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Prospective validation of a hospital triage predictive model to decrease undertriage: an EAST multicenter study

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ABSTRACT

Background Tiered trauma team activation (TTA) allows systems to optimally allocate resources to an injured patient. Target undertriage and overtriage rates of <5% and <35% are difficult for centers to achieve, and performance variability exists. The objective of this study was to optimize and externally validate a previously developed hospital trauma triage prediction model to predict the need for emergent intervention in 6 hours (NEI-6), an indicator of need for a full TTA.

Methods The model was previously developed and internally validated using data from 31 US trauma centers. Data were collected prospectively at five sites using a mobile application which hosted the NEI-6 model. A weighted multiple logistic regression model was used to retrain and optimize the model using the original data set and a portion of data from one of the prospective sites. The remaining data from the five sites were designated for external validation. The area under the receiver operating characteristic curve (AUROC) and the area under the precision-recall curve (AUPRC) were used to assess the validation cohort. Subanalyses were performed for age, race, and mechanism of injury.

Results 14 421 patients were included in the training data set and 2476 patients in the external validation data set across five sites. On validation, the model had an overall undertriage rate of 9.1% and overtriage rate of 53.7%, with an AUROC of 0.80 and an AUPRC of 0.63. Blunt injury had an undertriage rate of 8.8%, whereas penetrating injury had 31.2%. For those aged ≥65, the undertriage rate was 8.4%, and for Black or African American patients the undertriage rate was 7.7%.

Conclusion The optimized and externally validated NEI-6 model approaches the recommended undertriage and overtriage rates while significantly reducing variability of TTA across centers for blunt trauma patients. The model performs well for populations that traditionally have high rates of undertriage.

Level of evidence 2.

WHAT IS ALREADY KNOWN ON THIS TOPIC

⇒ Undertriage is a persistent problem in trauma care and contributes to preventable mortality.

⇒ Current hospital triage guidelines are not standardized and are difficult for providers and centers to follow.

WHAT THIS STUDY ADDS

⇒ This study optimizes and externally validates a mobile application-based hospital triage prediction model (Trauma Intervention Prediction - Need for Emergent Intervention in 6 Hours, TIP-NEI-6) for improving undertriage rates.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY

⇒ The TIP-NEI-6 mobile application-based model is available in the prehospital setting and will contribute to ease of use and standardization of hospital triage guidelines to reduce practice variability and improve preventable mortality in trauma.

BACKGROUND

In the USA, approximately 30 000 patients per year suffer from preventable death after traumatic injury due to a lack of appropriate and timely medical care.[1] The hospital trauma triage process aims to allocate the appropriate hospital resources to injured patients by attempting to match the level of trauma team activation (TTA) to patient injury severity. A tiered trauma response system is the standard model in which patients are triaged to have a lower resource (partial) or greater resource (full) TTA based on the prehospital assessment of the patient's anatomic injuries, mechanism of injury, and physiological data.[2–4] This process is referred to as "hospital" triage, compared with "field" triage which matches a traumatically injured patient with the appropriate trauma center.[5] The hospital triage process is both challenging and nuanced for trauma systems. It has implications on patient outcomes, particularly for those who are undertriaged or not immediately assigned the appropriate resources for their level of injury. In-hospital mortality for severely injured undertriaged patients has been reported at 14%[6] when using an Injury Severity Score (ISS) of ≥25 for trauma activation criteria. For patients who met the American College of

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Surgeons' Committee on Trauma (ACSCOT) minimum criteria but did not receive a full TTA, mortality is up to 30%.[7] These are at least double of what general overall in-hospital mortality for traumatically injured patients is, at 5% to 7.9%.[8,9]

The ACSCOT recommends undertriage and overtriage rates of <5% and <25% to 35%, respectively.[10,11] Recommendations allow for higher rates of overtriage as there is significant risk of mortality in critically injured patients who are undertriaged.[5,6,12] Whereas the risk of undertriage is increased mortality, the risk of overtriage is increased resource utilization and cost.[13,14] The ACSCOT established the minimum criteria for full hospital TTA, including systolic blood pressure <90 mm Hg; gunshot wound to the neck, chest, abdomen, or extremity proximal to the elbow or knee; Glasgow Coma Scale (GCS) score <9; respiratory compromise or need for an emergent airway; and emergency medicine physician discretion.[10,11] Despite these minimum guidelines, there are no comprehensive consensus criteria for the appropriate hospital triage of injured patients. Individual centers rely on their own protocols to supplement the minimum criteria, which are often complex and multitiered. Compliance with these protocols, including the minimum criteria, is substandard.[2–4,15–18] Providers often make triage decisions based on criteria not represented in the minimum criteria, including mechanism of injury.[18] Non-compliance with the minimum criteria for full TTA is associated with an increased risk of mortality.[7,16] For these reasons, the undertriage and overtriage rates are highly variable across centers and remain a persistent challenge in trauma care.[19]

