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Cost Calculation and Prediction in Adult Intensive Care: A Ground-up Utilization Study

J. L. MORAN*, A. R. PEISACH†, P. J. SOLOMON‡, J. MARTIN§

Department of Intensive Care Medicine, The Queen Elizabeth Hospital, Woodville, South Australia

SUMMARY

The ability of various proxy cost measures, including therapeutic activity scores (TISS and Omega) and cumulative daily severity of illness scores, to predict individual ICU patient costs was assessed in a prospective "ground-up" utilization costing study over a six month period in 1991.

Daily activity (TISS and Omega scores) and utilization in consecutive admissions to three adult university associated ICUs was recorded by dedicated data collectors. Cost prediction used linear regression with determination (80%) and validation (20%) data sets. The cohort, 1333 patients, had a mean (SD) age 57.5 (19.4) years, (41% female) and admission APACHE III score of 58 (27). ICU length of stay and mortality were 3.9 (6.1) days and 17.6% respectively. Mean total TISS and Omega scores were 117 (157) and 72 (113) respectively. Mean patient costs per ICU episode (1991 $AUS) were $6801 ($10311), with median costs of $2534, range $106 to $95,602. Dominant cost fractions were nursing 43.3% and overheads 16.9%. Inflation adjusted year 2002 (mean) costs were $9343 ($ AUS). Total costs in survivors were predicted by Omega score, summed APACHE III score and ICU length of stay; determination R^2, 0.91; validation 0.88. Omega was the preferred activity score. Without the Omega score, predictors were age, summed APACHE III score and ICU length of stay; determination R^2, 0.73; validation 0.73. In non-survivors, predictors were age and ICU length of stay (plus interaction), and Omega score (determination R^2, 0.97; validation 0.91).

Patient costs may be predicted by a combination of ICU activity indices and severity scores.

Key Words: INTENSIVE CARE: cost, calculation, prediction

Analysis of cost data collected in the ICU has been beset by a number of distinctive problems: methodological study differences[1]; differing methods of costing[2], patient specific and non-specific, "top-down" and "bottom-up" costing; the ambiguous relation between costs and proxy variables, such as activity indices (Therapeutic Intervention Scoring System (TISS)[3], the Omega score[4,5]) and hospital length of stay[6]; and particular modelling difficulties[7], the distinct skewed distribution of the cost variable[8], the lack of a standard variable set compared with mortality algorithms[9], and the variably low multivariable predictive power of the developed models[10,11].

* M.B.B.S., F.R.A.C.P., F.J.F.I.C.M., Senior Consultant, Department of Intensive Care Medicine.
† M.B.B.S., F.J.F.I.C.M., Director, Department of Intensive Care Medicine.
‡ Ph.D., B.Sc., Associate Professor, School of Applied Mathematics.
§ B.Ap.Sc., Business Manager, Critical Care Business Management.

Address for reprints: Dr J. L. Moran, Department of Intensive Care Medicine, The Queen Elizabeth Hospital, 28 Woodville Road, Woodville, S.A. 5011.

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Studies have looked at the predictive ability of the TISS and Omega scores with respect to ICU patient costs, with varying results[5,10,12]. Similarly, the correlation of costs with severity of illness scores, in particular the APACHE II score, has also been inconsistent, but confounded by the restriction of measurement of the score to day of ICU admission[13-15]. The purpose of this study was to assess the ability of proxy cost measures, TISS and Omega scores and, in particular, cumulative daily severity of illness scores and ventilation days, to predict individual patient costs, derived from a "ground-up" utilization study.

METHODS

Costing Methodology

Cost data for ICU patient stay, including all related management activity, but excluding costs associated with provision of services external to the ICU, was generated from a nine-month study (1991) in three South Australian adult ICUs, using dedicated unit data collectors, recording daily activity (TISS, 1983 version 3 and Omega scores) and utilization. The source of the data was from a South Australian

Health Commission study conducted by the South Australian Intensive Care Costing and Casemix Study Group (report by KPMG Peat Marwick, Management Consultants, dated March 1994); components of this data have been previously used to report costing of specific ICU interventions[16]. The specific utilization elements were:

Drugs: Data on actual drug usage, including parenterally administered fluids were collected daily.

Procedural: Medical and surgical supplies, all medical and surgical supplies were identified and recorded, by procedure or by individual item.

Pathology costs: All pathology tests consumed were recorded by individual patient and costed using the current Commonwealth Government of Australia Benefits Schedule reimbursement rates.

Radiology costs: These were recorded by individual patient and costed using procedure costs developed by the South Australian Government Health Commission.

Physiotherapy costs: Each physiotherapy intervention was recorded by individual patient and costed using a standard unit of time.

Nursing staff costs: Nursing salary and wage costs were derived using actual minutes of nursing time for each ICU patient day (time spent on educational activities was excluded), standard nursing practice was 1-1 nurse patient ratio.

Medical staff costs: Medical salary costs were allocated to patients on the basis of days of ICU stay (time spent on educational activities was excluded), all medical staff were "full-time".

Overhead costs: Overhead costs attributable to the operation of each ICU were derived using the Yale DRG costing methodology[17], and allocated to patients on the basis of ICU length of stay.

Other costs: These were the residual costs reported in the ICU cost centre that remained unallocated to patients (such as administration, repairs and maintenance, orderlies salaries and wages, linen and domestic supplies) and were allocated to patients on the basis of ICU length of stay.

