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# Paediatric index of mortality (PIM): a mortality prediction model for children in intensive care

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**Abstract** *Objective*: To develop a logistic regression model that predicts the risk of death for children less than 16 years of age in intensive care, using information collected at the time of admission to the unit.
*Design*: Three prospective cohort studies, from 1988 to 1995, were used to determine the variables for the final model. A fourth cohort study, from 1994 to 1996, collected information from consecutive admissions to all seven dedicated paediatric intensive care units in Australia and one in Britain.
*Results*: 2904 patients were included in the first three parts of the study, which identified ten variables for further evaluation. 5695 children were in the fourth part of the study (including 1412 from the third part); a model that used eight variables was developed on data from four of the units and tested on data from the other four units. The model fitted the test data well (deciles of risk goodness-of-fit test $p$=0.40) and discriminated well between death and survival (area under the receiver operating characteristic plot 0.90). The final PIM model used the data from all 5695 children and also fitted well ($p$=0.37) and discriminated well (area 0.90).
*Conclusions*: Scores that use the worst value of their predictor variables in the first 12–24 h should not be used to compare different units: patients mismanaged in a bad unit will have higher scores than similar patients managed in a good unit, and the bad unit's high mortality rate will be incorrectly attributed to its having sicker patients. PIM is a simple model that is based on only eight explanatory variables collected at the time of admission to intensive care. It is accurate enough to be used to describe the risk of mortality in groups of children.

**Key words** Critical care · Intensive care units, paediatric · Logistic models · Outcome assessment · Prospective studies · Severity of illness index

## Introduction

Models that predict the risk of mortality in children in intensive care are needed to allow evaluation of the effectiveness and efficiency of paediatric intensive care [1]. They enable us to investigate the best ways of organising paediatric intensive care (by comparing different units), to monitor the effects of changes in practice (by observing trends within units over time), to assess the relationship between severity of illness and length-of-stay or cost, and to monitor the effects of rationing intensive care [1].

The standard mortality prediction model for paediatric intensive care is PRISM [2], which was developed from the PSI model [3]. This score is calculated from the most abnormal values in the first 24 h of 14 physiological variables and the patient's age and operative status [2]. The score has been widely used for mortality risk assessment,

outcome-based quality assurance and cost containment [1], and it provides an excellent indication of the risk of mortality for groups of children at the end of the first 24 h of intensive care. A new version of PRISM has been developed recently, PRISM III [4], which uses data collected in the first 12 or 24 h to predict mortality, but it is not in the public domain, and a licence fee has to be paid to use the algorithms.

There are several problems with PRISM. Because it is calculated from the most abnormal values of 14 variables over a 24-h period, it is very difficult to collect the large amount of information needed to calculate PRISM – so that many paediatric intensive care units do not calculate it routinely. Further, worst-in-24-h scores such as PRISM have two serious methodological problems. First, they appear to be more accurate than they really are: in the units involved in this study, over 40% of the deaths occurred in the first 24 h, so there is a danger that the score is really diagnosing death rather than predicting it. Second, worst-in-24-h scores blur the differences between units: a child admitted to a good unit who rapidly recovers will have a score that suggests a mild illness, while the same child who is mismanaged in a bad unit will have a score that suggests severe illness – the bad unit's high mortality will be incorrectly attributed to its having sicker patients than the good unit. To overcome these problems, we have developed a new paediatric index of mortality (PIM) model that is based on just eight variables, all collected at the time of admission to intensive care.

## Methods

The development of PIM began in 1988, when information was collected about 678 consecutive admissions over 6 months to the paediatric intensive care unit (PICU) at the Royal Children's Hospital, Melbourne (RCHM). The variables collected were the 34 PSI variables [3], plus mean arterial pressure, ventilator peak inspiratory pressure (PIP), ventilator positive end-expiratory pressure (PEEP), motor response to pain, immature neutrophil count, total neutrophil count, base excess, and rectal temperature. The worst value of each variable in the first 24 h after admission was recorded for all 678 patients, and the admission values were also recorded for the last 230 patients.