The lack of standardized, comprehensive, and easy-to-follow hospital triage criteria is a major driver of undertriage and thus preventable death. As such, improvement and standardization of hospital triage will save lives.[7] Hospital triage prediction models are a potential way to standardize the process. Van Rein *et al*[20] developed a field triage machine learning model to predict ISS to assist with the field triage of traumatically injured patients. However, this has not been widely implemented nor validated in US cohorts. Additionally, this model is limited in that it predicts major trauma as defined by ISS, which is strictly anatomically based and calculated late in the hospitalization. In contrast, the Need for Emergent Intervention in 6 Hours (NEI-6), which predicts the need for emergent interventions such as operative intervention or chest tube placement, is a more appropriate assessment of triage than ISS.[14,21] The objective of this prospective, multicenter, international study was to optimize and externally validate a previously developed hospital trauma triage predictive model for NEI-6 deployed via the Trauma Intervention Prediction (TIP) mobile application.

METHODS

Center and patient enrollment

This was a prospective, multicenter, observational trial sponsored by the Eastern Association for the Surgery of Trauma (EAST). Participating centers were recruited via the EAST Multicenter Trials website. Centers that had infrastructure for data collection by an emergency department triage nurse or an emergency medical services (EMS) communication center were eligible to participate. There were four enrolled centers in the United States and one international center. All United States centers were urban, university-based institutions with over 700 beds and 3000 trauma activations yearly. Each center had a tiered trauma activation system and had different criteria for full and partial TTAs. All centers incorporated the American College of Surgeons's six minimum criteria for a full TTA, but other variables were added. Three out of four of the United States centers were Level 1 trauma centers, and the remaining was Level 2. The international site represented the Middle East region and was also a university-based Level 1 trauma center. All United States centers were serviced by multiple EMS agencies that had flight or ground transport available with advanced life support-trained personnel. The international center had a single EMS agency with advanced life support-trained personnel, but without flight transport.

Data collection

Traumatically injured patients who underwent trauma activation from April 2021 to December 2022 and met the study inclusion criteria were enrolled. Study inclusion criteria included any hospital triage activation level (level 1 or level 2 TTA) and adult age (≥18 years of age). Exclusion criteria were patients without any signs of life on initial evaluation, defined as systolic blood pressure of zero and pulse of zero,[22] or direct admission (no TTA). Patients who had no valid International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM or ICD-10-CDM) trauma code, or no traumatic injuries, were also excluded from the study. The primary outcome was undertriage rate as defined by the NEI-6 criteria (need for any emergent intervention within 6 hours of arrival to the emergency department). Any patient needing an emergent intervention was considered to have required a full trauma activation. NEI-6 interventions included tube thoracostomy (chest tube) placement, operative or angiographic intervention, central line placement, intubation, or intracranial monitor placement within 6 hours, or massive transfusion (transfusion of greater than 4 units of blood within 4 hours of arrival). Secondary outcomes were overtriage and in-hospital mortality.

Field patient data were collected on the mobile TIP application per the protocol outlined in online supplemental appendix 1. Field data variables were based on a previously developed and published NEI-6 predictive model, and included variables such as field heart rate, blood pressure, mechanism of injury, and presence of central penetrating injury, among others.[21] Field data were input into the TIP app which housed the NEI-6 predictive model (TIP-NEI-6). Via the TIP app, the model predicted whether the patient would meet the NEI-6 criteria and therefore require a full TTA. The TIP app stated either "Emergent intervention predicted. Full trauma activation recommended" or "Emergent intervention not predicted" and generated a random identifier. Field patient data were matched with hospital outcomes data using institutional trauma registry data and the random identifier generated by the TIP app.[23]

This was an observational study and therefore trauma centers enrolled in the study used their standard of care and preferred method of triage to determine if patients required a full TTA. Hospital destination and level of TTA were not influenced by the model prediction.

