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Using Trauma Injury Severity Score (TRISS) variables to predict length of hospital stay following trauma in New Zealand

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Abstract

Aim To develop and assess the predictive capabilities of a statistical model that relates routinely collected Trauma Injury Severity Score (TRISS) variables to length of hospital stay (LOS) in survivors of traumatic injury.

Method Retrospective cohort study of adults who sustained a serious traumatic injury, and who survived until discharge from Auckland City, Middlemore, Waikato, or North Shore Hospitals between 2002 and 2006. Cubic-root transformed LOS was analysed using two-level mixed-effects regression models.

Results 1498 eligible patients were identified, 1446 (97%) injured from a blunt mechanism and 52 (3%) from a penetrating mechanism. For blunt mechanism trauma, 1096 (76%) were male, average age was 37 years (range: 15–94 years), and LOS and TRISS score information was available for 1362 patients. Spearman's correlation and the median absolute prediction error between LOS and the original TRISS model was ρ=0.31 and 10.8 days, respectively, and between LOS and the final multivariable two-level mixed-effects regression model was ρ=0.38 and 6.0 days, respectively. Insufficient data were available for the analysis of penetrating mechanism models.

Conclusions Neither the original TRISS model nor the refined model has sufficient ability to accurately or reliably predict LOS. Additional predictor variables for LOS and other indicators for morbidity need to be considered.

In New Zealand, injuries account for approximately 1600 deaths and 42,000 hospitalisations per annum; with associated social and economic costs of NZ$6–7 billion per year.[1]

Reducing preventable injuries is one of the main public health challenges for New Zealand in the 21st Century.[2] The national burden of injury can be addressed by the primary prevention of injury occurrence, improving acute care of injury and maximising opportunities for rehabilitation of the injured person.

Improvements in trauma care over the last few decades have been responsible for substantial improvements in survival rates following major trauma,[3–5] although further safety and error reductions are achievable. A recent South Western Sydney trauma death review analysis found that 22.5% of all deaths were avoidable;[5] a result consistent with other preventable death studies conducted in Australia and New Zealand.[6–8] However, little is known about the extent that improvements in trauma

care have lead to decreased injury-related morbidity and improved long-term outcomes.

Quality control programs for existing trauma systems focus on fatality indicators and pay scant attention to improving measures of long-term outcome of injury patients.[5,9] Given that the majority of patients survive their injuries, and a large proportion of these experience disability up to 12 months following injury,[10–13] ignoring non-fatality indicators neglects a fundamental component of trauma system performance measurement.[3,14]

Capturing both fatality and non-fatality indicators would enable trauma management to facilitate improvements that aim to reduce mortality and morbidity. For instance, a 2007 United Kingdom national confidential enquiry into patient outcome and death following trauma showed that almost 60% of the patients received a standard of care that was less than good practice.[15] It is naturally of interest to determine the effect of mortality and morbidity rates by increasing the level of good practice standard care.

The focus on fatality indicators in existing trauma systems is due, in part, to the lack of a valid "threat to morbidity" injury severity score available for use in routine trauma data collection. Further, there is no international consensus on appropriate morbidity scores that can be used to benchmark non-fatal outcomes from injury.[3,10]

The trauma injury severity score (TRISS) methodology is a simply applied parsimonious model with good predictive capabilities for threat to survival and has become the backbone of trauma system quality assurance.[9] Attempts to develop a "threat to morbidity" injury severity score have focused on modelling length of stay (LOS), a commonly adopted proxy measure of morbidity obtainable from routine hospital data.[11,16] Many complicated techniques have been advocated and a multiplicity of variables used to model LOS.[17–19] These techniques are limited by the need for additional information and techniques above those already collected or available in many trauma registries around the world.

Given the universal acceptance of the TRISS methodology, and that a recent paper has confirmed its utility in the New Zealand context for quantifying threat to life,[20] it is important to quantify the extent to which the variables used in the TRISS methodology can be used to predict LOS before embarking upon the development of complex models to predict threat to morbidity. This question has not yet been addressed within the New Zealand trauma care context.

The TRISS variables (age, Injury Severity Score [ISS], Glasgow Coma Scale [GCS], systolic blood pressure [SBP], and respiratory rate [RR]) are universally collected and consistently defined in registries throughout the world. Using data from four New Zealand trauma registries, serving approximately half New Zealand's population, this study aimed to develop and assess the capabilities of a multivariable two-level mixed-effects regression model that predicts LOS in survivors of traumatic injury based on the routinely collected TRISS variables.

Method

Detailed information about the sample and procedure is described elsewhere.[20]
Study design—Retrospective cohort study.

