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A novel mortality prediction model for the current population in an adult intensive care unit

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ABSTRACT

Background: The accurate and reliable mortality prediction is very useful, in critical care medicine. There are various new variables proposed in the literature that could potentially increase the predictive ability for death in ICU of the new predictive scoring model.
Objective: To develop and validate a new intensive care unit (ICU) mortality prediction model, using data that are routinely collected during the first 24 h of ICU admission, and compare its performance to the most widely used conventional scoring systems.
Methods: Prospective observational study in a medical/surgical, multidisciplinary ICU, using multivariate logistic regression modeling. The new model was developed using data from a medical record review of 400 adult intensive care unit patients and was validated on a separate sample of 36 patients, to accurately predict mortality in ICU.
Results: The new model is simple, flexible and shows improved performance (ROC AUC = 0.85, SMR = 1.25), compared to the conventional scoring models (APACHE II: AUC = 0.76, SMR = 2.50, SAPS III: AUC = 0.76, SMR = 1.50), as well as higher predictive capability regarding ICU mortality (predicted mortality: 41.63 ± 31.61, observed mortality: 41.67%).
Conclusion: The newly developed model is a quite simple risk-adjusted outcome prediction tool based on 12 routinely collected demographic and clinical variables obtained from the medical record data. It appears to be a reliable predictor of ICU mortality and is proposed for further investigation aiming at its evaluation, validation and applicability to other ICUs.

Introduction

A large amount of healthcare resources are spent for the care of patients in Intensive Care Units (ICUs), who constitute only a small proportion of the total hospital patient population.[1] In addition, mortality in the ICU is higher than in hospital wards. Thus, mortality seems to be a suitable, sensitive and meaningful outcome for the assessment of care provided in ICUs.[2] However, ICU mortality depends not only the efficiency of the care, the nature of the disease, patient reserve, previous health status, and response to treatment, but also on the casemix of the patients. ICUs, by definition include high-risk patients who exhibit higher rates.[1]

For several decades, researchers have evaluated various scoring systems to assess illness severity. These systems estimate the

Abbreviations list: APACHE, Acute Physiology and Chronic Health Evaluation; AUC, Area Under the Curve; CI, Confidence Interval; CRP, C-reactive protein; FDR, False Discovery Rate; GCS, Glasgow Coma Scale; HIV, Human Immunodeficiency Virus; HL, Hosmer-Lemeshow X^2 test; ICU, Intensive Care Unit; NAS, Nursing Activities Score; OCC, Overall Correct Classification rate; OR, Odds Ratio; ROC, Receiver Operating Characteristic; SAPS, Simplified Acute Physiology Score; SMR, Standard Mortality Ratio; SOFA, Sequential Organ Failure Assessment; SPSS, Statistical Package for the Social Sciences; TISS-28, Therapeutic Intervention Scoring System-28; TPN, Total Parenteral Nutrition.

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likelihood of death for a given patient in a given clinical situation as if this patient was hospitalized in a hypothetical reference unit used for the development of the prototype scoring systems.[3] The sample case-mix may affect the predictive ability of these scoring systems.[4]

Conventional predictive scoring models may not be well-calibrated in various geographical regions and often display lack of fit when evaluated in different critical care populations. This contributes to failure to predict actual mortality with an accepted degree of accuracy.[5–13] For instance, in a surgical ICU, the Acute Physiology and Chronic Health Evaluation (APACHE) II[14] and the Simplified Acute Physiology Score (SAPS) III[15] showed poor calibration. Additionally, the APACHE II showed less than satisfactory calibration and adequate mortality prediction in medical and surgical patients,[12] in head injury patients[13] and in sepsis patients of a medical and surgical ICU.[11] Moreover, illness severity and treatments of certain diseases are continuously changing. For these reasons, researchers in different countries propose new models,[16–18] develop locally customized variants of conventional prediction models[6,8,19,20] or suggest new variables which can be incorporated in new models.[21–26]

The goal of the present study was to develop a new ICU mortality prediction model for the casemix of the patients in our ICU, based on administrative and clinical data from the first day of the patients' stay in the ICU. In our study we incorporated variables used in the existing models and some new ones as well that are proposed in the literature. Also, we aimed to assess whether this model could improve the ICU mortality prediction compared to conventional scoring systems.

