Statistical Validation of the Revised Trauma Score

Lynne Moore, MSc, André Lavoie, PhD, Natalie LeSage, MD, MSc, Belkacem Abdous, PhD, Eric Bergeron, MD, MSc, Moishe Liberman, MD, PhD, and Marcel Emond, MD, MSc

Background: To validate the accuracy of the Revised Trauma Score (RTS) and its components for predicting in-hospital mortality.

Methods: Analyses were based on 22,388 patients from the trauma registries of three urban Level I trauma centers in the province of Quebec, Canada. The accuracy of RTS coded variables for the Glasgow Coma Score (GCS_c), Systolic Blood Pressure (SBP_c), and Respiratory Rate (RR_c) for predicting mortality was evaluated in logistic regression models with measures of discrimination and model fit and compared with Fractional Polynomial (FP) transformations of each component.

Results: RTS coded variables were associated with sparse data distributions and did not accurately represent the relation of GCS, SBP, and RR to mortality. FP models were always associated with significantly better discrimination (all $p <$ 0.00001) and model fit. Survival probability estimates generated by the model with FP transformations were significantly different to those generated by the model with RTS-coded variables.

Conclusions: The RTS in its present form does not accurately describe the relation of GCS, SBP, and RR to mortality. FP transformation would improve the accuracy of predicted survival probabilities used for performance evaluation and may improve control of confounding caused by of physiologic severity case mix in trauma research.

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The Revised Trauma Score (RTS)[1] is currently the most widely used physiologic score in general trauma populations. Whereas the Glasgow Coma Score (GCS) was designed to evaluate injury severity in patients with head injuries,[2] the RTS incorporates two other physiologic variables, Systolic Blood Pressure (SBP) and Respiratory Rate (RR), to provide a severity indicator for general trauma populations. Five coded categories are created from initial vital signs for the GCS, SBP, and RR (Table 1). The coded values from each variable can be used in one of two ways. Firstly, they can be summed to give the Triage-RTS (T-RTS),[1] that is used for clinical triage. Secondly, they can be applied to a system of weights to give the RTS, which was designed for outcome prediction. The RTS is used for case-mix control in trauma research and benchmarking for performance evaluation along with the ISS and age in the Trauma Injury Severity Score (TRISS)[3] and A Severity Characterization of Trauma (ASCOT).[4] The RTS is generally used with weights derived from parameter estimates of the logistic regression model of mortality in the Major Trauma Outcome Study (MTOS).[1] However, the RTS with population-based weights predicts mortality more accurately.[5]

The statistical validity of the GCS for predicting mortality has been the subject of a few studies[6-9] but to our knowledge, that of the RTS has not been explored in detail.[10] We have previously reported that the T-RTS is a more efficient predictor of mortality than the RTS with MTOS weights and is equivalent to the RTS with population-based weights.[5]

The aim of this study was to evaluate the accuracy of the RTS with population-based weights, for predicting in-hospital mortality. The study had three specific goals: (1) describe the relation of GCS, SBP, and RR to mortality and the adequacy of RTS coded variables to describe this relation, (2) describe the relative contribution of each of the RTS components in trauma populations with and without head injuries, (3) investigate the possibility that mathematical transformation of GCS, SBP, and RR with fractional polynomials could improve survival prediction.

PATIENTS AND METHODS

The sample used for analyses was drawn from the trauma registries of three Level I trauma centers in the province of Quebec, Canada; Sacré-Coeur Hospital and Montreal General Hospital in Montreal; and Enfant-Jésus Hospital in Quebec City. Patients are prospectively included in these registries according to the following criteria: Hospital stay of 3 or more days, transfer from another hospital, admission to the Intensive Care Unit (ICU), or death following trauma. Deaths on arrival, isolated hip fractures, and patients under 16 years of age were excluded. Between April 1995 and March 2003, 22,388 patients were available for analyses.