Study population and period—All adult New Zealanders (aged ≥15 years) who sustained a serious traumatic injury, defined as having Injury Severity Score (ISS)>15, and who survived until discharge from Auckland City, Middlemore, Waikato, or North Shore Hospitals between 1 January 2002 and 31 December 2006. The ISS is a sum of the square of the three most injured body regions (head, face, thorax, abdomen, lower and upper extremities), each having severity assessed via the Abbreviated Injury Scale: 1 Minor, 2 Moderate, 3 Serious, 4 Severe, 5 Critical.[21] Cases of poisoning, burns, hangings, and simple fractured necks of femurs were excluded.

Procedure—Unit record data was extracted from each of the participating trauma registries. Not all registries operated for the duration of the data collection period, thus data was obtained for the period of times available at each registry (Auckland City and Middlemore Hospitals: full coverage from 1 January 2002–31 December 2006; Waikato Hospital: 1 January 2002–31 December 2003; and North Shore Hospital: 14 June 2004–31 December 2006). Waikato Hospital's Trauma Registry was restarted in June 2006 but data from this period was unavailable for extraction.

Extracted variables included: date of birth or age, and gender; anatomical and physiological parameters of injury severity before and after arrival in the emergency department; external cause and intent of injury; hospital stay and survival status. A hospital trauma number was also extracted for data validating purposes. De-identified data were downloaded into separate password protected Microsoft Excel files.

TRISS model—The TRISS model, which estimates the probability of survival (P_S), has two separate specifications:

- For injuries sustained from a blunt mechanism, and
- For injures sustained from a penetrating mechanism.

The $P_S = 1/(1 + e\text{-}b)$ where: $b = -0.4499 + (0.2351 \times RR) + (0.5923 \times SBP) + (0.7574 \times GCS) - (0.0835 \times ISS) - (1.7430 \times Age)$ for blunt mechanism trauma, and $b = -2.5355 + (0.2889 \times RR) + (0.7278 \times SBP) + (0.9306 \times GCS) - (0.0651 \times ISS) - (1.1360 \times Age)$ for penetrating mechanism trauma.[22]

In these expressions, ISS has values from 16 to 75; Age is coded: '0' if patient age is 15–54 years, and '1' if patient age is ≥55 years; respiratory rate (RR) is coded '0' if patient has 0 breaths/minute, '1' for 1-5 breaths/minute, '2' for 6–9 breaths/minute, '3' for >29 breaths/minute, and '4' for 10–29 breaths/minute; systolic blood pressure (SBP) is coded '0' if patient has 0 mmHg pressure, '1' for 1–49 mm Hg, '2' for 50–75 mmHg, '3' for 76–89 mmHg, and '4' for >89 mmHg; and the Glasgow Coma Scale (GCS) is coded '0' for a score of 3, '1' for scores 4–5, '2' for scores 6–-8, '3' for scores 9–12, and '4' for scores 13–15.

Statistical analyses—Raw data from each hospital registry was converted into a separate file that used consistent variable names and definitions. Consistency and range checks were performed to identify any discrepant or anomalous data. When identified, checks were made to the raw data file or, where permitted, to the hospital registries for data verification. No data trimming or replacing aberrant unvalidated data with missing values was undertaken. The separate databases were then combined using SAS version 9.1 (SAS Institute Inc, Cary, NC, USA) and exported into one Microsoft Excel file for subsequent analysis in Stata version 10 software (StataCorp, College Station, TX, USA).

LOS was calculated as: discharge date-admission date. As the trauma registries in the sample do not track patients between hospitals, and data were de-identified, it was not possible determine the cumulative LOS of an injury event for a patient who had a hospitals transfer. Instead, these transfers and readmissions were generally counted as separate admissions in each registry, each having a separate non-cumulative LOS value. Recognising that patients were nested within hospitals, two-level mixed-effects regression models were employed to model LOS. Hospitals were treated as random effects within the model.

Given the skewed distribution of LOS, three standard power transformations of the LOS data were considered (logarithmic, square-root and cubic-root), and residuals assessed from two-level mixed-effects regression models using the TRISS variables and their original specifications to determine:

- Which transformation was most appropriate for the data, and
- Whether the assumptions of the regression model would be importantly violated. Shapiro-Wilk's W statistics and a visual assessment of a histogram of the residuals was used to make this assessment.

Various characterisations of all candidate predictive variables were the derived and compared in bivariable two-level mixed-effects regression models using the Bayesian information criterion (BIC).[23]

The BIC penalises for model complexity and rewards for goodness-of-fit; with the preferred model balancing these competing demands and yielding the lowest BIC value. Separate regression models were then developed for each potential explanatory measure. Those that were statistically significant were entered into a multivariable model and a manual backward selection process was used to eliminate non-significant variables until the most parsimonious main effects model was determined. Then all two-factor interactions were included and again a backward selection method was employed to eliminate non-significant variables.