Re-admissions were included in the study and each stay was costed individually. Total costs (1991 $AUS) were computed as the sum of various cost fractions: (i) medication and procedural, (ii) nursing, physiotherapy and medical, (iii) radiology and pathology, (iv) overhead and other. Individual (patient) day costs were not available for analysis. Similarly, TISS and Omega score are presented as total scores per patient ICU episode.

Additional patient data recorded included:

Demographics: Age, gender, ethnicity, comorbidities consistent with the APACHE III algorithm[9].

ICU stay variables: Patient source, admission diagnosis and principal physiological system dysfunction on admission, ventilatory status, cardiorespiratory (heart and respiratory rate, systolic and diastolic blood pressure), arterial blood gas (pH, P_aO_2, P_aCO_2) and biochemical variables such that a daily APACHE III score could be computed for the first 8 days of ICU admission or until death or ICU discharge, ICU length of stay and outcome.

Hospital stay variables: Treating hospital, principal DRG, hospital length of stay and outcome.

Daily patient APACHE III scores were (raw) summed over the first 8 days or until discharge or death, to yield a "summed APACHE III score". Two extreme (cost) outliers (ICU costs >$AUS100,000) were omitted in analysis.

Statistical Analysis

Variables are reported as mean (SD) unless otherwise indicated. Interval data were analysed by t-test, and categorical data by Fisher exact test, where appropriate. Stata® statistical software (Version 8.0; 2003. Stata Corp, College Station, TX) was used.

Ordinary least squares regression (OLS) was used to predict costs in the untransformed (raw) form[7]. Analysis was divided into two parts, the prediction of total costs and non-overhead costs (that is total costs-overhead costs), on the basis that the independent variables used in analysis reflected (intrinsic) ICU activity[1]. Separate regression analyses were formed for ICU survivors and non-survivors[18]. Predictive equations were generated on a determination set (random sample of 80% of data, for both survivors and non-survivors) and validated upon a validation set (20% of data). As the survivor set was larger than the non-survivor, random sampling for determination/validation sets in the survivor subset reflected the proportional contribution of each of the three hospitals to that data set. The distribution of total costs was displayed using a kernel density plot[19] and graphical relationships between costs and potential predictor variables were rendered with the "lowess" smoothing technique[20] (details of these techniques are provided in the Appendix, section 1).

The selection of final predictor variables from an initial ensemble of potential predictors (n=15) was accomplished by minimization of the Akaike information criterion (a function of the model likelihood and number of covariates[21]) to yield a parsimonious final model(s). Non-linearity of covariate effect was determined using (parametric) fractional polynomials, which are flexible extensions of conven-

tional polynomials[22]. Details of selection processes between non-nested, competing models is also provided in the Appendix, Section 1. Final model performance was assessed by R^2 and, for the validation set, the R^2 was computed as the square of the correlation of cost and the predicted (cost) variable.

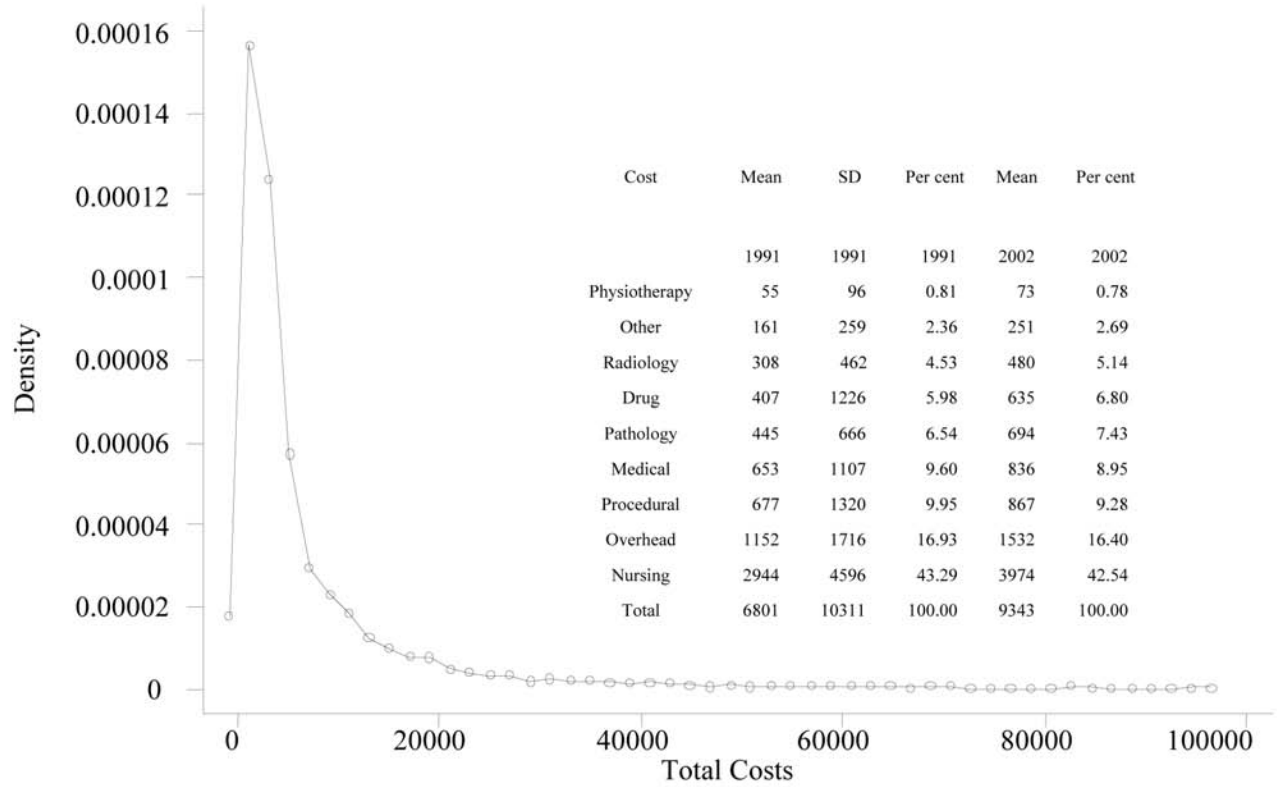
Predictive equations were determined for:

(a) total and non-overhead costs using all potential predictors, including TISS and Omega scores and raw-summed ventilated-days and APACHE III scores over the first 8 ICU days or until death or ICU discharge. The expectation was that the inclusion of one of the activity scores would yield high R^2 on the basis of their correlation with costs
(b) total and non-overhead costs using all potential predictors, but excluding TISS and/or Omega scores.

The relevance of the study for contemporary (year 2002) ICU costing was maintained by adjusting the cost estimates upwards by various inflation estimators, the details of which are given in the Appendix, Section 2.

RESULTS

The cohort consisted of 1333 patients of mean (SD) age 57.4 (19.6) years with 59% male; ICU and hospital mortalities were 17.6% and 27.5% respectively. On the first day of ICU admission, 57% were ventilated and the APACHE III score was 58 (27). Further patient characterization, including costs, is seen in Table 1 for all patients and survivors versus non-survivors. Classification of the most represented (n=18) DRGs, covering 50% of the patients is given in the Appendix, Section 3, Table A1. Mean patient costs per ICU episode were $AUS 6801 (year 1991) and $AUS 9343 (year 2002). The total cost distribution, with a table-insert revealing cost decomposition for the years 1991 and 2002, is shown in Figure 1. The majority of the cost data, as shown, was within the sharp peak of the curve (25th percentile=$1609 and 75th percentile=$7186); nursing salary and wages and overheads were the two dominant fractions of total costs. Both total and non-overhead costs exhibited marked kurtosis and skewness (P=0.001) and the variance differed significantly (P=0.0001) between survivors and non-survivors. Routine transformations of both cost variables did not produce normality, and log transformation did not stabilise the variance with respect to survivors/non-survivors. For ICU survivors and non-survivors, a significant difference existed between the means of the continuous variables: age, total and non-overhead costs, ICU and



Cost	Mean	SD	Per cent	Mean	Per cent
	1991	1991	1991	2002	2002
Physiotherapy	55	96	0.81	73	0.78
Other	161	259	2.36	251	2.69
Radiology	308	462	4.53	480	5.14
Drug	407	1226	5.98	635	6.80
Pathology	445	666	6.54	694	7.43
Medical	653	1107	9.60	836	8.95
Procedural	677	1320	9.95	867	9.28
Overhead	1152	1716	16.93	1532	16.40
Nursing	2944	4596	43.29	3974	42.54
Total	6801	10311	100.00	9343	100.00

FIGURE 1: Kernel density plot of total costs. Vertical axis, density; horizontal axis, costs in 1991 $AUS. Insert shows cost fractions for: 1991, mean, SD and per cent of total for each component. 2002, mean and per cent costs per component.

TABLE 1
Patient variables, mean(SD) or counts unless otherwise indicated for ICU survivors and non-survivors

Variable	Total	Survivors	Non-Survivors
n	1333	1099	234
Total costs	6801 (10311)	6230 (9383)	9485 (13567)
	*3025 (106-95602)	*2965 (106-95602)	*3692 (132-83085)
Costs: no overhead	5649 (8653)	5141 (7803)	8034 (11581)
	*2534 (73-81518)	*2432 (73-81518)	*3124 (128-70957)
ICU LOS (days)	3.9 (6.1)	3.6 (5.7)	5.3 (7.6)
	*2 (0.5-67)	2 (0.5-67)	2 (0.5-55)
Hospital LOS (days)	20.3 (23.0)	22.6 (24.0)	9.5 (13.0)
	*14 (0.5-248)	*16 (0.5-248)	*4 (0.5-84)
Total TISS score	117 (157)	104 (137)	179 (218)
	*63 (6-1433)	*58 (6-1433)	*92 (16-1428)
Total Omega score	72 (113)	62 (97)	123 (160)
	*37 (4-1153)	*32 (4-1121)	*61 (14-1153)
Age	57.5 (19.4)	56.3 (19.6)	63.3 (17.7)
APACHE III: day 1	58 (27)	51 (23)	90 (26)
Ventilation: summed days	1.7 (2.2)	1.4 (2.0)	2.9 (2.7)
APACHE III: summed	168 (170)	145 (148)	275 (217)
Hospital (patient number)			
1	494	417	77
2	301	257	44
3	538	425	113
Patient subsets:			
Ethnicity (Non Caucasian)	51	40	11
Readmissions	61	50	11
Elective surgery	268	257	11
Emergency surgery	267	218	49
Non-surgical	798	624	174
Trauma	119	106	13
COPD	15	14	1
Chronic dialysis	13	11	2
AIDS	3	3	0
Leukemia	20	12	8
Lymphoma	10	5	5
Immunosuppression	82	73	9
Metastatic carcinoma	38	26	12
Cirrhosis	32	25	7
Hepatic failure	8	6	2

*Median (range). LOS: length of stay. Total costs: costs in 1991 Australian dollars. AIDS: history of AIDS. Immunosuppression: immunosuppression by therapy. Trauma: blunt and penetrating trauma.

hospital length of stay, total TISS and Omega scores, APACHE III (1st day and summed) and ventilation days (Table 1, Hotelling's T-squared test, $P=0.0001$). Again, routine transformations did not resolve the non-normality of the above variables (Shapiro-Wilk test, $P=0.0001$).