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From the Centre hospitalier affilié universitaire de Québec, Enfant-Jésus Hospital, Quebec City, Canada (L.M., N.L., M.E.); Laval University, Quebec City, Canada (A.L., B.A.); Sherbrooke University, Sherbrooke, Canada (E.B.); McGill University, Montreal, Canada (M.L.).
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Address for reprints: Lynne Moore, Unité de recherche en traumatologie, Centre hospitalier affilié universitaire de Québec, 1401, 18ème rue, Quebec City, Canada, G1J 1Z4; email: Lynne.moore@cha.quebec.qc.ca.
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Table 1 Revised Trauma Score

GCS	SBP	RR	Coded Value
13–15	>89	10–29	4
9–12	76–89	>29	3
6–8	50–75	6–9	2
4–5	1–49	1–5	1
3	0	0	0

GCS, Glasgow Coma Score; SBP, Systolic Blood Pressure; RR, Respiratory Rate.

The first GCS, SBP, and RR obtained on arrival at the emergency department of the treating hospital were used for analyses. Nearly 40% of GCS were missing. According to emergency physicians, trauma surgeons, and archivists working on the registry, the most common cause of missing scores was the fact that the GCS was not recorded for patients with evident minor extra cranial trauma and normal consciousness. Prehospital interventions are not performed in the province of Quebec. However, missing GCS were also present in patients who were intubated or sedated before transfer from another hospital. Patients with missing GCS had lower mortality (4% vs. 10%), were older (41% vs. 23% > = 65 years of age), had lower injury severity (8% vs. 50% with ISS >15), and were less likely to have a head injury (10% vs. 58%) than those with GCS recorded.

SBP was missing in 341 (1.6%) patients. Patients with missing SBP had much higher mortality (40% vs. 7%), were younger (20% vs. 30% > = 65 years of age), and had higher injury severity (7% vs. 1% with ISS > 50) than those with SBP recorded. RR was missing for 1,248 (5.6%) patients. Patients with missing RR had much higher mortality (27% vs. 6%), were slightly younger (25% vs. 30% > = 65 years of age), and had higher injury severity (5% vs. 1% with ISS > 50) than those with RR recorded. Although patients with missing SBP or RR represent a small proportion of the population (5.8% of patients with either value missing), they account for 22% of all deaths.

We decided to impute missing data to provide results representative of all observations in our database. Missing GCS, SBP, and RR values were imputed using Multiple Imputation[11] with SAS software.[12] This method and the results of a simulation study using the study population are explained in detail in a previous publication.[13] Briefly, an imputation model was constructed using all registry variables related to either the GCS/SBP/RR or the fact that they were missing. The Markov Chain Monte Carlo method with a single chain was used to impute five possible values, as recommended by Rubin,[11] for each missing GCS/SBP/RR. Further simulations were conducted on the study population to verify the reliability of our multiple imputation model for imputing the missing GCS, TAS, and RR of three different trauma centers simultaneously. To account for heterogeneity between centers, a set of indicator variables representing trauma center was added to the imputation model as suggested by Little.[11] The results of simulations where missing GCS, TAS, and RR were imposed and then imputed with multiple imputation were encouraging. Logistic regression coefficients in a model predicting mortality were all within one SD of coefficients generated by the real data set.

To evaluate the ability of RTS categories to describe the relation between each component and mortality, observed and predicted mortality were compared graphically for each component. Observed mortality and 95% Confidence Intervals (CI) were calculated for each value of the GCS and for SBP and RR. SBP and RR were both represented by 18 intervals. Cut-points were assigned with the goal of creating as many intervals as possible while conserving sufficiently large sample sizes and respecting existing RTS categories. Predicted mortality was estimated from logistic regression models of GCS_c, SBP_c, and RR_c, where subscript "c" indicates that coded categories were used, and from FP transformations of the continuous variables GCS, SBP, and RR.

Logistic regression was used to evaluate the predictive performance of the RTS and each of its components. The following four models were fit: (1) GCS_c, (2) SBP_c, (3) RR_c, (4) $GCS_c + SBP_c + RR_c$. The same four models were then repeated with fractional polynomial transformations. Introduced by Royston and Altman in 1994,[14] fractional polynomials (FP) are a very simple yet flexible way of modeling nonlinear relationships. Instead of limiting the model to the traditional quadratic and cubic polynomial powers, a wider range of powers is used. Royston suggests that the following group of powers gives all the flexibility needed: −2, −1, −0.5, 0, 0.5, 1, 2, and 3, where 0 represents the logarithm. Models can be first degree (with only one polynomial term) or can include more terms. According to Royston, no more than two terms (second degree model) should be needed. The optimal FP transformation is chosen according to the model with the smallest deviance.

