Development and validation of a local trauma severity score for adult trauma patients in urban India

Study plan

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# Background

Trauma accounts for one-tenth of all deaths and disability-adjusted life-years (DALYs) [1–3]. Nearly 90% of trauma-related deaths occur in low-and-middle-income countries (LMICs), and improving trauma care in these settings can save nearly 2 million lives each year [4, 5]. Patient-related variables affect trauma outcomes. Therefore, it is important to quantify the variables in a standardized process [6, 7]. Standardized variables can be used to develop prediction models to estimate the probability of defined trauma outcomes [8, 9]. Such models can play a crucial role in managing and improving care in over-burdened and resoruce-constrained settings [10, 11].

Among the multiple variables that affect trauma outcomes, trauma severity strongly informs clinical practice at different stages such as pre-hospital triage, in-hospital decision-making [10, 12]. Consequently, it is the most commonly used variable for prediction in trauma outcomes [13, 14].There are several trauma scoring systems designed to quantify trauma severity. They use different physiological, anatomical parameters, injury features, and patient characteristics to determine severity, which is then used to predict outcomes, specifically mortality [15–24].

The most widely used trauma severity prediction model is the Trauma and Injury Severity Score (TRISS) [25]. This model was developed using a large sample from North America, and it predicts mortality using age, physiological status, anatomical severity of the injury, and the nature of the injury [17, 26]. Ideally, prediction models should be objective, replicable in different settings, less resource-intensive, and revised over time [8, 10, 27]. Despite subsequent revisions [28, 29], TRISS continues to have considerable limitations. the predictive ability of TRISS is affected by the nature of the included variables like Glasgow Coma Scale (GCS) which has a high propensity for misclassification among severly injured patients and respirtaory rate (RR) which is not rountinely recorded [25, 30–33]. TRISS has also limited external validation in different settings, especially in LMICs [34–44].

Machine learning algorithms are increasingly used in medicine, including trauma, to accurately predict complex outcomes across different settings [45–47]. Ensemble machine learning algorithms combine several different statistical techniques to build an optimal prediction model rather than relying on a single technique [48]. Thus, they are flexible and can be used to capture the complex relationships in trauma data. The aim of this study is to develop a local trauma severity model using an ensemble machine learning algorithm and to compare this model with TRISS.

# Methodology

## Sources of Data

This is a retrospective analysis of a prospectively collected multi-center observational cohort from three public hospitals in urban India between August 2016 to December 2019. The study will be reported using the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD) guidelines [9].

## Participants

*Setting*

The three hospitals participating in this study are Maulana Azad Medical College (MAMC), New Delhi; KB Bhabha Hospital (KBBH), Mumbai; and the Institute of Post-Graduate Medical Education and Seth Sukhlal Karnani Memorial Hospital (IPGMER & SSKM), Kolkata. They are part of an on-going study Trauma Triage Study (TTRIS). Each of the three hospitals have trauma units that receive patients from across the cities. These are public hospital with free or nominal fees, providing access to low socio-economic groups.KBBH is a public secondary-care hospital with 436 inpatient beds. It includes departments for general surgery, orthopaedics, and anaesthesia along with intensive care units and a general emergency department (ED). It has in-house diagnostic services such as x-rays and ultrasonography and a day-time computed tomography (CT) service. Most patients are directly admitted to KBBH and then if required referred to tertiary-care facilities. MAMC and SSKM are both public tertiary-care teaching hospitals with all departments and diagnostic facilities available in-house 24x7 with general EDs. MAMC has approximately 2200 inpatient beds, and SSKM has approximately 1775 inpatient beds. As tertiary-care hospitals, both MAMC and SSKM have a large proportion of patients who are transferred as referrals from other public and private health facilities.

*Eligibility Criteria*

We included all adult patients (≥ 18 years of age) who presented alive to the ED at the participating centers with a history of trauma - Chapter XX, block V01-Y36, in the International Classification of Disease 10th-revision (ICD 10) [49].

## Outcome

The primary outcome variable will be all-cause mortality within 30-days of arrival at the participating center. Each participating center has a dedicated project officer collecting data in 8-hour shifts per day by prospectively enrolling patients. The project officer would follow-up with the patients in the hospital and if discharged telephonically to record the mortality at 24-hours and 30-day. The shifts would alternate between morning, evening, and night in rotation.The project officers have continuous training and supervision throughout the study period. The collected data is uploaded to a central database and each week reviewed by the research team.