Demographic data (age, gender, admission APACHE III score and length of stay) per total cost decile is seen in Table 2. Significant incremental trends (non-parametric trend test across ordered groups; $P=0.01$) across the deciles of costs were seen for admission APACHE III score, length of stay (ICU and hospital) and cost per day (computed, per patient, as total cost/ICU length of stay). Significant correlations (Bonferroni adjusted) were seen between costs and the proxy variables: TISS and Omega scores, ICU length of stay, summed APACHE III score and ventilation days (Table 3). Relationships between total costs and key proxy variables (Omega and TISS scores, ICU length of stay, summed ventilation days and summed APACHE III scores) are seen in Figure 2 using "lowess" plots. Generally linear or mild curvilinear univariate relationships are seen, except for summed APACHE III score in non-survivors, where a plateau for costs was seen at high summed APACHE III scores. However, this plateau appeared to be a function of the four extreme summed APACHE III scores (>800); deletion of these scores in the lowess plot produced a linear relationship.

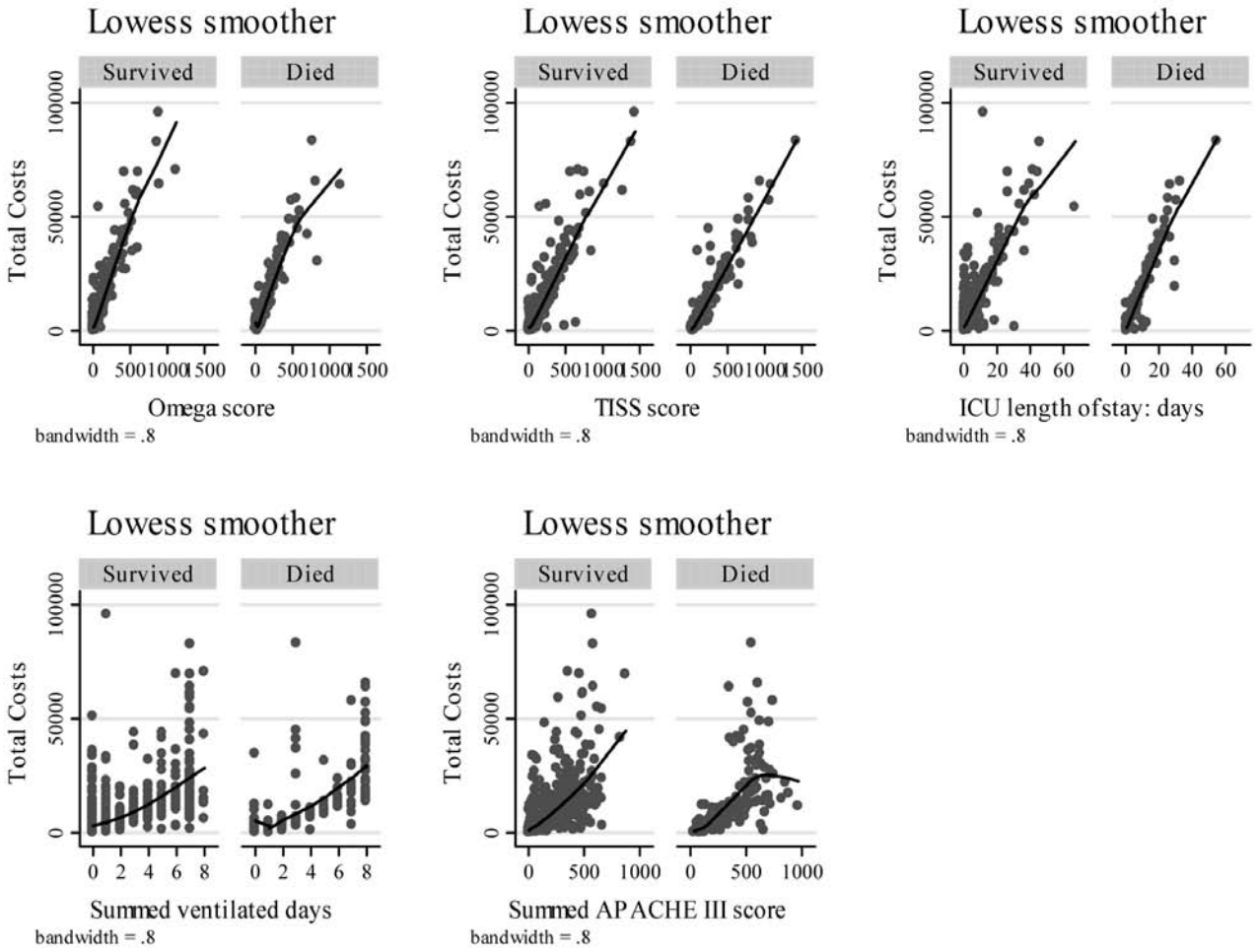


FIGURE 2: Smoothed "lowess" plot revealing relationship between total costs and key predictors, for survivors and non-survivors. Top panel, left to right: Omega score, TISS score, ICU length of stay. Bottom panel, left to right: summed ventilated days, summed APACHE III score.