Model performance was evaluated with discrimination and model fit statistics. Discrimination is the ability of a model to correctly classify deaths and survivors and was measured by the area under the Receiver Operating Characteristic curve (AUC). An AUC close to 1 indicates perfect discrimination. AUC were compared using the completely non-parametric method of Delong et al.[15] Model fit was evaluated with Akaike's Information Criterion (AIC). The AIC is a measure of deviance where a low value indicates less deviance from the saturated model and therefore better fit. Logistic regression analysis was performed on the whole population and then within the sub-populations of patients with no head injury and at least one head injury.

Under the hypothesis that the predictive superiority of the FP model over the RTS model would be demonstrated with discrimination and model fit statistics, we also wanted to show that the use of the FP model made a real difference on a practical level. Survival probability estimates from the population-based RTS model were compared with those from the FP model. Estimates generated by each model were di-

Table 2 Population Characteristics

Characteristic		n	%
Age	17–54	13,289	59.4
	55–64	2,393	10.7
	65–74	2,566	11.5
	75–84	2,715	12.1
	85–106	1,425	6.4
ISS	1–8	6,862	30.8
	9–15	7,935	35.6
	16–24	3,344	15.0
	25–40	3,474	15.6
	41–49	382	1.7
	50–66	244	1.1
	75	54	0.2
Injury mechanism	Motor vehicle collision	7,352	32.9
	Fall	10,363	46.4
	Fire arm	435	2.0
	Stab wound	565	2.5
	Blunt object	1,878	8.4
	Other	1,795	7.8

ISS, Injury Severity Score.

vided into five categories: 0 to 0.49, 0.5 to 0.74, 0.75 to 0.89, 0.9 to 0.94, and 0.95 to 1.0 for graphical representation. The choice of these cut-points was based solely on the goal of creating categories with sufficiently large sample sizes. Means are not a representative measure of such a skewed distribution and are too crude for comparison purposes. The frequency distribution of estimates from each model along with exact 95% CI was plotted with a log transformation to facilitate visualization of the first four categories, which had relatively small sample sizes.

Because multiple imputation led to the creation of five possible values for each missing GCS, SBP, and RR, analyses were performed separately for five databases and results were combined using the method described by Rubin.[11] Optimal fractional polynomials were identified using STATA software.[16] All other analyses were performed with SAS software (version 8.2, SAS institute, Cary, NC).

RESULTS

Overall, mortality was 7.4% (1,655 patients). The study population was relatively old with a high proportion of falls and very little penetrating injury (Table 2). At least one head injury was present in 8,734 (39%) patients and 4,609 (20.6%) of patients had a severe head injury (maximum AIS of the head of four or greater).

GCS_c and particularly SBP_c and RR_c had very sparse data distributions. Categories 0 to 3 of SBP contained only 0.39, 0.20, 0.89, and 1.39% of patients, respectively. The same categories of RR contained only 0.31, 0.13, 0.52, and 1.98% of patients, respectively.

Observed and predicted mortality rates according to the GCS are illustrated in Figure 1. Observed mortality is 57% among patients with initial GCS = 3. Mortality then decreases rapidly until GCS = 7, changes little between GCS = 7, and GCS = 13 and decreases again between GCS = 13 and GCS = 15. Predicted probability estimates, generated by logistic regression models of GCS_c, miss the decrease in mortality from GCS = 4 to 5, 6 to 7, 11 to 12, and 13 to 15 and are outside the 95% CI of observed values for 9 of the 13 GCS values. Predicted mortality estimates generated by FP transformation of the GCS follow observed probabilities much more closely and only fall outside of 95% confidence intervals for 6 of the 13 GCS values.

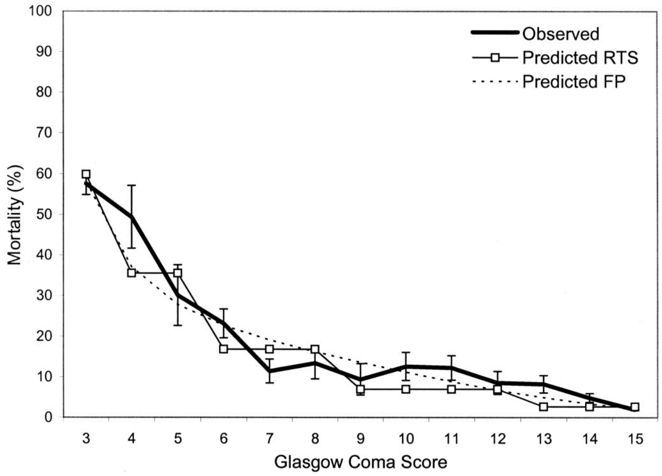


Fig. 1. *Probability of mortality according to the Glasgow Coma Score; observed and predicted by logistic regression models with Revised Trauma Score categories (RTS) and Fractional polynomial transformations (FP).*

