Jurnal Ners

Volume 21 Issue 1, February 2026, p. 42-50
http://dx.doi.org/10.20473/jn.v21i1.86367

Original Article Open Access

Predictive performance and statistical calibration of the TRISS method in patients with traumatic brain injury: a retrospective data analysis

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Responsible Editor: Ferry Efendi

Received: 16 January 2025○ Revised: 14 February 2026 ○ Accepted: 19 February 2026

ABSTRACT

Introduction: Major trauma is a leading cause of death, particularly in young adults. The Trauma and Injury Severity Score (TRISS) is commonly used for mortality prediction, but its performance in patients with head trauma, especially in non-Western populations, remains unclear. The applicability of the TRISS, validated on North American cohorts, in different healthcare settings and injury patterns, such as those in North Africa, has not been thoroughly assessed. This study evaluated the predictive performance of the TRISS for hospital mortality in a cohort of Moroccan patients with traumatic brain injury. (TBI).

Methods: A single-center retrospective study was conducted at Hassan II University Hospital in Fez, Morocco, over 24 months (January 2022 to December 2023), including 133 patients. The TRISS score was calculated using the Revised Trauma Score (RTS), Injury Severity Score (ISS), and age. The primary endpoint was all-cause mortality, and model performance was assessed through ROC curve analysis and calibration using graphical methods. Owing to the modest sample size, formal calibration tests were not emphasized.

Results: The mortality rate was 27.8%. The TRISS demonstrated modest discriminative ability (AUC = 0.654). Although the specificity was high, the sensitivity was very low, resulting in a high false-negative rate (83.8%). Calibration analysis showed paradoxical mortality in the highest predicted survival group, indicating a significant miscalibration.

Conclusions: The TRISS method displayed limited predictive performance in the TBI cohort, largely owing to its low sensitivity. This underscores the need for population-specific validation and development of more accurate predictive models to improve patient triage and outcomes.

Keywords: calibration, head trauma, injury severity score (ISS), mortality prediction, revised trauma score (RTS), traumatic brain injury, trauma prediction, TRISS

Introduction

Major trauma is a global public health problem and a leading cause of death and permanent disability, particularly among young adults (Miller *et al.*, 2021). The initial management of these patients requires a rapid and accurate severity assessment to guide treatment decisions and optimize the allocation of limited medical resources (Reddy *et al.*, 2019). In this context, the development of robust prognostic tools has become a crucial issue for trauma teams (Beucler *et al.*, 2022; Johnstone, Mitrofanis, and Stone, 2023), making it possible to identify patients at high risk of death early and thus adapt their management.

Among the available prognostic scores, the Trauma and Injury Severity Score (TRISS) method has emerged since the 1980s as a reference tool in traumatology (Yang *et al.*, 2024; Wong *et al.*, 2013). This model combines physiological parameters via the Revised Trauma Score (RTS) (Davis *et al.*, 2006), anatomical severity of the lesions based on the Injury Severity Score (ISS), and the patient's age to calculate the probability of survival (Hörauf *et al.*, 2024). Initially validated on large North American databases, TRISS is widely used in trauma registries worldwide for the standardization of quality of care assessments (Maeda *et al.*, 2019; Hörauf *et al.*, 2024).

However, TRISS performance varies significantly across populations, injury mechanisms, and healthcare systems (Bernhardt *et al.*, 2023; Bernhardt *et al.*, 2025). Studies have reported limitations in specific subpopulations, including elderly patients, penetrating trauma victims, and non-North American cohorts, where injury patterns and management delays differ from those of the original validation populations (Hörauf *et al.*, 2024; Kiwanuka *et al.*, 2024; Bernhardt *et al.*, 2025). This interpopulation variation raises questions regarding the generalizability of the model. In traumatic brain injury (TBI) populations (Bernhardt *et al.*, 2024; Bernhardt *et al.*, 2025), specifically, TRISS prognostic performance of TRISS remains controversial (Maeda *et al.*, 2019). Critics argue that RTS physiological parameters fail to capture TBI complexity and progression (Hörauf *et al.*, 2024), whereas ISS may inadequately reflect the severity of multiple or combined head injuries (Kazemi *et al.*, 2024).

Despite extensive TRISS validation in high-income countries, no published data exists on its performance in Moroccan or North African TBI populations. This represents a critical gap, as trauma epidemiology, prehospital transport times, and intensive care resources in our setting differ substantially from the North American cohorts in which TRISS coefficients were derived. Furthermore, the original TRISS coefficients were based on trauma data from the 1980s to the 1990s, raising questions about their applicability to contemporary trauma care with advances in resuscitation, neuromonitoring, and surgical techniques. Given the high burden of road traffic accidents in Morocco, accounting for over 80,000 injuries annually (Khyara *et al.*, 2022), validating prognostic tools in our population is essential for appropriate triage, resource allocation, and benchmarking the quality of care. This study aimed to evaluate the discrimination and calibration of the TRISS method in a cohort of patients with Moroccan traumatic brain injury (TBI), focusing on its clinical implications for frontline healthcare providers. The primary objective was to assess the model's discriminatory power and calibration ability, while secondary objectives included examining the components of the Revised Trauma Score (RTS) and exploring factors that may explain discrepancies between model predictions and observed outcomes.

Materials and Methods

Study Design

Our research adopted a retrospective observational design conducted over a 24-month period from January 2022 to December 2023. This single-center study was conducted in the multipurpose resuscitation and neurosurgery department of the HASSAN II University Hospital in Fez, a reference institution for the management of severe trauma in the Fez-Meknes region.

