

# THE NEW ZEALAND MEDICAL JOURNAL

Journal of the New Zealand Medical Association



## Contemporary New Zealand coefficients for the Trauma Injury Severity Score: TRISS(NZ)

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### Abstract

**Aims** To develop local contemporary coefficients for the Trauma Injury Severity Score in New Zealand, TRISS(NZ), and to evaluate their performance at predicting survival against the original TRISS coefficients.

**Methods** Retrospective cohort study of adults who sustained a serious traumatic injury, and who survived until presentation at Auckland City, Middlemore, Waikato, or North Shore Hospitals between 2002 and 2006. Coefficients were estimated using ordinary and multilevel mixed-effects logistic regression models.

**Results** 1735 eligible patients were identified, 1672 (96%) injured from a blunt mechanism and 63 (4%) from a penetrating mechanism. For blunt mechanism trauma, 1250 (75%) were male and average age was 38 years (range: 15–94 years). TRISS information was available for 1565 patients of whom 204 (13%) died. Area under the Receiver Operating Characteristic (ROC) curves was 0.901 (95%CI: 0.879–0.923) for the TRISS(NZ) model and 0.890 (95% CI: 0.866–0.913) for TRISS ( $P<0.001$ ). Insufficient data were available to determine coefficients for penetrating mechanism TRISS(NZ) models.

**Conclusions** Both TRISS models accurately predicted survival for blunt mechanism trauma. However, TRISS(NZ) coefficients were statistically superior to TRISS coefficients. A strong case exists for replacing TRISS coefficients in the New Zealand benchmarking software with these updated TRISS(NZ) estimates.

A fundamental component of any trauma system is a defined performance improvement programme centred on the audit capacity provided by a properly functioning trauma registry.<sup>1,2</sup>

Trauma system quality control programmes have traditionally focused on decreasing the number of preventable deaths.<sup>3</sup> Thus while trauma system performance monitoring can be a complex multifaceted activity, in its most simple form it can be reduced to the question *For any trauma system, is the proportion of patients who survive a given injury as high as that achieved by the best systems in the country (and comparable systems internationally)?*

A negative answer to this question does not necessarily imply suboptimal care, but it does prompt a search for explanations that may lead to better outcomes for injured patients. The importance of a continued search for improved trauma system performance is that even after trauma system implementation, 15–20% of trauma-related deaths continue to be preventable.<sup>4–8</sup>

Performance monitoring essentially involves comparing actual survival outcomes with expected norms.<sup>9</sup> The Trauma Injury Severity Score (TRISS), a weighted combination of patient age, Injury Severity Score (ISS) and Revised Trauma Score (RTS), is one score developed to estimate this expected survival.<sup>3</sup>

The TRISS is not without limitations, many of which have been extensively documented elsewhere.<sup>10-12</sup> However, despite these limitations, TRISS continues to be the most commonly used tool for benchmarking trauma outcomes.<sup>10,13,14</sup> Until a superior score is developed and widely adopted, it is likely that the TRISS will continued to be used for this purpose in the coming years. As such, the question of interest is *Is the TRISS a valid predictor of survival in contemporary localized populations?*

The TRISS coefficients used for weighting were derived using ordinary logistic regression models from the Major Trauma Outcome Study (MTOS), a cross-sectional United States of America (USA) study conducted over 20 years ago.<sup>3</sup> At that time it was acknowledged that “as improvements in trauma care over time result in decreased mortality, these [TRISS] coefficients can be expected to change.”<sup>3</sup>

Advances in trauma management over the past 20 years coupled with the considerable differences in case mix between the USA and other countries, including New Zealand, suggests that these TRISS coefficients may not reflect current optimal performance benchmarks.<sup>11,15,16</sup> Should important differences be found between the existing and re-estimated contemporary local jurisdiction coefficients, then these re-estimated coefficients might be employed to allow relevant and valid routine benchmarking of the performance of trauma systems within that jurisdiction.

Using data from four New Zealand Trauma Registries, serving approximately half the nation’s population, this study aimed to develop local contemporary coefficients for the Trauma Injury Severity Score in New Zealand, TRISS(NZ). Once estimated, we then sought to evaluate the predictive performance of TRISS(NZ) against TRISS.