Observed and predicted mortality rates according to SBP are illustrated in Figure 2. As expected, initial SBP = 0 is associated with 100% mortality. Percent mortality drops rapidly until SBP = 108 then slowly until SBP = 128. Mortality is lowest between SBP = 119 and 148 (4.2-4.5%) then rises

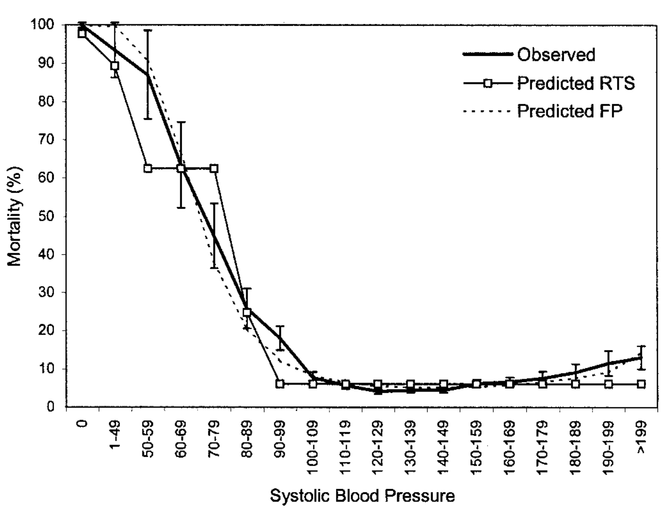


Fig. 2. *Probability of mortality according to systolic blood pressure; observed and predicted by logistic regression models with Revised Trauma Score categories (RTS) and Fractional polynomial transformations (FP).*

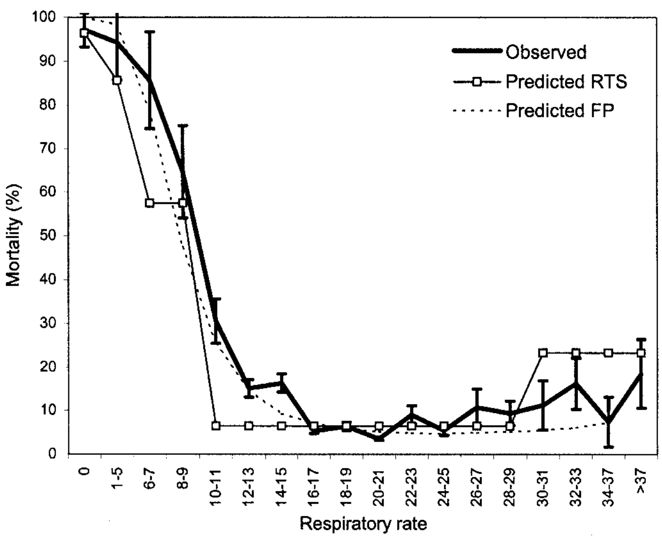


Fig. 3. *Probability of mortality according to respiratory rate; observed and predicted by logistic regression models with Revised Trauma Score categories (RTS) and Fractional polynomial transformations (FP).*

slightly until SBP > 198. SBP_c misses the observed drop in mortality from SBP = 49 to 78 and 89 to 128 and also the increase in mortality for the higher values of SBP. Eleven of the 18 SBP categories have predicted mortality probabilities which fall outside the 95% CI of observed values. Predicted values generated by FP transformation of SBP are again closer to observed values and fall outside of 95% confidence intervals for only 4 of out 18 categories.