TABLE 2

Demographic data across total cost deciles (mean (SD))

Cost deciles (n=)	Min tot cost $	Max tot cost $	Cost/day* $	Age years	Gender % males	Adm APIII*	ICU LOS* days	Hosp LOS* days
134	106	1049	1031 (505)	56 (21)	0.51	54 (34)	0.9 (1.1)	10.3 (19.6)
133	1052	1430	1446 (592)	54 (21)	0.55	47 (26)	1.3 (2.9)	13.7 (15.5)
133	1436	1788	1642 (538)	59 (18)	0.57	48 (25)	1.3 (1.6)	17.1 (19.2)
133	1801	2360	1975 (640)	58 (19)	0.66	57 (31)	1.2 (0.7)	12.0 (11.2)
134	2364	3024	1997 (865)	56 (20)	0.58	57 (27)	1.7 (1.3)	16.2 (18.1)
133	3041	4083	2026 (848)	59 (19)	0.62	59 (28)	2.0 (1.1)	16.4 (14.4)
134	4084	5795	2088 (1560)	62 (18)	0.56	61 (24)	3.0 (1.8)	24.0 (28.3)
133	5801	9421	2304 (2663)	58 (20)	0.62	62 (22)	4.4 (1.6)	26.9 (22.7)
133	9424	16532	3014 (3953)	56 (19)	0.59	64 (25)	6.5 (2.7)	23.8 (18.3)
133	16600	95602	3456 (5698)	59 (18)	0.66	67 (23)	17.0 (11.2)	42.5 (33.8)

Cost decile: deciles of total cost. Min tot cost: minimum total cost for the decile. Max tot cost: maximum total cost for the decile. Adm APIII: admission APACHE III score. ICU LOS: ICU length of stay. Hosp LOS: Hospital length of stay.
*Significant (P=0.01) increment across cost deciles.

TABLE 3
Costs, age and proxy variable correlations: all data

	Total	Nvh Costs	Age	Omega	TISS	ICU LOS	APIIIrs	Vdaysrs	ICU surv
Total	1.000								
Nvh Costs	0.999	1.000							
P	0.0001								
Age	0.016	0.014	1.000						
P	1.0000	1.0000							
Omega	0.930	0.928	0.015	1.000					
P	0.0001	0.0001	1.0000						
TISS	0.921	0.918	0.033	0.901	1.000				
P	0.0001	0.0001	1.0000	0.0001					
ICU LOS	0.876	0.872	0.033	0.810	0.786	1.000			
P	0.0001	0.0001	1.0000	0.0001	0.0001				
APIIIrs	0.675	0.676	0.175	0.627	0.672	0.696	1.000		
P	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001			
Vdaysrs	0.643	0.642	0.023	0.644	0.660	0.676	0.804	1.000	
P	0.0001	0.0001	1.0000	0.0001	0.0001	0.0001	0.0001		
ICU surv	0.120	0.127	0.137	0.205	0.183	0.103	0.291	0.247	1.000
P	0.001	0.0004	0.0001	0.0001	0.0001	0.006	0.0001	0.0001	

Total: total costs. NvhCosts: No overhead costs. Omega: Omega score. TISS: TISS score. ICU LOS: ICU length of stay (days). APIIIrs: APACHE III score summed over 8 days. Vdaysrs: Ventilated days, summed over 8 days. ICU surv: ICU outcome (binary variable).

Variables predicting total costs in ICU survivors and in non-survivors are seen in Tables 4 and 5 respectively. These variables were a combination of age, Omega score, ICU length of stay, summed APACHE III score and summed ventilation days. No significant colinearity was demonstrated. For models where activity indices (TISS and Omega scores) were considered, a significant advantage of the Omega score was apparent ($P=0.0001$). Non-linear effects were demonstrated in:

(a) survivors for the Omega score (with respect to total costs) and ICU length of stay (total and non-overhead costs)
(b) non-survivors for summed ventilated days and ICU length of stay (total and non-overhead costs).

These effects were, however, of mild degree and poor performance was demonstrated for models with non-linear terms with respect to validation R^2, except for survivors where the Omega score was not considered. Here a fractional polynomial was used to model ICU length of stay (Table 4, model (ii)); the functional form of this fractional polynomial is seen in Appendix, Section 4 as Figure A1. A significant interaction between age and ICU length of stay (both modelled linearly) was included in the final model for non-survivors (Table 5, model(i)). In survivors (Table 4), predictive performance in the determination and validation sets was impressive with the full ensemble of predictors but declined when the Omega score was not considered. In non-survivors (Table 5), predictive performance was consistent across models.

No difference existed in model performances (R^2) when non-overhead costs were substituted for total costs (data not shown). The significant covariates, not surprisingly, differed somewhat, although the Omega score was still the preferred ICU activity index.

In survivors, summed ventilation days was not a predictor.

In non-survivors, when the Omega score was not considered, neither age nor the age-ICU length of stay interactions were significant. Summed APACHE III score was a significant predictor (β (SE): 14.57 (3.35), $P=0.0001$) as was its interaction with age (β (SE): –0.203 (0.042), $P=0.0001$).

DISCUSSION

Three important aspects of the general problem of costs analysis have been illuminated by the above results: calculation of costs and their fractions, the use of proxy and transformed variables in cost analysis and appropriate predictive models.

