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Characterization of intensive care unit patients using a model based on the presence or absence of organ dysfunctions and/or infection: the ODIN model

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Abstract. *Objective:* To evaluate the sensitivity, specificity and overall accuracy of a model based on the presence or absence of organ dysfunctions and/or infection (ODIN) to predict the outcome for intensive care unit patients.
Design: Prospective study.
Setting: General intensive care unit in a university teaching hospital.
Patients: 1070 consecutive, unselected patients.
Interventions: There were no interventions.
Measurements and main results: We recorded within the first 24 h of admission the presence or absence of dysfunction in 6 organ systems: respiratory, cardiovascular, renal, hematologic, hepatic and neurologic, and/or infection (ODIN) in all patients admitted to our ICU, thus establishing a profile of organ dysfunctions in each patient. Using univariate analysis, a strong correlation was found between the number of ODIN and the death rate (2.6, 9.7, 16.7, 32.3, 64.9, 75.9, 94.4 and 100% for 0, 1, 2, 3, 4, 5, 6 and 7 ODIN, respectively; ($p < 0.001$). In addition, the highest mortality rates were associated with hepatic (60.8%), hematologic (58.1%) and renal (54.8%) dysfunctions, and the lowest with respiratory dysfunction (36.5%) and infection (38.3%). For taking into account both the number and the type of organ dysfunction, a logistic regression model was then used to calculate individual probabilities of death that depended upon the statistical weight assigned to each ODIN (in the following order of descending severity: cardiovascular, renal, respiratory, neurologic, hematologic, hepatic dysfunctions and infection). The ability of this severity-of-disease classification system to stratify a wide variety of patients prognostically (sensitivity 51.4%, specificity 93.4%, overall accuracy 82.1%) was not different from that of currently used scoring systems.
Conclusions: These findings suggest that determination of the number and the type of organ dysfunctions and infection offers a clear and reliable method for characterizing ICU patients. Before a widespread use, this model requires to be validated in other institutions.

Key words: Organ dysfunctions – Infection – Severity of disease – Prognosis

Patients hospitalized in intensive care units (ICU) are usually characterized by the degree of severity of their illness and by one or more diagnoses. Unfortunately, the precise disease(s) responsible for hospitalization is not always diagnosed within the first 24 h of admission. Consequently, critically ill patients are usually classified as suffering from a syndrome or organ dysfunction(s) (OD), for example, "acute respiratory failure", "cardiovascular insufficiency", "sepsis syndrome", "coma", "multiple-organ failure". In order to evaluate the severity of illness of ICU patients, general classification systems have been developed. They provide a basis for within- and between-unit comparisons of performance, demonstrate the effect of changes in the delivery of care, and may help in the assessment of new therapies. These severity indices are defined as a scale of probability of death and are validated by comparing predicted mortality to observed mortality; they are truly prognostic scoring systems. The currently popular scoring systems including the Apache II classification system devised by Knaus and associates [1], the simplified acute physiologic score (SAPS) described by Le Gall et al. [2] and the mortality prediction model (MPM) formulated by Lemeshow et al. [3], can prognostically stratify many patients by estimating the relative risk of death for patient groups and have great potential for guiding decision-making for individual patients by computing the individual's probability of death. However, these systems were not designed to give information concerning medical diagnosis or status.

In 1985, Knaus et al. reported on their study which provided estimates for the probability of survival following acute organ-system failure (OSF) [4]. This approach is very interesting because of the major influence of or-

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gan dysfunction on ICU mortality [5–7]. The authors demonstrated that the number and the duration of organ-system failures were linked to the outcome at hospital discharge for each of the 2,719 ICU patients who developed OSF. However, this study had several limitations: 1) the patients evaluated had at least one OSF and represented only 48% of the total population; 2) "Do Not Resuscitate" patients were excluded from the analysis; 3) despite the description of 5 OSF (cardiovascular, respiratory, renal, hematologic and neurologic), the presence of only 3 OSF for more than 72 h resulted in mortality risks approaching 100%. Finally, in this study, only the number of OSF present was considered and every OSF was considered as having the same degree of severity.

Considering the role that organ dysfunctions play in determining the prognosis of ICU patients, we have ascertained that either a direct and accurate measurement of the degree of multiple organ system failure, or another equally reproducible measurement of patient severity-of-illness is critical for characterization of individual patients, risk stratification and outcome prediction. Therefore the aim of this prospective study was to specify the number and the type of organ dysfunctions and/or infection (ODIN) in critically ill patients and, using these epidemiologic data, to estabish a classification system of disease severity based upon the calculation of an individual's probability of death.