Figure 3 presents observed and predicted mortality rates for RR. Mortality approaches 100% for initial RR = 0, then decreases until RR = 17, with no change however, between RR = 12 and 15. Mortality oscillates from RR = 16, with the lowest point being at RR = 20 to 21 (3.5%). The slight increase observed for respiratory rates over 28 per minute is associated with a statistically significant positive slope despite overlapping confidence intervals ($\beta = 0.0261$, $p < 0.0001$, in a logistic regression model). Mortality probabilities generated by the logistic regression model of RR_c miss the observed decrease in mortality from RR = 6 to 9, 10 to 17 and assume a much larger increase in mortality from RR = 30 than the observed data. Twelve of the 18 RR categories have predicted mortality probabilities which fall outside the 95% CI of observed values. Once again, predicted values generated by FP transformation follow observed mortality probabilities much more closely and fall outside of 95% CI of observed values for 9 out of 18 categories.

In logistic regression models predicting mortality, GCS provides by far the most information of the three RTS components (Table 3). SBP_c and RR_c provide little information but when both are added to GCS_c, they do improve discrimination (AUC = 0.841 vs. 0.823 for GCS_c alone, $p < 0.000001$) and model fit (AIC = 8,012 vs. AIC = 8,423 for GCS_c alone).

The optimal FP model for the combination of GCS, SBP, and RR in the study population can be expressed as follows:

$$Log(p/(1-p)) = \alpha + \beta_1 GCS^{-2} + \beta_2 GCS^3 + \beta_3 SBP^{0.5}$$

$$+ \beta_4 (SBP^{0.5} \times \log(SBP)) + \beta_5 \log(RR) + \beta_6 RR^{0.5}$$

All FP models perform much better than their RTS category counterparts in terms of both discrimination (all $p < 0.000001$) and model fit. In fact, even the FP transformation of the GCS alone performs just as well as the full RTS model (AUC = 0.844 vs. 0.841, $p = 0.15$).

The contribution of RTS components to predicting mortality according to head injury is shown in Table 4. FP transformations are used to compare the best performance of each model assessed by discrimination. AIC are not shown, as in the presence of FP transformation, model fit is close to optimal. As expected, the GCS has better discrimination among head-injured patients. It also remains the most important RTS component among patients with no head injuries. The SBP and RR seem to provide equivalent discrimination in either population but they provide a more important contribution to the RTS among patients with no head injury.

Figure 4 compares the frequency distribution of survival probability estimates of the RTS model with that of the FP model. More accurate modeling of RTS components with FP transformations results in a real change in predicted proba-

Table 3 **Performance of RTS Components for Predicting Mortality in Logistic Regression Models**

Model	Model	AUC	AIC
RTS categories	GCS_c	0.823	8,423
	SBP_c	0.594	10,660
	RR_c	0.563	11,040
	$GCS_c + SBP_c + RR_c$	0.841	8,012
Fractional Polynomials (powers)	GCS (−02,3)	0.844	8,300
	SBP (0,0)	0.666	10,524
	RESP (0,0)	0.655	10,772
	GCS(−2,3) + SBP(0.5,0.5) + RR(0,0.5)	0.874	7,789

RTS, Revised Trauma Score; GCS, Glasgow Coma Score; SBP, Systolic Blood Pressure; RR, Respiratory Rate; AUC, Area under Receiving Operator Curve; AIC, Akaike's Information Criterion.

Table 4 Performance of Fractional Polynomial (FP) Transformations of GCS, SBP, and RR for Predicting Mortality According to Head Injury

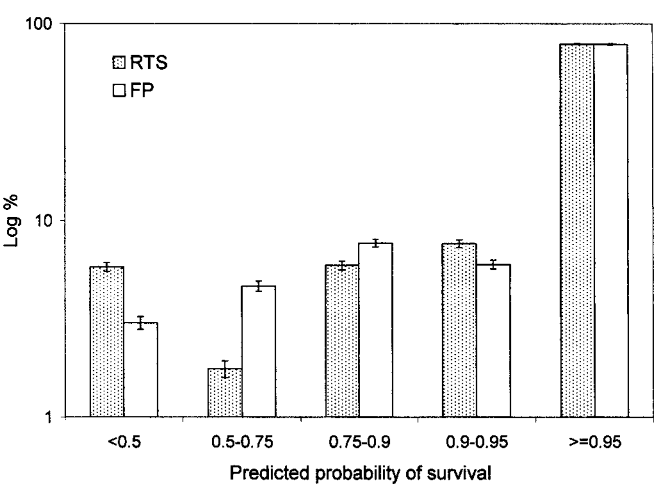
Model	Head injury AUC	
	Absent (n = 13,654)	Present (n = 8,734)
GCS	0.707	0.835
SBP	0.662	0.659
RR	0.628	0.642
GCS + SBP + RR	0.783	0.858

