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ORIGINAL ARTICLE

# Validation of a base deficit-based trauma prediction model and comparison with TRISS and ASCOT

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**Abstract**
*Background* Base deficit provides a more objective indicator of physiological stress following injury as compared with vital signs constituting the revised trauma score (RTS). We have previously developed a base deficit-based trauma survival prediction model [base deficit and injury severity score model (BISS)], in which RTS was replaced by base deficit as a measurement of physiological imbalance.
*Purpose* To externally validate BISS in a large cohort of trauma patients and to compare its performance with established trauma survival prediction models including trauma and injury severity score (TRISS) and a severity characterization of trauma (ASCOT). Moreover, we examined whether the predictive accuracy of BISS model could be improved by replacement of injury severity score (ISS) by new injury severity score (NISS) in the BISS model (BNISS).
*Methods* In this retrospective, observational study, clinical data of 3737 trauma patients (age ≥15 years) admitted consecutively from 2003 to 2007 were obtained from a prospective trauma registry to calculate BISS, TRISS, and ASCOT models. The models were evaluated in terms of discrimination [area under curve (AUC)] and calibration.
*Results* The in-hospital mortality rate was 8.1 %. The discriminative performance of BISS to predict survival was similar to that of TRISS and ASCOT [AUCs of 0.883, 95 % confidence interval (CI) 0.865–0.901 for BISS, 0.902, 95 % CI 0.858–0.946 for TRISS and 0.864, 95 % CI 0.816–0.913 for ASCOT]. Calibration tended to be optimistic in all three models. The updated BNISS had an AUC of 0.918 indicating that substitution of ISS with NISS improved model performance.
*Conclusions* The BISS model, a base deficit-based trauma model for survival prediction, showed equivalent performance as compared with that of TRISS and ASCOT and may offer a more simplified calculation method and a more objective assessment. Calibration of BISS model was, however, less good than that of other models. Replacing ISS by NISS can considerably improve model accuracy, but further confirmation is needed.

**Keywords** Trauma prediction model · Base deficit · TRISS · ASCOT

## Background

The quality of trauma care in reducing mortality of injured patients is of indisputable importance. Trauma prediction models have been developed as an important tool to evaluate quality of trauma care across a range of injury severities and to compare performance among trauma centers. One of the most widely used trauma prediction models is trauma and injury severity score (TRISS) [1], which combines trauma mechanism, age, injury severity score (ISS), and weighted revised trauma score (RTS) to calculate patient's survival probability (Table 1). The predictive performance of TRISS is, however, hampered by well-documented limitations of RTS and ISS, which reflect physiological derangements and anatomical injuries, respectively.

RTS includes Glasgow coma scale (GCS), respiratory rate (RR), and systolic blood pressure to estimate physiological

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**Table 1** Predictors and regression coefficients of original BISS, TRISS, and ASCOT models

| Trauma models | Constant term | Model predictors and regression coefficients | | | | | | |
|---|---|---|---|---|---|---|---|---|
| BISS | | | | | | | | |
| Blunt and penetrating | 5.78 | −0.096 × delta base deficit (cont.)[†] | −0.082 × ISS (cont.) | −0.046 × age (cont.) | | | | |
| TRISS | | | | | | | | |
| Blunt | −0.4499 | 0.7574 × GCS (interval) | 0.5923 × SBP (interval) | 0.2351 × RR (interval) | −0.0835 × ISS (cont.) | −1.7430 × age (dichotomous) | | |
| Penetrating | −2.5355 | 0.9300 × GCS (interval) | 0.7278 × SBP (interval) | 0.2889 × RR (interval) | −0.0651 × ISS (cont.) | −1.1360 × age (dichotomous) | | |
| ASCOT[‡] | | | | | | | | |
| Blunt | −1.157 | 0.7705 × GCS (interval) | 0.6583 × SBP (interval) | 0.2810 × RR (interval) | −0.3002 × (no. of AIS ≥ 3 head, brain spinal cord) | −0.1961 × (no. of AIS ≥ 3 thorax, the front of neck) | −0.2086 × (no. of AIS ≥ 3 all other injuries) | −0.6355 × age (interval) |
| Penetrating | −1.130 | 1.0626 × GCS (interval) | 0.3638 × SBP (interval) | 0.3332 × RR (interval) | −0.3702 × (no. of AIS ≥ 3 head, brain spinal cord) | −0.2053 × (no. of AIS ≥ 3 thorax, the front of neck) | −0.3188 × (no. of AIS ≥ 3 all other injuries) | −0.8365 × age (interval) |