Methods

Patient population

All patients admitted to the general Intensive Care Unit (ICU) of Bichat Hospital, Paris, France, from October 1, 1987, to March 1, 1990, were included in the study. This ICU is a 17-bed unit that receives patients from the emergency ward, from all the hospital's departments and from the intensive care units of other hospitals. The unit has a full-time staff composed of 6 certified ICU specialists and a 1/2 to 1/3 nurse/patient ratio. During the 29 months of the study, there were 1093 patients admitted to the ICU. Of these, 23 were excluded from further analysis because of incomplete data. The remaining 1070 patients (including 427 post-operative patients) constituted the study group.

Data collection

For each patient, the following variables were recorded: age; sex; prior location before admission to the unit; and severity of underlying medical conditions, stratified according to the criteria of McCabe and Jackson [8] as fatal, ultimately fatal and non-fatal. After the patients had been in the unit for 24 h, each clinical record was reviewed for physiologic data that would enable prognostic stratification using the SAPS [2], the Apache II score [1] and our model of organ dysfunction and/or infection (ODIN). In all cases, we recorded the worst value for all the variables taken into consideration. In addition, the specific diagnosis, the length of ICU stay, the reason for discharge and the vital status at ICU discharge were routinely noted.

Definitions of organ dysfunction

The criteria for defining OD were obtained from a review of the clinical literature [7, 9–12]. The definitions of respiratory (R), cardiovascular (C), renal (Rn), neurologic (N), hepatic (H), hematologic (Hm) dysfunctions, and infection (IN) are indicated in Table 1. For the purpose of this article, infection was considered as an organ dysfunction. These definitions were applied to all patients except those receiving chronic hemodialysis prior to hospital admission. Such patients could develop one or more of the 6 other organ dysfunctions but were not categorized as suffering from acute renal dysfunction. To designate neurologic dysfunction, we used the Glasgow coma scale [13] which is obtained by summing the best responses during a simultaneous examination of ocular, motor and verbal activities. The worst score over the 24 h period was recorded for each patient. Patients that were paralysed or sedated throughout the entire 23 h period were not considered to suffer from neurologic dysfunction. The best responses of patients that were intubated but not sedated, were estimated based upon clinical judgment. All data were recorded on standardized forms and were carefully reviewed during a daily meeting between at least 4 of the 5 investigators, taking great care to avoid introducing new errors or entering inaccurate information, and then analyzed. Disagreements concering presence or absence of organ dysfunction and/or infection in patients enrolled in the study were usually minor and easily resolved by reviewing the chart of the patients and using consensus opinion. To assess the reliability of this method, data collectors independently abstracted the same 30 charts. Reliability was high and differences were not statistically significant for each data collector.

Table 1. Definitions of organ dysfunctions

I. Respiratory dysfunction (presence of one or more of the following):
   A. $PaO_2 < 60$ mmHg on $FIO_2 = 0.21$
   B. Need for ventilatory support
II. Cardiovascular dysfunction (presence of one or more of the following, in the absence of hypovolemia[a]):
   A. Systolic arterial pressure < 90 mmHg with signs of peripheral hypoperfusion
   B. Continuous infusion of vasopressor or inotropic agents required to maintain systolic pressure > 90 mmHg
III. Renal dysfunction (presence of one or more of the following)[b]):
   A. Serum creatinine > 300 µmol/l
   B. Urine output < 500 ml/24 h or < 180 ml/8 h
   C. Need for hemodialysis or peritoneal dialysis
IV. Neurologic dysfunction (presence of one or more of the following):
   A. Glasgow coma scale ≤ 6 (in the absence of sedation at any one point in day)
   B. Sudden onset of confusion or psychosis
V. Hepatic dysfunction (presence of one or more of the following):
   A. Serum bilirubin > 100 µmol/l
   B. Alkaline phosphatase $> 3\times$ normal
VI. Hematologic failure (presence of one or more of the following):
   A. Hematocrit $\leq 20\%$
   B. White blood cell count $< 2000/mm^3$
   C. Platelet count $< 40000/mm^3$
VII. Infection (presence of one or more of the following associated with clinical evidence of infection):
   A. 2 or more positive blood cultures
   B. Presence of gros pus in a closed space
   C. Source of the infection determined during hospitalization, or at autopsy in case of death within the 24 h

[a] Excluding patients with a central venous pressure less than 5 mmHg
[b] Excluding patients on chronic dialysis before hospital admission

Analysis

To evaluate our classification system and to compare it with SAPS in the total population and with Apache II in specific diagnostic groups, we used death in the ICU as the measurement of outcome. The risk evaluation for SAPS was performed with a score > 19 as the cutoff point, since this score was the most powerful one for a 0.50 risk of dying in studied patients. The probability of dying (risk of death) was calculated

for Apache II according to the recommendations of the original publication [1].