GCS, Glasgow Coma Score; SBP, Systolic Blood Pressure; RR, Respiratory Rate; AUC, Area under Receiving Operator Curve.

bilities of survival. Confidence intervals indicate an important difference in frequency for four of the five categories of survival probabilities. Notably, according to the RTS model, 1,302 patients (5.8%) have a survival probability of less than 50% whereas the FP model places 679 patients (3.0%) in this category. Conversely, the RTS model predicts a survival probability of between 50% and 75% for 396 patients (1.8%) and the FP predicts the same probability for 1,041 patients (4.7%). According to calibration graphs (not shown), the FP model provides a better fit over the entire range of survival probabilities. The RTS model overestimates survival below 0.95 and underestimates survival over 0.95. The FP model overestimates survival between 0.9 and 0.95 but to a lesser extent than the RTS model. In addition, because of more detailed information contained in the continuous variables, the FP model produces a wider range of survival estimates (0.543-0.985) than the RTS model (0.629-0.975).

DISCUSSION

RTS categories are inadequate for modeling mortality in trauma. They create sparse data distributions and miss important information in the relationship between GCS, SBP, RR, and mortality. FP transformations of RTS components lead to a considerable improvement in discrimination and model fit, which result in a real change in predicted survival probabilities.



	<0.5		0.5-0.75		0.75-0.9		0.9-0.95		>=0.95	
%	5.8	3.0	1.8	4.7	5.9	7.7	7.7	6.0	78.8	78.6
N	1302	679	396	1041	1327	1725	1713	1341	17650	17602

Fig. 4. *Comparison of the frequency of predicted survival probabilities for logistic regression models with Revised Trauma Score categories (RTS) and Fractional polynomial transformations (FP).*

Our findings have direct implications for performance evaluation of trauma centers and for the control of confounding caused by severity case mix in trauma research. Using FP transformations over traditional RTS categories could considerably improve the accuracy of predicted survival probabilities generated by models such as TRISS and ASCOT and the accuracy of results of regression analyses requiring control for confounding by physiologic injury severity.

The RTS was created for mathematical modeling of mortality from trauma but is based on a model designed for triage. The choice of GCS categories was based on the intervals widely used by surgeons at the time and SBP and RR categories were chosen so that their associated survival probabilities approximated those of GCS intervals.[1] These intervals were used for both the T-RTS and the RTS to provide consistency between the triage and outcome measures. However, while standardization of the three components is useful for clinical decision purposes, the variables do not need to be comparable and should in fact convey information as independently as possible for outcome prediction. In addition, while in a triage context the instrument must be as easy to calculate and interpret as possible, for outcome prediction, computing systems make it less necessary to compromise predictive information for simplicity. Modeling RTS components as categorical variables implies step changes in mortality, a situation that bares little resemblance to clinical reality. In addition, modeling the categories as ordinal variables rather than indicator variables implies that the change in mortality from one step to the next is always the same (in logit terms). In the National Trauma Data Bank reference manual, the American College of Surgeons Committee on Trauma suggests using RTS categories as a group of four indicator variables (with the coded value four being the reference category).[17] Although this modeling strategy is more likely to portray the real variation in mortality from one RTS category to the next, it is unrealistic in most trauma populations because the first four categories of SBP and RR contain very small sample sizes (<2%). This leads to parameter estimates that are either associated with very large error terms or cannot be estimated.

FP modeling reflects the more natural smooth change of predicted mortality from one value to another and allows for a different graduation of mortality between values. Another considerable advantage of FP modeling of RTS components is that, unlike fixed intervals, it will provide a better fit in any study population. FP powers for the GCS seem to be fairly constant as the same powers were observed in the univariate and multivariate model and in the populations with and without head injuries in our study population and in the study of Healy and al. in the National Trauma Data Base.[6] However, FP powers for SBP and RR do vary from the univariate to multivariate model and are different according to head-injury status. Each study population has specific inclusion and exclusion criteria, socio-demographic characteristics and organizational differences that lead to variation in the distribution of RTS components, mortality, and the relation between the two. The flexibility of FP modeling allows an investigator to adapt to these differences and provide the most efficient control for physiologic severity in any trauma population.