Ethics approval

This study was conducted in accordance with the ethical standards of the institutional and national research committee and with the 1964 Helsinki declaration and its later amendments. The research protocol was submitted to the Comité d'Ethique Hospitalo-Universitaire de Fès (Faculty of Medicine and Pharmacy, University Sidi Mohammed Ben Abdellah, Fez, Morocco) in December 2025. Following the committee's meeting in January 2026, ethical approval was granted, and data collection and analysis were initiated accordingly. The official approval document was subsequently issued under reference number N° 01/2026 on February 19, 2026. The ethics committee approved the retrospective collection and analysis of anonymized patient data from medical records and waived the requirement for informed consent due to the observational nature of the study and the use of de-identified data.

Study population and selection criteria

The study population included 133 consecutive patients admitted for moderate-to-severe head trauma. The inclusion criteria were as follows: age > 15 years, diagnosis of head trauma with an initial Glasgow coma scale (GCS) score between 3 and 13, and comprehensive care at our institution. Exclusion criteria included prehospital deaths, isolated limb injuries without cranial involvement, and incomplete medical records lacking essential data for calculating severity scores.

Data collection and variables studied

Data collection was performed according to a standardized protocol from electronic medical records (OSIX) and supplemented by paper files. The demographic variables collected included age, sex, and significant medical history (De los Rios-Pérez *et al.*, 2024). The initial clinical parameters included GCS, systolic blood pressure (SBP), respiratory rate (RR), and pulsed oxygen saturation. The severity of the lesions was quantified using the Injury Severity Score (ISS) calculated using the Abbreviated Injury Scale. The primary endpoint was all-cause mortality rate.

Calculation of scores

The TRISS score was calculated for each patient according to the standard formula (Legrand *et al.*, 2015): P(survival) = 1 / (1 + e^(-b)), where b represents the logistic regression equation combining the Revised Trauma Score (RTS), ISS, and age. RTS was determined from the coded values of GCS, SBP, and RR according to the validated weights (De los Rios-Pérez *et al.*, 2024). Age was dichotomized using a threshold of 55, as specified in the original TRISS method. All analyses were based on the standard regression coefficients for blunt trauma (Debiasi-Laigle et al., 2015).

Revised Trauma Score (RTS) Calculation

The Revised Trauma Score (RTS) was calculated using a conventional formula established in trauma studies (Sheikhi *et al.*, 2025). This index of physiological severity is based on three key parameters: GCS, BP, and RR (Briese *et al.*, 2023): GCS, BP and RR (Indurkar *et al.*, 2023). The formula applied was as follows:

$$\mathrm{RTS} = (0.9368 \cdot C_{\mathrm{GCS}}) + (0.7326 \cdot C_{\mathrm{SBP}}) + (0.2908 \cdot C_{\mathrm{RR}}) \quad (1)$$

Where each parameter is transformed using the following coding functions:

$$C_{\mathrm{GCS}} = \begin{cases} 4 & \text{if } 13 \le \mathrm{GCS} \le 15 \\ 3 & \text{if } 9 \le \mathrm{GCS} \le 12 \\ 2 & \text{if } 6 \le \mathrm{GCS} \le 8 \\ 1 & \text{if } 4 \le \mathrm{GCS} \le 5 \\ 0 & \text{if } \mathrm{GCS} = 3 \end{cases}$$

$$C_{\mathrm{SBP}} = \begin{cases} 4 & \text{if SBP} > 89 mmHg \\ 3 & \text{if } 76 \le \mathrm{SBP} \le 89\mathrm{mmHg} \\ 2 & \text{if } 50 \le \mathrm{SBP} \le 75\mathrm{mmHg} \\ 1 & \text{if } 1 \le \mathrm{SBP} \le 49\mathrm{mmHg} \\ 0 & \text{if SBP} = 0\mathrm{mmHg} \end{cases}$$

$$C_{\mathrm{RR}} = \begin{cases} 4 & \text{if } 10 \le \mathrm{RR} \le 29/\mathrm{min} \\ 3 & \text{if RR} > 29/min \\ 2 & \text{if } 6 \le \mathrm{RR} \le 9/\mathrm{min} \\ 1 & \text{if } 1 \le \mathrm{RR} \le 5/\mathrm{min} \\ 0 & \text{if RR} = 0/\mathrm{min} \end{cases}$$

In this equation, each physiological parameter was coded according to a specific ordinal scale. The Glasgow scale is transformed according to the function C_{GCS} that assigns 4 points for a GCS between 13 and 15.3 points for a GCS of 9 to 12.2 points for a GCS of 6 to 8.1 points for a GCS of 4 to 5, and 0 points for a GCS of 3. SBP was coded by C_{SBP} with four points for one SBP$> 89 mmHg$, three points for$76 - 89$mmHg, two points for $50 - 75$mmHg, 1 point for$1 - 49$mmHg, and zero points for zero SBP. RR was quantified by C_{RR} assigning 4 points for an RR of 10-29/min, 3 points for an RR $> 29/min$, 2 points for RR $6 - 9/\mathrm{min}$, 1 point for RR $1 - 5/\mathrm{min}$, and 0 points for RR=0/min.

Calculation of the probability of survival by the TRISS method

The probability of survival according to the TRISS (Trauma and Injury Severity Score) method was determined using a logistic regression model that incorporates the RTS, the Injury Severity Score (ISS) and the patient's age(Sheikhi *et al.*, 2025; Wong *et al.*, 2013). The mathematical model is based on a standard logistics function:

$$P(\text{ survival}) = \frac{1}{1+e^{-\beta}}$$

The linear predictor, β is specifically tailored to the type of trauma. For our exclusively blunt trauma cohort, we applied the following validated regression coefficients. where b is the linear predictor calculated as:

$\beta = b_0 + b_1 . RTS + b_2 . ISS + b_3 . I_{age}$

For blunt trauma, the standard regression coefficients from the Major Trauma Outcome Study (MTOS) are:

- b_0 (intercept) = -0.4499
- b_1 (RTS coefficient) = +0.8085
- b_2 (ISS coefficient) = -0.0835
- b_3 (age coefficient) = -1.7430

Thus, for our exclusively blunt trauma cohort, the linear predictor was calculated as

β = -0.4499 + (0.8085 × RTS) + (-0.0835 × ISS) + (-1.7430 × I_age)

or equivalently:

$$\beta = -0.4499 + 0.8085 \cdot \mathrm{RTS} - 0.0835 \cdot \mathrm{ISS} - 1.7430 \cdot I_{\mathrm{age}}$$

Where I_age is an age indicator variable:

- I_age = 1 for patients aged ≥ 55 years.
- I_age = 0 for patients aged < 55 years.

