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Validation of The TRISS Model of Survival in Blunt Trauma Patients Using The Ontario Trauma Registry

by

© Bryan G Garber MD FRCSC

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ABSTRACT

Objective: To compare outcomes in blunt trauma by using Trauma and Injury Severity Score (TRISS) models derived from the Major Trauma Outcome Study (MTOS) and the Ontario Trauma Registry as well as to evaluate the role of the Revised Trauma Score (RTS) within the TRISS model.

Methods: Consecutive blunt trauma cases from 11 Level I trauma centres over a 4 - year period were identified from the OTR. Coefficients of the Revised Trauma Score were modified using the Ontario data and this scores ability to predict mortality was compared to the Revised Trauma Score derived from MTOS. Two Ontario-specific TRISS models were developed with revised coefficients. The first used the standard Revised Trauma Score and the second used the Revised Score with regenerated coefficients. An expanded TRISS model was developed using all the component variables of TRISS and the Revised Trauma Score using forward step-wise logistic regression analysis. The accuracy of mortality predictions for all models were assessed using a Hosmer-Lemeshow Goodness of Fit statistic as well as by estimating sensitivity, specificity (using probability of survival cutpoint of 50%) and the area under the receiver operating characteristic (ROC) curve.

Results: A total of 5,436 cases were incorporated in the analysis. Patients with all component TRISS variables had a significantly lower mortality (7.0%, 95% CI: 6.2 - 7.7) compared to all blunt trauma cases (15.5%, 95% CI: 14.2 - 16.2). Use of the Revised Trauma Score led to the exclusion of 36% of cases largely due to the absence of a recorded value for respiratory rate or the verbal component of the Glasgow Coma Scale. The Revised Trauma Score models demonstrated poor predictive ability with an ROC area ranging from 0.7154 - 0.6014 and a

Hosmer-Lemeshow Goodness of Fit statistic that ranged from 34.9 to greater than 100 for the OTR and MTOS models respectively. All TRISS variables demonstrated strong association with survival. The MTOS-TRISS model showed poor fit to the data with a Hosmer-Lemeshow Goodness of Fit statistic of 25.62 while both Ontario TRISS models demonstrated good fit with values ranging from 11.42 - 13.10. ROC area of all three TRISS models ranged from 0.89 - 0.91, sensitivities ranged from 98.4- 99.2 and specificities ranged from 24.2 - 35.2.

Conclusions: All TRISS variables were significantly associated with survival. Although revision of coefficients led to a better fit on the Hosmer-Lemeshow statistic, ROC curve analysis showed virtually identical performance of the MTOS and Ontario-based TRISS models. The low specificity of all of these models indicates an inferior ability to identify mortalities in this Canadian trauma population. The poor performance of the Revised Trauma Score and the observation that its use led to the exclusion of a substantial number of cases with a higher . mortality raises serious concerns regarding its use in the TRISS

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Conclusions drawn from the study reported here are those of the author and are not necessarily those of the Ontario Trauma Registry.

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INTRODUCTION

Background:

Traumatic injury is a leading cause of mortality and morbidity in the under 40 years of age population in North America [1-3]. Despite the magnitude of this problem, the lack of basic epidemiologic data available at the time prompted the National Academy of Sciences in the USA in 1966 to identify this area as requiring urgent investigation [4]. This resulted in the initiation of the Major Trauma Outcome Study (MTOS) in the United States which is a central registry that has been collecting demographic, injury and outcome data on 120,000 patients from 140 acute care hospitals in both the USA and Canada [5].

The Trauma and Injury Severity Score (TRISS) model of survival following trauma was developed from the MTOS and has been widely utilized as a method of predicting survival following trauma thereby allowing individual trauma centres to compare their results against a standardized norm as well as measure their results over time [6]. TRISS is a logistic regression model which consists of three components: 1) the Injury Severity Score (ISS) [7]; The Revised Trauma Score (RTS) [8]; and, 3) Age, which is dichotomized into those under or equal to 55 years of age and those above.