Univariate analyses involving dimensional data were conducted using Student's t-test, and categorical data were analyzed using χ^2 analysis. Statistical significance was established at $p<0.05$. Survival curves were calculated using the Kaplan-Meier method and compared by standard log-rank tests.

For our purposes, the multivariate analysis of ICU survival was based on the multiple logistic regression model which gives an estimate of the probability that a patient will die conditional on the presence or absence of the 7 ODIN. All possible ODIN associations ($n = 128$) were permitted to enter the model. The result was a 7-variable model (the ODIN model), comprised of the 7 ODIN elements noted as present or absent. The method of maximum likelihood was used to determine, in an objective manner, the statistical weight to be assigned to each variable.

Sensitivity (Sen), specificity (Spe) and overall accuracy (OA) were calculated using the SAPS, Apache II score and ODIN model for the whole studied population, and using Apache II probability of dying for selected groups of patients. Sen is the proportion of true-positives, i.e., the ratio of the correctly predicted number of non-survivors to the number of non-survivors. Spe is the proportion of true-negatives, i.e., the ratio of the correctly predicted number of survivors to the number of survivors. OA is the total correct classification rate, i.e., the ratio of the correctly predicted number of non-survivors and survivors to the number of non-survivors and survivors. The accuracy of the ODIN model, Apache II score and SAPS to predict outcome was determined by comparing the areas under their receiver operating characteristic (ROC) curves. A ROC curve depicts the relationship between the proportion of true-positives i.e., Sen, and the proportion of false-positives (which is equal to 1-Spe). Each ROC curve represents the ability of the model to discriminate between death and survival. The greater the area under the curve, the greater the discriminating power of the model. These areas were statistically compared according to the method of Hanley and McNeil, using the Wilcoxon statistic [14]. The calibration of the model was assessed by comparing the observed and expected number of deaths by category of predicted risk.

For validation, the models were applied to 434 new patients admitted to the ICU between March 1, 1990, and March 1, 1991. Inclusion criteria and data collection methods were the same as those applied to the original population.

Results

Table 2 shows the characteristics of the 1070 patients, among whom 286 (26.7%) died. Comparisons between survivors ($n = 784$) and non-survivors showed significant differences for mean age (54±19 years and 62±18 years, respectively; $p<0.001$), mean severity-of-illness scores (Apache II: 15±8 vs 28±10, respectively; $p<0.001$; SAPS: 11±5 vs 19±7, respectively; $p<0.001$), presence of ultimately or rapidly fatal underlying disease (25% vs 40%; $p<0.001$) and location before admission to our ICU (55% of non-survivors were admitted to our ICU from another ICU vs 38% of survivors; $p<0.001$).

Incidence of organ dysfunctions

Table 3 shows the distribution of the studied patients by number of and type of ODIN. There were 152 patients (14.2%) who had no dysfunction within the first 24 h of admission had 237 (22.1%) had only one dysfunction. Consequently, 681 patients (63.6%) and 2 or more ODIN, i.e., multiple organ dysfunction. Of these 681 patients, 259 (38%) died, compared to only 27 (7%) of the 389 patients who had no or only one ODIN ($p<0.001$).

Table 2. Admission characteristics of the 1070 patients studied

	All patients $n = 1070$ (%)	Survivors $n = 784$ (%)	Non-survivors $n = 286$ (%)
Mean age (years)*	55±19	54±19	62±18
Sex (% male)	65	64	67
Severity of underlying disease*			
– None or non-fatal	763 (71)	592 (76)	171 (60)
– Ultimately fatal	259 (24)	169 (22)	90 (31)
– Rapidly fatal	48 (5)	23 (3)	25 (9)
Indication for ventilatory support*			
– Non-ventilated	415 (39)	394 (50)	21 (7)
– Chronic airway obstruction	26 (2)	20 (3)	6 (2)
– Other pulmonary diseases	90 (8)	44 (6)	46 (16)
– Postoperative respiratory failure	357 (33)	223 (28)	134 (47)
– Drug overdose	30 (3)	29 (4)	1 (<1)
– Neurologic emergencies	84 (8)	48 (6)	36 (13)
– Miscellaneous	68 (6)	26 (3)	42 (15)
Admitted from*			
– Community	298 (28)	247 (32)	51 (18)
– Wards	320 (30)	241 (31)	79 (28)
– Another ICU	452 (42)	296 (38)	156 (55)
Mean Apache II score*	19±10	15± 8	28±10
Mean SAPS*	13± 7	11± 5	19± 7

*$p<0.001$ comparing survivors to non-survivors

Only 94 patients (8.8%) had 5 ODIN or more (including 5 patients who had 7/7 dysfunctions (0.5%)). Excluding infection from the list of organ dysfunctions, 586 (55%) patients had multiple organ-system failure.