Residual checks were undertaken after the derivation of the final multivariable two-level mixed-effects regression model to determine whether important violations of the model's assumptions existed. Finally, the predictive abilities of the final regression model was assessed using Spearman's correlation coefficient and the median absolute prediction error (MAPE), derived by taking the absolute difference between predicted and observed LOS values. For comparison, the MAPE analysis was repeated using predicted values derived from a regression model that included the original TRISS variables and their original specifications. The $\alpha=0.05$ was used to defined significance for all statistical tests.

Ethics—Patients were identified by each registry according to the inclusion criteria and all data was made anonymous before study investigator access. The study was conducted in accordance with a protocol approved by the Griffith University Ethics Committee, Australia; Auckland District Health Board and the Northern X Regional Ethics Committee in Auckland, New Zealand. For the remaining participating registries Gatekeeper Approvals were sought as the project was assessed to be a de-identified audit activity and was deemed not to require ethics approval (North Shore, Middlemore, and Waikato Hospitals).

Results

There were 1498 eligible patients identified, 1446 (97%) injured from a blunt mechanism and 52 (3%) injured from a penetrating mechanism.

Blunt mechanism trauma

The average age of the 1446 blunt mechanism trauma survivors was 37 years (range: 15–94 years) and 1096 (76%) were male. All 1446 patients had a valid LOS value. Overall, the median LOS was 11 days (range: 0–171 days). For those who were transferred from another hospital, their median LOS was 10 days (range: 0–121 days), while for those who made no hospital transfer, their median LOS was 11 days (range: 0–171 days). LOS of 0 days represents the situation where discharge date and admission date were the same. Figure 1 reveals that the LOS distribution is highly positively skewed; confirmed by the empirical dispersion index (variance/mean ratio)=18.3.

Sufficient information was available to calculate TRISS scores for 1362 (94%) patients. There was no difference in LOS between patients with and without available information to calculate TRISS scores (two-sample Wilcoxon rank-sum test, P=0.77).

Data transformation

Table 1 includes the Shapiro-Wilk's W statistics from the standardised residuals yielded from the two-level mixed-effects regressions using untransformed and three standard power transformations of LOS (logarithmic, square-root, and cubic-root). Note that the W statistic must lie in the range $0<W\leq1$ and small values of W lead to the rejection of the normality assumption. Table 1 reveals that the cubic-root transformation yields residuals most consistent with the normality assumption (having

the largest W statistic). A histogram of these residuals provided little evidence that the assumption of normality was importantly violated.

Figure 1. Histogram of length of stay for traumatic injuries resulting from blunt mechanisms in New Zealand adult (≥15 years)
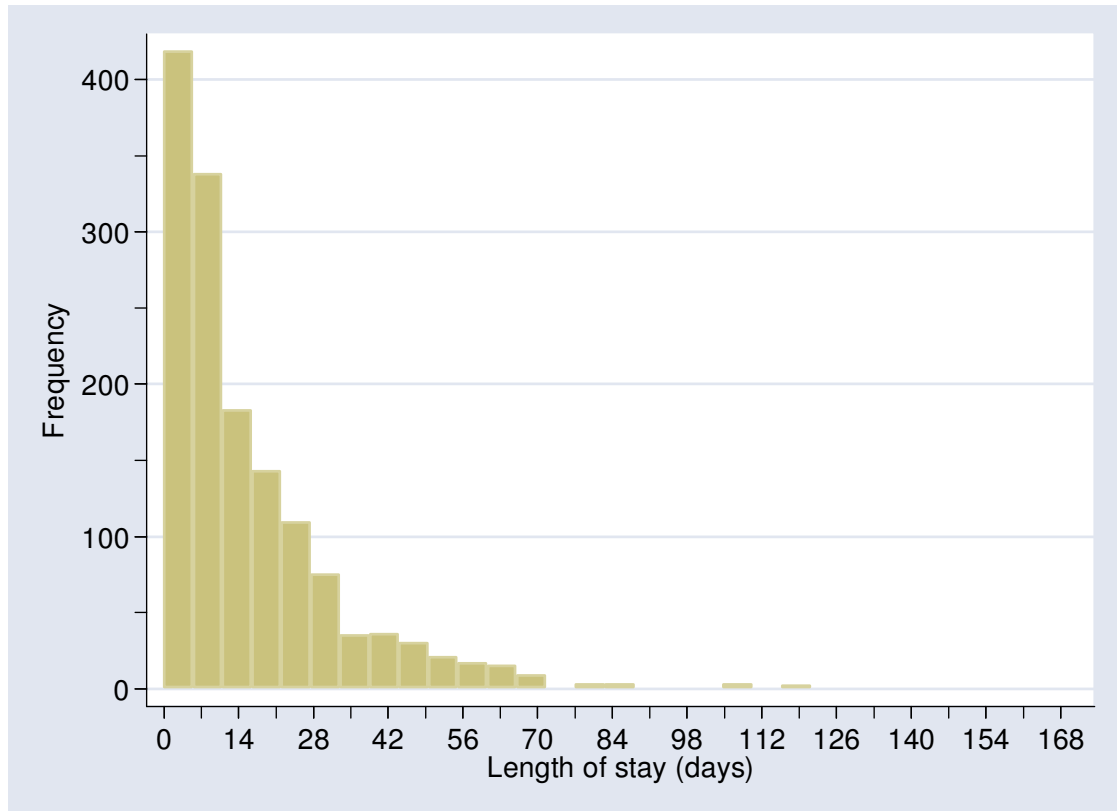
Table 1. Shapiro-Wilk's W statistics for the standardised residuals of various power transformations of the length of stay (LOS) data regressed from two-level mixed-effects regression models using the TRISS variables and their original specifications