This model makes it possible to estimate the probability of hospital survival for each patient according to physiological conditions (RTS), anatomical severity of lesions (ISS), and age (Rapsang and Shyam, 2015).

In this equation, the variable I_{age} represents a dichotomous indicator of age, taking the value of 1 for patients aged 55 years or older and 0 for younger patients. This modeling makes it possible to estimate the

Table 1 : RTS Parameter Coding

GCS	C_GCS	SBP (mmHg)	C_SBP	RR (breaths/min)	C_RR
13–15	4	> 89	4	10–29	4
9–12	3	76–89	3	> 29	3
6–8	2	50–75	2	6–9	2
4–5	1	1–49	1	1–5	1
3	0	0	0	0	0

Example calculation: For a patient with GCS = 10 (C_GCS = 3), SBP = 120 mmHg (C_SBP = 4), and RR = 22/min (C_RR = 4)
RTS = (0.9368 × 3) + (0.7326 × 4) + (0.2908 × 4) = 2.81 + 2.93 + 1.16 = 6.90

probability of hospital survival for each patient according to his physiological condition (RTS), anatomical severity of the lesions (ISS), and age (Rapsang and Shyam, 2015).

Definition of injury severity score (ISS)

The ISS was calculated using the classical AIS method (Davis *et al.*, 2006; Briese *et al.*, 2023). ISS is a score that measures the total injury severity of anatomical lesions and is based on six body regions as specified in AIS: head/neck, face, thorax, abdomen, extremities/pelvis, and skin surface(Rapsang and Shyam, 2015; Eidenbenz *et al.*, 2025; Frankema *et al.*, 2005). The computation is based on the following formula :

$$\mathrm{ISS} = \max_{1 \le i < j < k \le 6} \left(\mathrm{AIS}_i^2 + \mathrm{AIS}_j^2 + \mathrm{AIS}_k^2 \right)$$

This formula indicates the maximization of the sum of squares of the three largest AIS scores from three different body regions. For each patient, the ISS was calculated by summing the squares of the three highest Abbreviated Injury Scale (AIS) scores from the three body regions. This method minimizes the influence of widespread but less severe injuries across multiple locations, ensuring that the final score reflects the overall trauma burden. The ISS ranges from 0 to 75, with higher scores indicating greater severity. Scores >15 are generally considered to represent major trauma in injured patients.

Application and validation of calculations

All mathematical computations were performed using Python (version 3.9) and appropriate scientific libraries. The regression coefficients used in the TRISS model were initially validated using the Major Trauma Outcome Study (mTOS) database for blunt trauma. As the TRISS coefficients were externally derived and fixed, no model training or statistical cross-validation was performed. Instead, the computational accuracy was verified through reproducibility checks. The correctness of the mathematical transformations and probability estimates was confirmed by independent manual recalculation of TRISS scores in a random sub-sample of 10% of the cohort, with full concordance. This mathematical rigor ensures the reproducibility of our study and validity of the estimated survival probabilities.

To ensure full reproducibility, all Python scripts used for data processing, statistical analysis, and figure generation were archived and are available from the corresponding author upon request. Key parameters for reproducibility included Python version 3.9.16, random seed 42 for bootstrap procedures, and the specific library versions listed in the statistical analysis section.

Statistical analysis

Statistical analyses were performed using Python version 3.9 with the pandas, scikit-learn, and matplotlib libraries. Continuous variables were described by their means and standard deviations, and categorical variables by their numbers and percentages. The discriminatory performance of TRISS was assessed using the area under the Receiver Operating Characteristic (ROC) curve. The optimal classification threshold for TRISS probability was determined using the Youden index (J = sensitivity + specificity - 1), which maximizes the discriminatory ability of the model by balancing sensitivity and specificity. This method identifies the cutoff value that optimizes the overall classification performance, which is particularly important in clinical settings, where both false positives and false negatives have significant consequences. The Youden index yielded an optimal probability threshold of 0.78 for our cohort. This threshold was subsequently used to calculate the sensitivity, specificity, predictive value, and confusion matrix. Alternative thresholds (0.50, 0.70, and 0.85) were explored in the sensitivity analyses but did not substantially improve the sensitivity-specificity trade-off. This threshold was used for the calculation of the sensitivity (16.2%), specificity (91.7%), and other classification metrics. The performance metrics included sensitivity, specificity, positive and negative predictive values, and overall accuracy. For the confusion matrix and derived metrics (sensitivity, specificity, predictive values), patients were classified as "predicted death" if their TRISS-predicted probability of survival was below the selected threshold (τ), and "predicted survival" if the probability was $\geq \tau$. Because TRISS calculates P(survival), this is equivalent to using P(death) = 1 − P(survival) with a threshold of 1-τ.

Sample size consideration: Given the retrospective design, all consecutive eligible patients were included during the 24-month study period, resulting in a final sample of 133 patients. No formal a priori sample size calculations were performed. The precision of the estimates was reflected in the 95% confidence intervals reported for all performance metrics. The relatively wide intervals (e.g., AUC 95% CI: 0.556–0.752) highlight the limited statistical precision and underscore the need for confirmation in larger multicenter cohorts.