The second stage of the study began in 1990, when 814 consecutive admissions to PICU at RCHM were studied. Information was collected at the time of admission and over the first 24 h in PICU about age, gestational age, pupil reaction to light, motor response to pain, base excess, mean arterial pressure, respiratory rate, arterial carbon dioxide tension ($PaCO_2$), PIP and PEEP.

In the third stage of the study, from February 1994 to March 1995, 1412 consecutive admissions to RCHM PICU were studied. Information was collected at the time of admission to PICU and during the first 24 h about all PRISM variables plus information about sex, time in hospital before admission to PICU, need for mechanical ventilation, diagnosis, the presence of a right-to-left cardiac shunt, estimated fractional inspired oxygen concentration ($FIO_2$) in unintubated patients, weight, mean blood pressure, each pupil's size and reaction to light, PIP, PEEP, $PaCO_2$, base excess, and plasma sodium. Univariate analysis for an association with mortality in PICU was performed using the $\chi^2$ test for dichotomous variables. The continuous variables were examined using Copas p by x plots [5], then appropriately transformed and tested for an association with mortality using the Mann-Whitney U test. With the exception of age and time in hospital before admission to intensive care (lead time), variables that were not associated with mortality on univariate testing ($p>0.1$) were excluded from further analysis. Forward and backward logistic regression was then performed using Systat (Systat Inc, Evanston, Ilinois) and Stata (Stata Corp, College Station, Texas) to develop a preliminary model.

In the fourth stage of the study, in 1994–1996, information about the variables in the preliminary model (plus plasma sodium and prothrombin time) was collected from consecutive admissions less than 16 years of age to four PICUs in Australia (the learning sample) and one PICU in Britain and three PICUs in Australia (the test sample). Each unit collected data from enough consecutive admissions to include at least 20 deaths. As a check on the accuracy of data collection, a sample of the data was collected in duplicate.

The information from RCHM, New Children's Hospital, Sydney, Princess Margaret Hospital, Perth, and Sydney Children's Hospital was used as a learning sample to determine the regression coefficients of a logistic model. Stata was used to examine the fit of the model with graphs and tabulations of Pearson residuals, deviance residuals and leverage, and the change in Pearson goodness-of-fit $\chi^2$ and the deviance residuals and the coefficient vector that would be caused by deleting an observation (and all others sharing the covariate pattern). The transformations of the variables were assessed with Box-Tidwell analysis [6], and partial residual plots [7].

The fit of the model developed on the learning sample was then tested on children admitted to the PICUs at Birmingham Children's Hospital, Mater Misericordiae Children's Hospital, Brisbane, Royal Children's Hospital, Brisbane, and Women's and Children's Hospital,

**Table 1** Details of the paediatric intensive care units in the fourth study

| Unit | Number died | Number survived | Admissions per month | Admissions ventilated | PICU beds open | Paediatric beds in hospital | PICU residents | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | | Usual years of specialist training | On only for PICU |
| 1 | 19 | 656 | 45 | 23% | 8 | 225 | 3 | All times |
| 2 | 21 | 259 | 76 | 80% | 11 | 221 | 5 | All times |
| 3 | 38 | 888 | 39 | 26% | 4 | 139 | 3 | All times |
| 4 | 20 | 421 | 34 | 31% | 7 | 200 | 2–3 | All times |
| 5 | 24 | 610 | 50 | 27% | 5 | 240 | 4[a] | Weekdays |
| 6 | 21 | 556 | 66 | 57% | 15 | 350 | 3 | All times |
| 7 | 21 | 423 | 34 | 45% | 6 | 168 | 2 | All times |
| 8 | 114 | 1604 | 105 | 66% | 11 | 310 | 4–5 | All times |

[a] 2 years at night and on weekends

Adelaide. Calibration was assessed using the Hosmer-Lemeshow goodness-of-fit $\chi^2$ test based on deciles of risk [6] and by inspection of the number of observed and expected deaths and survivors in five groups with <1%, 1–4%, 5–14%, 15–29% and 30% or more predicted mortality [2, 8, 9]; calibration evaluates how well the model classifies subjects into low, medium and high risk categories. Discrimination was assessed using the area under the receiver operating characteristic plot [10]; discrimination estimates how well the model distinguishes between patients who lived and patients who died. Once we were satisfied with the fit of the model in both the development and the validation groups, we re-estimated the logistic regression coefficients using the entire sample [11].