Table 3 indicates that each ODIN was not equally represented. Respiratory dysfunction was observed in 65.8% of patients, cardiovascular dysfunction in 44.1%, infection in 38.9%, neurologic failure in 29.9% and renal failure in 26.4%; hepatic and hematologic dysfunctions were rare in this series (7.4% and 5.8%, respectively). More precisely, some of the 128 possible ODIN associations were more common than others. Respiratory dysfunction

Table 3. Incidence of organ dysfunctions in 1070 patients studied

ODIN	All patients $n = 1070$ (%)	Survivors $n = 784$ (%)	Non-survivors $n = 286$ (%)
Number*			
0	152 (14.2)	148 (18.9)	4 (1.4)
1	237 (22.1)	214 (27.3)	23 (8.0)
2	287 (26.8)	239 (30.5)	48 (16.8)
3	189 (17.7)	128 (16.3)	61 (21.3)
4	111 (10.4)	39 (5.0)	72 (25.2)
5	58 (5.4)	14 (1.8)	44 (15.4)
6	31 (2.9)	2 (0.3)	29 (10.1)
7	5 (0.5)	0 (–)	5 (1.7)
Type			
Respiratory*	704 (65.8)	447 (57.0)	257 (89.9)
Cardiovascular*	472 (44.1)	251 (32.0)	221 (77.3)
Infection*	416 (38.9)	256 (32.7)	160 (55.9)
Neurologic*	320 (29.9)	176 (22.4)	144 (50.3)
Renal*	283 (26.4)	128 (16.3)	155 (54.2)
Hepatic*	79 (7.4)	31 (4.0)	48 (16.8)
Hematologic*	62 (5.8)	26 (3.3)	36 (12.6)

*$p<0.001$ comparing survivors to non-survivors

was present in 79% (227/287) of patients with 2 ODIN; respiratory and cardiac failures were present in 66% (125/189) of patients with 3 ODIN; respiratory, cardiac and neurologic insufficiencies were present in 60% (67/111) of patients with 4 ODIN; and 57% (33/58) of patients with 5 ODIN had respiratory, cardiac and neurologic dysfunctions plus infection.

Analysis of outcome data

Figures 1 and 2 illustrate the direct relationships we observed between the number of organ dysfunctions and the ICU death rate. For each increase in the number of dysfunctions, there was a significant increase in the death rate ($p<0.001$). For example, the 2.6% death rate for patients with 0 ODIN was significantly lower the 9.7% death rate for patients with 1 ODIN, the 64.9% death rate for patients with 4 ODIN was significantly different from the death rates for patients with 3 or 5 ODIN. Using Kaplan-Meier survival curves stratified according to the number of organ dysfunctions, probability of survival of patients having 7 ODIN was 0% after 11 days; at the other end of the spectrum, the probability of survival of patients with 0 ODIN was superior to 90% after 50 days (Fig. 2).

There was also a relationship between the type of organ system that failed and the observed ICU death rate in patients with at least 1 ODIN. The highest mortality rates were associated with hepatic (60.8%), hematologic (58.1%) and renal (54.8%) dysfunctions, the intermediate mortality rates were associated with cardiovascular (46.8%) and neurologic (45.0%) dysfunctions, and the lowest mortality rates were observed in patients with respiratory dysfunction and those with infection (36.5% and 38.5%, respectively).

However, these analyses were incomplete; analysis of death rate as a function of the number of ODIN did not take into account the type of ODIN and, conversely, analysis of death as a function of the type of ODIN did not take into account the influence of the number of ODIN. Thus, multiple logistic regression analysis was used to demonstrate the relationship between organ dysfunction and outcome. This type of analysis allowed the conversion of every ODIN profile into probabilities of ICU mortality. Table 4 presents the details of the model with the respective weights of each ODIN in determining mortality according to the definition used for each ODIN. The odds-ratio varied from 1.70 for infection to 3.28 for cardiovascular dysfunction and 3.25 for renal dysfunction, two factors that greatly influenced mortality. The predicted probability of death (P) calculated from data on the entire population studied was: $P = 1/(1+e^{-q})$, where $q = -3.59+(1.09.\times R)(1.19.\times C)+(1.18.\times Rn)+(0.86.\times Hm)+(0.57.\times H)+(0.99.\times N)+(0.53.\times IN)$.