Age groups for TRISS: ≥15 to <55, ≥55

Age groups for ASCOT: ≤54, 55–64, 65–74, 75–84, ≥85

The lowest numbered group was used as the reference group

*AIS* abbreviated injury scale, *GCS* Glasgow coma scale (interval: 3, 4–5, 6–8, 9–12, 13–15), *ISS* injury severity score, *SBP* systolic blood pressure (interval mmHg: 0, 1–49, 50–75, 76–89, ≥90), *RR* respiratory rate (interval per min: 0, 1–5, 6–9, 10–29, ≥30

[†] Delta base deficit is defined as the deviation of the base deficit from its normal range (−2 to 2)

[‡] ASCOT model has specified probability of survival for patients with severe injuries (AIS = 6) or no vital signs (RTS = 0) and for patients with mild injuries (AIS < 3 and RTS > 0):

Maximum AIS = 6 and RTS = 0, Ps (blunt) = 0.000, Ps (penetrating) = 0.000

Maximum AIS = 6 and RTS > 0, Ps (blunt) = 0.229, Ps (penetrating) = 0.222

Maximum AIS < 6 and RTS = 0, Ps (blunt) = 0.014, Ps (penetrating) = 0.026

Maximum AIS < 3 and RTS > 0, Ps (blunt) = 0.998, Ps (penetrating) = 0.999

disturbance in trauma patients. Accurate assessment of GCS and RR may be difficult in chemically paralyzed or intubated patients leading to inaccurate estimates [2]. Base deficit has been shown to correlate with mortality in trauma patients, transfusion requirements as well as the development of various complications and may provide an alternative and objective means of assessing physiological disturbances [3–5]. Motivated by these findings, we have developed a base deficit and injury severity score model (BISS), in which RTS has been replaced with base deficit at admission [6]. We have previously demonstrated that the BISS model performed equivalent to TRISS, while providing a simplified method for objective assessments of outcome. Since the performance of prediction models tends to be over-optimistic on the developmental data, from which the model is derived, external validation is essential to determine its reliability and generalizability. In this study, we externally validate the BISS prediction model in a general trauma population.

The ISS has been developed for describing the overall burden of injury and is calculated as the sum of squares of the three most severely injured body regions. In particular in patients with multiple injuries located in one body region, ISS led to an underestimation of injury severity [7]. A severity characterization of trauma (ASCOT) [8] with a refined anatomical scoring system has shown a marginally improved accuracy in estimating overall injury severity compared to TRISS, but the calculation method is too complex to be clinically useful [9]. The new injury severity score (NISS) considering the three most severe injuries regardless of body regions has shown to reflect the overall injury burden more accurately than ISS [10, 11]. Hence, NISS replacing ISS may improve performance of trauma prediction models.

The aim of this study was first to determine whether the BISS model performed adequately and to compare its performance with established trauma survival prediction models including TRISS and ASCOT. Second, we determined whether the performance of BISS model could be improved by replacement of ISS by NISS.

## Methods

### Data collection and trauma population

This was a retrospective, observational study at the University Medical Center Utrecht, an academic level 1 trauma center in the Netherlands. The prospective trauma registry was used to identify trauma patients of 15 years and older, who were admitted at the department of Traumatology between January 1, 2003, and December 31, 2007. Deaths on arrival at the emergency department and patients without anatomical injuries such as burns, hanging, drowning, or intoxication were excluded. Clinical data were prospectively collected by a specialized data manager with knowledge of medical terminology and abbreviated injury scale coding. The collected data are reviewed periodically to maintain accuracy and completeness of records (SWL). Missing data were retrieved by medical record's review if possible. For this retrospective study, the requirement for ethical approval was waived by the Institutional Review Board.

### Trauma survival prediction models

The original TRISS (revision 1995), ASCOT and BISS models were determined according to previously published methods [6, 8, 12]. The probability of survival (Ps) of individual trauma patients was calculated using the following equation: $\text{Ps} = 1/(1 + e^{-b})$, where $b = \beta_0 + \beta_1 (X_1) + \beta_2 (X_2)\ldots\beta_n (X_n)$. In the equation, $\beta_0$ is the intercept and $\beta_{1-n}$ are the regression coefficients of the specified predictors $X_{1-n}$. Regression coefficients were different for blunt and penetrating injuries in TRISS and ASCOT, whereas these were identical for both types of injury in BISS. Moreover in ASCOT, Ps was specified in defined groups of trauma patients with extremely good or poor prognosis (Table 1). The original regression coefficients and predictors of the three trauma survival prediction models are shown in Table 1.