Interpretation of performance metrics: Model performance was interpreted according to established guidelines: AUC values were considered excellent (>0.90), good (0.80-0.90), fair (0.70-0.80), poor (0.60-0.70), or failing (0.50-0.60) (Hosmer, Lemeshow and Sturdivant, 2013). For clinical prediction models of trauma, a sensitivity >80% is generally required for triage tools to avoid missing high-risk patients, while a specificity >85% is desirable to prevent unnecessary resource allocation (Bouamra *et al.*, 2006). Although the generally acceptable accuracy for prognostic models in heterogeneous trauma populations is above 75%, our model, with an accuracy of 70.7%, remains within an acceptable range for models of this type, considering the specific characteristics of our population and methodological limitations.

Calibration assessment: Model calibration—the agreement between predicted probabilities and observed outcomes—was evaluated graphically by plotting observed mortality rates against mean predicted probabilities across five equally spaced risk strata (0.00-0.20, 0.21-0.40, 0.41-0.60, 0.61-0.80, 0.81-1.00). A calibration curve was generated using locally weighted scatterplot smoothing (LOESS) to visualize the relationship between the predictions and observations. Formal statistical tests for calibration, including the Hosmer-Lemeshow goodness-of-fit test and Brier score, were not emphasized due to the modest sample size (n=133). The Hosmer-Lemeshow test is known to be sensitive to sample size and can produce unreliable results with sparse data in extreme risk categories. The Brier score was calculated to assess overall predictive performance, reflecting both the calibration and discrimination components. As the Brier score is sensitive to the outcome prevalence, its magnitude was interpreted in relation to the observed mortality rate within the study cohort. External validation is required to assess generalizability, but not for internal performance estimation. Therefore, we prioritized graphical calibration assessment, which provides a transparent visualization of calibration patterns and is recommended for clinical prediction models in moderate-sized cohorts. However, graphical assessment provides a transparent visualization of calibration patterns and is recommended for clinical prediction models (Steyerberg *et al.*, 2010). Owing to the modest sample size and sparse data in extreme risk categories, we also performed a sensitivity analysis using quantile-based bins (deciles) to assess the stability of the calibration estimates. However, the results were consistent with the equally spaced strata approach, and the small number of events precluded a reliable estimation of the calibration slope and intercept.

Confidence intervals and reproducibility: The 95% confidence interval for the AUC was calculated using the DeLong method, which is a non-parametric approach appropriate for correlated ROC curves (DeLong, DeLong and Clarke-Pearson, 1988). For all other performance metrics (sensitivity, specificity, accuracy, and predictive values), 95% confidence intervals were estimated using the bootstrap method with 1,000 resamples to account for sampling variability. A fixed random seed (seed = 42) was used for all bootstrap resampling procedures, to ensure replicability. A complete analysis code is available from the corresponding author upon request.

Results

Our study involved a cohort of 133 TBI patients with an overall mortality rate of 27.8%. The population was characterized by an average age of 44.1 years and moderate to severe trauma severity, as evidenced by the average ISS severity score of 24.5 and the predominance of impaired consciousness, with 33.8% of patients having severe GCS (≤ 8) (see Table 2).

Mean physiological parameters, such as SBP (114.5 mm Hg) and RR (19.2/min), reflected an overall stable hemodynamic state at admission for the majority of patients. The calculated mean RTS score was 6.07, indicating significant physiological impairment across the cohort, which was primarily attributable to the neurological component (Table 3).

Table 2: Characteristics of the population (n=133)

Feature	Value
Total patients	133
Mortality	37 (27.8%)
Mean Age ±SD	44.1 ± 15.5
GCS average ±SD	9.59 ± 3.13
SBP mean ± SD	114.5 ± 22.6
Mean RR ± SD	19.2 ± 5.2
ISS average ± SD	24.5 ± 10.0

Table 3 : components of the revised trauma score (RTS)

Component	Average Score	Range
GCS	2.70 ± 0.97	0-4
SBP	3.85 ± 0.45	2-4
RR	2.47 ± 0.62	1-4
RTS total	6.07 ± 0.98	3.27-7.55

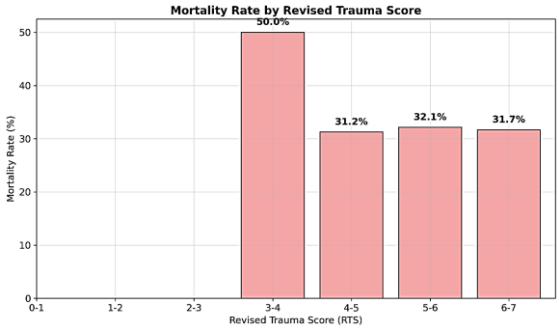

Figure 1: Mortality rate stratified by Revised Trauma Score (RTS) categories. Bars represent observed mortality rates with 95% confidence intervals. The inverse relationship between RTS and mortality demonstrates the expected physiological severity gradient, with higher mortality in lower RTS categories.

Table 4: Distribution of TRISS-predicted survival probabilities

TRISS probability	Patients	Percentage	Mortality
0.00-0.20	2	1.5%	50.0%
0.21-0.40	6	4.5%	33.3%
0.41-0.60	15	11.3%	30.8%
0.61-0.80	28	21.1%	42.9%
0.81-1.00	82	61.7%	20.7%

Note: Due to the small sample sizes in some strata (e.g., n=2 in 0.00-0.20), mortality rates in extreme categories should be interpreted with caution. Quantile-based binning (deciles) produced consistent results, but did not resolve the instability in extreme strata owing to the limited number of events.