Model training

The prior predictive model[21] was retrained due to poor performance in penetrating trauma patients, older adults, and patients belonging to racial and ethnic minority groups. Data from the Michigan Trauma Quality Improvement Program, which is a collaborative data registry quality initiative composed of 35 ACSCOT certified Level 1 and 2 trauma centers, along with the first half of data (April 2021–January 2022) from the prospective site which contained the largest number of patients, were used to retrain the model. Descriptive statistics were used to summarize patient demographic characteristics. Student's t-test

Table 1 Patient demographic characteristics in the training and validation cohorts

Demographics	Training	External validation	P value
n	14 421	2476	
Female, n (%)	7210 (50.0)	780 (31.5)	<0.001*
Age, mean (SD)	58.4 (23.0)	46.6 (21.0)	<0.001†
Age ≥65, n (%)	6503 (45.1)	583 (23.6)	<0.001*
Race, n (%)			<0.001*
White	10 522 (73.3)	1252 (51.4)	
Black or African American	3080 (21.5)	763 (31.3)	
Other	748 (5.2)	422 (17.3)	
Trauma type, n (%)			<0.001*
Blunt	13 321 (92.4)	1961 (79.2)	
Penetrating	1100 (7.6)	515 (20.8)	
Mechanism of injury, n (%)			<0.001*
Fall	7210 (50.0)	658 (26.6)	
Motor vehicle collision	3497 (24.2)	736 (29.7)	
Firearm injury	821 (5.7)	425 (17.2)	
Cut or stab	279 (1.9)	90 (3.6)	
Motorcycle collision	740 (5.1)	172 (6.9)	
Bicycle	758 (5.3)	39 (1.6)	
Pedestrian struck	629 (4.4)	130 (5.3)	
Other	487 (3.4)	226 (9.1)	
In-hospital mortality, n (%)	765 (5.3)	151 (6.1)	0.111*

*χ^2 test.
†Student's t-test.

and χ^2 test were performed to compare the demographic characteristics between the model retraining and the validation cohorts (table 1).

The variables considered in the model included 3 demographic variables (age, gender, and obesity), 11 injury-related variables (cut or stab injury, central gunshot wound, fracture, firearm injury, motor vehicle collision, motorcycle collision, motorcycle collision without helmet, bicycle collision, bicycle collision without helmet, pedestrian struck, or other type of injury), 4 intentionality variables (assault, self-inflicted, other legal interventions, or undetermined), 3 clinical variables (GCS, field systolic blood pressure, field pulse), and 4 transport variables (transport time <15 minutes, transport time 15–30 minutes, evening arrival, and interfacility transfer) (table 3). All missing data were handled by weighted mean imputation from training data, which were used to impute missing data from both the training and external validation data.[24–26] There were a total of 27 variables collected, and all missing data (a total of 11 variables) underwent imputation. Three variables had greater than 5% missing data (field obesity, field systolic blood pressure, and field GCS) (online supplemental appendix 2). Analyses were performed using R V.4.0.3 (R Foundation for Statistical Computing, Vienna, Austria).

A weighted multivariable logistic regression model was implemented to revise the model using the need for emergent intervention as the primary outcome of interest. The weight assigned was proportional to the ratio of sample sizes from two sites to achieve equal impact of both sites on the fit. Natural cubic splines were used to model non-linear predictors.[27] For systolic blood pressure and pulse, five internal knots located at approximately the 10th, 25th, 50th, 75th, and 90th percentiles were used. For age, four internal knots were used at 30, 45, 60, and 75 years of age. For GCS, three internal knots were used at 4, 9, and 13.

The receiver operating characteristic (ROC) curve and the precision-recall curve were generated along with the area under the curves (AUROC and AUPRC, respectively) as model performance metrics. The optimal cut-off value on the ROC curve was selected using a weighted Youden-like index,[28] assuming that a false negative (undertriage) was four times as detrimental as a false positive (overtriage) based on sensitivity and specificity.[29] A confusion matrix was computed using the optimal cut-off value, and sensitivity, specificity, undertriage rate, and overtriage rates were calculated.

Model external validation

Model validation was then performed using the second half of data from the prospective site with the largest amount of data (February 2022–December 2022), along with data from the additional four sites. An optimal cut-off value on the ROC curve was selected for each site using the same Youden-like index approach.

The Enhancing the Quality and Transparency of Health Research (EQUATOR) Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD) guidelines were used for model retraining and validation (online supplemental digital content).