Cost Calculation

The methodology in the current paper was consonant with recent recommendations for the conduct of "bottom-up" prospective studies[2,23,24]. The fractionation of costs was also comparable, in particular the dominant nursing salary/wages component at approximately 40%[13,14,25]. However, major variances in other cost components have been found in the comparator literature[26]. For example: "room" costs were reported at 52% of total in two recent charge based

TABLE 4

Parameters and performance indices of cost predictive models: ICU survivors

Model	(i) Total costs			(ii) Total costs		
Variable	Coefficient	SE	*P*	Coefficient	SE	*P*
Age				–16.6	8.81	0.05
Omega score	77.61	1.77	0.0001	Not considered		
APIIIrs	5.12	0.92	0.0001	11.33	1.96	0.0001
ICUlos	239.14	34.70	0.0001	6904.45*	576.19	0.0001
				–2776.1*	402.03	0.0001
_cons	–135.60	132.12	0.31	5325.58	169.41	0.001
R^2_det (n=877)	0.91			0.73		
R^2_val (n=222)	0.88			0.73		

Model: (i) all potential predictors considered, (ii) all potential predictors considered, except activity indices (TISS or Omega score). Ventdayrs: summed ventilation days. APIIIrs: summed APACHE III score. ICU LOS: ICU length of stay in days. R^2_det: R^2 in determination set. R^2_val: R^2 in validation set.
*Fractional polynomial describing the variable effect, with powers 2,2

TABLE 5

Parameters and performance indices of predictive models: ICU non-survivors

Model	(i) Total costs			(ii) Total costs		
Variable	Coefficient	SE	*P*	Coefficient	SE	*P*
Age	26.71	11.00	0.02	–28.79	15.0	0.05
Omega score	55.89	3.30	0.0001	Not considered		
Ventdayrs				294.56	142.85	0.04
ICU LOS	1422.3	128.1	0.0001	1697.3	62.3	0.0001
Interaction						
Age*ICU LOS	–9.49	1.69	0.0001			
_cons	2923.9	735.4	0.0001	1627	1050	0.12
R^2_det (n=186)	0.97			0.91		
R^2_val (n=48)	0.91			0.89		

Model: (i) all potential predictors considered, (ii) all potential predictors considered, except activity indices (TISS or Omega score). Ventdayrs: summed ventilation days. ICU LOS: ICU length of stay in days.Interaction: interactions between variables, modelled linearly. R^2_det: R^2 in determination set. R^2_val: R^2 in validation set.

studies, these included pharmacy and "supply" costs in one study[27] but not in the other[28]. Laboratory and radiology costs have varied from 22 to 25% in both charge[28] and cost based studies[25] to 8 to 16% in activity based studies[14,29], including the current.

Cost Predictor Variables

A wide variety of variables, some of which are cost-proxies, have been shown to predict costs, however calculated. When potential predictors are restricted to patient demographic data (for example, age and gender) and first day ICU admission variables (for example, type of surgery and acute physiology score), the R^2 for multivariable OLS is low; for example, 0.13[10]. Such was the case in this study with an R^2=0.09 for OLS predicting total costs in ICU survivors, with predictors age, gender and admission APACHE III score (data not shown). The proxy variables ICU length of stay, TISS and Omega scores, all had cost correlations of 0.85 (Table 3), similar to results from other adult ICU studies[5,15,30], but not uniformly[31]. The latter inconsistency provoked editorial comment[12] with respect to the lack of correlation, in a paediatric environment, between TISS scores and costs.

This reported lack of correlation between activity and cost is somewhat perplexing. The study in question, by de Keizer et al[31], used regression models based upon the assessment of a limited number of patient admissions (n=33) during a calibration period, to estimate physician and nurse activity-time and medication use. The authors, defending their methodology, noted that the basic unit of measurement was resolved to a ten-minute activity period, which, expanding over patient days, yield approximately 300,000 counts as a seeming stable calibration base. However, in the formal OLS calibration equations, the unit of consideration was patient day and these days were considered as being independent,

which ignored the clustering effect of days in patients, and furthermore, no validation set was utilized. That conventional step-wise techniques used in the study prevented "over"-estimation is also a questionable claim, given the recent critiques of this technique, and the assurance of "acceptable reliability" belies the known optimism of "determination" regressions[32].

Of interest in the current study was the superior predictive ability of the Omega score compared with TISS. Few reports have looked at the comparative predictive efficacy of therapeutic activity scores. Where this has occurred, in the assessment of risk factors for nosocomial infection, both indices performed similarly, although no formal statistical comparison was undertaken[33]. A similar situation pertains to the optimal severity of illness score. APACHE III[10], APACHE II[14,15], SAPS II[23] and MPM[34] have all been used singularly to "predict" or adjust for costs (or charges). Some evidence, albeit in non-ICU patients, suggests that differential performance may exist[35].

Due to its labour-intense character, ground-up utilization studies appear non-sustainable in the long term[23,24]. As collection of therapeutic activity scores (TISS and Omega) may not be routine, evidence was sought for the efficacy of more accessible predictive indices, such as the (raw) summed ventilator days and APACHE III scores, both of which had high correlation (0.63) with costs. Somewhat surprisingly, age as an independent predictor, had a negative β coefficient in both survivors and non-survivors, although the effect was modest given the range of age (16-96 years) and the scalar quantity of the coefficient (–16.6 and –28.79), relatively small compared with other covariates.