All the dedicated PICUs in Australia participated in the fourth part of this study, and all of these units and the one in Britain have at least one full-time specialist in paediatric intensive care, and all are in specialist paediatric, non-profit, public, university teaching hospitals. The characteristics of the participating PICUs are shown in Table 1.

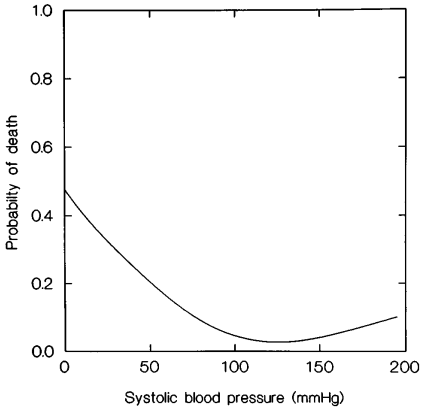


**Fig. 1** Distance weighted least squares plot of probability of death against systolic blood pressure

## Results

The first, second and third parts of the study were used to determine the variables that were included in the fourth part of the study. A total of 5695 children were in the fourth part of the study, and 278 of them died (Table 2). Six of the 278 deaths occurred within 24 h of discharge from intensive care. No patient was lost to follow-up. Physiological variables that were not measured were considered to be normal. One PICU did not provide information about the age of its patients; of the 5117 patients for whom the age was known, 8.1% were less than 1 month old, 15.9% were 1–5 months, 9.8% were 6–11 months, 14.5% were 12–23 months, 20.6% were 24–59 months, 15.7% were 60–119 months, and 15.6% were 120–191 months.

Continuous variables were examined using Copas p by x plots [5]. For example, when systolic blood pressure was graphed against mortality in a distance-weighted least squares plot (Fig. 1), the curve was symmetrical about 120 mmHg, so systolic blood pressure was transformed by subtracting 120 mmHg and taking the absolute value. The effectiveness of the transformation was then checked using Box-Tidwell analysis [6] and a partial residual plot [7]. A similar process was used to transform base excess by taking the absolute value and arterial oxygen tension ($PaO_2$) and $FIO_2$ by using $100\times FIO_2/PaO_2$. Cross-tabulation and the likelihood ratio test [6] were used to determine the predictive power of pupil size, unequal size and reaction to light; almost all the predictive power was obtained from knowing whether or not both pupils were fixed in size in response to bright light.

Data were collected by two different observers in 60 children; there were no differences in any of the observations on pupils, elective admission, ventilation and base excess, but one child had a difference in $100\times FIO_2/PaO_2$ of >0.1, two children had different entries for specified diagnosis, and six children had a difference in systolic blood pressure of >10 mmHg.

Table 3 shows the instructions for collecting the information required to calculate PIM. Each child was allocated one of 214 different diagnoses; nine diagnoses were associated with an increased risk of mortality, even when information from the other PIM variables was taken into account (see Table 3). Prediction was not improved by having a different coefficient for each of the nine diagnoses, by the inclusion of interaction terms in the model, or by including the square of the transformed base excess variable, the square of $FIO_2/PaO_2$, or the logarithm of transformed systolic blood pressure.

Variables that did not predict death on univariate analysis were serum bilirubin, pulse rate, central venous pressure, haemoglobin, the presence of convulsions, left atrial pressure, and days in hospital before admission to intensive care (the lead time). Two variables were statistically significant when added to the final model (Table 4), but were excluded because they had little effect on the fit of the model or the area under the ROC plot: the prothrombin time increased the area under the ROC plot by only 0.1%, and serum sodium increased the area by only 0.01%.