## Predictors

Predictor variables were selected based on clinically relevant variables from literature as well as consultations with trauma surgeons experience in working in the urban Indian setting. These included physiological measures: systolic blood pressure (SBP), respiratory rate (RR), heart rate (HR), oxygen saturation, and Glasgow Coma Scale (GCS); injury etiology:mode of transport, type of injury, mechanism of injury, and injury severity scores (ISS); and demographic measures: age and sex. Similar to outcome measure, project officers in each centre will collect information on these variables. Demographic and injury etiology will be collected from the patients or their caregivers and if required from the medical records. On-arrival of the patients the project officer would measure SBP, HR, RR, and oxygen saturation independently but would not be part of patient care. Based on injury details, ISS was computed for each participant by accredited coders.

For the local model we constructed a priori consisting of the predictor variables mentioned above. For the TRISS model, we calculated the Revised Trauma Score (RTS) based on GCS, SBP and RR. Age, type of injury (blunt or penetrating) RTS and ISS were used to calculate the probability of survival (P) ranging from 0 to 1, where 0 corresponds to 0% and 1 to 100% probability of survival [26, 50].

## Sample Size

To develop a prediction model with a binary outcome the current recommendation is to include at least ten events, i.e. participants with the outcome, and at least as many non-events per free parameter in the model [51]. Depending on the data structure as many as 25 events and non-events or more per free parameter may be required to obtain stable estimates [52]. These recommendations are however mainly for logistic regression, whereas no recommendations exist for ensemble learners except that more data is likely needed [53]. We will therefore include at least 25 events and non-events per free parameter in the training sample.

The training sample constitute 80% of the total sample and the remaining 20% of the cohort will be used as the test sample.A previous study on the a subset of the same population found the 30-day mortality to be around 8% [54]. We will assume it to be around 10%. With 12 predictor variables and around 40 free parameters .The training sample would require 10,000 patients.For the validation and the test sample wold include around 200 events, that is 2000 patients. Therfore, the total sample requird for this study is around 14,000 patients.

## Missing Data

We will use multiple imputation using chained equations to handle missing data [Vergouwe2010].

## Analyses and Statistical Methods

We will use R for all statistical analyses [55].

The ensemble machine learning procedure SuperLearner will be used in the study [56]. It will combine different statistical techniques (also called machine learning algorithms) such as generalized linear and additive models, random forests, etc. to create a local model that best fits with the data. SuperLearner uses cross-validation to optimize prediction by separating the data into a “training sample” which will be used to generate a model and then using another “test sample” for validating model. We will use the training set to build the ensemble learner and to update TRISS. We will use the test set to estimate the performance of each of the ensemble learner, the original TRISS, and the updated TRISS.

Based on a recent review of machine learners for predicting outcomes in trauma patients [57], we will include the seven most commonly used learners in our ensemble model: support vector machines (SVM), artificial neural networks (ANN), decision trees (DT), Bayes classification (BC), k-nearest neighbor (KNN), random forest (RF), and logistic regression (LR). We will then compare the performance of all models in a pair-wise fashion. Performance and differences in performance will be estimated as medians across imputations and 95% confidence intervals will be estimated using bootstrapping.

## Model Assessment

We will assess the local model and TRISS model for overall performance, discrimination, and calibration [58]. Discrimination, if the higher scores correspond to higher mortality, will be measured using sensitivity, specificity, and the cross-validated area under the receiver-operating characteristic curve (AUROC), reported with corresponding 95% confidence interval (95% CI). Calibration, if the predicted mortality coincides well with the observed mortality, will be assessed by either Hosmer-Lemeshow statistic or Cox calibration test.

## Ethical Considerations

The institutional ethics committee of each participating center has individually approved the collation and analysis of the TTRIS dataset. The reference numbers are: Maulana Azad Medical College, New Delhi (F.1/IEC/MAMC/(53/2/2016/No.97); KB Bhabha Hospital, Mumbai (HO/4882/KBBH of 3/8/2016); and Institute of Post-Graduate Medical Education and Seth Sukhlal Karnani Memorial Hospital (IPGMER & SSKM), Kolkata (Inst/IEC/2016/328).