## Methods

**Study design**—Retrospective cohort study.

**Study population and period**—All adult New Zealanders (aged  $\geq 15$  years) who sustained a serious traumatic injury, defined as having  $ISS > 15$ , who survived until presentation at Auckland City Hospital, Middlemore Hospital, Waikato Hospital, or North Shore Hospital between 1 January 2002 and 31 December 2006. Cases of poisoning, burns, hangings, and simple fractured neck of femurs were excluded.

**Procedure**—Unit record data was extracted from each of the participating trauma registries. Three of the four registries used the Collector Trauma Registry software and database, and the fourth has replicated the data collection tool manually. However, 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 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. Data from this period was not available at the time of data extraction.

Data extraction included demographic characteristics (date of birth or age, gender); anatomical and physiological parameters of injury severity, where available 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 for cleaning, combining, and subsequent data analysis.

**The TRISS model**—Derived from ordinary logistic regression models on the MTOS data, the TRISS model has two separate specifications for adults:

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

TRISS coefficients give the probability of survival ( $P_S$ ) rather than the probability of death ( $P_D$ ); naturally  $P_D = 1 - P_S$ . The probability of survival for any one patient can be estimated from:

$$P_S = 1/(1+e^{-b})$$

where, for blunt mechanism trauma

$$b = -0.4499 + (0.8085 \times \text{RTS}) - (0.0835 \times \text{ISS}) - (1.7430 \times \text{Age}), \text{ (1)}$$

for penetrating mechanism trauma

$$b = -2.5355 + (0.9934 \times \text{RTS}) - (0.0651 \times \text{ISS}) - (1.1360 \times \text{Age}), \text{ (2)}$$

Injury Severity Score (ISS) has values from 16 to 75; Age is coded: 0 if patient age is 15–54 years, and 1 if patient age is  $\geq 55$  years; and the Revised Trauma Score (RTS) is given by

$$\text{RTS} = (0.2908 \times \text{RR}) + (0.7326 \times \text{SBP}) + (0.9368 \times \text{GCS}). \text{ (3)}$$

Respiratory rate (RR), systolic blood pressure (SBP), and the Glasgow Coma Score (GCS) each have values assigned to them as included in Table 1. If the expression for the RTS (equation 3) is directly substituted into TRISS equations (1) and (2) above, then it is convenient to re-write the equation for blunt mechanism trauma as

$$B = -0.4499 + (0.2351 \times \text{RR}) + (0.5923 \times \text{SBP}) + (0.7574 \times \text{GCS}) - (0.0835 \times \text{ISS}) - (1.7430 \times \text{Age}) \text{ (4)}$$

and the equation for penetrating mechanism trauma as

$$b = -2.5355 + (0.2889 \times \text{RR}) + (0.7278 \times \text{SBP}) + (0.9306 \times \text{GCS}) - (0.0651 \times \text{ISS}) - (1.1360 \times \text{Age}) \text{ (5)}$$

**Table 1. Values associated with respiratory rate (RR), systolic blood pressure (SBP), and the Glasgow Coma Score (GCS) used in the calculation of the Revised Trauma Score (RTS), and when considered separately in logistic regression models**

Value	Respiratory rate (RR) per minute	Systolic blood pressure (SBP) mmHG	Glasgow Coma Score (GCS)
0	0	0	3
1	1–5	1–49	4–5
2	6–9	50–75	6–8
3	>9	76–89	9–12
4	10–29	>89	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 software (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). Comparisons of categorical variables between groups was made using Fisher’s exact test.

Like the TRISS model, it was intended that separate derivations would be undertaken for adults with:

- Injuries sustained from a blunt mechanism; and
- Injuries sustained from a penetrating mechanism.

A progressive model development approach was undertaken to derive TRISS(NZ). However, each considered model incorporated only those variables already used in TRISS, and the variable characterisations and values specified by equations 1–5 and Table 1.

Initially, the TRISS model was run on the New Zealand data and the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) statistics calculated. We label this model 1. Information criteria can be used to determine model superiority between competing nested or non-nested regression models.<sup>17</sup> A nested regression model is one which is completely subsumed within another larger regression model whereas non-nested regression models each have unique terms. Both the AIC and BIC penalise for model complexity and reward for goodness-of-fit; with the preferred model balancing these competing demands and yielding the lowest values.<sup>17</sup>

Next, employing the same statistical techniques used to determine the coefficients for TRISS, an ordinary logistic regression model was conducted on the New Zealand data to estimate local coefficients and calculate the AIC and BIC statistics. We label this model 2. If the AIC and BIC statistics for model 2 were not superior to model 1, then this would suggest that New Zealand coefficients are no better than those of the TRISS and the investigation would cease. Alternatively, if model 2 demonstrated superiority over model 1, then this would suggest that New Zealand coefficients are statistically superior to those of the TRISS.