RESULTS

Model training

A total of 12 469 patients from the prior model data set[21] and 1952 patients from the largest data collecting center (April 2021–January 2022) were included in the model training. Female patients constitute 50.0% of the cohort (n=7210), and the mean age was 58.4 years (SD=23). Most patients were white (73.3%, n=10 522), followed by Black or African American (21.5%, n=3080) and other (5.2%, n=748) race. A total of 7.6% of patients (n=1100) suffered a penetrating injury. In-hospital mortality was 5.3% (n=765) (table 1).

Variables with the greatest association with the need for emergent intervention were cut injury pattern (OR 4.13, 95% CI 3.22, 5.28; p<0.001), assault intentionality (OR 3.59, 95% CI 2.99, 4.33; p<0.001), central or truncal gunshot wound (OR 3.11, 95% CI 2.57, 3.77; p<0.001), and presence of open fracture (OR 2.74, 95% CI 2.24, 3.34; p<0.001) (table 2).

External validation

There were 2476 patients in the external validation cohort across five sites. Female patients constituted 31.5% (n=780) of the group, and the mean age was 46.6 years (SD=21). Most patients were white (51.4%, n=1252), followed by Black or African American (31.3%, n=763) and other (17.3%, n=422) race. A total of 20.8% (n=515) suffered a penetrating injury. In-hospital mortality was 6.1% (n=151) (table 1). Using NEI-6 for triage assessment, the baseline undertriage and overtriage rates for the validation cohort were 13.1% (95% CI 11.4%, 14.9%) and 50.4% (95% CI 47.2%, 53.6%), respectively.

On external validation, the model had an overall AUROC of 0.80 and an AUPRC of 0.63 (table 3, figure 1). Using the optimal cut-off value on the ROC curve for all external sites, the model's undertriage rate was 9.1% (95% CI 7.6%, 10.9%) and the overtriage rate was 53.7% (95% CI 50.9%, 56.5%) (table 4). This was a statistically significant difference from the standard of care undertriage rate, with p<0.0001. Table 4 highlights the model's performance at each individual center. AUROCs ranged from 0.75 to 0.89, with undertriage rates of 4.2% to 11.6% and overtriage rates of 41.2% to 59.1% at the individual

Table 2 Categorical variables associated with NEI-6 in weighted multiple logistic regression

Variable	OR	95% CI	P value
Cut injury	4.13	3.22, 5.28	<0.001
Assault intentionality	3.59	2.99, 4.33	<0.001
Central gunshot wound	3.11	2.57, 3.77	<0.001
Open fracture	2.74	2.24, 3.34	<0.001
Other injury	2.30	1.88, 2.81	<0.001
Firearm injury	2.26	1.82, 2.80	<0.001
Pedestrian struck injury	1.96	1.58, 2.43	<0.001
Self-inflicted intentionality	1.86	1.31, 2.61	<0.001
Motorcycle collision	1.69	1.16, 2.40	0.004
Unhelmeted motorcycle collision	1.52	1.05, 2.26	0.031
Transport distance <15 min	1.44	1.25, 1.66	<0.001
Motor vehicle collision	1.41	1.23, 1.61	<0.001
Bicycle injury	1.32	0.72, 2.30	0.348
Unhelmeted bicycle injury	1.32	0.74, 2.47	0.365
Other legal intentionality	1.32	0.99, 1.75	0.059
Interfacility transfer	1.15	1.04, 1.29	0.01
Gender	1.14	1.04, 1.25	0.004
Transport distance 15–30 min	1.13	0.96, 1.32	0.144
Evening arrival	1.07	0.98, 1.16	0.135
Obesity	0.95	0.78, 1.16	0.638
Undetermined intentionality	0.61	0.43, 0.85	0.004

NEI-6, Need for Emergent Intervention in 6 Hours.

centers. A comparison of undertriage rates for the standard of care local triage protocols and the TIP-NEI-6 model for each individual center is located in online supplemental appendix 3. Online supplemental appendix 4 indicates the performance of the model in detecting individual NEI-6 variables.

Subgroup analysis

Blunt versus penetrating

For blunt trauma, the AUROC was 0.78 and the AUPRC was 0.56. Using site-specific optimal probability cutpoints, the undertriage rate was 8.8% and the overtriage rate was 57.9%. For penetrating trauma, the AUROC was 0.67 and the AUPRC was 0.70. The undertriage rate was 31.2% and the overtriage rate was 47.7% (figure 2, table 3).