The ISS [7] is an anatomic measure of injury severity which is derived from an anatomic injury coding system called the Abbreviated Injury Scale (AIS) [9,10]. AIS divides the body into

six regions and injuries within each region are coded from 1 (minor injuries) to 5 (major injuries). The ISS is obtained by summing the squares of the three most severe injuries. Although the ISS does correlate with survival [11], it does not completely describe all injuries because substantial heterogeneity exists within each ISS level. Consequently, those with a given ISS could have a single severe injury within one organ system or multiple injuries in several organ systems [12]. This limitation of the ISS led to the development of other anatomic scoring systems such as the Anatomic Profile, none of which have gained wide popularity [13].

The RTS is a physiologic scoring system of injury severity [8]. It was developed separately from TRISS by logistic regression analysis using the MTOS database with survival as the outcome. It was subsequently incorporated into TRISS as the physiologic injury severity component. RTS is composed of three variables: 1) systolic blood pressure; 2) respiratory rate; and 3) the Glasgow Coma Scale (GCS). The GCS is a well validated measure of the level of consciousness following trauma and consists of a verbal, eye and motor component [14]. The potential difficulty with the RTS lies with the fact that both the respiratory rate and verbal component of the GCS may not be obtainable in intubated and mechanically ventilated trauma patients. Consequently, the development and utilization of this score could exclude a substantial proportion of trauma patients who might possibly represent some of the more severely injured individuals. Independent validation of the RTS compared to other physiologic scoring systems indicate that it performs poorly in predicting survival despite that fact that it remains one of the most widely utilized physiologic indices of injury severity [15].

Finally, the TRISS software marketed for trauma registries calculates a Z-statistic to compare observed survival versus that predicted by TRISS for a given population using a Z-value cutoff of 1.96. Substantial deviation below the predicted survival based on MTOS norms suggests substandard performance of that hospital. It has been estimated that a cohort size of at least 800 patients is required in order to detect a 20% difference in survival rates with a power of 80%[16]. Given that few Canadian trauma centres treat more than 300 trauma victims per year, this statistical comparison is entirely impractical [17]. Furthermore, normative standards based largely on a US trauma population may not reflect the differences in technology, population distribution and hospital transport systems that characterize most Canadian trauma centres.

These difficulties have led many traumatologists to question whether TRISS represents a useful model of trauma mortality both for the purposes of description of injury severity and prediction of outcome following traumatic injury. Only a few studies have been published which have attempted to validate TRISS in a non-MTOS data set [18-21]. None of these studies have shown TRISS to adequately characterize mortality in other trauma cohorts. Only a single study showed that revision of TRISS beta weights based on their own trauma population resulted in adequate fit of the model [21]. The purpose of this thesis is to validate TRISS in a population of Canadian blunt trauma victims, and to determine if revision of coefficients significantly improves model performance in predicting trauma deaths. The predictive role of the Revised Trauma Score both independently and as a component of the TRISS model will also be evaluated. Finally, the association of the other component variables of TRISS with mortality will be determined.

Epidemiology of Trauma Deaths:

Much of our knowledge about the epidemiology of traumatic death comes from studies within the United States of America and consequently may not be generalizable to a Canadian population. Nevertheless, these studies do represent detailed analysis of the cause of mortality as a consequence of trauma and much of their conclusions can be extrapolated. Three studies provide a population based analysis of the epidemiology of trauma deaths in two different populations [10,22,23]. One of these [22] consisted mostly of penetrating traumas while the others [10,23] dealt predominantly with blunt injuries. All studies were performed on urban populations and included detailed autopsy data derived from Coroner's records. Shackford et al [23] provided the most thorough population based analysis of the epidemiology of trauma deaths published to date. This was accomplished by prospectively identifying all trauma deaths in San Diego County over a one year period. All such deaths underwent a Coroner's autopsy and the report was entered via computerized registry which also included antemortem information on cause of injury, patient demographics and subsequent clinical data on treatment and complications. Operational definitions were employed to classify cause of death and ensure consistency. The incidence of trauma deaths was estimated at $27.3/10^5$ population/year and the case fatality rate ranged from 6.6% - 20 %. The majority of these deaths occurred in the young (less than 50 yrs) and of male sex (70%) similar to the demographics of all trauma victims. Brain injury accounted for almost half of the deaths in all of these studies followed by haemorrhage, cardiovascular injuries, sepsis and the syndrome of multiple organ failure.