Table 5 : TRISS performance metrics

Metric	Value (95% CI)
AUC	0.654 (0.556-0.752)
Accuracy	70.7% (62.3-78.2)
Sensitivity	16.2% (6.2-32.0)
Specificity	91.7% (85.3-96.2)
Positive Predictive Value (PPV)	42.9% (20.1-68.0)
Negative Predictive Value (NPV)	73.9% (69.7-77.7)

Table 6: Performance metrics at different probability thresholds

Threshold	Sensitivity (95% CI)	Specificity (95% CI)	False Negatives (n)
0.50	45.9% (29.5-63.1)	68.8% (59.8-76.8)	20
0.60	35.1% (20.2-52.5)	79.2% (70.8-86.0)	24
0.70	24.3% (11.8-41.2)	86.5% (78.9-92.1)	28
0.78 (Youden)	16.2% (6.2-32.0)	91.7% (85.3-96.2)	31
0.80	13.5% (4.5-28.8)	92.7% (86.5-96.6)	32

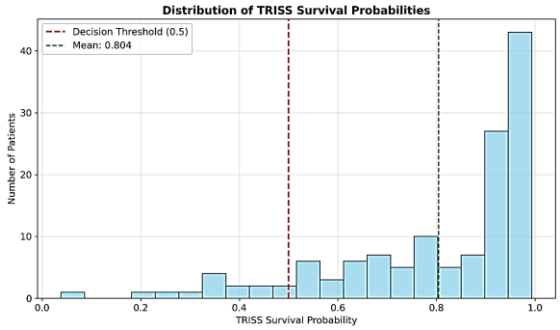

Figure 2: Distribution of TRISS-predicted survival probabilities stratified by actual mortality outcome. The substantial overlap between groups illustrates the model's limited discriminatory ability.

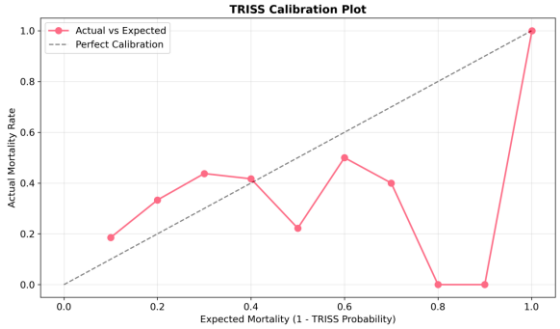

Figure 3: Calibration curve comparing TRISS-predicted survival probabilities with observed mortality rates. The diagonal dashed line represents perfect calibration. Points below the line indicate overestimation of survival (underestimation of mortality risk), particularly evident in the highest probability stratum (0.81-1.00) where observed mortality reaches 20.7%.

According to the TRISS method, the distribution of survival probabilities revealed that the majority of patients (61.7%) had the most favorable prognostic range (0.81-1.00). Paradoxically, this category still had a mortality rate of 20.7%, suggesting an underestimation of risk (see Table 4).

Performance analysis of the TRISS model demonstrated modest discriminatory accuracy, with an area under the ROC curve of 0.654. The model displayed a high specificity (91.7%) but a particularly low sensitivity (16.2%), making it possible to correctly identify only 6 of the 37 deaths (see Table 5).

Comparison of the TRISS probabilities between survivors (mean 0.829 Â ± 0.24, median 0.89, IQR: 0.78--0.95) and non-survivors (mean 0.742 Â ± 0.29, median 0.81, IQR: 0.56--0.94) revealed a statistically significant difference (Mann-Whitney U test, p = 0.041). The rank-biserial correlation (r = 0.28) indicated a small to moderate effect size, confirming a substantial overlap between the groups. This limited separation partly explains the modest discriminatory performance (AUC = 0.654) and poor sensitivity of the model.

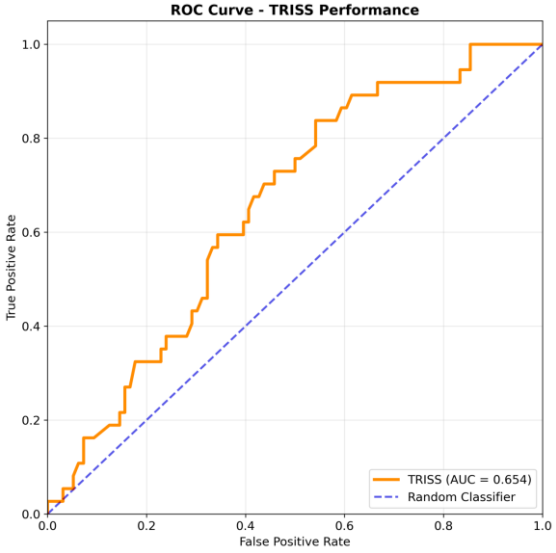

Figure 4: Receiver Operating Characteristic (ROC) curve for TRISS model discrimination. The area under the curve (AUC) is 0.654 (95% CI: 0.556-0.752), indicating modest discriminatory ability. The diagonal reference line represents random classification (AUC = 0.50).

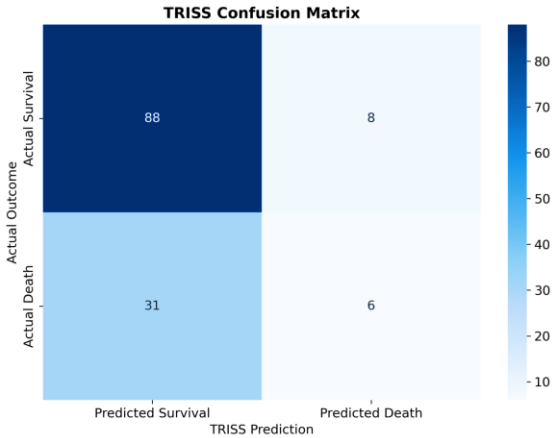

Figure 5: Confusion matrix of TRISS classification at the optimal Youden index threshold (0.78). True negatives (n=88): correctly identified survivors; False positives (n=8): survivors predicted to die; False negatives (n=31): deceased patients predicted to survive (missed high-risk patients); True positives (n=6): correctly identified deaths. The high false negative rate (83.8% of deaths) represents the model's critical limitation for triage applications.