Table 4. Prediction of outcome using logistic regression analysis

Variables	Coefficient	Odds-ratio	*p*-value
Constant	−3.59		<0.0001
Cardiovascular dysfunction	1.19	3.28	<0.0001
Renal dysfunction	1.18	3.25	<0.0001
Respiratory dysfunction	1.09	2.97	<0.0001
Neurologic dysfunction	0.99	2.69	<0.0001
Hematologic dysfunction	0.86	2.36	0.011
Hepatic dysfunction	0.57	1.78	0.055
Infection	0.53	1.70	0.002

Individual estimated death rates obtained from this equation were used with a decision criterion of 0.50 to derive a classification matrix (Table 5). A decision criterion of 0.50 means that every patient with a risk greater than 0.50 is predicted to die. The overall accuracy classification of this model was 82.1%. By comparison, the overall accuracy classification of SAPS was 81.2% (sensitivity: 49.5% vs. 51.4% for the ODIN model; specificity: 93.4% vs. 93.3% for the ODIN model, p = NS). Introduction of age into the ODIN model in association with the 7 ODIN did not affect its accuracy, the overall accuracy classification was then 82.4% (sensitivity: 53.0%, specificity: 92.9%). In 14 patients, the calculated probability of death was superior to 0.90; none of these patients survived. By contrast, only 25 to the 389 patients (6.4%) with a probability of death of less than 0.10 died. The observed death rates in the 1070 studied patients were compared with the predicted death rates by category of risk (Fig. 3 A). The correlation of observed to expected deaths

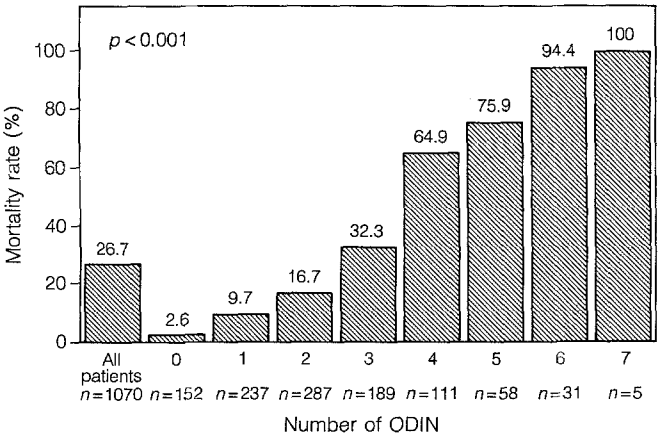

Fig. 1. Histogram showing the direct relationship between the number of organ dysfunctions (ODIN) and mortality

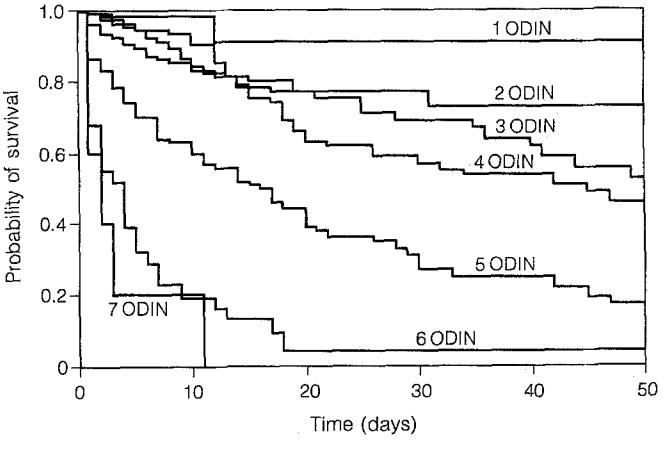

Fig. 2. Survival curves of patients stratified according to their number of organ dysfunctions

Table 5. Classification matrix of the 1070 patients obtained using a 0.50 probability of death[a]

True status	Predicted		
	Alive	Dead	Total
Alive	732	52	784
Dead	139	147	286
Total	871	199	1070

[a] Sensitivity: 51.4%; specificity: 93.4%; overall accuracy 82.1%; positive predictive value 73.9%; negative predictive value 84.0%

was high ($R^2 = 0.98$ using 10% risk categories; $p < 0.001$ and $R^2 = 0.27$ using individual case analysis; $p < 0.001$).

The ROC curves shown in Fig. 4 were used for evaluating performances of the ODIN model, Apache II score, and SAPS over the entire spectrum of possible cutoff points. Areas under the 3 curves were not significantly different (0.83 ± 0.015 for the 3 systems).