# References

1. Toroyan T, Peden MM, Iaych K. WHO launches second global status report on road safety. Injury prevention : journal of the International Society for Child and Adolescent Injury Prevention. 2013;19:150.

2. Chandran A, Hyder AA, Peek-Asa C. The global burden of unintentional injuries and an agenda for progress. Epidemiologic Reviews. 2010;32:110–20.

3. Haagsma JA, Graetz N, Bolliger I, Naghavi M, Higashi H, Mullany EC, et al. The global burden of injury: Incidence, mortality, disability-adjusted life years and time trends from the global burden of disease study 2013. Injury Prevention. 2015;1–16.

4. Mock C, Joshipura M, Quansah CA-rR. An estimate of the number of lives that could be saved through improvements in trauma care globally. 2012;959–63.

5. Gururaj G. Injury prevention and care : An important public health agenda for health, survival and safety of children. The Indian Journal of Pediatrics. 2013;80:100–8.

6. Roy N, Gerdin M, Schneider E, Kizhakke Veetil DK, Khajanchi M, Kumar V, et al. Validation of international trauma scoring systems in urban trauma centres in india. Injury. 2016;47:2459–64.

7. Shibahashi K, Nishida M, Okura Y, Hamabe Y. Epidemiological state, predictors of early mortality, and predictive models for traumatic spinal cord injury: A multicenter nationwide cohort study. Spine. 2019;44:479–87.

8. Altman DG, Vergouwe Y, Royston P, Moons KGM, Grobbee DE. Prognosis and prognostic research: What, why, and how? BMJ (Online). 2009;338:1373–7.

9. Collins GS, Reitsma JB, Altman DG, Moons KGM. Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (tripod): The tripod statement. European Urology. 2015;67:1142–51.

10. Rehn M, Perel P, Blackhall K, Lossius HM. Prognostic models for the early care of trauma patients: A systematic review. 2011.

11. Perel PA, Olldashi F, Muzha I, Filipi N, Lede R, Copertari P, et al. Predicting outcome after traumatic brain injury: Practical prognostic models based on large cohort of international patients. Bmj. 2008;336:425–9.

12. Fitzgerald M, Dewan Y, O’Reilly G. India and the management of road crashes: Towards a national trauma system. Indian Journal of Surgery. 2006;68:226–32.

13. Champion HR. Trauma scoring. Scandinavian Journal of Surgery. 2002;91:12–22.

14. Cook A, Weddle J, Baker S, Hosmer D, Glance L, Friedman L, et al. A comparison of the injury severity score and the trauma mortality prediction model. Journal of Trauma and Acute Care Surgery. 2014;76:47–53.

15. Moore L, Hanley JA, Turgeon AF, Lavoie A, Eric B. A new method for evaluating trauma centre outcome performance: Tram-adjusted mortality estimates. Annals of Surgery. 2010;251:952–8.

16. Skaga NO, Eken T, Søvik S. Validating performance of triss, tarn and normit survival prediction models in a norwegian trauma population. Acta Anaesthesiologica Scandinavica. 2018;62:253–66.

17. Boyd CR, Tolson MA, Copes WS. Evaluating trauma care: The triss method. Trauma score and the injury severity score. The Journal of trauma. 1987;27:370–8.

18. Champion HR, Sacco WJ, Copes WS, Gann DS, Gennarelli TA, Flanagan ME. A revision of the trauma score. The Journal of trauma. 1989;29:623–9.

19. Sartorius D, Le Manach Y, David J-S, Rancurel E, Smail N, Thicoïpé M, et al. Mechanism, glasgow coma scale, age, and arterial pressure (mgap): A new simple prehospital triage score to predict mortality in trauma patients\*. Critical Care Medicine. 2010;38:831–7.

20. Husum H, Modaghegh M, Wisborg T, Van Heng Y, Murad M. Respiratory rate as a prehospital triage tool in rural trauma. Journal of Trauma. 2003;55:466–70.

21. West AT, Rivara FP, Cummings P, Jurkovich GJ, Maier VR. Harborview assessment for risk of mortality: An improved measure of injury severity on the basis of icd-9-cm. Journal of Trauma - Injury, Infection and Critical Care. 2000;49:530–41.