Discussions

The results of our study highlight the limitations of the TRISS method in predicting the prognosis of patients with TBI in our cohort. Modest discriminatory performance (AUC 0.654) contrasts with values generally reported in the literature, which often exceed 0.80 (Sheikhi *et al.*, 2025; Kazemi *et al.*, 2024; Maeda *et al.*, 2019). This discrepancy could be explained by the particular characteristics of our population, including the

predominance of neurological trauma and the specific distribution of severity scores (Frankema *et al.*, 2005) The low sensitivity of the model (16.2%) represents a major concern for its use in routine clinical practice (Dasdar *et al.*, 2023).

Our results (AUC 0.654) were lower than those reported by Maeda et al. (Maeda *et al.*, 2019) (AUC 0.81) and Yang et al. (Yang *et al.*, 2024) (AUC 0.85) in head trauma cohorts. This difference could be explained by several factors: the higher proportion of severe head injuries in our cohort (33.8% vs. 28% in Maeda), the exclusion of prehospital deaths in our study, and the specificities of our care system with potentially longer treatment times. Unlike the CRASH study, which included scan variables (Maeda *et al.*, 2019), the TRISS is based on the ISS, which often underestimates the severity of single but multiple head injuries.

The paradoxical mortality distribution, particularly the 20.7% mortality rate in the highest predicted survival stratum (0.81-1.00), revealed suboptimal model calibration in our context. Detailed analysis of the 17 patients who died despite high TRISS probabilities (>0.80) provides insight into this miscalibration: 14 (82%) had severe head trauma (GCS ≤8) with significant brain lesions on the initial CT scan, yet initially stable physiological parameters (SBP, RR) that masked their true risk. Their mean ISS of 21.4, while moderate, failed to capture the specific severity of the brain injury. Additionally, 9 (53%) patients had unmeasured risk factors, including age >70 years (n=4), anticoagulation (n=3), or evacuation time >6 h (n=2). Similarly, analysis of the 31 false negatives, patients who died but were predicted to survive—reveals a characteristic profile: mean ISS 23.4 ± 8.7 (moderate anatomical injury) contrasting with mean GCS 5.2 ± 2.1 (severe neurological compromise). These findings demonstrate that standard TRISS coefficients calibrated on heterogeneous North American populations systematically underestimate the prognostic weight of dominant brain injuries in our setting. The model's failure to capture interactions between neurological status, anatomical injury patterns, and local healthcare delivery factors (delayed presentation, limited pre-hospital care) explains its critically low sensitivity and poor clinical utility in early triage decisions.

The choice of threshold significantly impacts the clinical utility of the TRISS model. While the Youden index (0.78) maximizes overall accuracy, it yields an unacceptably low sensitivity (16.2%) for triage applications. Even at a lower threshold of 0.50, the sensitivity reached only 45.9%, meaning that more than half of the deceased patients would still be misclassified as low-risk. This finding reinforces that TRISS, regardless of threshold selection, lacks sufficient sensitivity for safe triage decision making in this population.

Several methodological limitations should be considered when interpreting these findings. First, the small sample size (n=133) limits the statistical power and precludes split-sample validation or reliable subgroup analyses. Second, this was a single-center study conducted at a university hospital in Fez, which may limit the generalizability to other Moroccan or North African healthcare settings with different patient populations, resources, and pre-hospital care systems. Third, due to the retrospective design, we were unable to account for several potential confounders that may influence mortality, including the mechanism of injury, pre-hospital management times, comorbid conditions (e.g., hypertension, diabetes), and post-admission complications (e.g., sepsis and multi-organ failure). Fourth, retrospective bias is inherent in the data collected from medical records, which may contain inaccuracies or missing information despite standardized extraction protocols. Fifth, the absence of external validation on an independent dataset means that our findings require confirmation in larger multicenter studies before definitive conclusions can be drawn about TRISS performance in North African TBI populations. Sixth, as noted above, formal calibration tests (Hosmer-Lemeshow, Brier score, calibration slope/intercept) could not be performed because of sample size constraints, and the Youden threshold was selected without cross-validation, which may introduce optimism in performance estimates.

From a nursing research perspective, our study did not evaluate the impact of nursing assessment protocols or surveillance frequencies on patient outcomes. Future studies should explore how nursing-led interventions and monitoring schedules interact with prognostic scores such as TRISS, potentially developing nurse-sensitive indicators for traumatic brain injury deterioration that could complement existing prediction models.

In conclusion, our study further emphasizes the importance of trauma-specific validation of prognostic tools prior to their introduction into daily practice. The use of models tailored to the specificities of local populations and possibly integrating other variables could increase the prediction accuracy. Additional investigation is required to determine the factors responsible for the type of degradation encountered and ultimately devise ways to maximize the use of prognosis assessment in injured patients.

From a nursing perspective, these findings have direct implications in trauma care. The high false-negative rate of the TRISS model indicates that nurses cannot rely on this score alone when prioritizing patients for intensive monitoring. Bedside neurological assessment, including serial GCS evaluations, pupil reactivity, and vital sign trends, remains essential for early detection of deterioration in patients with TBI. Trauma nursing protocols should emphasize continuous clinical

observation along with any prognostic score, and nursing education programs should highlight the limitations of generic prediction tools in specific populations. Future research should explore nurse-led interventions and develop nurse-sensitive indicators that could complement the existing prognostic models and improve patient outcomes.