The timing of trauma related mortality follows a distinct pattern with 80% occurring by the first 48 hours and 90% by the first week [3,10,22]. Mortality risk persists to a lesser extent beyond the first week of injury resulting in an early and late period of trauma deaths. When aetiology is compared in these two time periods it is found that early deaths (≤ 7 days) occur largely from injuries to the central nervous system (CNS) and haemorrhage while late deaths (> 7 days) are attributable to sepsis and multiple organ failure.

This recognition of sepsis and the syndrome of multiple organ failure in trauma victims had been documented by earlier authors [24-27]. Indeed, Faist et al [28] documented in a retrospective cohort of blunt trauma victims that the incidence of multiple organ failure was 7.8% and that the total proportion of deaths attributable to this syndrome was 4%. However, the case fatality rate of patients who developed multiple organ failure was 56%, and sepsis was the ultimate cause of death in almost half of these patients. The authors described two patterns of multiple organ failure: the first was characterized by a rapid single phase due to trauma and shock while the second consisted of a delayed two phase initiated by trauma and shock followed by sepsis.

Several conclusions can be made based on these studies. First, traumatic deaths occur predominantly in young males primarily because these are the same demographics which characterize trauma victims in general [23]. Secondly. while the majority (90%) of trauma deaths occur within the first week, there is a persistent albeit diminished risk of death beyond that period of time [10]. Third, injuries to the central nervous system and haemorrhage account for the majority of deaths overall with sepsis incriminated in only 2.5%. However, when aetiology is

examined in early versus late deaths (defined as greater or less than 7 days following injury) it is found that CNS injury was the predominant cause of death in the early group while sepsis and multiple organ failure predominated in the late group [10].

Age as A Risk Factor in Trauma Mortality

The prevailing epidemiologic literature identified the young as the predominant victims of trauma and focused on the potential years of life lost as a consequence of injury. However, evidence has accumulated that the elderly are also prone to trauma and are more susceptible to traumatic death. In a US report in 1984, unintentional injury accounted for almost 24,500 deaths of persons age 65 years and older [1]. This constituted a death rate of 86 per 100,000 population which was more than twice the accidental death rate of all ages. The data suggested that age would be an extremely important prognostic factor in trauma deaths. This hypothesis was supported by two studies which provided a detailed evaluation of the effect of age on mortality in trauma [29,30]. Both studies prospectively followed trauma cases and one collected data on 47,000 trauma victims obtained from 111 trauma centres [29]. While the elderly (those 65 years and older) constituted only 8% of the trauma cases, their mortality was twice that of the younger victims (26.7% vs 14.1% in one study [30] and 19% vs 9.8%in the other [29]). When mortality was stratified by injury severity using the Injury Severity Score, it was clear that mortality in the older patients was higher than the younger group at every ISS level [29]. Older patients with good physiologic status on arrival to trauma centres still had poor outcomes compared to their younger counterparts [29].

Conclusions derived from these two papers are limited somewhat by the fact that they were not population based and were biased towards the more severely injured patients, since over 85% of data came from specialized trauma centres. However, the evidence suggests that there is a definite relationship between age and mortality in trauma victims treated at major trauma hospitals which persists after stratification by injury severity.