As the RTS variable in both models 1 and 2 also had its component coefficients estimated from the MTOS (equation 3), it is of interest to determine whether these component variables may also benefit from re-estimation. Thus the ordinary logistic regression was repeated on the New Zealand data except that the RTS variable was replaced by: RR, SBP and GCS. We label this model 3. If model 3 was no better than model 2, then this would suggest that New Zealand coefficients for ISS, age, and RTS are statistically superior to those of the TRISS, but that the New Zealand coefficients for the component variables of the RTS are no better than those derived from the original MTOS. However, if model 3 was superior to model 2, then this would suggest that all variables used in TRISS would be improved with New Zealand coefficients.

Finally, recognising that patients were nested within hospitals, and that there is likely variation in case-mix and survival rates between hospitals, a multilevel mixed-effects logistic regression model was employed. This regression model, labelled model 4, uses the variables defined by either model 2 or 3, depending upon which model was superior, and a higher-level hospital variable (with values indicated by an anonymous code) which is treated as a random effect within the model. Again AIC and BIC statistics were computed and compared to the previous models. Based on the AIC and BIC statistics, we defined TRISS(NZ) to be the best model from candidate models 2-4.

The predictive abilities of the fixed-effects portion of the TRISS(NZ) and TRISS models were then assessed using nonparametric Receiver Operating Characteristic (ROC) curves and analysis. A ROC curve is a graphical plot of the sensitivity vs. (1 – specificity) of survival as its discrimination threshold is varied. The ROC analysis comprised of a test of equality between the fixed-effects portion of the TRISS(NZ) and TRISS model ROC areas, and was undertaken using the  $\chi^2$  test.

We used only the fixed-effects portion so that the complexity of the final TRISS(NZ) model would be no different to that of TRISS for end-users, and the only potential changes would be in the specification of the predictor variable coefficients. An  $\alpha=0.05$  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 Hospital, Middlemore Hospital and Waikato Hospital).

## Results

There were 1735 eligible patients identified, 1672 (96%) injured from a blunt mechanism and 63 (4%) injured from a penetrating mechanism.

**Blunt mechanism trauma**—Of the 1672 patients suffering blunt mechanism trauma, 1250 (75%) were males and the average age was 38 years (range: 15 to 94 years). Complete information to calculate the TRISS was available for 1379 (82%) patients

and prehospital information allowed another 186 (11%) patients to be included in the analyses, yielding a total sample of 1565 (94%) trauma patients. Of these, 204 (13%) died and 1361 (87%) survived their injury.

Of the 107 patients with incomplete information (where a TRISS could not be calculated), 22 (21%) died and 85 (79%) survived their injury, a distribution with significantly more deaths than seen in the sample with complete information (Fisher's exact test  $P=0.04$ ).

**Table 2. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) statistics for the progressive model development of TRISS(NZ) using various coefficient estimation regression models and variable combinations**

Model	Method of coefficient estimation	Fix-effect variables	AIC	BIC
Model 1 [TRISS]	Ordinary logistic regression on MTOS data	ISS, Age, RTS	802.9	829.7
Model 2	Ordinary logistic regression on NZ data	ISS, Age, RTS	784.6	806.0
Model 3	Ordinary logistic regression on NZ data	ISS, Age, RR, SBP, GCS	760.0	792.2
Model 4 [TRISS(NZ)]	Multilevel mixed-effects logistic regression on NZ data	ISS, Age, RR, SBP, GCS	751.7	789.2

**Note:** The preferred model has the lowest AIC and BIC values.

**Deriving TRISS(NZ)**—AIC and BIC statistics for the progressive model development appear in Table 2. ISS, age and RTS coefficients estimated from the New Zealand data (model 2) yielded lower AIC and BIC statistics than those of TRISS (model 1). When the component variables of the RTS, namely RR, SBP and GCS, were also re-estimated with the New Zealand data (model 3), the resultant AIC and BIC statistics were lower still.