### Multiple imputation procedure

We employed multiple imputation method to impute missing data points that could not be retrieved by medical record's review. Missing data analysis of 3737 eligible trauma patients showed that eight of 13 variables had any missing value. These eight variables were base deficit (56 %), ISS (8.4 %), NISS (8.4 %), anatomic profile category head/brain/spinal cord (6.8 %), anatomic profile category thorax/front of the neck (6.8 %), anatomic profile all other body region (6.8 %), mechanism of injury (0.5 %), and death (0.1 %). The total amount of missing data points was 3514 of 48,581 (7.2 %). The missing data points were statistically imputed by using multivariable imputation function based on Markov Chain Monte Carlo algorithm of SPSS version 20. A total of 10 datasets (henceforth "imputation datasets") were imputed for further analyses.

### BNISS model development and updating trauma survival prediction models

To assess whether the predictive performance of BISS model might improve by the replacement of ISS with NISS in the BNISS model, we compared the discriminative performance of BNISS model with that of the BISS, TRISS, and ASCOT models. For such a comparison, the reference models should be optimized for the data to isolate the effect of replacement of ISS by NISS. Therefor the regression coefficients of predictors and the intercept were re-estimated by fitting each trauma survival prediction model in the dataset. A dataset of 1561 blunt trauma patients containing no missing value of all predictors was used for the model development and model updating.

### Model performance

BISS model was externally validated by measuring discrimination and calibration as model performance measures and was compared with the performance of TRISS and ASCOT models. Discrimination represents the ability of the prediction model to distinguish survivors from non-survivors and was evaluated using area under the receiver operating characteristics curve (ROC). An area close to 0.5 indicates a poor discriminative performance, whereas a prediction model with perfect discrimination will approximate an area of 1. Results from ROC analysis on the imputation datasets were averaged and 95 % confidence intervals (CIs) were pooled using Rubin's rule [13].

Calibration refers to the agreement between predicted and observed survival and was evaluated with calibration slope and intercept. The calibration slope represents the strength of the predictors in the validation data compared to the development data, and intercept represents the difference between mean predicted and mean survival rate. A perfectly calibrated model has a calibration slope of 1 and a calibration intercept of 0. The calibration slope and intercept were determined by fitting linear predictor of the trauma survival prediction model as the only covariate in a logistic regression model. Pooled calibration intercepts and slopes from the imputation datasets were reported. Representative calibration plots with observed survival probabilities ($y$ axis) and predicted survival probabilities ($x$ axis) for all models were generated. Statistical analyses were performed by using SPSS version 20. Calibration plots were generated by using R with the Design and Hmisc packages.

## Results

A total of 3737 patients were included for analysis. The median age was 44 years [interquartile range (IQR), 27–64] and 64 % of patients ($n = 2338$) were males. Most patients required hospital admission following blunt trauma (3604 of 3737 patients, 96.4 %). Median ISS and NISS were 9 (IQR 5–9) and 11 (IQR 6–22), respectively. Median RTS was 12 (IQR 12–12). The overall in-hospital mortality rate was 8.1 % ($n = 302$).

**Table 2** Discriminative and calibration performance of BISS, TRISS, and ASCOT models

| Trauma models | Discrimination area under curve (95 % CI) | Calibration | |
|---|---|---|---|
| | | Calibration slope | Calibration intercept |
| BISS | 0.883 (0.865–0.901) | 1.218 | 0.604 |
| TRISS | 0.902 (0.858–0.946) | 0.935 | −0.142 |
| ASCOT | 0.864 (0.816–0.913) | 0.873 | −0.096 |

## Validation of BISS model

All three trauma prediction models showed high discriminative performance. BISS had an area of 0.883 (95 % CI 0.865–0.901) and performed equivalent to TRISS and ASCOT with an area of 0.902 (95 % CI 0.858–0.946) and 0.864 (95 % CI 0.816–0.913), respectively (Table 2).

However, calibration was better in TRISS and ASCOT. BISS had a calibration intercept of >0 meaning that predicted survival rates were systematically lower than observed survival rates. TRISS and ASCOT had a calibration intercept <0 indicating that predicted survival rates were systematically higher than observed survival rates (Table 2). The calibration slopes of all three models were >1 indicating that the predictor effects were stronger in the validation dataset than in the developmental dataset. Representative calibration plots are shown in Fig. 1a–c.

## Extended BISS model improves performance

BISS, TRISS, and ASCOT models were updated in 1561 patients sustaining blunt injuries. When ISS was replaced by NISS, BNISS model showed an improvement in discriminative performance compared with updated BISS model. The area under ROC curve increased from 0.892 (95 % CI 0.870–0.913) in BISS model to 0.918 (95 % CI 0.899–0.936) in BNISS model (Table 3).