Power transformation	Shapiro-Wilk's W
Identity (untransformed)	0.795
Logarithmic [log(LOS)]	0.987
Square-root [√LOS]	0.962
Cubic-root [^{3}√LOS]	0.990

Optimising the components of the predictive model

All variables used in the original TRISS model were investigated. Each variable was investigated separately in the two-level mixed-effects regression model of cubic-root transformed LOS, and characterisations were assessed using the BIC statistic.

Age—Four characterisations of age were considered:

- Age (years) as a continuous variable (mean=36.6 years, SD=18.2 years);

- Log(age) as a continuous variable (mean=3.5, SD=0.5);

- Age partitioned into approximate quartile: 15–20 years (n=356, 25%), 21–35 years (n=458, 32%), 36–50 years (n=309, 21%), and >50 years (n=323, 22%); and

- Age dichotomised according to the original TRISS specifications: 15–54 years (n=1190, 82%), and ≥55 years (n=256, 18%).

The resultant BIC=3611.84, 3603.87, 3623.43, and 3606.34, respectively. Based on this BIC statistic, log(age) as a continuous variable best predicts LOS.

Injury Severity Score (ISS)—Four characterisations of ISS were considered:

- ISS as a continuous variable between 16 and 75, as used in the original TRISS model (mean=22.6, SD=7.5);

- Log(ISS) as a continuous variable (mean=3.1, SD=0.3);

- ISS trichotomised into clinically relevant groups: 16-24 (n=951, 66%), 25-41 (n=456, 32%), and 42-75 (n=39, 3%); and

- ISS partitioned into approximate quartiles: 16 (n=268, 19%); 17-20 (n=447, 31%); 21-25 (n=388, 27%); and 26-75 (n=343, 24%).

The resultant BIC=3503.93, 3484.02, 3532.80 and 3486.48, respectively. Based on this BIC statistic, log(ISS) as a continuous variable best predicts LOS.

Glasgow Coma Scale (GCS)—Two characterisations of GCS were considered:

- Categorising GCS according to the original TRISS specifications: 3 (n=74, 5%), 4–5 (n=46, 3%), 6–8 (n=129, 9%), 9–12 (n=140, 10%), 13–15 (n=1,024, 72%), and then treating these groups as a continuous variable as used in the original TRISS model; and

- Treating the GCS groups as a categorical variable.

The resultant BIC=3450.41 and 3477.64, respectively. Based on this BIC statistic, treating GCS groups as a continuous variable best predicts LOS.

Systolic blood pressure (SBP)—Two characterisations of SBP were considered:

- Categorising SBP according to the original TRISS specifications: 0–49 mmHg (n=14, 1%), 50–75 mmHg (n=22, 2%), 76–89 mmHg (n=50, 4%), and >89 mm Hg (n=1,311, 94%), and then treating these groups as a continuous variable as used in the original TRISS model; and

- Treating the SBP groups as a categorical variable.

The resultant BIC=3418.43 and 3403.55, respectively. Based on this BIC statistic, treating the SBP groups as categories best predicts LOS.

Table 2. Coefficient estimates (Est.) and associated 95% confidence intervals (95%CI) of the 2-level mixed-effects regression models, with patients nested in hospitals, and hospitals treated as random effects, for bivariable comparisons between each candidate predictor variable and the cubic-root transformed length of stay (LOS) variable, for the multivariable main-effects model of all significant candidate predictor variables, and for the full multivariable two-level mixed-effects regression model which includes the main-effects model and all significant two-factor interactions