Effect of Comorbid Illnesses on Mortality

The relationship between age and traumatic death suggests that other factors such as the presence of preinjury comorbid illnesses and prior functional status may play a role in outcome following trauma. Precedent for this comes from outcome models in critically ill patients such as the APACHE (Acute Physiologic and Chronic Health) Score where in fact comorbid illness is an essential component in addition to age [31].

Several studies sought to examine whether the presence of preexisting disease, independent of age, defined a subgroup of patients at increased risk of dying from trauma [32-35]. Comparison between these studies is made difficult because of the use of different definitions of the comorbid illnesses, varied study designs, and the use of different study populations. Furthermore, because data on the presence of these conditions was not collected prospectively in all studies, a selection bias may have occurred whereby only nonsurvivors had comorbid illnesses identified. This could lead to a magnification of the effect this variable has on survival.

However, the evidence from these studies indicates that although premorbid illnesses in this population are rare, occurring in 4 .8 - 16% of trauma patients [34,35], they do appear to be associated with an increased risk of mortality which persists after adjustment for age, and injury severity. The effect is present in prospective studies [35] where the risk of differential misclassification is minimized. Additionally, the performance of TRISS is improved by including these conditions in at least a subset of trauma patients [36]. It remains to be determined whether this improvement in model performance persists when premorbid illnesses are included in evaluating all trauma patients.

The Development of Trauma Registries and The Major Trauma Outcome Study

Industrial models of continuous quality improvement have been increasingly applied to the health care industry in the United States [37] and outcomes measurement through continuous monitoring systems is an integral component of this endeavour. The computerized trauma registry is the direct application of a continuous monitoring system of injury care outcomes.

Trauma registries have simultaneously developed in several North American centres and include The National Pediatric Trauma Registry [38], The National Eye Trauma System Registry [39], The Maine Trauma Registry [40], The Pennsylvania Trauma Systems Foundation [41] and The North Carolina Trauma Registry [42]. In June 1989, the Ontario Ministry of Health established the Ontario Trauma Registry [43]. The principal goal of the OTR was to develop a provincial database to identify, describe and quantify traumatic injury and death in the province of Ontario. Greater

detail on the structure of the OTR is provided in the METHODS section while more elaborate historical information is provided in Appendix 1.

In 1982, the American College of Surgeons Committee on Trauma recognized the need for improved methods to evaluate trauma care . They pooled data on injured patients to develop and test survival probability norms based on the existing severity indices of the time. The result of this effort was the Major Trauma Outcome Study (MTOS) [6]. It was hoped that these national norms could be used for quality assurance but more importantly it was also anticipated that research into outcome, rehabilitation and costs of trauma would evolve from such a national database.

The study centre received data forms including information on demographics, etiology, injury severity and outcome on 120,000 trauma patients treated at over 140 hospitals primarily in the United States, Canada, Australia and the United Kingdom beginning in 1982. Champion et al [6] presented the results of an analysis of 80,544 patients from 139 U.S. and Canadian institutions collected over the period 1982-1987. Patients qualifying for the database included all in-hospital trauma deaths *and* either all hospital admissions due to trauma or all injured patients admitted to intensive care during their hospital stay. Data forms were sent to Washington DC where anatomic injury descriptions were coded according to ICD-9-CM, and for severity using the Abbreviated Injury Scale (AIS) 1980 and 1985 version. Injury severity indices consisted of the ISS and Revised Trauma Score (RTS). Centralized coding was performed by a small group of data analysts and extensive quality control check were instituted.

The majority of the MTOS population was young (74% between the ages 15-55 yrs) and male (71.1%). The ratio of blunt to penetrating injuries was 4:1 and motor vehicle accidents were the most frequent cause of injury (35%). The overall mortality in the study population was 9.0%. The distribution of mortality with respect to time was skewed towards the origin with 60% of deaths occurring within 24 hours of admission. A linear relationship was observed between both the RTS and ISS with mortality. It is of importance to note that 11% of patients were excluded from analysis. The primary reason for this was the absence of one or more Revised Trauma Score variables at emergency department admission.