Patient cohorts: race

As one of the centers represented the Middle East and its cohort was homogenously of other race, this cohort was excluded from racial subgroup analysis. Therefore, external validation for the racial subgroup analysis included 2222 patients. For white patients, the AUROC and the AUPRC were 0.78 and 0.59, respectively. The undertriage rate was 9.8% and the overtriage rate was 54.5%. For Black or African American patients, the AUROC and the AUPRC were 0.79 and 0.67, respectively. The undertriage rate was 7.7% and the overtriage rate was 53.9%. Finally, for other races, the AUROC was 0.78, the AUPRC was 0.59, the undertriage rate was 11.4%, and the overtriage was 53.5% (figure 2, table 3).

Patient cohorts: age

For age <65 years, the AUROC was 0.79 and the AUPRC was 0.64. The undertriage rate was 9.5% and the overtriage rate was 54.1%. For age ≥65, the AUROC was 0.79 and the AUPRC was 0.53. The undertriage rate was 8.4% and the overtriage was 50.4% (figure 2, table 3).

DISCUSSION

This study optimized and externally validated a hospital triage predictive tool deployed via the TIP mobile application in the prehospital setting, which aids triage providers by offering real-time cognitive decision support. The tool is intended to be used in conjunction with provider judgment to aid in the decision-making process for hospital trauma triage. TIP-NEI-6 predicts the need for emergent intervention in blunt trauma with an undertriage rate of 8.8%. Notably, TIP-NEI-6 performance was particularly efficacious for Black or African American patients and older adults, with undertriage rates of 7.7% and 8.4%, respectively. Artificial intelligence and machine learning models are emerging tools with the potential to reduce health inequities.[30 31] Although TIP-NEI-6 did not fully meet the standards for ACSCOT's recommended undertriage and overtriage rates, particularly for penetrating trauma, it is an important step toward standardization and improvement of triage protocols, especially for patient populations who traditionally have high rates of undertriage.

The lack of validated, user-friendly national hospital trauma activation criteria breeds variability and the development of complex individual institutional criteria for trauma triage.[19] In a study of Pennsylvania trauma centers, undertriage rates were reported as anywhere from 0% to 20.5%, and overtriage rates ranged from 52% to 78%.[32] Reducing this variability will allow for timely medical care, thus contributing to improvement in the 20% of preventable deaths after traumatic injury.[1 33] TIP-NEI-6 is an opportunity to standardize trauma triage, and standardization of triage processes leads to improved undertriage outcomes.[34]

There has been previous development of field triage, or hospital destination, protocols with variable success and limited implementation.[35 36] Notably, van Rein *et al*[20] from the Netherlands created a field triage prediction model and validated the model in a mobile application across multiple Dutch regions.[37] On validation of the model, a total of 80 738 adult patients were included: 40 427 (50.1%) before implementation of the triage intervention and 40 311 (49.9%) after implementation. After implementation of the mobile application with the model, undertriage decreased from 31.8% to 26.8%. Overtriage rates did not increase (20.9% vs. 20.4% of patients).[37] The model was also externally validated in a cohort of patients from the UK, and the AUROC was 0.75, while undertriage remained at 17% with an overtriage of 50%. The authors concluded that the model did not meet the ACSCOT recommendations,[38] and it is unclear how this model would perform in the USA. The original model was based on ISS ≥16, which is not an accurate predictor of severe injury.[14 39] The authors plan to create a new model that, similar to TIP-NEI-6, will incorporate need for emergent resource use, including operative intervention, admission to the intensive care unit, or emergent operative or radiological intervention.[40]

Certain populations including older adults, females, and patients belonging to racial and ethnic minority groups present an additional challenge to trauma triage.[41–44] Compared with appropriately triaged adult patients, undertriaged older adult patients have a twofold increased risk of mortality and a 50% increased risk of complications.[12] Prior studies have reported an undertriage rate of up to 61% for severely injured older adults,[42] and the TIP-NEI-6 undertriage rate was much closer to the suggested ACSCOT rate at 8.4%. For Black or African American patients, the TIP-NEI-6 undertriage rate was the best overall at

Table 3 Undertriage and overtriage rates for the overall training and validation data sets