## Discussion

In the current study including a large trauma population, we externally validated a novel base deficit-based prediction model for evaluation of trauma care. We demonstrated that the discriminative performance of BISS model was equally excellent as that of widely used TRISS and ASCOT models. BISS model potentially allows simplified calculation offering a more objective assessment using data routinely collected in the clinical practice. Calibration of BISS model was, however, less good than that of other models. As

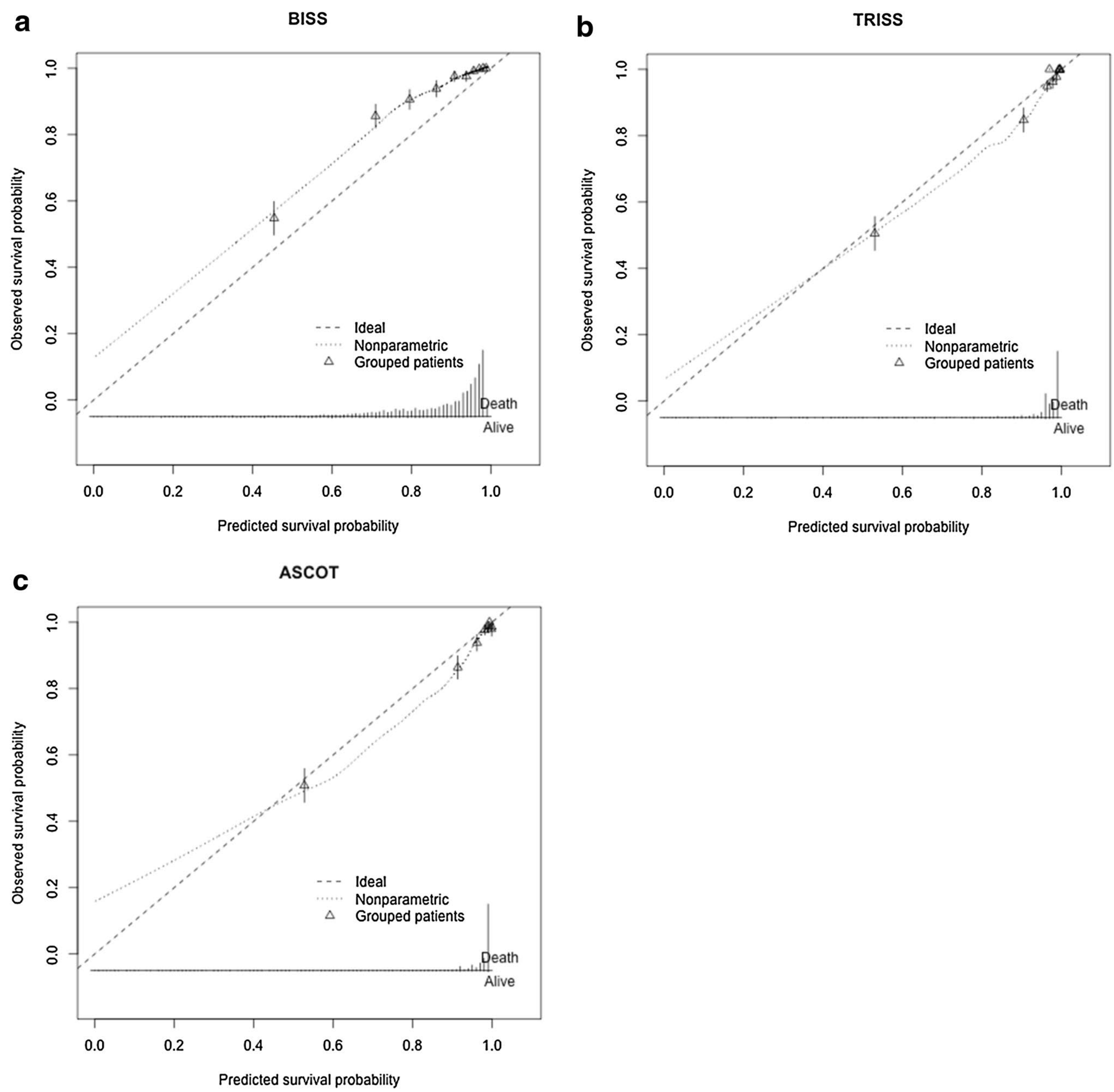


**Fig. 1** **a** Calibration plot of BISS. **b** Calibration plot of TRISS. **c** Calibration plot of ASCOT

**Table 3** Discriminative performance of BNISS and updated BISS, TRISS, and ASCOT models

| Trauma models | Area under curve (95 % CI) |
|---|---|
| BNISS | 0.918 (0.899–0.936) |
| Updated BISS | 0.892 (0.870–0.913) |
| Updated TRISS | 0.908 (0.888–0.929) |
| Updated ASCOT | 0.901 (0.876-0.927) |

apparent from the calibration slopes, the predictor effects were generally stronger in the validation data than in the development data for all three trauma models. The calibration intercepts differed among trauma models. Survival rate was higher than predicted by BISS. Such a difference in calibration intercepts may be explained by a difference between the developmental population and validation population and may highlight the need for continuous updating of trauma prediction models when they are applied to a new setting.