Predictor variables	Bivariable analysis			Multivariable main effects			Full multivariable model		
	Est.	(95%CI)	P-value	Est.	(95% CI)	P-value	Est.	(95%CI)	P value
log(Age in years)	0.120	(0.032–0.208)	0.008	0.160	(0.076–0.244)	<0.001	0.159	(0.075–0.243)	<0.001
log(Injury Severity Score)	0.855	(0.709–1.001)	<0.001	0.760	(0.608–0.912)	<0.001	0.756	(0.604–0.908)	<0.001
Glasgow Coma Score	-0.105	(-0.143–-0.067)	<0.001	-0.081	(-0.121–-0.041)	<0.001	-0.088	(-0.130–-0.047)	<0.001
Systolic blood pressure mm Hg			<0.001			0.02			0.007
0-49	-0.792	(-1.216–-0.369)		-0.635	(-1.169–-0.100)		-3.002	(-5.059–-0.945)	
50-75	0.370	(0.032–0.709)		0.107	(-0.214–0.429)		-0.734	(-1.666–0.197)	
76-89	0.413	(0.186–0.640)		0.234	(0.003–0.444)		0.442	(-0.267–1.152)	
>89	0.000	reference		0.000	reference		0.000	reference	
Respiratory rate breath/minute			<0.001			0.007			0.005
0-5	0.407	(0.276–0.538)		-0.057	(-0.443–0.330)		-0.112	(-0.500–0.276)	
6-9	0.267	(-0.115–0.649)		-0.066	(-0.449–0.318)		-0.093	(-0.476–0.290)	
10-29	0.000	reference		0.000	reference		0.000	reference	
>29	0.407	(0.276–0.538)		0.225	(0.097–0.353)		0.224	(0.096–0.352)	
Systolic blood pressure (SBP) × Glasgow Coma Score (GCS) interaction									0.02
0-49 × GCS							0.664	(0.111–1.218)	
50-75 × GCS							0.251	(-0.009–0.511)	
76-89 × GCS							-0.063	(-0.258–0.132)	
>89 × GCS							0.000	reference	

Respiratory rate (RR)—Two characterisations of RR were considered:

- Categorising RR according to the original TRISS specifications (with 0 and 1-5 breaths per minute groups combined): 0–5 breaths per minute (n=28, 2%), 6–9 breaths pre minute (n=17, 1%), 10–29 breaths per minute (n=1,157, 85%), and >29 breaths per minute (n=163, 12%) and then treating these groups as a continuous variable as used in the original TRISS model; and

- Treating the RR groups as a categorical variable.

The resultant BIC=3326.87 and 3306.30, respectively. Based on this BIC statistic, treating the RR groups as categories best predicts LOS.

Multivariable model development

Bivariable comparisons between each of the predictor variables listed above and the cubic-root transformed LOS variable were conducted and results appear in Table 2. All candidate variables were significantly associated with LOS. The main effects model then combined all variables significant in the bivariable comparisons and eliminated those variables no longer significant. However, all variables significant in the bivariable comparisons remained statistically significant in the multivariable main effects model.

Once the main effects model was found, all two-factor interactions were investigated separately. Only the interaction between SBP×GCS (P=0.02) was statistically significant. The full multivariable two-level mixed-effects regression model was thus derived by combining this significant interaction with the main effects model (Table 2). The hospitals, treated as random effects, had a significant variance component estimated at 0.079 (95%CI: 0.016–0.386); and this final multivariable two-level mixed-effects regression model was superior to an ordinary regression model (P=0.03).

Residual checks included a scatter-plot of the standardised residuals against the untransformed predicted LOS values (in days) together with a superimposed lowess curve (a nonparametric estimator of the mean function over time[24]), and a histogram of the standardised residuals together with a superimposed normal curve (Figure 2). No evidence was found that demonstrated that the assumptions of the final multivariable regression model had been importantly violated. Henceforth, we refer to this final multivariable two-level mixed-effects regression model as the final or refined model.

Predictive ability of final multivariable two-level mixed-effects regression model

Spearman's correlation between LOS and the final model's untransformed predicted values was ρ=0.38, a substantial improvement over the model using the TRISS variables and their original characterisations with ρ=0.31. A scatter-plot of the untransformed predicted LOS values from the final model and the observed LOS records appears in Figure 3. The absolute prediction error (APE) between untransformed predicted LOS from the final model and the actual LOS had a 25th

percentile of 3.3 days, median of 6.0 days, 75th percentile of 11.6 days, 90th percentile of 25.1 days, and 95th percentile of 35.9 days. This implies that for 50% of patients, the difference between the predicted LOS and the actual LOS was between 0 and 6.0 days.

The APE between untransformed predicted LOS from a regression model using the TRISS variables and their original characterisations and the actual LOS had a 25th percentile of 5.0 days, median of 10.8 days, 75th percentile of 22.0 days, 90th percentile of 38.0 days, and 95th percentile of 49.8 days.