	AUROC	AUPRC	Undertriage (%)	Overtriage (%)	Sensitivity (%)	Specificity (%)
Training	0.84	0.64	6.4	43.6	62.5	91.9
External validation	0.80	0.63	9.1	53.7	83.0	63.7
Injury mechanism*						
Blunt	0.78	0.56	8.8	57.9	73.3	73.2
Penetrating	0.67	0.70	31.2	47.7	98.1	4.4
Race*						
White	0.78	0.59	9.8	54.5	74.6	72.5
Black or African American	0.79	0.67	7.7	53.9	93.6	41.0
Other	0.78	0.59	11.4	53.5	85.2	53.9
Age*						
<65	0.79	0.64	9.5	54.1	86.6	55.6
≥65	0.79	0.53	8.4	50.4	63.5	86.0

The validation data set is broken down into individual patient cohorts.
*Only external validation data.
AUPRC, area under the precision-recall curve; AUROC, area under the receiver operating characteristic curve.

7.7%. Racial disparities are well established in trauma and emergency care. Black or African American and Hispanic patients have higher mortality rates after trauma compared with white patients.[45 46] Patients belonging to racial and ethnic minority groups are more likely to be undertriaged both in the field[47 48] and in the hospital as they have been found to have delays in trauma team activation or consultation.[44 49] Standardization and improvement of trauma triage are the first steps toward reducing trauma mortality in these under-represented populations.

Trauma triage is also notoriously difficult in those with certain injury patterns, particularly blunt trauma. In studies characterizing undertriaged or severely undertriaged (defined as undertriage with an ISS ≥25) patients, >95% of undertriaged patients have a blunt mechanism of injury.[6 50] Cherry *et al*[51] reported a blunt undertriage rate of 22% at their institution[51], and within blunt trauma, thoracic and head injuries have the highest risk of undertriage.[6 52–55] Although TIP-NEI-6 poorly predicted interventions needed for penetrating injury with an undertriage rate of 31%, penetrating injury triage is generally more straightforward for providers as the ACSCOT minimum criteria guidelines are more comprehensive in this population. For example, a patient with a central gunshot wound to the abdomen requires a full TTA. Further variables, such as GCS, do not influence the decision to activate the full trauma team. The model's blunt undertriage rate was appropriate at 8.8%. Therefore, the TIP-NEI-6 model should currently only be used for blunt mechanisms of injury. However, due to the difficulty in triaging this population, it also has the most substantial potential for impact in triage processes and improvement in care for this population.

This study is limited mainly by the differences in populations and injury patterns across centers. Most notably, penetrating injury was under-represented in the training cohort (7.6%) compared with the external validation cohort (21%), which posed difficulty in creating an accurate model for penetrating injury. An attempt was made to create an additional penetrating-only multiple logistic regression model; however, the model performance remained poor. It is likely that the model was missing important injury pattern variables for penetrating injury, such as the location of injury on the trunk, type of firearm used, or number of wounds. Likewise, the overtriage rates were near