**Table 2** Characteristics of the fourth study cohort [*BE* base excess, *SBP* systolic blood pressure, $FIO_2$ fractional inspired oxygen, $PaO_2$ arterial oxygen tension (mmHg)]

| | Died ($n=278$) | Survived ($n=5417$) |
|---|---|---|
| Pupils fixed | 61 | 55 |
| Ventilated | 240 | 2344 |
| Elective admission | 34 | 2309 |
| Specified diagnosis | 73 | 196 |
| BE (mmol/l): mean (SD) *n* | –5.4 (9.18) 250 | –1.6 (5.19) 3561 |
| SBP (mm Hg): mean (SD) *n* | 84 (32.2) 263 | 103 (23.8) 4732 |
| $100\times FIO_2/PaO_2$: median (25%, 75%) *n* | 0.55 (0.24, 1.45) 195 | 0.35 (0.22, 0.78) 1781 |

**Table 3** Instructions for collecting the information needed to calculate PIM

PIM is calculated from information collected at the time a child is admitted to your ICU. Because PIM describes how ill the child was at the time you started intensive care, the observations to be recorded are those made at or about the time of first face-to-face (not telephone) contact between the patient and a doctor from your intensive care unit (or a doctor from a specialist paediatric transport team). Use the first value of each variable measured within the period from the time of first contact to 1 h after arrival in your ICU. The first contact may be in your ICU, or your emergency department, or a ward in your own hospital, or in another hospital (e.g. on a retrieval). The pupils' reactions to light are used as an index of brain function; do not record an abnormal finding if this is probably caused by drugs, toxins or local injury to the eye. If information is missing (e.g. base excess not measured), record zero (except for systolic blood pressure, which should be recorded as 120); do not leave the space blank.

1. Booked admission to ICU after elective surgery, or elective admission to ICU for a procedure such as insertion of a central line or monitoring or review of home ventilation (no=0, yes=1):

2. If there is one of these underlying conditions, record the code [number in square brackets]:
   [0] none
   [1] cardiac arrest out of hospital
   [2] severe combined immune deficiency
   [3] leukaemia/lymphoma after 1st induction
   [4] cerebral haemorrhage
   [5] cardiomyopathy or myocarditis
   [6] hypoplastic left heart syndrome
   [7] HIV infection
   [8] IQ probably <35, worse than Down's
   [9] a neurodegenerative disorder

3. Response of pupils to bright light (both >3 mm and both fixed=1, other=0, unknown=0):

4. Base excess in arterial or capillary blood, mmol/l (unknown = 0):

5. $PaO_2$, mmHg (unknown=0):

6. $FIO_2$ at time of $PaO_2$ if oxygen via ETT or headbox (unknown=0):

7. Systolic blood pressure, mmHg (unknown=120):

8. Mechanical ventilation at any time during first hour in ICU (no=0, yes=1):

9. Outcome of ICU admission (discharged alive from ICU=0, died in ICU=1):

Also consider collecting: ICU admission number, age, diagnosis, days in PICU, intubation (no=0, or yes=1=an endotracheal tube in situ at any time during the ICU admission), gestational age (neonates), Apgar score at 5 min (neontes).

**Table 4** PIM logistic regression models (*SBP* systolic blood pressure)

| | Test ($n=3370$) Coefficients | Model derived from entire fourth study sample ($n=5695$) | | |
|---|---|---|---|---|
| | | Coefficient (95% CI) | Odds ratio (95% CI) | $\chi^2$ (1 *df*)[a] |
| Pupils fixed to light, yes/no | 2.779 | 2.357 (1.871 to 2.843) | 10.560 (6.498–17.163) | 86.10 ($p<0.00005$) |
| Specified diagnosis, yes/no | 2.306 | 1.826 (1.453 to 2.199) | 6.209 (4.277–9.013) | 80.61 ($p<0.00005$) |
| Elective admission, yes/no | –1.395 | –1.552 (–1.941 to –1.163) | 0.212 (0.144–0.313) | 77.40 ($p<0.00005$) |
| Mechanical ventilation, yes/no | 1.157 | 1.342 (0.955 to 1.729) | 3.826 (2.598–5.634) | 53.02 ($p<0.00005$) |
| Absolute (SBP-120), mmHg | 0.017 | 0.021 (0.014 to 0.027) | 1.021 (1.014–1.028) | 37.61 ($p<0.00005$) |
| Absolute (base excess), mmol/l | 0.083 | 0.071 (0.046 to 0.095) | 1.073 (1.048–1.099) | 30.33 ($p<0.00005$) |
| $100\times FiO_2/PaO_2$ ($mmHg^{-1}$)[b] | 0.491 | 0.415 (0.231 to 0.599) | 1.514 (1.260–1.820) | 19.82 ($p<0.00005$) |
| Constant | –4.805 | –4.873 (–5.250 to –4.497) | | |