Figure 2. (i) Scatter-plot of the standardised residuals for the final multivariable two-level mixed-effects regression model against the untransformed predicted length of stay values (in days) together with a superimposed lowess curve, and (ii) a histogram of the standardised residuals together with a superimposed normal curve
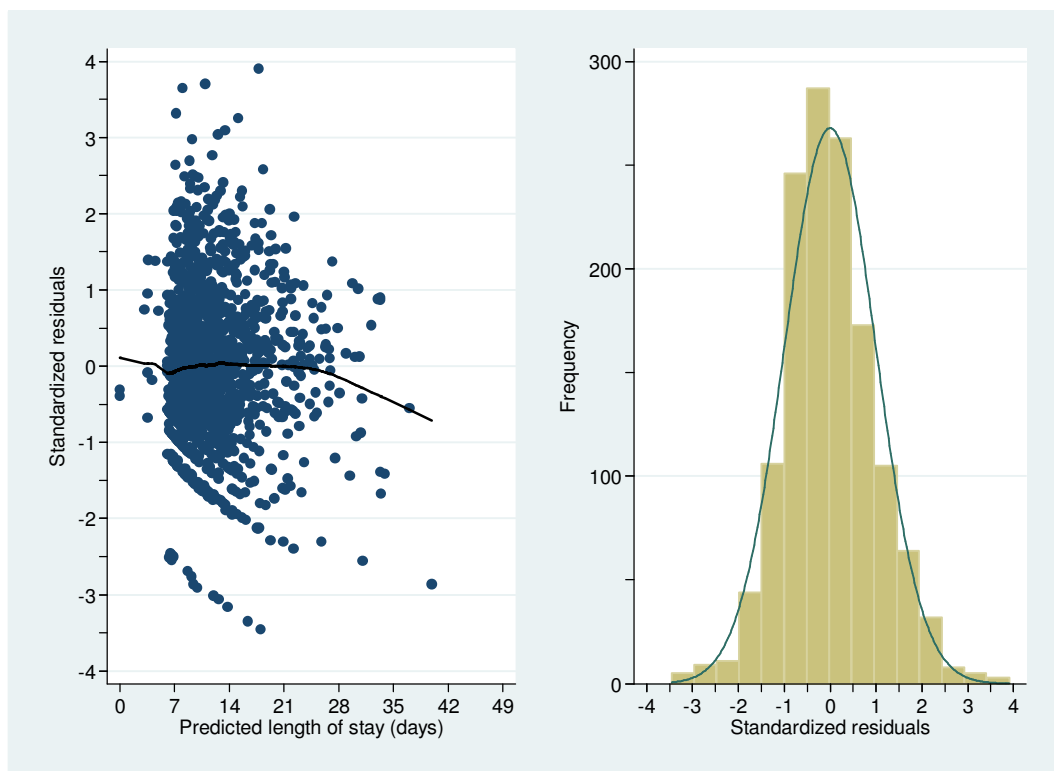
Penetrating mechanism trauma—The average age of the 52 blunt mechanism trauma survivors was 33 years (range: 16 to 74 years) and 43 (83%) were male. Unfortunately, a total sample of 52 is insufficient to produce a valid statistical model.

Discussion

All the TRISS variables were significantly associated with LOS for adults with blunt traumatic injuries. The original TRISS model had a moderate correlation with LOS

(ρ=0.31), which was improved when the variables were refined and re-estimated using a multivariable two-level mixed-effects regression model on these New Zealand data (ρ=0.38). However, the MAPE was 10.8 days for the original TRISS model and 6.0 days for the refined model.

So while the TRISS methodology provides a sound benchmarking tool for performance monitoring of trauma systems in terms of expected survival,[20] this study demonstrates that neither the original TRISS model nor a refined model based on the same TRISS variables provided adequate predictive capacity to allow it to be used to benchmark trauma systems in terms length of stay of non-fatal injuries. This finding is consistent with published work in the field.[11,13,14,25,26]