Conclusion

This retrospective analysis of 133 patients with moderate-to-severe traumatic brain injury (TBI) underscores the limitations of the TRISS model in predicting mortality in a Moroccan cohort. Although the model showed high specificity, its low sensitivity and poor calibration prevented it from being an effective standalone tool for triage in this population. The significant false-negative rate and paradoxical mortality in high-risk survival strata highlight the model's inability to accurately identify patients at high risk of death. This limitation, particularly in the early triage of critically ill patients, poses an ethical and clinical challenge as it may lead to delayed interventions for high-risk individuals. Furthermore, the model's lack of fine discrimination between survivors and non-survivors diminishes its utility in guiding critical care decisions and resource allocation in trauma settings.

Given these limitations, our findings emphasize the urgent need for more contextually relevant predictive models of TBI in Morocco. We recommend that future studies focus on recalibrating the TRISS model with locally relevant variables such as the severity of brain injury, intracranial bleeding, and pre-hospital management times. Additionally, exploring machine-learning-based approaches could provide more accurate and adaptable models for this population. Larger multicenter studies should further investigate the factors influencing trauma outcomes in Morocco and refine the existing predictive algorithms. Ultimately, developing population-specific models is crucial for improving trauma care and clinical decision-making in our healthcare system.

Declaration Of Generative Artificial Intelligence (AI) Use

The authors confirmed that generative artificial intelligence tools were not employed for data analysis, interpretation, or creation of scientific content. The authors take full responsibility for the originality, accuracy, and integrity of all aspects of this study.

Acknowledgments

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Funding source

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Availability of data and materials

All data generated or analyzed during this study are included in this published article. The datasets are also available from the corresponding author on reasonable request.

Authors' contributions

Salama El Haddad study concept, data analysis and interpretation, manuscript original drafting; Rachid El chaal , oualid Hmamouche, Bahia Bennani, statistical analyses, contribution to manuscript writing and editing; Mohammed Chaoui El Faiz work manager. All the authors read and approved the final version of the manuscript and agreed to be accountable for all aspects of the work.

Declaration of Interest

I declare that I have no financial interest or other relationship in the commercial product(s) or its (their) manufacturer(s) or distributor(s) discussed in this manuscript. This includes, but is not limited to, any affiliations such as consultancies, stock ownership, other equity interests, or patent-licensing arrangements.

References

Bernhardt, I. M. *et al.* (2025) "Timing of trauma deaths due to uncontrolled bleeding have not changed in three decades: A multicenter study of patients in hemorrhagic shock," *AMERICAN JOURNAL OF SURGERY*, 250. doi: 10.1016/j.amjsurg.2025.116510 WE - Science Citation Index Expanded (SCI-EXPANDED).

Beucler, N. *et al.* (2022) "Severe trauma patients requiring undelayable combined cranial and extracranial surgery: A scoping review of an emerging concept," *JOURNAL OF NEUROSCIENCES IN RURAL PRACTICE*, 13(4), pp. 585–607. doi: 10.25259/JNRP-2022-1-38-R1-(2348).

Bouamra, O. *et al.* (2006) "A new approach to outcome prediction in trauma: A comparison with the triss model," *Journal of Trauma - Injury, Infection and Critical Care*, 61(3), pp. 701–710. doi: 10.1097/01.ta.0000197175.91116.10.

Briese, A. *et al.* (2023) "The Trauma Activation Review Committee: Response to Undertriage During a Period of Rapid Growth at a Level II Trauma Center," *AMERICAN SURGEON*, 89(9), pp. 3982–3984. doi: 10.1177/00031348231180922.

Dasdar, S. *et al.* (2023) "Frequency of posttrauma complications during hospital admission and their association with Injury Severity Score," *CLINICAL AND EXPERIMENTAL EMERGENCY MEDICINE*, 10(4), pp. 410–417. doi: 10.15441/ceem.23.053.

Davis, D. P. *et al.* (2006) "The predictive value of field versus arrival Glasgow coma scale score and TRISS calculations in moderate-to-severe traumatic brain injury," *JOURNAL OF TRAUMA-INJURY INFECTION AND CRITICAL CARE*, 60(64th Annual Meeting of the American-Association-for-the-Surgery-of-Trauma), pp. 985–990. doi: 10.1097/01.ta.0000205860.96209.1c WE - Science Citation Index Expanded (SCI-EXPANDED) WE - Conference Proceedings Citation Index - Science (CPCI-S).

Debiasi-Laigle, J. *et al.* (2015) "Traumatisés très graves : la plus-value d'un Trauma System à la française ?," *Anesthésie & Réanimation*, 1, pp. A25–A26. doi: https://doi.org/10.1016/j.anrea.2015.07.038.

DeLong, E. R., DeLong, D. M. and Clarke-Pearson, D. L. (1988) "Comparing the areas under two or more correlated receiver

operating characteristic curves: a nonparametric approach," *Biometrics*, 44(3), pp. 837–845. doi: 10.2307/2531595.

Eidenbenz, D. *et al.* (2025) "Identification of major trauma using the simplified abbreviated injury scale to estimate the injury severity score: a diagnostic accuracy and validation study," *SCANDINAVIAN JOURNAL OF TRAUMA RESUSCITATION & EMERGENCY MEDICINE*, 33(1). doi: 10.1186/s13049-025-01320-7.

Fokkema, A. T. *et al.* (2023) "Comorbidities, injury severity and complications predict mortality in thoracic trauma," *EUROPEAN JOURNAL OF TRAUMA AND EMERGENCY SURGERY*, 49(2), pp. 1131–1143. doi: 10.1007/s00068-022-02177-6.

Frankema, S. P. G. *et al.* (2005) "Comparison of current injury scales for survival chance estimation: An evaluation comparing the predictive performance of the ISS, NISS, and AP scores in a dutch local trauma registration," *JOURNAL OF TRAUMA-INJURY INFECTION AND CRITICAL CARE*, 58(3), pp. 596–604. doi: 10.1097/01.TA.0000152551.39400.6F.