Our model was also able to establish a probability of death for each ODIN profile. Figure 5 summarizes these calculated probabilities of death; for example, the probability of death varied from 4.6% to 8.3% (95% CI: 2.2% – 13.4%) for the 7 possible ODIN profiles in patiens with 1 dysfunction, and from 16.4% to 46.8% (95% CI: 7.2% – 56.4%) for the 35 different ODIN profiles possible in patients with 3 ODIN. For each number of

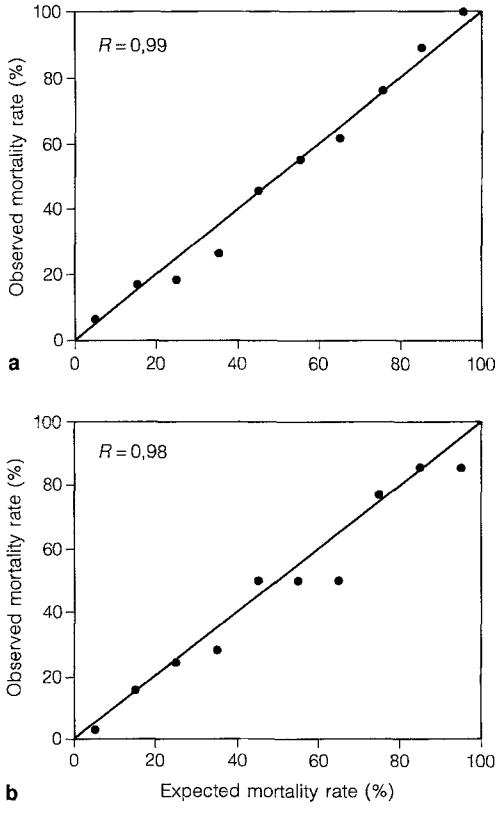

Fig. 3. Observed versus expected mortality by ODIN predicted risk category among patients in the initial data set (**a**) and those in the validation data set (**b**). Risk categories were <10% and each 10% increase in the ODIN model calculated probabilities

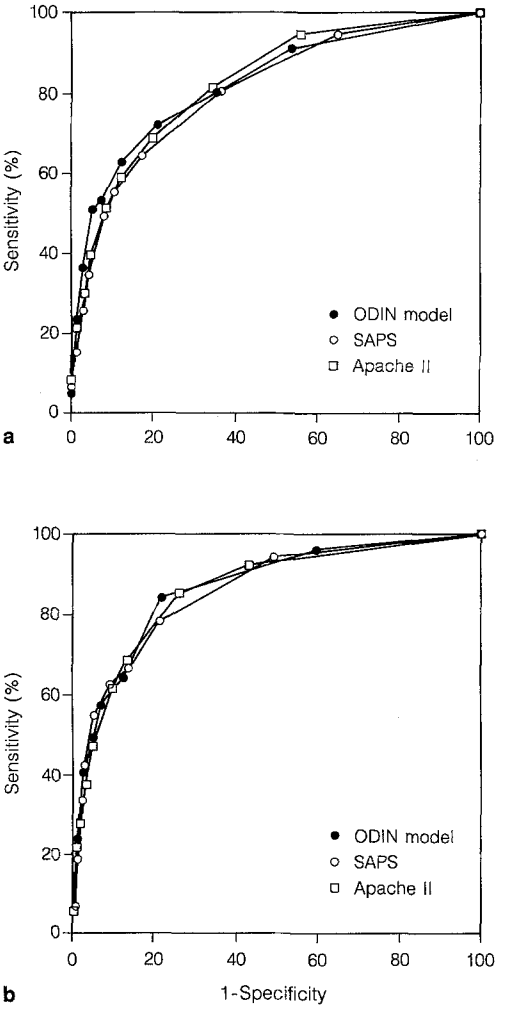

Fig. 4. Plots showing receiver operating characteristic (ROC) curves for the ODIN model. Apache II and SAPS, in the initial data set (**a**) and in the validation data set (**b**)

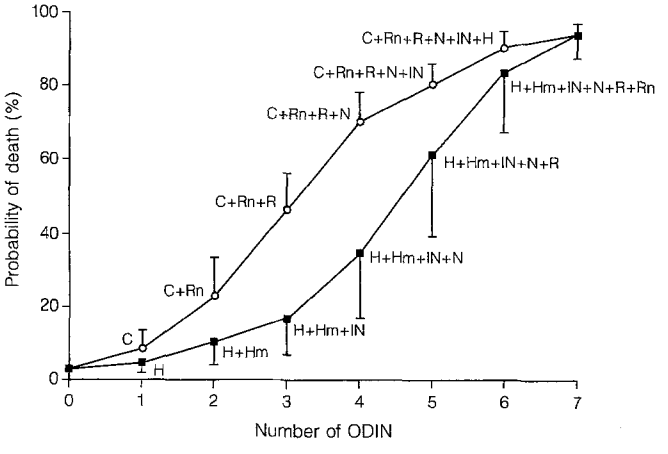

Fig. 5. Calculated probability of death according to the number and type of organ dysfunction using the ODIN model. For each number of organ dysfunctions, the probabilities of death corresponding to the most (*open circle*) and the least (*closed square*) lethal ODIN profiles are indicated. The *vertical bars* denote half of the 95% confidence interval (CI) of each probability of death