Finally, the introduction of the higher-level hospital random effect into the regression (model 4) yielded the lowest and best AIC and BIC statistics. The fixed-effect component of this multilevel model thus defined TRISS(NZ). The coefficients and associated 95% confidence intervals (95% CI) for TRISS(NZ) appear in Table 3.

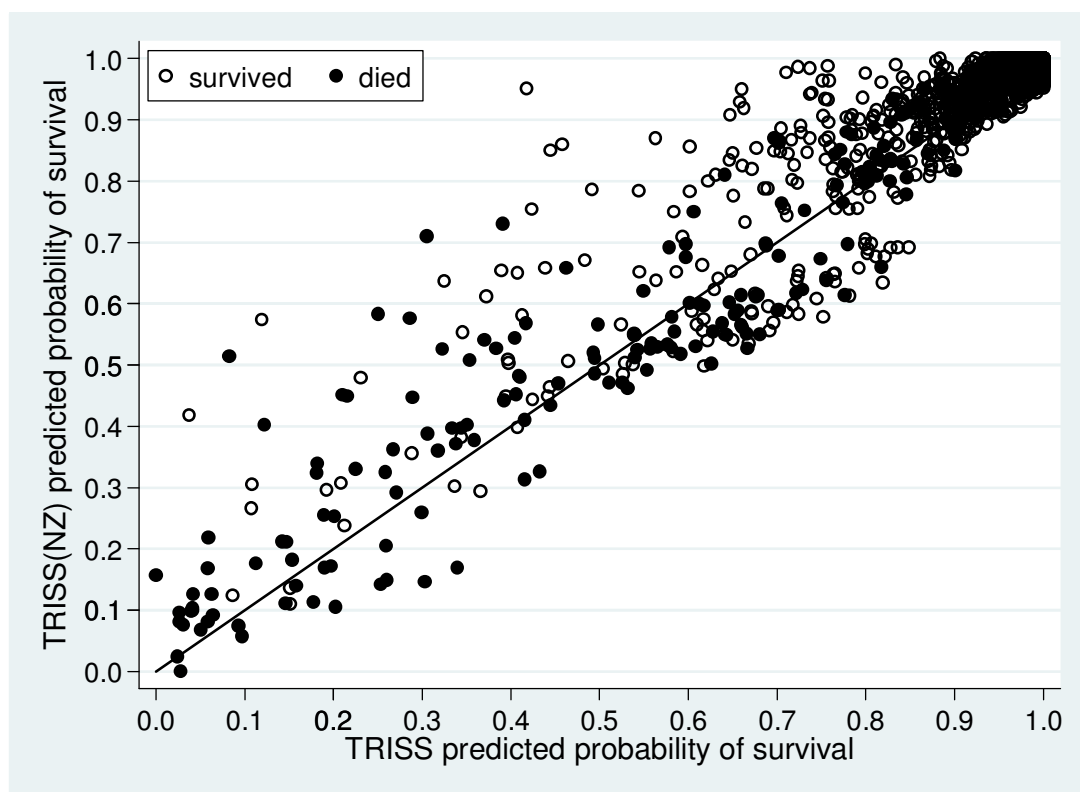
**Table 3. Estimated coefficients of blunt mechanism injury for TRISS (equation 4) and the fixed-effects portion of the TRISS(NZ) model, together with the 95% confidence intervals (95% CI)**

Variables	TRISS Coefficient	TRISS(NZ) Coefficient (95% CI)
<b>Intercept</b>	-0.4499	-0.8118 (-2.1353 – 0.5117)
<b>ISS</b>	-0.0835	-0.0443 (-0.0639 – -0.0248)
<b>Age</b>	-1.7430	-2.1864 (-2.6867 – -1.6862)
<b>RTS</b>		
RR	0.2351	0.0031 (-0.1958 – 0.2020)
SBP	0.5923	0.5594 (0.2899 – 0.8289)
GCS	0.7574	1.0749 (0.9266 – 1.2232)

A scatter-plot of the predicted values from the fixed-effects portion of the TRISS(NZ) model and those derived from TRISS appears in Figure 1. Departures from the 45° degree line give the magnitude of difference between predicted values from the two models. The mean difference between the predicted values from the two models was 0.019 (standard deviation 0.062) and ranged from -0.202 to 0.510.

