p_i}{1-p_i}) = 1.452 - 0.063X_i^A + 0.059X_i^G$, with a significant survival rate by Table 3. Hence the higher the assessed degree of severity of illness, the lower the survival rate, and the higher the coma index, the higher the survival rate.

Table 3.
Survival Rate by Logistic Regression Model

Variable	Estimated value (β)	Standard error (*SE*)	Wald χ^2 value	*p*
X_i^A	-0.063	0.009	46.86	.000
X_i^G	0.059	0.018	10.95	.001
Constant	1.452	0.326	19.80	.000

Table 4.
Logistic Regression: Predictive Accuracy Model

Item	Predictive Death	Predictive Survival	Total
Real			
Death	100	37	137
Survival	159	202	361
Total	259	239	498

Table 5.
Artificial Neural Network: Predictive Accuracy Model

Item	Predictive Death	Predictive Survival	Total
Real			
Death	72	65	137
Survival	87	274	361
Total	159	339	498

Then, according to the above cutoff value of 0.72, we get the explained accuracy of 76.23% and by Cross Verification, the predictive accuracy of 60.64%. The details are shown below in Table 4.

Artificial Neural Network Model

As the Artificial Neural Network does not have a specific and fixed formula, we try to get the model with a better-predictive ability through different parameters. This study uses the hidden layer with three neurons and the learning rate (α) = 0.1 by Cross Verification (See Table 5). The predictive accuracy is 69.47%.

Comparison

As the study uses two different models the Logistic Regression and the Artificial Neural Network, to predict patient survival in the MICU, different cutoff values of the survival rate will influence the predictive accuracy. The predictive accuracy by the different adopted cutoff values is shown in Figure 2.

The effectiveness prediction of patients' survival or death in the MICU is co-influenced by sensitivity and specificity. Figure 3 shows the sensitivity of survival predictive accuracy and Figure 4 shows the specificity of death predictive accuracy. As shown in Figures 3 and 4, the sensitivity of the Artificial Neural Network Model is relatively better than the Logistic Regression Model, but the specificity varies by different cutoff values. However, in order to favor the comparison between these two models and achieve a higher predictive accuracy in both models, the research set the cutoff value as 0.6. It means when the predictive survival rate of these two models is greater than or equal to 0.6, the research predicts the patient survived, whereas dead. The result of the overall predictive accuracy is as shown in Table 6.

The study result indicates that the predictive accuracy of survival (86.7%, n = 361) and total patients (74.7%, n = 498) in the Artificial Neural Network Model is better than those in the Logistic Regression Model. Thus, the effectiveness of the Artificial Neural Network Model to predict patient survival in a Taiwanese MICU is better than that of the Logistic Regression Model.

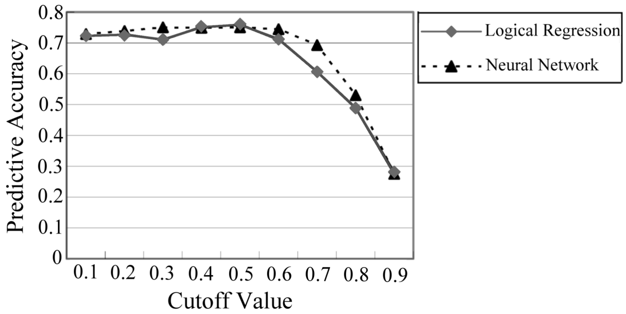

Figure 2. Predictive accuracy (survival and death).

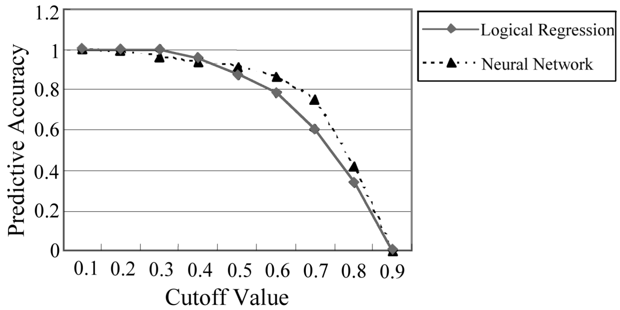

Figure 3. Sensitivity (survival accuracy).

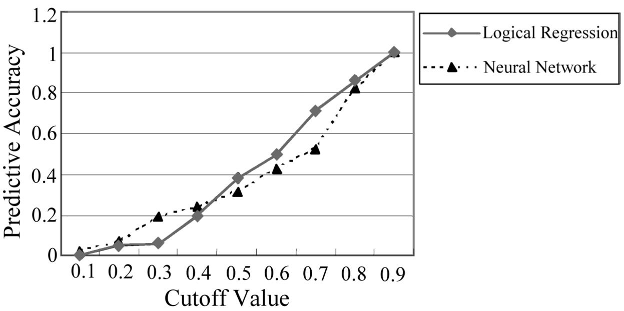

Figure 4. Specificity (death accuracy).