ODIN, the probability of death corresponding to the most frequent ODIN profile was the following: 7.6% (95% CI: 5.3% – 10.8%) in patients with respiratory dysfunction, 21.2% (95% CI: 16.2% – 27.4%) in patients with respiratory and cardiovascular failures, 46.8% (95% CI: 33.7% – 51.9%) in patients with respiratory, cardiovascular and neurologic dysfunctions, 73.4% (95% CI, 61.3 – 78.1%) in patients with respiratory, cardioavascular, neurologic and renal failures and 80.2% (95% CI: 72.7% – 86.1%) in those with respiratory, cardiovascular, neurologic, renal failure and infection.

Among the 434 patients included in the prospective validation group for the model, mortality was 23.0%. Using a probability of 0.50 and greater to predict death, the ODIN model had a sensitivity of 46.0% and a specificity of 95.8%. Figure 3b indicates observed death rate for each 10% increase in the ODIN model calculated probabilities in the validation group. The overall accuracy was 84.3% compared to 82.1% for the studied group (p = NS). By comparison, overall accuracies of the SAPS and the Apache II score were 85% and 83.8% (sensitivities: 54.9% and 47.1%; specificities 94.6% and 94.9%, respectively). When the observed death rates in the validation set were compared with the ODIN predicted death rates the correlation coefficient $R^2 = 0.92$ using 10% risk categories ($p < 0.001$) and 0.38 using individual case analysis ($p < 0.001$). The performances of the 3 systems in the validation set, as depicted by their ROC curves, are shown on Fig. 4b. No differences were noted when areas under the curves of each system were compared to those obtained in the initial data set. The estimates of the areas under the ROC curves for the initial set of data were 0.83 ± 0.015, whereas that on the validation set were 0.85 ± 0.015.

We also compared classification rates obtained with the SAPS, Apache II and ODIN systems in subgroups of patients with specific disease categories, such as ketoacidosis, acute asthma, bacterial pneumonia, septic shock, and acute respiratory failure in chronic obstructive pulmonary disease patients. Although no differences were significant, the sensitivity of the ODIN model was equal or superior to the sensitivities of other systems in 9/10 comparisons, its specificity was higher in 8/10 comparisons and its overall accuracy was better in 9/10 comparisons (data not shown).

Discussion

This report describes a new and simple means of characterizing critically ill patients. The model is based upon the presence or absence of 6 organ dysfunctions and/or infection (ODIN) that enables a "profile" of ODIN to be established and a probability of death to be calculated for each patient. Using epidemiologic data on the presence of different ODIN in ICU patients, we demonstrated that the outcome at ICU discharge for each of the 1070 patients studied was closely linked to both the number and the type of ODIN. With these data, we devised a classification system of disease severity based upon the number and the type of organ dysfunction and/or infection: the ODIN model. The ability of this model to stratify a wide variety of patients prognostically was not different from currently used scoring systems or slightly better; the results were strong and stable in subgroups of patients within specific disease categories.

We based our system on signs of organ dysfunction because these data can always be obtained within the first 24 h of admission, when precise diagnostic evaluation is not possible in all patients. The criteria used for defining organ dysfunction were obtained from an extensive review of the clinical literature [7, 9 – 12] and later modified through an informal consensus of subspecialists who identified 3 essential elements. The first priority was to use clear and easily obtainable parameters. All parameters used in our model require little interpretation on the part of the data collector and a maximum of 8 biological measurements are needed. Although the inclusion of treatment variables to define organ dysfunction may be viewed as problematic as variations in practice style could influence use of therapeutic modalities and introduce a bias between ICUs having very different therapeutic practices, we concurred that cardiovascular, respiratory and renal dysfunctions cannot be accurately defined in the ICU without the use of therapeutic criteria. Therefore, we decided to follow the consensus opinion established with our colleagues and these therapeutic criteria were specified in the corresponding definitions.

The second priority was to be as descriptive as possible of the patient's clinical condition. Therefore, we enlarged upon the organ dysfunctions usually considered in the literature [4] by adding hepatic dysfunction [15] and a seventh criterion, infection. The latter plays an important role in determining the onset of organ dysfunctions [9, 11] and has an important impact on ICU mortality [6, 16]. The final objective was to be able to apply the model successfully to predict the outcome of all patients admitted to the ICU. Thus, we chose less severe criteria for each definition of ODIN than those used by other [4] who found 100% mortality in patients with 3 or more organ failures. Consequently, in our study, only 14.2% of the patients had no organ dysfunction compared to 52% in the study by Knaus et al. based upon organ-system failure ($p < 0.0001$) [4].