So while the average difference was small, there were substantial positive and negative differences between predicted values for many patients.

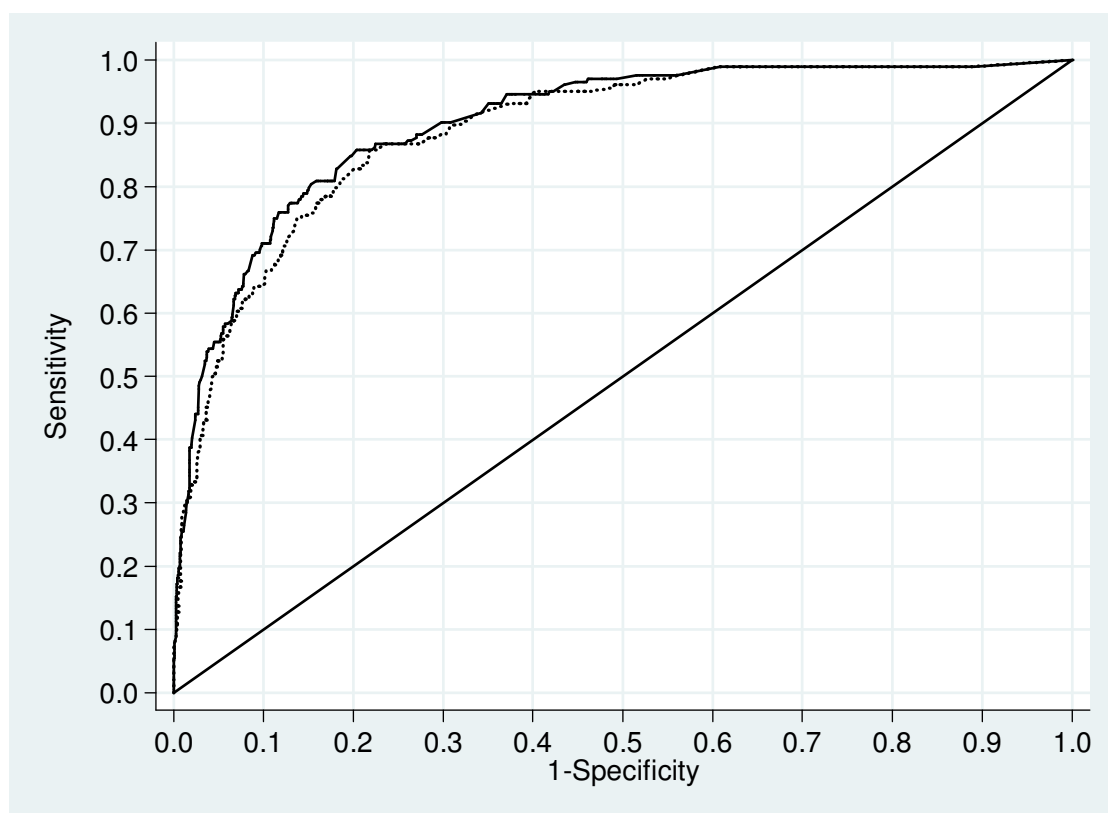
**Figure 1. Scatter-plot of predicted probability of survival ( $P_S$ ) from the fixed-effects portion of the TRISS(NZ) model against values derived from TRISS, together with the 45-degree reference line**



The ROC curves corresponding to the fixed-effects portion of the TRISS(NZ) and TRISS models, together with the 45-degree reference line, appears in Figure 2. The area under the ROC curves was 0.901 (95%CI: 0.879–0.923) for the TRISS(NZ) model and 0.890 (95%CI: 0.866–0.913) for TRISS; a difference that was statistically significant ( $P < 0.001$ ). This implies that, for these empirical data, the TRISS(NZ) model's predictive capacity is significantly better than that of the TRISS model.



**Figure 2. Nonparametric Receiver Operating Characteristic (ROC) curves corresponding to the fixed-effects portion of the TRISS(NZ) model (solid-line) and TRISS (dotted-line), together with the 45-degree reference line**



**Penetrating mechanism trauma**—Of the 63 eligible patients suffering trauma from a penetrating mechanism, 53 (84%) were male and the average age was 35 years (range: 16 to 74 years). Complete information to calculate the TRISS was available for 45 (71%) patients and prehospital information allowed another 10 (16%) patients to be included in the analyses, yielding a total sample of 55 (87%) trauma patients. Of these, 9 (16%) died and 46 (84%) survived their injury.