[a] Likelihood ratio test [6]
[b] 100 × fractional inspired oxygen concentration / arterial oxygen tension

Neonates had a higher mortality than older children, but inclusion of age did not improve the prediction of the model. Correction for age did not improve the predictive power of systolic or mean blood pressure, pulse rate, or respiratory rate. None of the PICUs had a significant effect when they were included in the model as dummy variables (all the *p* values were >0.20).

## Performance of the model

Partial residual plots of the transformed continuous variables in the model revealed no marked departures from our assumptions. The model estimated on the learning sample of data from four PICUs calibrated well (deciles of risk goodness-of-fit test $p=0.21$, $\chi^2$ 10.80, 8 *df*) and discriminated well (area under the ROC plot 0.90). This model was then tested on data from the other four PICUs; again the model calibrated well (goodness-of-fit test $p=0.40$, $\chi^2$

**Table 5** Outcome by diagnostic category: deaths (predicted deaths) total

| | Predicted risk of death | | | | | Total | ROC area |
|---|---|---|---|---|---|---|---|
| | <1% | 1–4% | 5–14% | 15–29% | 30% or more | | |
| Cardiac | 1 (1.4) 266 | 21 (19.4) 870 | 16 (13.3) 148 | 14 (10.5) 54 | 14 (21.7) 39 | 66 (66.2) 1377 | 0.83 |
| Respiratory | 1 (4.3) 586 | 9 (9.8) 488 | 13 (14.0) 178 | 5 (8.6) 42 | 9 (9.9) 19 | 37 (46.6) 1313 | 0.88 |
| Postoperative[a] | 2 (2.6) 747 | 2 (3.7) 195 | 1 (1.9) 27 | 1 (1.5) 7 | 0 (1.2) 3 | 6 (11.0) 979 | 0.72 |
| Miscellaneous | 2 (1.4) 325 | 10 (6.7) 299 | 16 (14.2) 160 | 17 (11.2) 55 | 42 (37.4) 62 | 87 (70.9) 901 | 0.90 |
| Accidents | 0 (1.0) 126 | 3 (8.1) 283 | 11 (9.0) 128 | 3 (3.5) 16 | 30 (27.5) 45 | 47 (49.1) 598 | 0.94 |
| Neurology | 0 (0.7) 130 | 7 (6.0) 235 | 8 (8.4) 111 | 5 (4.8) 23 | 15 (14.3) 28 | 35 (34.1) 527 | 0.87 |
| Total | 6 (11.5) 2180 | 52 (53.7) 2370 | 65 (60.8) 752 | 45 (40.1) 197 | 110 (112.0) 196 | 278 (278.0) 5695 | 0.90 |

[a] Excluding cardiac patients

8.38, 8 *df*) and discriminated well (area under the ROC plot 0.90).

The final model was estimated using the entire sample from the fourth part of the study (see Table 4). The deciles of risk goodness-of-fit test gave $p=0.37$ ($\chi^2$ 8.73, 8 *df*) and the area under the ROC plot was 0.90. The performance of the model by mortality risk stratum and diagnostic category is shown in Table 5; although only five risk groups are shown in this table, ten groups were used for the goodness-of-fit tests. The area under the ROC plot for the eight PICUs was 0.92, 0.92, 0.91, 0.89, 0.89, 0.86, 0.85 and 0.80. There were 414 babies less than 1 month of age in the sample, and the model described their risk of mortality well (goodness-of-fit $p$=0.22, area under ROC plot 0.80); 227 of the 414 babies had cardiac disease.