In our investigation, outcome data were analyzed by comparison to ICU mortality and not hospital mortality as in almost all previous studies [1 – 4]. Although the use of ICU mortality as the measurement of outcome excludes important considerations, such as the quality and length of survival after discharge from the ICU, it can be easily and accurately determined and is no more subject to the individual discharge decisions than hospital death rates. Furthermore, in our opinion, studies using hospital mortality to evaluate mortality prediction models for patients introduce in-hospital but ouf-of-ICU outcome into the analysis.

Overall mortality observed in this study (26.7%) is important to consider for comparing results observed in this investigation to those found in previous studies [1 – 3, 17 – 19]. Because of the better ability of models predicting outcome to predict survival (specificity) rather than death (sensitivity), studies reporting the best results were

conducted on ICU populations with low death rates [19–21]. This was illustrated in our investigation by the fact that the model performed slightly better in the validation group than in the first group studied (overall accuracy 84.3% and 82.1%, respectively). This result was probably associated with the lower mortality rate observed in the validation group (23.0% vs. 26.7% in the group studied; p = NS) which, therefore, exhibited better specificity (95.8% in the validation group vs. 93.4% in the first group studied). Sensitivity, specificity and overall accuracy of a predicting model must be interpreted in light of the death rate observed in the study population.

As shown in previous studies, there was a strong relationship between the number of ODIN and the mortality [4, 7]. Our results also demonstrated that for each number of ODIN [0–7], the probability of death depended upon the type of ODIN present. For example, patients with 3 abnormal organ functions had probabilities of death which could range from 7.2%–56.4%, depending upon whether hematologic and hepatic dysfunctions plus infection were present or if cardiovascular, renal and respiratory dysfunctions were present. Higher death rates were observed in patients suffering from renal and hepatic insufficiencies. This high mortality rate observed in patients with hepatic dysfunction confirms our choice to include this organ in our model. In contrast, the moderate role that hematologic dysfunction played in this study probably reflects the type of patients hospitalized and treated in our unit. Only 5.8% had haematologic dysfunction using our definition (Table 1). The influence of hematologic dysfunction on outcome would probably be different in units admitting large numbers of cancer, immunocompromised or bleeding patients.

The profile of organ dysfunctions established for each patient provided the basis for a classification system of disease severity. A logistic regression model was used to calculate each patient's probability of death which depended upon the statistical weight assigned to each ODIN. By comparison with other state of the art predicting indices the ODIN model described herein presents several characteristics. First, as described above, collection of the required data is easy. The resulting model contains only 7 variables that are present or not, and predictions can be computed quickly and easily using microcomputer spreadsheet packages or programmable calculators. In contrast, the conversion of Apache II or III scores into a probability of death needs additional information beyond the 14 variables used to obtain the scores, including whether the patient had undergone emergency surgery, and also requires a single selection of either a principal diagnostic category leading to ICU admission or a major organ-system dysfunction if the diagnosis is not included on the list [1, 24].

Second, we consider that more than just a numeric score, knowing the number and the type of ODIN present within the first 24 h in critically ill patients is epidemiologically and medically relevant. By providing a global measure of severity-of-disease as well by specifying the function of different organ systems, our model will help investigators to precisely characterize studied patients, for example to determine whether control and treatment groups of patients included in a clinical trial are really similar. It would probably be useful for researchers to know which non pulmonary organ dysfunctions are present (or not) in patients included in a study evaluating a new drug for respiratory disease and not only the severity of illness.

Third, the ODIN model that we devised was constructed as an evolutive model. Since the calculated probability of death established by logistic regression analysis for one patient with a definite ODIN "profile" is influenced by the outcome of all previous patients recorded in the data base, each new patient discharged from the unit can be included in the data base and his outcome used for establishing a new equation for calculating the probability of death. This possibility of adaptation will therefore enable the comparison of historical groups of patients hospitalized within the same unit, or between different critical care units [22, 23]. For this reason and because of the type of criteria used for defining organ dysfunctions, it is particularly important to validate the generated models in other institutions before widespread implementation.

In conclusion, evaluation of the number, the type of organ dysfunctions and/or infection provides a good basis for a reliable method for characterizing critically ill patients, giving a precise description of medical status and an exact measurement of severity-of-disease with a calculated individual probability of death. Therefore, this model, which requires further validation by multicenter evaluation, may enable objective charting of patients' clinical courses, prediction of ICU outcome and ICU-efficiency analysis, and may provide an objective means to stratify patients into severity-of-illness groups.

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