22. Burd RS, Ouyang M, Madigan D. Bayesian logistic injury severity score: A method for predicting mortality using international classification of disease-9 codes. Academic Emergency Medicine. 2008;15:466–75.

23. MacLeod JBA, Kobusingye O, Frost C, Lett R, Kirya F, Shulman C. A comparison of the kampala trauma score (kts) with the revised trauma score (rts), injury severity score (iss) and the triss method in a ugandan trauma registry: Is equal performance achieved with fewer resources? European Journal of Trauma. 2003;29:392–8.

24. Kondo Y, Abe T, Kohshi K, Tokuda Y, Cook EF, Kukita I. Revised trauma scoring system to predict in-hospital mortality in the emergency department: Glasgow coma scale, age, and systolic blood pressure score. Critical Care. 2011;15:R191.

25. Gabbe BJ, Cameron PA, Wolfe R. TRISS: Does It Get Better than This? Academic Emergency Medicine. 2004;11:181–6.

26. Champion HR, Copes WS, Sacco WJ, Lawnick MM, Keast SL, Bain LW, et al. The major trauma outcome study: Establishing national norms for trauma care. Journal of Trauma - Injury, Infection and Critical Care. 1990;30:1356–65.

27. Rozenfeld M, Radomislensky I, Freedman L, Givon A, Novikov I, Peleg K. ISS groups: Are we speaking the same language? Injury Prevention. 2014;20:330–5.

28. Domingues C de A, Coimbra R, Poggetti RS, Nogueira L de S, Sousa RMC de. New trauma and injury severity score (triss) adjustments for survival prediction. World Journal of Emergency Surgery. 2018;13:1–6.

29. Schluter PJ, Nathens A, Neal ML, Goble S, Cameron CM, Davey TM, et al. Trauma and injury severity score (triss) coefficients 2009 revision. Journal of Trauma - Injury, Infection and Critical Care. 2010;68:761–70.

30. Ringdal KG, Coats TJ, Lefering R, Bartolomeo DS, Steen PA, Røise O, et al. The utstein template for uniform reporting of data following major trauma: A joint revision by scantem, tarn, dgu-tr and ritg. Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine. 2008;16:1–19.

31. Demetriades D, Chan LS, Velmahos G, Berne VT, Cornwell EE, Belzberg H, et al. TRISS methodology in trauma: The need for alternatives. British Journal of Surgery. 1998;85:379–84.

32. Domingues CDA, Nogueira LDS, Settervall CHC, De Sousa RMC. Performance of trauma and injury severity score (triss) adjustments: An integrative review. Revista da Escola de Enfermagem. 2015;49 SpecialIssue:135–43.

33. Munter L de, Polinder S, Lansink KWW, Cnossen MC, Steyerberg EW, Jongh MAC de. Mortality prediction models in the general trauma population: A systematic review. Injury. 2017;48:221–9.

34. Zafar H, Rehmani R, Raja AJ, Ali A, Ahmed M. Registry based trauma outcome: Perspective of a developing country. Emergency Medicine Journal. 2002;19:391–4.

35. Khajanchi MU, Kumar V, Gerdin M, Roy N. Indians fit the asian trauma model. World Journal of Surgery. 2013;37:705–6.

36. Perel P, Edwards P, Wentz R, Roberts I. Systematic review of prognostic models in traumatic brain injury. BMC Medical Informatics and Decision Making. 2006;6:1–10.

37. Hung YW, He H, Mehmood A, Botchey I, Saidi H, Hyder AA, et al. Exploring injury severity measures and in-hospital mortality: A multi-hospital study in kenya. Injury. 2017;48:2112–8.

38. Laytin AD, Kumar V, Juillard CJ, Sarang B, Lashoher A, Roy N, et al. Choice of injury scoring system in low- and middle-income countries: Lessons from mumbai. Injury. 2015;46:2491–7.

39. Kimura A, Chadbunchachai W, Nakahara S. Modification of the trauma and injury severity score (triss) method provides better survival prediction in asian blunt trauma victims. World Journal of Surgery. 2012;36:813–8.

40. Podang J, Singhasivanon P, Podhipak A, Santikarn C, Sarol-jr J, Ancheta C. Primary verification : Is the triss appropriate for thailand ? Southeast Asian J Trop Med Public Health. 2004;35.