Note that while FP transformations provide better model fit and are conceptually very simple, they can be difficult to interpret. However, Royston et al. have published a very useful guide to presenting odds ratios generated by FP models.[18] In addition, the RTS is usually used either to produce survival estimates in a predictive model or to control for confounding caused by injury severity case-mix in explicative models. Effect estimates for the RTS are therefore rarely of direct interest when presenting the results of trauma research.

Although previous studies have evaluated the statistical validity of the GCS for predicting mortality in trauma,[6–9] there is, to our knowledge, no literature on the relation between SBP or RR and mortality in a trauma population. The GCS is by far the most important component of the RTS. This is not because mortality drops more rapidly with increasing GCS_c than with increasing SBP_c or RR_c. Similar parameter estimates for the three components indicate that a one-point increase in GCS_c, SBP_c, or RR_c is associated with an equivalent drop in mortality. The main reason that the GCS is the best predictor of mortality is that it is more sensitive (only 26% of deaths have a normal GCS where 80% and 86% have normal SBP and RR, respectively). SBP and RR probably have very little correlation with late deaths ($>$48 hours) and would have more value in a population including on-scene deaths and deaths on arrival. Although RR and SBP add little information to the GCS, in part because the three variables are correlated and therefore partially convey the same information, they do improve prediction of mortality slightly in a general trauma population and considerably among patients without head injury. In addition, they are readily available in trauma registries and less prone to missing values than the GCS.

Two possible limitations of this study that should be addressed are the generalization of results and the imputation of missing GCS, TAS, and RR values. This was an internal validation study, performed on a trauma population with a high percentage of elderly patients (30% $\geq$ 65) and a low percentage of penetrating injuries (3.7%). A lower proportion of patients aged $\geq$65 would improve the performance of the GCS[9] and probably SBP and RR because of reduced confounding by co-morbidities. A higher proportion of penetrating injury is likely to lead to an increased frequency of lower SBP and upper RR values, which implies a greater contribution of these variables. Note that the original RTS with MTOS coefficients was calibrated using the global population of both blunt and penetrating trauma.[1] In our trauma population, numbers of penetrating trauma were low but coefficients did not differ considerably between groups. For GCS_c, SBP_c, and RR_c, respectively, the coefficients were -0.918, -1.001, -0.871 in the population with blunt injuries only and -0.8061, -1.1962, -0.9109 in the population with at least one penetrating injury. Despite this, future research must investigate whether the RTS should be modeled differently for these two distinct populations. Varying distributions of age and injury mechanism may influence the relation between RTS components and mortality and may therefore change the powers of optimal fractional polynomials but would not change the superiority of FP over RTS categories.

The imputation of missing values may have biased our results. The problem of missing GCS data is widespread in trauma registries. Healy et al. report only 1% of missing GCS in the National Trauma Data Bank[6] but the authors themselves find this small proportion quite improbable and suggest that ad hoc methods are probably used to impute GCS data. Multiple imputation is a method which has been shown to provide unbiased results for data imputation[11] and we have previously confirmed the accuracy of imputed GCS using this method.[13] Imputation of SBP and RR was important because exclusion of observations with missing values would have deprived us of over 20% of deaths. Analyses on the data set of 13,099 patients with missing values excluded did not notably change results. AUC and AIC were 0.822 and 5592 for the RTS model and 0.858 and 5395 for the FP model. Under the assumption that imputations are accurate, multiple imputation gives our study a great advantage. We have previously shown that the exclusion of observations with missing GCS leads to biased frequency distributions, biased parameter estimates in logistic regression models and biased probability estimates.[13] Though avoidance of missing values at the source remains the best solution, our validation of the RTS is likely to represent a general trauma population much more accurately than a validation performed on a database where missing observations are excluded or imputed with ad hoc methods.

CONCLUSION

The RTS in its current form does not accurately reflect the relation of the GCS, SBP and RR to mortality. FP transformation improves mortality prediction and can be adapted to any type of trauma population or sub-population. The results of this study have immediate implications for the accuracy of predicted survival probabilities in models such as TRISS and ASCOT, which include the RTS in their calculations, and for the control for confounding caused by physiologic severity case mix in trauma research.

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