### PIM compared with PRISM

Both PRISM (worst in 24 h) and PIM (time of admission to PICU) variables were collected from 1182 children (78 died) less than 16 years of age at RCHM in the 12 months from April 1994 to March 1995. PRISM predicted 118.6 deaths and PIM 71.6, so that PRISM predicted 66% more deaths than PIM. The Hosmer-Lemeshow test [6] showed that PRISM fitted the data poorly ($\chi^2$ 33.16, 8 *df*, $p<0.00005$); the area under the ROC plot was 0.87. Because these patients were part of the sample from which the PIM model was derived, it is not surprising that PIM fitted the data well ($\chi^2$ 8.96, 8 *df*, $p$=0.35) with an area under the ROC plot of 0.91.

Admission and worst-in-24-h PIM data were available on 1587 children less than 16 years of age from RCHM. The area under the ROC plot was 0.877 for a model based on the admission data and 0.910 for a model based on the 24-h data, suggesting that the use of 24-h data increases the area under the ROC plot by 3–4%.

## Discussion

We have developed a simple model of mortality in paediatric intensive care; it is based on admission data and uses only eight explanatory variables, with two of them combined in the final model. We were able to restrict the number of variables in the model by identifying appropriate transformations of the continuous variables using Copas p by x plots [5], Box-Tidwell analysis [6], partial residual plots [7], and residual, leverage and deviance plots [7]. We improved the performance of categorical variables by identifying which component had predictive power and modifying the variable accordingly; for example, we found that whether the pupils change in size or are fixed in response to bright light conveys much more information than their absolute or relative size or their speed of response. New variables, transformations or interactions were used only if they improved the performance of the model, as judged by the goodness-of-fit [6] and the area under the ROC plot [10] in the validation set and the full data set.

We derived a training model on one group of intensive care units and applied this model to another group of units to provide a more stringent test than just randomizing individual patients to the training or test set [12]. However, we report the coefficients of the model derived from all the available data, as suggested by Normand [11]; in fact, there was little difference between the model derived on the training set and the model derived using all the data (Table 4). The training model performed well on the test data with high values for the goodness-of-fit test ($p$=0.40) and the area under the ROC plot (0.90), and the full model fitted the full database well ($p$=0.37) with an area under the ROC plot of 0.90. An example that illustrates the calculation of PIM is given in the Appendix. PIM had an area under the ROC plot of only 0.72 for non-cardiac postoperative patients (Table 5) but, although there were 979 patients in this group, there were only six deaths, so there are very wide confidence limits of 0.49–0.95 for the area under the plot.

We chose to use death in PICU as the dependent variable in our model, rather than death in hospital or death

within 1 month of admission to PICU. Death in PICU is the mortality outcome that is of most practical interest to paediatric intensivists and is the outcome used by PRISM [2]. We included multiple admissions for an individual in our database because the model will be used on data that includes children who are admitted several times.

Inevitably, our model will be compared with PRISM [2,4], which is the de facto standard that has been used for several important studies of paediatric intensive care [1, 13–15]. PRISM is accurate and widely accepted, but many units do not use it routinely because it is difficult to collect the large amount of information needed to calculate it (e.g. if systolic and diastolic blood pressure are recorded half-hourly, 96 readings will have to be assessed). The variables used by PRISM that are not used by PIM are diastolic blood pressure, heart rate, respiratory rate, arterial partial pressure of carbon dioxide, the Glasgow Coma Score (which is calculated from three separate variables), prothrombin time, serum bilirubin, serum potassium, serum calcium, blood glucose and plasma bicarbonate. The variables used by PIM that are not used by PRISM are the presence of a specified diagnosis, use of mechanical ventilation and the plasma base excess. The latest version of PRISM, PRISM III [4] has an area under the ROC plot of 0.94 for both the 12-h and 24-h models – but it is even more complicated than the previous version [2], and an annual licence fee has to be paid for its use.