Figure 3. Scatter-plot of the predicted length of stay, untransformed from the final multivariable two-level mixed-effects regression model, against the actual length of stay observed from hospital records
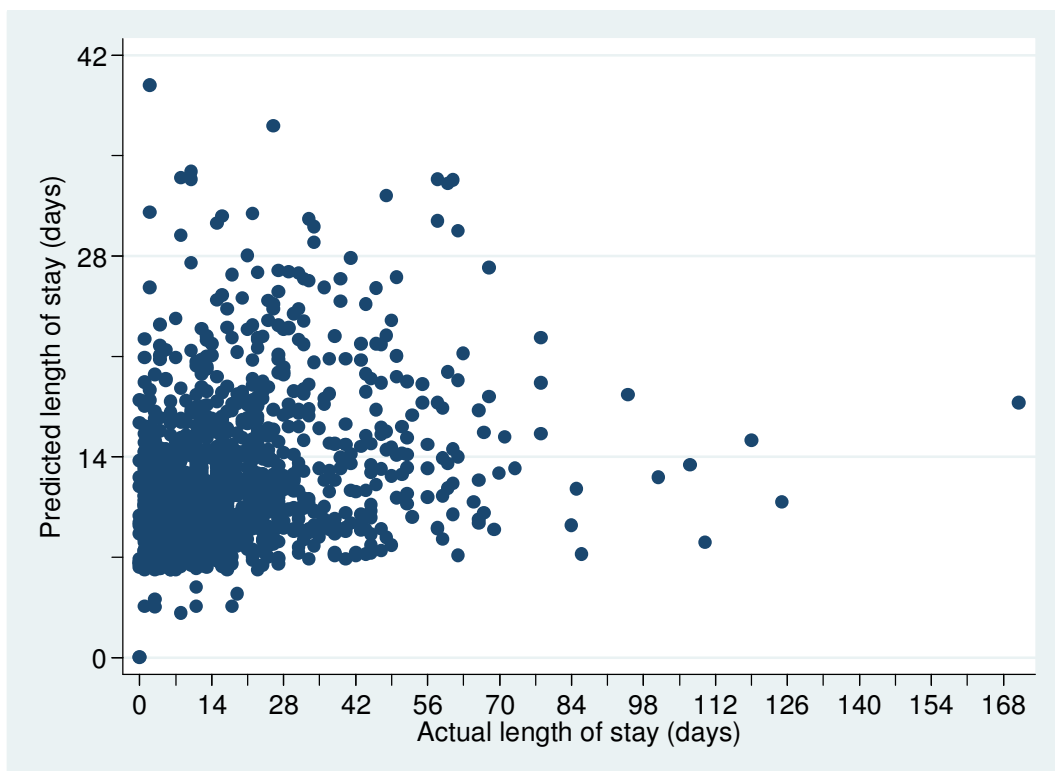
Morbidity, the degree or severity of a health condition associated with the injury event, is also influenced by personal (such as personality, education, resilience), social (such as support, family, networks) and environmental (such as housing, location, employment) factors in which the person is situated.[27]

It may be possible to identify other issues about the personal, social and environmental characteristics of an injured person at the time of injury occurrence to insert into an appropriate statistical model that will better predict LOS. However,

much of this additional information is not routinely available in administrative data sets and would need to be included on the trauma registry data collection form.[12] Elicitation of additional patient information is likely to present a significant barrier to most registries worldwide.

Another important assumption used here and elsewhere is that LOS is a valid measure of injury-attributable health status. While there is face validity in using LOS as a measure of morbidity,[11, 16, 19] there are no studies reported in the literature that have formally explored the extent to which LOS is valid for use in this context (although LOS has been shown to predict functional outcomes 12-months post-injury[12]).

Moreover, as there is no international consensus on appropriate morbidity scores or the use of LOS in benchmarking non-fatal injury outcomes, there is considerable variability in how LOS is analysed and reported. For example, some treat LOS categorically as a binary variable, using a 5-day threshold,[11] a 7-day threshold,[19] or a 10-day threshold[16], whereas we treated the transformed LOS as a continuous variable. These different definitions make comparisons between studies and registries difficult.

While the study had salient strengths, including the large sample and sophisticated methods of statistical analysis, it also suffers from weakness. These include: some data quality issues, as described elsewhere[20]; the fact that data transformation was required, as two-level mixed-effects negative binomial regression models which might yield improved predictions are not currently available in Stata or SAS specialist statistical software packages; and there is potential inaccuracy of some LOS values for patients transferred to another hospital.

Currently, trauma registries in New Zealand do not track patients between hospitals; primarily because these registries operate independently and are hospital-specific. So there is no readily available mechanism to match de-identified patient records between hospital registries. As such, patients with hospital transfers and readmissions will be generally counted as separate admissions in each registry, each having a separate non-cumulative LOS value. However, given the median LOS for those with hospital transfers (10 days) was similar to those without transfers (11 days), the bias associated with this limitation is likely to be negligible compared to the poor overall predictive performance of the TRISS models noted in this paper.

Even if all these limitations were resolved, it is unlikely that the predictive capacity of the final model would improve substantially or sufficiently for its use as a prognostic tool. Another limitation is the lack of data available for the modelling of penetrating injuries.

Conclusion

Neither the original TRISS model nor a refined model based on the same TRISS variables has predictive capacity with sufficient utility for benchmarking LOS and, by proxy, morbidity. This New Zealand analysis adds to the consensus from the few studies conducted in the international literature that TRISS scores currently calculated in trauma registry software need to be supplemented by additional score(s) which enables performance monitoring of trauma systems in terms of expected outcomes of patients with non-fatal injury.[3,11,12]

Given that the vast majority of trauma patients survive and the substantial costs related to long term morbidity arising from non-fatal injury, it is imperative that trauma systems maximise their care to ensure the best possible outcomes are being achieved. There is an urgent need to develop a "threat to morbidity" and a "threat to disability" based injury severity score. It will be important to build these severity scores into the trauma audit and performance management systems of existing trauma centres and into the computer based trauma registries that support these audits. A substantial focus of research in this area is critically needed.