Predictive Models

Although the cost variables (total and non-overhead costs) demonstrated non-normality, OLS regression with the dependent variable un-transformed was used, after the recommendations of Diehr et al[7], as the focus of this study was to predict individual patient dollar costs. In the complete data set, OLS regression of total cost against: ICU length of stay, Omega score, summed APACHE III score and ventilated days, and ICU outcome, found all predictors significant at $P=0.0001$ with an R^2 of 0.91. Siegel et al[36] similarly found that survival was the "most important" determinant of hospital costs in a trauma centre, but survival was not a predictor in multivariable, as opposed to univariate, analysis in the paediatric study of Chalom et al[28]. In the current study, survivors and non-survivors had significantly different variances of the cost variables. As pointed out by Clarke and Ryan[18], using an outcome variable (ICU survival) as an independent variable to predict an alternate outcome (in this case, cost) is problematic. Thus survivors and non-survivors were considered separately; this point is further expanded in the Appendix, Section 5.

The poor predictive capability (in the validation sets) of the non-linear modelling of covariates (see Results, above) was undoubtedly due to the effect in the determination set of outlying data points in the skewed covariates (Omega score, ICU length of stay and summed ventilated days) unduly influencing the degree (of non-linearity) of the fractional polynomials. A similar influence was noted in the "lowess" plot of total costs against summed APACHE III score in non-survivors (see Figure 2 and Results, above), albeit the APACHE III score was not a significant predictor for total costs in non-survivors.

The predictive performance of the multivariable equations for total (and non-overhead) costs in survivors without the Omega score (validation $R^2=0.73$) was acceptable, but obviously suffered from the exclusion of a covariate highly correlated with cost. The reasons for the improved performance of the non-Omega score regressions in non-survivors were not immediately apparent, but the data-set size was probably a factor. When non-overhead costs were considered in non-survivors, the summed APACHE III score became an additional significant predictor (compared with total costs; see Results, above), but performance was not enhanced. The actual components of direct (fixed and variable) and indirect ICU costs vary within the reports in literature[5,25,28], as pointed out above.

Critique of Methodology

Although systematic inflation adjustment was able to generate calendar year 2002 costs and cost fractions (Figure 1), these estimates may be biased due to changes in the structure of care and case-mix that occurred during the period 1991 to 2002. In particular, cost composition may have shifted due to, for example, modification of the staffing profile, in treatment regimens and pathology-radiology utilization. Similarly, independent predictor variables may also have shown temporal change; most likely a decrease in ICU length of stay and an increase in age profile and severity of illness. Such changes may not have maintained the predictive performance advantage of the Omega system with respect to TISS, as found in this study. New simplified utilization/activity indices, TISS-28[37], and Nursing Activities Score[38], may now be

more cost-effective[39] for routine collection and would be appropriate candidate predictors of total costs.

Thus the import of the present study is methodological, to the extent that what has been demonstrated is the ability of "simple" indices, length of stay and (summed) severity of illness scores, to predict total ICU costs. Moreover, these indices retained predictive ability in the validation sets. An approach to modelling these predictors was also developed, with importance given to the elucidation of non-linear covariate effect and interactions and the appropriate analysis of the survivor and non-survivor subsets. The robustness of the above models to different formulations of total costs[15] and combinations of costs fractions approximating "direct" ICU activity is obviously an empirical question in need of further investigation.

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APPENDIX

Section 1

A kernel density plot is a modification of the simplest density estimator, the histogram. Densities are the continuous analogues of proportions (formally, they are derivatives of the cumulative distribution function, so that areas under the density function read off as probabilities[18]. The data is divided into intervals (which may overlap) and estimates of the density at the interval centres are produced; the "kernel" is the function (a number are available) which weights the observations by the distance from the centre of the interval.

"Lowess" is a scatter plot smoothing technique (of y on x) which uses locally weighted regression to summarize the middle of the distribution of a dependent variable (for example, cost=y) for each value of an independent variable (for example, Omega score= x). Lowess plots effectively let the data "speak for itself"[19].

Selection between non-nested models was determined by the J and Cox-Pesaran tests and the BIC score (Bayesian information criterion, a likelihood-based method of choosing a model, similar to AIC; critical difference=10 and model with lower value preferred)[40]. Nested models are those in which covariates in one model form a subset of the covariates in a larger model and formal goodness-of-fit to the data can be compared using standard tests. In the present context, two competing models predicting costs with covariates, say: (i) Omega score, ICU length of stay and age versus (ii) TISS score, ventilated days and summed APACHE III score as a fractional polynomial, would be considered non-nested.

Section 2

The relevance of the study for contemporary (year 2002) ICU costing was maintained by adjusting the cost estimates upwards by various inflation estimators, based upon: (i) South Australian public sector wage rises for the period 31/08/1991-01/10/2002 for a Professional Service Officer (PSO1 6th year of experience), (ii) Australian Bureau of Statistics Consumer price index, subset Health, subset Hospital and medical services for the period Sept quarter 1991 to December quarter 2002, (iii) South Australian public sector wage rises for the period 07/09/1991-01/01/2002 for a Medical consultant classification MD-2 8th year of experience, (iv) South Australian public sector wage rises for the period 06/08/1991-01/10/2002 for a registered nurse classification RN-1 8th year of experience. The inflation factors were: Physiotherapy (1.33), Other (1.56), Radiology (1.56), Drug (1.56), Pathology (1.56), Medical (1.28), Procedural (1.28), Overhead (1.33), Nursing (1.35).