Of the 8 patients with incomplete information, 2 (25%) died and 6 (75%) survived their injury, a distribution not significantly different to that seen in the sample with complete information (Fisher's exact test  $P=0.62$ ). Unfortunately, a total sample of 55 is insufficient to produce a valid statistical model for TRISS(NZ).

## Discussion

The TRISS methodology for evaluating the performance of trauma systems has been well established, and is widely used. Recent publications however have tended to focus on identifying and highlighting its limitations,<sup>10</sup> and often present the authors' own alternative.<sup>18–22</sup> Most new alternatives perform only marginally better, and usually at the expense of parsimony and often tautologically including outcome (e.g.

complications) as a predictive variable. In this context the first major finding of the current study was to illustrate how robust the simple TRISS model is.

In yet another sample of patients the simple TRISS(NZ) model accurately predicted survival with area under the ROC curves of 0.901 (95%CI: 0.879, 0.923). For a simple algorithm with only five variables easily obtained at time of admission with injury, this is a remarkable feat.

The second main finding of this study was that for trauma caused from a blunt mechanism, contemporary locally specified coefficients of the TRISS variables were statistically superior to the original coefficients. This improvement was seen when employing the same method of estimation as that used to define TRISS (i.e. ordinary logistic regression).

Further improvements were observed when locally specified coefficients for the components variables of the RTS were derived and by extending the model to include hospitals as a higher level random effect. The use of multilevel models in this analysis has theoretic and conceptual advantages, particularly when there is likely variation in case-mix and survival rates between hospitals.<sup>17</sup>

On the basis of this finding, there is a strong case to be made for replacing TRISS coefficients in the New Zealand benchmarking software with these updated TRISS(NZ) estimates. With the development of a New Zealand national registry, or a bi-national trauma registry in Australia and New Zealand, the estimates obtained in this sample could be retested in a second sample to validate the calculations.<sup>2</sup>

A national (or bi-national) sample encompassing a greater time period would increase the case numbers for analysis and improve the precision of the estimates. With a functioning national trauma database, coefficient revisions might be made on a regular basis (say every 3-5 years) thereby accommodating changes in demographics and case-mixing.

Unfortunately, we have insufficient data for penetrating trauma to make a similar assessment in this study. However, it is likely that with greater case numbers that locally specified coefficients would also be significantly superior.

There are several data quality issues mostly relating to consistency of data management between hospitals that may be usefully addressed at the time of establishing a national New Zealand trauma registry. The first of these issues are the discrepancies across registries for case inclusion and recording of individual fields. These were investigated during the data management phase of the current study and for major trauma cases (ISS>15) consistency of variable collection across New Zealand trauma registries was found to be high.

Multiple fields were collected in all registries with similar systems of collection. However, some key discrepancies did exist. A particular problem recognised in trauma registries worldwide is the measurement of the physiological state of the patient using the components of the Revised Trauma Score (RTS).<sup>23, 24</sup> There was variation in whether prehospital scores were recorded, when they were done, and at what point after presentation emergency department scores were measured and recorded.



These issues are accentuated in cases of patient transfer or when the patient was intubated. All but one hospital in the sample used AIS-98 (the exception used AIS-90), although the literature suggests this difference is unlikely to have affected the resulting TRISS calculations.<sup>25</sup>

## Conclusion

TRISS has proved to be a valid predictor of survival from major trauma and a simple, robust instrument for benchmarking in the New Zealand trauma system. The use of locally derived contemporary New Zealand coefficients, TRISS(NZ), increases the predictive capabilities of the methodology. There would appear to be little reason to replace TRISS(NZ) with a more complex statistical model that uses variables that may be less universally collected or inconsistently defined.

Future studies might consider testing the sensitivity of the TRISS(NZ) model, and perhaps make improvements by using re-specifications or re-categorizations of the original predictor variables, consider variable interactions, and by investigating power components.<sup>20,26</sup>

**Competing interests:** None known.

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**Acknowledgements:** We thank participating trauma registries and staff, including Dr Alex Ng and Dr Stuart Caldwell. Dr Cameron was supported by a Public Health Fellowship from the National Health and Medical Research Council, Australia.

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