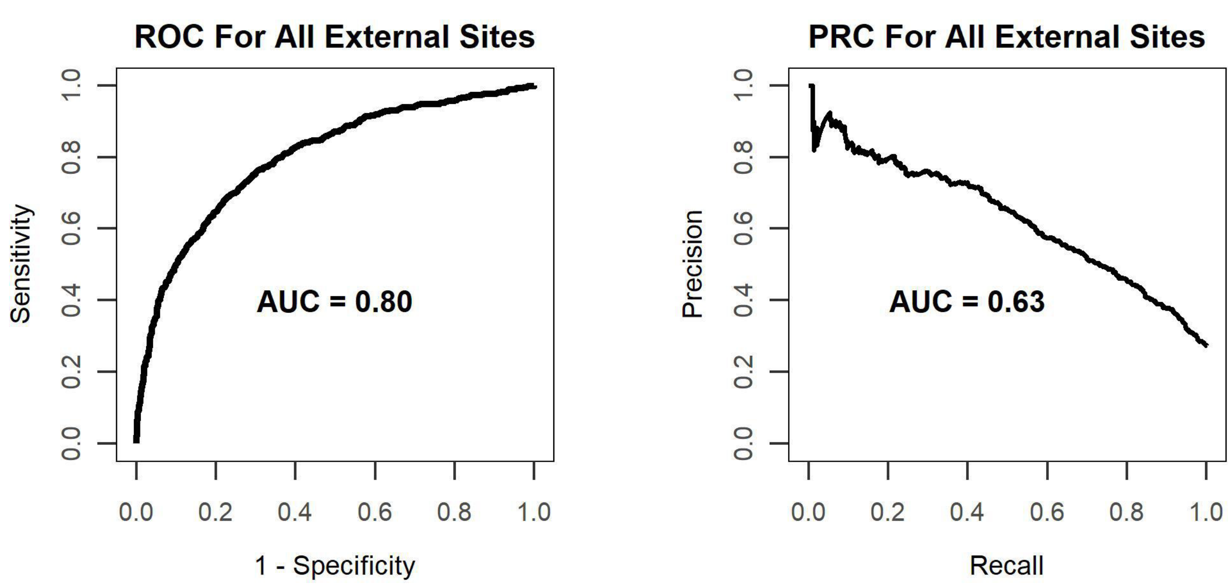

Figure 1 Area under the receiver operating characteristic curve and area under the precision recall curve for the full external validation data set. AUC, area under the curve; PRC, precision-recall curve; ROC, receiver operating characteristic curve.

Table 4 Optimal receiver operating curve cutpoints for each individual center with associated undertriage and overtriage rates

Center	n	Overall AUROC	Overall AUPRC	Cutpoint	Undertriage (%)	Undertriage (95% CI)	Overtriage (%)	Overtriage (95% CI)
All external sites: Standard of Care *	2476	0.72	–	–	13.1	11.4, 14.9	50.40	47.2, 53.6
All external sites: universal†	2476	0.80	0.63	0.245	13.0	11.3, 14.8	48.8	45.6, 52.1
All external sites: optimal‡	2476	0.80	0.63	Variable	9.1	7.6, 10.9	53.7	50.9, 56.5
Medical College of Wisconsin	1748	0.77	0.62	0.141	11.6	9.3, 14.3	54.1	50.9, 57.2
University of Kentucky	269	0.85	0.69	0.352	5.4	2.8, 9.2	39.1	25.1, 54.6
King Saud Medical City	254	0.75	0.60	0.137	8.1	4.6, 13.0	57.4	44.8, 69.3
OhioHealth	223	0.84	0.64	0.164	6.2	2.7, 11.8	59.1	48.5, 69.2
University of Florida	82	0.89	0.76	0.221	4.2	0.5, 14.3	41.2	24.6, 59.3

*Represents the undertriage and overtriage rates evaluated by NEI-6 interventions for the standard of care triage processes at each individual center.
†Represents the undertriage and overtriage rates calculated by the model using a universal cutpoint on the receiver operating characteristic curve.
‡Represents the undertriage and overtriage rates calculated by the model using the optimal cutpoint for each individual center.
AUPRC, area under the precision-recall curve; AUROC, area under the receiver operating characteristic curve; NEI-6, Need for Emergent Intervention in 6 Hours.

50% in our model, which is not nearing the ACSCOT recommendations; however, overtriage accuracy was sacrificed to optimize undertriage rates and will improve with larger data sets. This also illustrates the need for large databanks linking prehospital and hospital data to improve the care of trauma patients. TIP has potential to create this linkage through future integration into the electronic health record. An additional limitation was the nature of the TIP app, in which not all data fields were required and thus contributed to missing data. It also required utilization of the trauma registry to match patients to clinical data, necessitating exclusion of patients who did not meet trauma registry data collection criteria. These will be addressed in future