Hörauf, J. A. *et al.* (2024) "Settlement Is at the End-Common Trauma Scores Require a Critical Reassessment Due to the Possible Dynamics of Traumatic Brain Injuries in Patients' Clinical Course," *JOURNAL OF CLINICAL MEDICINE*, 13(11). doi: 10.3390/jcm13113333 WE - Science Citation Index Expanded (SCI-EXPANDED).

Hosmer, D. W., Lemeshow, S. and Sturdivant, R. X. (2013) *Applied Logistic Regression: Third Edition*, *Applied Logistic Regression: Third Edition*. doi: 10.1002/9781118548387.

Indurkar, S. K. *et al.* (2023) "Use of the Trauma and Injury Severity Score (TRISS) as a Predictor of Patient Outcome in Cases of Trauma Presenting in the Trauma and Emergency Department of a Tertiary Care Institute," *CUREUS JOURNAL OF MEDICAL SCIENCE*, 15(6). doi: 10.7759/cureus.40410.

Johnstone, D. M., Mitrofanis, J. and Stone, J. (2023) "The brain's weakness in the face of trauma: How head trauma causes the destruction of the brain," *FRONTIERS IN NEUROSCIENCE*, 17. doi: 10.3389/fnins.2023.1141568.

Kazemi, F. *et al.* (2024) "A comparative analysis of the Trauma and Injury Severity Score and the Injury Severity Score in predicting high-value care outcomes in children with traumatic brain injury," *JOURNAL OF NEUROSURGERY-PEDIATRICS*, 34(6), pp. 557–565. doi: 10.3171/2024.8.PEDS24309 WE - Science Citation Index Expanded (SCI-EXPANDED).

Khyara, H., Amine, A. and Nassih, B. (2022) "Road Traffic Accidents in Morocco: Exploratory Analysis of Driver, Vehicle, and Pedestrian Factors," *SN Computer Science*, 4(2), p. 101. doi: 10.1007/s42979-022-01501-6.

Kiwanuka, O. *et al.* (2024) "ASA-score is associated with 90-day mortality after complicated mild traumatic brain injury - a retrospective cohort study," *ACTA NEUROCHIRURGICA*, 166(1). doi: 10.1007/s00701-024-06247-z WE - Science Citation Index Expanded (SCI-EXPANDED).

Legrand, R. *et al.* (2015) "Comparaison des scores de prédiction de la mortalité intra-hospitalière en traumatologie grave : une étude de cohorte issue du Trauma System du réseau Nord Alpin des urgences," *Anesthésie & Réanimation*, 1, p. A26. doi: https://doi.org/10.1016/j.anrea.2015.07.039.

De los Rios-Pérez, A. *et al.* (2024) "Quality of pediatric trauma care: development of an age-adjusted TRISS model and survival benchmarking in a major trauma center," *FRONTIERS IN PEDIATRICS*, 12. doi: 10.3389/fped.2024.1481467 WE - Science Citation Index Expanded (SCI-EXPANDED).

Maeda, Y. *et al.* (2019) "External validation of the TRISS, CRASH, and IMPACT prognostic models in severe traumatic brain injury in Japan," *PLOS ONE*, 14(8). doi: 10.1371/journal.pone.0221791 WE - Science Citation Index Expanded (SCI-EXPANDED).

Miller, G. F. *et al.* (2021) "Predictors of traumatic brain injury morbidity and mortality: Examination of data from the national trauma data bank: Predictors of TBI morbidity & mortality," *Injury*, 52(5), pp. 1138–1144. doi: https://doi.org/10.1016/j.injury.2021.01.042.

Rapsang, A. G. and Shyam, D. C. (2015) "Scoring systems of severity in patients with multiple trauma," *CIRUGIA ESPANOLA*, 93(4), pp. 213–221. doi: 10.1016/j.ciresp.2013.12.021.

Reddy, S. P. *et al.* (2019) "Neurologic injuries following road traffic accidents in the Dominican Republic: Examining causes and potential solutions," *TRAFFIC INJURY PREVENTION*, 20(7), pp. 690–695. doi: 10.1080/15389588.2019.1643016.

Sheikhi, S. *et al.* (2025) "TRISS, Base Excess, and RTS as Predictors of Outcomes in Polytrauma Patients: A Retrospective Analytical Study from a Trauma Center," *INDIAN JOURNAL OF SURGERY*, 87(5), pp. 892–898. doi: 10.1007/s12262-025-04307-x.

Steyerberg, E. W. *et al.* (2010) "Assessing the performance of prediction models: A framework for traditional and novel measures," *Epidemiology*, 21(1), pp. 128–138. doi: 10.1097/EDE.0b013e3181c30fb2.

Wong, G. K. C. *et al.* (2013) "Outcomes of traumatic brain injury in Hong Kong: Validation with the TRISS, CRASH, and IMPACT models," *JOURNAL OF CLINICAL NEUROSCIENCE*, 20(12), pp. 1693–1696. doi: 10.1016/j.jocn.2012.12.032 WE - Science Citation Index Expanded (SCI-EXPANDED).

Yang, S. M. *et al.* (2024) "Utilizing ultra-early continuous physiologic data to develop automated measures of clinical severity in a traumatic brain injury population," *SCIENTIFIC REPORTS*, 14(1). doi: 10.1038/s41598-024-57538-5 WE - Science Citation Index Expanded (SCI-EXPANDED).

How to cite this article: El Haddad, S., El Chaal, R., Hmamouche, O.M., Bennani, B., and Chaoui, M.E.F. (2026) 'Predictive performance and statistical calibration of the TRISS method in patients with traumatic brain injury: a retrospective data analysis', *Jurnal Ners*, 21(1), pp. 42-50. doi: http://dx.doi.org/10.20473/jn.v21i1.86367