Competing interests: None known.

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References:

1. Accident Compensation Corporation. New Zealand Injury Prevention Strategy 2004/05 Implementation Plan. Wellington: ACC; 2003.

2. Krug EG. Injury surveillance is key to preventing injuries. Lancet. 2004;364(9445):1563–6.

3. Kossmann T. The need to move on from mortality to morbidity outcome predictions. ANZ J Surg. 2005;75(8):623.

4. Cummings GE, Mayes DC. A comparative study of designated Trauma Team Leaders on trauma patient survival and emergency department length-of-stay. CJEM. 2007;9(2):105–10.

5. Sugrue M, Caldwell E, D'Amours S, et al. Time for a change in injury and trauma care delivery: a trauma death review analysis. ANZ J Surg. 2008;78(11):949–54.

6. McDermott FT, Cooper GJ, Hogan PL, et al. Evaluation of the prehospital management of road traffic fatalities in Victoria, Australia. Prehosp Disaster Med. 2005;20(4):219–27.

7. Ministry of Health. Our Health, Our Future: The Health of New Zealanders. Wellington: Ministry of Health; 1999.

8. Chiara O, Cimbanassi S, Pitidis A, Vesconi S. Preventable trauma deaths: from panel review to population based-studies. World J Emerg Surg. 2006;1:12.

9. Boyd CR, Tolson MA, Copes WS. Evaluating trauma care: the TRISS method. Trauma Score and the Injury Severity Score. J Trauma. 1987;27(4):370–8.

10. Cameron PA, Gabbe BJ, McNeil JJ. The importance of quality of survival as an outcome measure for an integrated trauma system. Injury. 2006;37(12):1178–84.

11. Gabbe BJ, Cameron PA, Wolfe R, et al. Predictors of mortality, length of stay and discharge destination in blunt trauma. ANZ J Surg. 2005;75(8):650–6.

12. Schluter PJ, McClure RJ. Predicting functional capacity outcome 12 months after hospitalized injury. ANZ J Surg. 2006;76(10):886–93.

13. Schluter PJ, Neale R, Scott D, et al. Validating the functional capacity index: a comparison of predicted versus observed total body scores. J Trauma. 2005;58(2):259–63.

14. Cameron PA, Gabbe BJ, McNeil JJ, et al. The trauma registry as a statewide quality improvement tool. J Trauma. 2005;59(6):1469–76.

15. Findlay G, Martin IC, Carter S, et al. Trauma: Who cares? London: National Confidential Enquiry into Patient Outcome and Death; 2007.

16. Tamim H, Al Hazzouri AZ, Mahfoud Z, et al. The injury severity score or the new injury severity score for predicting mortality, intensive care unit admission and length of hospital stay: experience from a university hospital in a developing country. Injury. 2008;39(1):115–20.

17. Chung L, Wang YH, Chen TJ, Pan AW. The predictive factors for length of stay for stroke patients in Taiwan using the path model. Int J Rehabil Res. 2006;29(2):137–43.

18. Perez A, Chan W, Dennis RJ. Predicting the length of stay of patients admitted for intensive care using a First Step analysis. Health Serv Outcomes Res Methodol. 2006;6(3-4):127–38.

19. Verduijn M, Peek N, Voorbraak V, et al. Modeling length of stay as an optimized two-class prediction problem. Methods Inf Med. 2007;46(3):352–9.

20. Schluter PJ, Cameron CM, Davey TM, et al. Contemporary New Zealand coefficients for the trauma injury severity score: TRISS(NZ). N Z Med J. 2009;122(1302). http://www.nzma.org.nz/journal/122-1302/3774

21. Baker SP, O'Neill B. The injury severity score: an update. J Trauma. 1976;16(11):882–5.

22. Champion HR, Sacco WJ, Copes WS. Injury severity scoring again. J Trauma. 1995;38(1):94–5.

23. Schwarz G. Estimating the dimension of a model. Ann Stat. 1978;7(2):461–4.

24. Dupont WD. Statistical Modeling for Biomedical Researchers: A Simple Introduction to the Analysis of Complex Data. Cambridge: Cambridge University Press; 2002.

25. Schluter PJ, Cameron CM, Purdie DM, et al. How well do anatomical-based injury severity scores predict health service use in the 12 months after injury? Int J Inj Contr Saf Promot. 2005;12(4):241–6.

26. Wolfe R, McKenzie DP, Black J, et al. Models developed by three techniques did not achieve acceptable prediction of binary trauma outcomes. J Clin Epidemiol. 2006;59(1):26–35.

27. Kuipers K, Foster M, Sykes C. Injury and disability outcome measurement. In: McClure RJ, Stevenson M, McEvoy S, eds. The Scientific Basis of Injury Prevention and Control. Melbourne: IP Communications; 2004:75–86.