41. Gerdin M, Roy N, Khajanchi M, Kumar V, Dharap S, Felländer-Tsai L, et al. Predicting early mortality in adult trauma patients admitted to three public university hospitals in urban india: A prospective multicentre cohort study. PLoS ONE. 2014;9:1–7.

42. Deshmukh VU, Ketkar MN, Bharucha EK. Analysis of trauma outcome using the triss method at a tertiary care centre in pune. Indian Journal of Surgery. 2012;74:440–4.

43. Agarwal A, Agrawal A, Maheshwari R. Evaluation of probability of survival using apache ii and triss method in orthopaedic polytrauma patients in a tertiary care centre. Journal of Clinical and Diagnostic Research. 2015;9:RC01–4.

44. Samanamalee S, Sigera PC, De Silva AP, Thilakasiri K, Rashan A, Wadanambi S, et al. Traumatic brain injury (TBI) outcomes in an LMIC tertiary care centre and performance of trauma scores. BMC Anesthesiology. 2018;18:1–7.

45. Christie SA, Hubbard A, Callcut RA, Hameed M, Dissak-Delon FN, Mekolo D, et al. Machine learning without borders? An adaptable tool to optimize mortality prediction in diverse clinical settings. Journal of Trauma and Acute Care Surgery. 2018;85:921–7.

46. Gorczyca MT, Toscano NC, Cheng JD. The trauma severity model: An ensemble machine learning approach to risk prediction. Computers in Biology and Medicine. 2019;108 February:9–19.

47. Hubbard A, Munoz ID, Decker A, Holcomb JB, Schreiber MA, Bulger EM, et al. Time-dependent prediction and evaluation of variable importance using superlearning in high-dimensional clinical data. Journal of Trauma and Acute Care Surgery. 2013;75:53–60.

48. Pirracchio R, Petersen ML, Carone M, Rigon MR, Chevret S, Laan MJ van der. Mortality prediction in intensive care units with the super icu learner algorithm (sicula): A population-based study. The Lancet Respiratory Medicine. 2015;3:42–52.

49. Organization WH. International statistical classification of diseases and related health problems 10th revision (icd-10)-who version for ;2016. 1BC. <http://apps.who.int/classifications/icd10/browse/2016/en#/XX>.

50. Meredith JW, Evans G, Kilgo PD, Mackenzie E, Osler T, Mcgwin G, et al. A comparison of the abilities of nine scoring algorithms in predicting mortality. Journal of Trauma: Injury, Infection, and Critical Care. 1996;53:621–9.

51. Courvoisier DS, Combescure C, Agoritsas T, Gayet-Ageron A, Perneger VT. Performance of logistic regression modeling: Beyond the number of events per variable, the role of data structure. Journal of Clinical Epidemiology. 2011;64:993–1000.

52. Van Der Ploeg T, Austin PC, Steyerberg EW. Modern modelling techniques are data hungry: A simulation study for predicting dichotomous endpoints. BMC Medical Research Methodology. 2014;14:1–13.

53. Laan MJ van der, Polley EC, Hubbard AE. Super Learner. Statistical Applications in Genetics and Molecular Biology. 2007;6. doi:[10.2202/1544-6115.1309](https://doi.org/10.2202/1544-6115.1309).

54. Wärnberg Gerdin L, Khajanchi M, Kumar V, Roy N, Saha ML, Soni KD, et al. Comparison of emergency department trauma triage performance of clinicians and clinical prediction models: A cohort study in India. BMJ Open. 2020;10:1–9.

55. R Core Team. R: A language and environment for statistical computing. 2015.

56. Peduzzi P, Concato J, Kemper E, Holford TR, Feinstem AR. A simulation study of the number of events per variable in logistic regression analysis. Journal of Clinical Epidemiology. 1996;49:1373–9.

57. Liu NT, Salinas J. Machine learning for predicting outcomes in trauma. Shock. 2017;48:504–10.

58. Steyerberg EW, Vickers AJ, Cook NR, Gerds T, Gonen M, Obuchowski N, et al. Assessing the performance of prediction models: A framework for traditional and novel measures. Epidemiology. 2010;21:128–38.