Table 6.
Comparison of Predictive Accuracy Between Logical Regression and Artificial Neural Network Models

Item	*n*	Logical Regression (%)	Artificial Neural Network (%)
Predictive Accuracy			
Survival	361	79.5	86.7
Death	137	50.4	43.1
Total patients	498	71.5	74.7

Conclusion

The study evaluates the predictive accuracy of patient survival in a Taiwanese MICU using the Artificial Neural Network Model and the Logistic Regression Model. The conclusion that the Artificial Neural Network Model provides an assurance of outcome prediction in ICU treatment, is the same as the conclusions reached with regard to prediction of ICU patient survival by the Neural Network Models by Goss and Ramchandani (1998) and Wong and Young (1999). Under the pressures of the policy of restraint in medical expenditure and the continuously increasing demand for critical care services, how to reduce unnecessary medical care, shorten length of stay and save medical costs and resources are goals pursued by every medical organization. Rapoport, Teres, Zhao, and Lemeshow (2003) found that compared with non-ICU care, the cost of first day in the ICU was approximately four times greater, and the cost of each subsequent ICU day was approximately 2.5 times greater. Stricker, Rothen, and Takala (2003) also pointed out that resources consumed by the 10.6% ICU patients hospitalized for more than seven days were 53.4% of the total consumed resources. Tarnow-Mordi, Hau, Warden, and Shearer (2000) found using multiple logistic regression analysis, that adjusted mortality was more than twice as high in patients exposed to high ICU workload than in those exposed to low workload. Therefore, using a good predictive system, medical organizations can adjust the workload of the ICU personnel at the appropriate time. Additionally, during bed shortages faced by the ICU daily, the system can help to lessen the pressure of bed allocation on medical personnel. Moreover, if by additionally setting up a high-dependency unit (HDU), the medical organization can provide different medical resources and equipment, to enable critical care patients to receive appropriate care both on transfer into the ICU and on transfer out of the ICU, then it will be possible to optimize management in terms of both quality and cost.

Previous studies have found that impracticable family expectations were associated with increased resource utilization without significant survival benefit (Berge et al., 2005), and physicians's decisions were often influenced by factors other than medical necessity (Giannini & Consonni, 2006). The fact that the goal of the ICU is to reduce patients' short-term death rate; however, when the disease is uncured, related ethical problems may follow one by one. Therefore, how to make a decision or take care of both problems with the limited medical resources and humanity is a tough job. In society nowadays, social value is decided by the ability to pay, not by the benefits obtained. This causes makes expensive medical resources not to be effectively utilized, especially in as much as some invasive, complex and expensive medical instruments or equipment are used on patients who are unable to benefit from the treatment, in maintaining or monitoring their physiological signs and consuming massive medical expenses. From an ethical and moral point of view and without losing the sense of humanity, the meaning of life is not only to extend the patients' time, but also to give them a better chance to face life. Therefore, in recent years, people have gradually come to value more the quality of life after treatment and good death. It becomes very important to use a good predictive system to decrease the difficulty of clinical decision-making by medical personnel, to assist medical personnel in using more scientific and objective methods and give guidance in allocating expensive medical resources, to change the practice of distributing limited resources by paying ability or age, and ensure patients receive active and proper care in accordance with their objective prospects of survival.

Therefore by including the Artificial Neural Network Model in medical care information, medical care organizations not only can assist clinical medical personnel in providing medical care services, but can also compare their performance with care providers internationally as a basis for improving their standards of clinical and medical care and for strengthening their competitiveness.

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比較邏輯迴歸模式與類神經網路模式對內科加護病房存活率之預測

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摘　要： 在醫療費用支出緊縮的政策下，隨著醫療技術的發展與人口老化的雙重壓力下，將可預見重症醫療照護對有限醫療資源將造成更大的壓力。因此本研究的目的係比較邏輯迴歸與類神經網路二種模式，對內科加護病房病人存活率之預測能力，提供一更倫理與客觀的存活率預測系統，以進一步促使內科加護病房資源能更有效率之營運。此二個模式使用於 2002 年 1 月至 2004 年 1 月期間住進台灣某醫學中心內科加護病房 1,496 位病人的 APACHE-II (Acute Physiology and Chronic Health Evaluation-II) 及 GCS (Glasgow Coma Scale) 分數來進行存活率之預測。研究結果顯示類神經網路模式相較於邏輯迴歸模式在存活者 (86.7%, n = 361) 與整體病患 (74.7%, n = 498) 之預測能力均較佳。

關鍵詞： 存活率、內科加護病房、類神經網路模式、邏輯迴歸模式。

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