Treatment given just before admission to intensive care is likely to affect admission scores (such as PIM) more than 24-h scores. For example, in a patient with shock, appropriate administration of fluid and sympathomimetics in the emergency department may increase blood pressure and restore the base excess to normal, which will affect the PIM score. However, if this treatment improves the patient‘s prognosis at the time of admission to intensive care, it is appropriate that it alters the PIM score. It has been suggested that patients with a given severity-of-illness score may have a higher mortality rate if they have been extensively treated before they are admitted to intensive care [16], a problem known as lead time bias, but we found that the time spent in hospital before admission to intensive care was not statistically significant when added to the PIM model.

PRISM uses data collected over the first 24 h after admission to intensive care (12 or 24 h for PRISM III), and many of the deaths occur during this time, so that the score may be diagnosing death rather than predicting it in some patients; although this effect is reduced by excluding the period just before death, our data suggest that it artificially increases the area under the ROC plot by 3–4%. However, the most serious problem with 12 or 24-h scores is that they are affected by treatment given after admission to intensive care, so that they are not valid instruments for comparing the quality of care between different units, or within a single unit over time. Children admitted to a good PICU who recover will have lower PRISM scores than similar children admitted to a bad PICU who are mismanaged in the first 12–24 h, and the bad unit‘s high mortality rate will be incorrectly attributed to its having sicker patients.

We found that PRISM [2] predicts 66% more deaths than PIM in an Australian PICU. This may be because paediatric intensive care is highly centralised in Australia and almost all very ill children are looked after in one of the eight PICUs in this study, all of which have at least one full-time paediatric intensivist who has extensive involvement in patient care, and relatively senior resident staff (Table 1; [13]).

Mortality prediction models, such as PIM and PRISM, are developed by finding variables that predict the probability of death in groups of children. These models are then often used as a measure of severity of illness, which assumes that children with a high risk of death are sicker than children with a low risk of death. This assumption is true for many types of PICU patients, but not all. For example, children with epiglottitis or severe croup are very likely to die without intensive care, but they have a very low mortality if they are properly managed – so mortality prediction models give these children a low score despite the fact that they are very ill. Although mortality prediction models provide a fairly good description of groups of patients, they are not accurate enough to be used to make decisions about the management of individual patients. One study in children has found that a high specificity in predicting death can be achieved by evaluating changes in PRISM over time [17]; however, although none of the 62 children who were predicted to die in that study actually survived, the upper 95% confidence limit for this proportion (0/62) is 5.8% – so specificity may have been as low as 94.2%, and sensitivity was only 21.9%.

The PIM model is simple enough for it to be widely used in paediatric intensive care – it requires the collection of only eight variables at the time of admission to intensive care, and it has good predictive power. PIM has been developed in dedicated PICUs where there are high levels of consultant input, senior resident staff and trained PICU nurses, so that it sets a high standard of care. We would be very grateful if units that use PIM were to send copies of their data on computer disk to the first author (FS), so that PIM can be further developed.

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## Appendix

Sample calculation of PIM

Consider a child who is admitted to intensive care with pupils that react to light (pupils fixed = no = 0), has myocarditis (specified diagnosis = yes = 1), is an emergency admission (elective = no = 0), is ventilated immediately after admission (mechanical ventilation = yes = 1), has a systolic blood pressure (SBP) of 40 mmHg, has a base excess of –16.0 mmol/l, and has a fractional inspired oxygen concentration ($FIO_2$) of 1.00 with an arterial oxygen tension ($PaO_2$) of 60 mmHg.

Using the coefficients in Table 4 for the final PIM model derived from the entire fourth study sample, the PIM logit $=(2.357\times0)+(1.826\times1)+(-1.552\times0)+(1.342\times1)+(0.021\times\text{absolute}(40-120))+(0.071\times\text{absolute}(-16.0))+(0.415\times100\times1.00/60)-4.873=1.803$. The logit should not be used as an index of severity-of-illness or the probability of death, but should be converted to the predicted probability of death.

The predicted probability of death $= e^{\text{logit}}/(1+e^{\text{logit}})=2.7183^{1.803}/(1+2.7183^{1.803})=0.8585$, or 86%.

## References


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