Materials and methods

Setting and procedure

We conducted a prospective observational cohort study in our multidisciplinary 27-bed hospital adult medical/surgical ICU in Athens, Greece. We used three scoring systems to evaluate the disease severity for patients admitted in the ICU: the APACHE II,[14] the SAPS III.[15] and the Sequential Organ Failure Assessment (SOFA).[27] We additionally measured the Glasgow Coma Scale (GCS),[28] and nursing workload scores: the Therapeutic Intervention Scoring System (TISS-28)[29] and the Nursing Activity Score (NAS).[30]

Participants

All patients consecutively hospitalized in our university, multidisciplinary, medical/surgical, ICU, in a 1000-bed tertiary care medical center, during the study period (from January 2012 to July 2013), were enrolled in the study. Patients younger than 18 years old, pregnant or burned patients, patients with an ICU length of stay of less than 48 h, and patients with the diagnosis of brain death or end-stage malignancy were excluded from the final analysis. Both medical and surgical patients are admitted to our ICU. Patients with cardiovascular disease or myocardial infarction as admission diagnosis, patients who had undergone cardiac surgery, and patients with transplantation were admitted in cardiology and transplantation ICUs and were not included in the study.

Data collection methods

On ICU admission, all scoring systems were calculated for every patient, and a set of variables were collected according to the literature and recorded for each patient by the data collectors. The data collectors were trained and well-qualified, while the variables considered were derived from a regularly audited dataset that is available in a timely manner. These data were included in the original dataset to enable investigation of alternative approaches to predictive modeling. We collected data on previous health status, demographic characteristics (age, sex, type of patient, admission diagnosis) and data on vital signs and other physiology variables from the first day in the ICU, as required by the conventional models. In the set of the variables we collected, we incorporated variables used in the existing models and some new ones that are routinely selected in our ICU and they are proposed in the related literature. Data used include information on an hourly basis. We recorded the most abnormal values recorded during the first 24 h after admission to the ICU. We also recorded ICU discharged to ward or death in ICU and length of ICU stay. Data accuracy and patients' care was not affected by the study because all staff was blinded to the study except data collectors.

Death was defined as the patients who died in ICU and survival was defined as the patients who were discharged alive from ICU. Cardiac disease was defined as any preexisting cardiac disease recorded in the history of the patients, such as coronary artery disease, chronic heart failure, atrial fibrillation, hypertensive heart disease and congestive heart failure. Pneumonia on admission was diagnosed by the ICU doctors based on culture results of lower respiratory tract aspirates and fever or leucocytosis/leucopenia or purulent secretions and chest X-ray infiltrates. Regarding noradrenaline and dobutamine, we assessed the need for their use within 24 h regardless of the dose required.

The computation of an appropriate sample size for a logistic regression analysis requires prior knowledge regarding the model, such as the expected effect size, the percentage of observations in either group of the dependent variable under study, the distribution of each explanatory variable, as well as the correlation among the explanatory variables. In absence of this information, it is more appropriate to use a rule of thumb to determine an appropriate minimum sample size; for instance acquiring a minimum of 10–20 observations per explanatory variable in the model[31] or a minimum of 30 observations per explanatory variable.[32] Based on these suggestions and on the fact that we did not expect more than 20 variables to enter our multiple logistic regression model, a minimum sample size of 400 (20 predictors $\times$ 20 observations) to 600 (20 predictors $\times$ 30 observations) was sought to achieve empirical validity. Based on the mean number of adults entering the specific ICU per month (37 admissions) and the time constraints we had, it was estimated that in $\sim$18 months we would exceed the lower threshold of $N = 400$.

Data analysis

Data analysis was performed with SPSS 22.0 (Statistical Package for Social Sciences) for WINDOWS and R 2.15 (R Foundation for Statistics, Austria). All continuous variables are presented by their mean (M) $\pm$ standard deviation (SD) or median and interquartile range, as appropriate to the analyses. Categorical variables are presented as absolute frequencies (number of cases, N) and relative cases (percentage, %). The normality of a distribution was assessed using the Kolmogorof-Smirnof test. In order to compare the distributions of continuous variables between two groups of patients we used the independent samples Student's t-test, or Mann-Whitney *U* test in the case of non-symmetric distribution, whereas association between qualitative factors was appropriately investigated via the chi-squared statistic or the Fisher's exact test. The odds ratio (OR) and the corresponding 95% confidence interval (CI) are also reported in relation to the binary logistic regression covariates.

Statistical significance was generally set at 0.05. For controlling the type-I error or the false discovery rate (FDR) in case of multiple