In the current study, the substitution of RTS for admission base deficit as a measurement of physiological derangement did not affect the overall model performance of BISS. Our findings are in agreement with previous studies [6, 14] reporting significant correlation between base deficit and RTS. Although RTS was initially intended for prehospital triage, it has become widely used for trauma research mostly as part of TRISS and ASCOT models. However, scoring of vital signs is less reliable in case of intubation, sedation, or intoxication potentially leading to inaccurate assessment of RTS. This may also explained previous findings reporting the variable prognostic value of RTS [7].

Base deficit provides an accurate reflection in acid–base disturbance induced by injuries and has, therefore, been well investigated in trauma patients. In numerous studies in trauma patients, disturbance in base deficit has been correlated with an increased rate of mortality and blood transfusion, prolonged length of intensive care unit stay as well as the development of a wide range of complications [4]. Moreover, the sensitivity of vital signs to differentiate between minor and major injuries was poor, but it increased when combined with metabolic parameters including base deficit [15]. Base deficit has an established normal range and can be obtained by routine laboratory testing, therefore interpretation and collection of data is less influenced by subjective assessment and measurement variability. Implementation point of care devices may allow data collection at bedside and may increase the availability of base deficit.

The optimal anatomical scoring system providing adequate description of a variety of injuries and severity has not been established. This is underscored by many anatomical scores existing in the literature. ISS remains one of the widely used anatomical systems in spite of inherent limitations, among which is the inability to account for multiple injuries [7]. NISS has been developed to address this limitation of ISS and has been shown to better predict mortality in trauma patients than ISS [10]. In the current study, the substitution of ISS for NISS in the BNISS model improved overall model performance compared with BISS. Moreover, BNISS performed better than TRISS and ASCOT, but confirmation of these findings as well as comparison with other anatomical scoring systems is needed.

Prediction models using clinical information offers investigators a simple tool for trauma research, but they may not completely capture the impact of sustained injuries on patients' prognosis. Several hematological and biochemical markers have been associated with outcome in trauma patients and may provide additional prognostic information not reflected by solely clinical information [16, 17]. Hence, incorporation of these blood-based markers in trauma prediction models may substantially improve predictive performance. The implementation of data collection infrastructure enabling automated processing and storage of laboratory testing results may open new opportunity for trauma research without compromising patients' privacy and the development of novel trauma prediction models combining clinical information and laboratory parameters [18].

The current study has several limitations that warrant discussion. First, admission base deficit was determined at the discretion of the attending emergency physician and was therefore not available for all trauma patients. In particular, admission base deficit was not routinely determined in patients with minor injuries (ISS $< 16$). Multiple imputation method was used to deal with missing values. As a sensitivity analysis, we performed a complete case analysis as well, which demonstrated similar findings (results not shown). Therefore selection bias is unlikely to cause a misinterpretation of the results. Second, since our hospital served as a regional referral trauma center of patients with multiple injuries, the generalizability of the study population may be reduced. We believe that the influence is of limited magnitude, because recent data were included over a four-year period and the criteria for inclusion and exclusion were broadly defined to obtain a heterogeneous group of trauma patients. Lastly, penetrating injuries are not a common cause of injuries in the Dutch trauma population. A larger proportion of penetrating injuries may increase the rate of abnormal base deficit due to hemodynamic instability, which may improve the performance of a base deficit-based model.

In conclusion, we externally validate a base deficit-based trauma prediction model in a large cohort of trauma patients and demonstrated equivalent discriminative ability compared to the traditional TRISS and ASCOT models. Calibration of BISS model was, however, less good than that of other models. Since these models are hampered by practical shortcomings, base deficit-based model may provide a more objective alternative for case-mix adjustment in trauma research and quality assessment of trauma care. The replacement of ISS by NISS further improves the predictive performance of base deficit-based model, but further confirmation is needed.

**Compliance with ethical requirements** According to Dutch regulation, this type of study does not require consent by the medical ethical review board.

**Conflict of interest** Siu Lam, Hester Lingsma, Ed van Beeck, Loek Leenen declare that they have no conflict of interest.

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