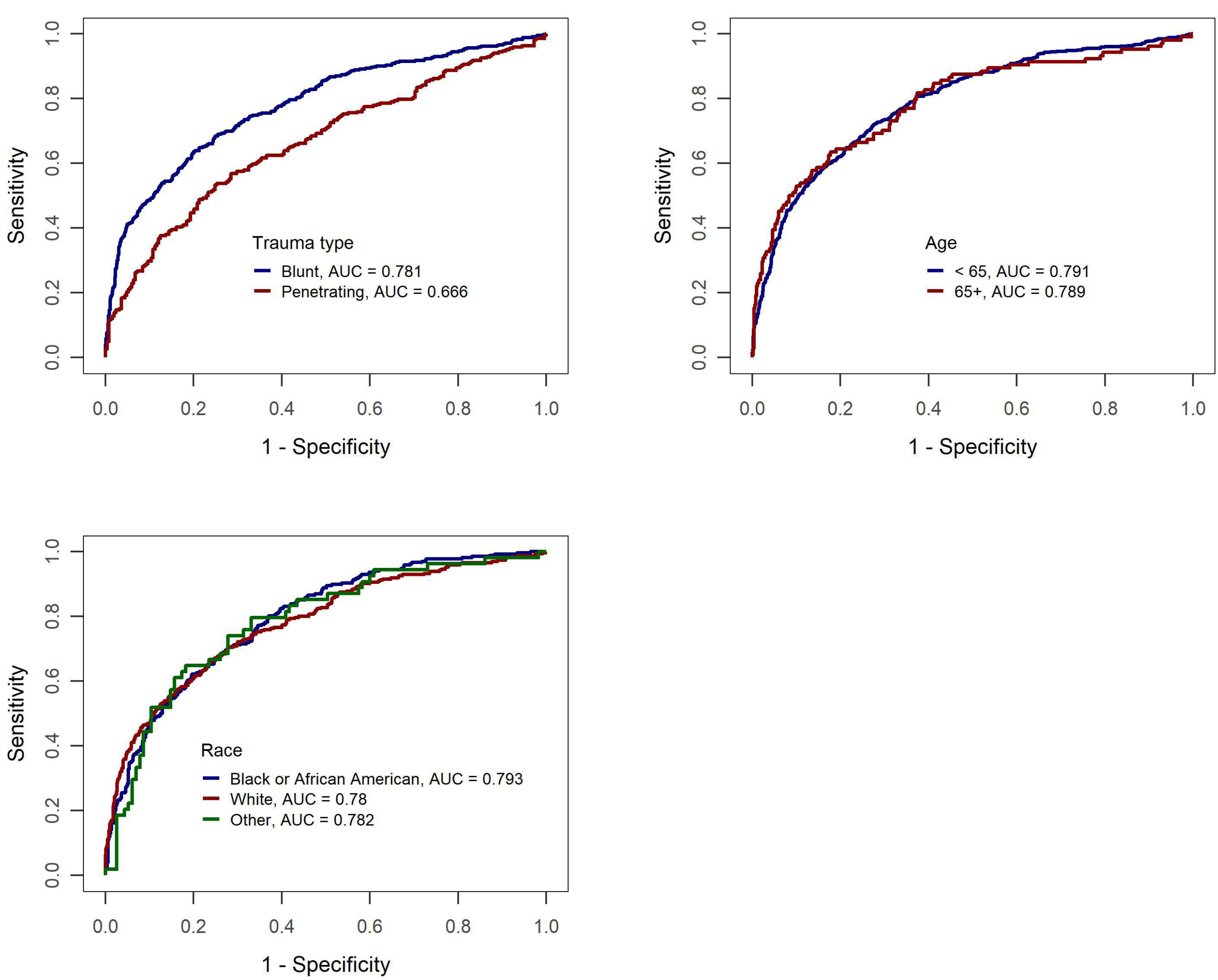

Figure 2 Receiver operating characteristic curves for blunt vs penetrating mechanism, age, and race subgroup analyses. AUC, area under the curve.

iterations of the model and mobile application, particularly with linkage to the electronic health record. Finally, clinical practice varies by center, which may influence the number and timing of NEI-6 procedures performed.

Likely due to differences in patient populations at each individual center, the model required selection of varying cutpoints on the AUROC to optimize performance at each individual center. Notably, this did not require changes in the data collection processes, manipulation of the model, or differences in utilization of the app, which could limit generalizability. It simply required evaluation of a data sample from each center and selection of the optimal cutpoint to address both undertriage and overtriage.

A lack of robust prehospital data is a major gap in trauma care that limited our ability to train the model to individual centers. The TIP mobile application has since become compliant with the Health Insurance Portability and Accountability Act of 1996 (HIPAA), and therefore future work will include developing a new databank for prehospital and hospital data through the TIP application. Linkage of these systems will allow for improved data collection to further optimize the model for all types of injuries. Consideration of additional model variables, such as intraosseous device or pelvic binder placement, may improve model accuracy. Further studies will involve a multicenter, stepwise, randomized controlled trial to compare TIP-NEI-6 and the Dutch prediction model and standard of care.

CONCLUSION

TIP-NEI-6 was modified and prospectively externally validated in a multicenter study for blunt traumatic injury. The TIP-NEI-6 model attempts to minimize undertriage while standardizing hospital triage criteria and allowing centers to use thresholds that best meet the need of their unique population. The TIP app delivers immediate decision-making support to assist triage providers with appropriate trauma triage and allocation of resources. Further work is necessary to continue to optimize the model, particularly for penetrating injury, and to determine how TIP-NEI-6 performs compared with standard of care processes. Future directions include scaling this system across trauma centers to further standardize trauma triage.

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