Section 3

Table A1. Top 18 DRGs

DRG	% of total
Major vascular surgery	7.13
Extensive surgery unrelated to principal diagnosis	4.28
Gastric surgery	3.98
Uncomplicated Self poisoning	3.83
Small and large bowel surgery	3.53
Craniotomy	3.45
Craniotomy for trauma	3.45
Acute heart failure and shock	2.78
Complicated self poisoning	2.70
Circulatory disorders with MI	2.18
COPD	2.03
Pulmonary oedema and respiratory failure	1.88
Major head and neck procedures	1.65
Cardiac arrest	1.65
Pneumonia with complications	1.58
Extracranial vascular procedures	1.35
Other surgical procedures for injuries	1.35
Circulatory disorders	1.28

DRG classification from the Health Care Financing DRG listing provided by the Healthcare Cost and Utilization Project[41].

Section 4

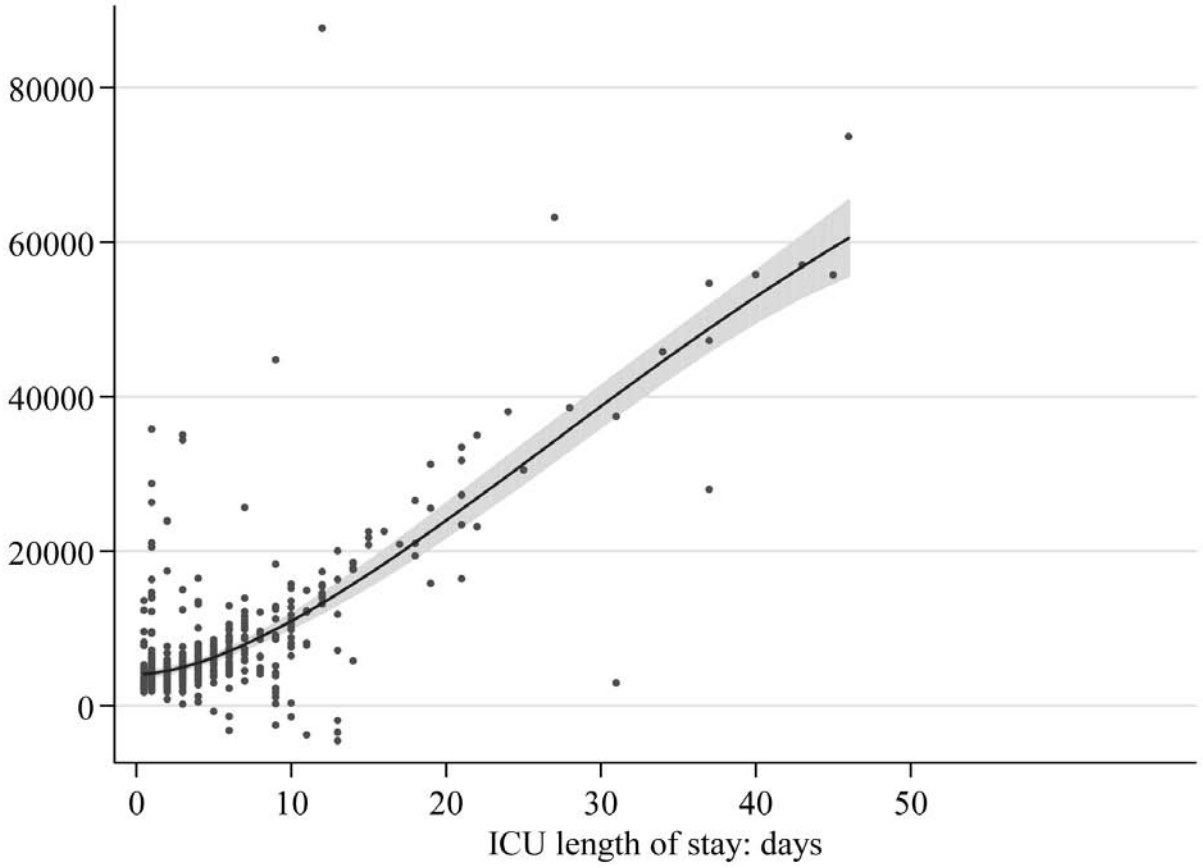

FIGURE A1: Functional form of the 2,2 fractional polynomial relating Total costs to ICU length of stay in survivors (Table 4, model ii). Horizontal axis, length of stay in days. Vertical axis, total costs ($ Australian). Solid line, fitted values plus weighted residuals adjusted for other covariates. Shaded area, 95% CI of fitted values. Solid circles, individual data points.
Added note: fractional polynomials, are extensions of the conventional polynomial, allowing unique and repeated powers of a (positive) continuous variable, the powers being (–2, –1, –0.5, 0, 0.5, 1, 2, 3) and the power 0=logarithm. Thus a 2,2 fractional polynomial has the general form: $\beta_0+\beta_1x^2+\beta_2x^2\log x$, where β_0 is the intercept and x, the continuous covariate.

Section 5

The question of whether data can be pooled (in this case, consideration of survivors and non-survivors) together within the same regression equation is subject to formal testing by the Chow test[42], which assesses the equality of sets of coefficients estimated over two sets of linear regressions (survivors and non-survivors). A significant Chow test indicates the inappropriateness of combining the regressions (that is, pooling survivors and non-survivors). In the current study, the Chow test was highly significant, $P=0.0001$.