The Injury Severity Score and other Anatomic Injury Scores

The inability of existing taxonomy systems for disease classification such as The *International Statistical Classification of Diseases, Injuries, and Causes of Death* [44] and the current *International Classification of Diseases-9* (ICD-9) [45] to rate severity of accidental injury from motor vehicle accidents led to the development of The Abbreviated Injury Scale (AIS) [9, 46-48]. The current modification of this, AIS-90 [49] is used by the vast majority of trauma registries including MTOS and OTR. The AIS contains several hundred injuries and divides the body into nine anatomic regions. Each injury is assigned a score from 1 (minor injuries) to 5 (nearly always fatal). Because AIS assigns severities to individual injuries, summary scores are needed to characterize the multiple injuries typically sustained by the trauma patient.

The Injury Severity Score [7,50] was derived as a summary measure of anatomic injury severity based on the AIS. Baker and colleagues investigated the relationship between AIS grade

of severity and mortality and found it to be nonlinear with a disproportionate increase in mortality for the most severe AIS score. They applied a quadratic equation to compensate for this by squaring the AIS grades. The optimum result was obtained by summing the squares of the highest AIS grade in each of the three most severely injured areas. This resulted in the Injury Severity Score. Despite the fact that the ISS has been demonstrated to correlate with mortality [7,11,12,50], it has several substantial limitations . The exclusion of all but the most severe injury in any body region, the diversity of injury severity combinations and injury locations which produce the same ISS value, and the equal weightings given each body region all contribute to substantial heterogeneity within any given ISS value [12].

These limitations have led to ongoing research for different anatomic injury scoring systems. Champion et al [13] described Anatomic Profile (AP) which describes *all* AIS injuries greater than grade 2 to all body regions. AP is used in the logistic model of survival, ASCOT, together with Age and RTS. Despite several validation studies comparing ASCOT to TRISS, there have been no independent comparisons of AP and ISS. Consequently, it cannot be concluded that benefits of AP over ISS have been strongly supported by the literature.

The Revised Trauma Score

The development of the current Revised Trauma Score (RTS) can be chronicled in three key papers [8,51,52]. This score was developed as a physiologic scale of injury severity in contrast to the Injury Severity Score which is an anatomic measure. While several other physiologic scores

of injury have been developed [53,54], the RTS remains the most popular.

The final refinement of this physiologic scoring system is embodied in the current RTS [8] which consists of the patient's systolic blood pressure (SBP), respiratory rate (RR) and Glasgow Coma Scale (GCS). The GCS is a widely utilized, well validated and easily applicable measure of level of consciousness which consists of a verbal, motor and eye movement component [14]. This revision came about because capillary refill and respiratory expansion, which were used in the earlier Triage Index [51] and Trauma Score [52], were often difficult to assess and frequently unreliable. The RTS adopted the commonly used and accepted interval scaling of the GCS that indicate mild, moderate and severe head injuries. It also contained intervals for systolic blood pressure and respiratory rate with values whose associated survival probabilities were equivalent to the corresponding GCS intervals (see Table 1).

Table 1: Revised Trauma Score. Variable interval scaling.

Glasgow Coma Scale	Systolic Blood Pressure	Respiratory Rate	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

Using both the Washington Hospital data set and subsequently the MTOS data set, beta weights were derived for the three RTS variables (SBP, RR, and GCS) using logistic regression analysis to predict probability of survival. When used as a triage tool (labelled T-RTS) the score takes on integer values from 0 - 12. Alternatively, when used to evaluate survival the RTS is calculated by summing the weighted logistic variables and varies from 0 to 8 with non-integer values and corresponding survival probabilities. Model performance was evaluated using the Hosmer-Lemeshow Goodness of Fit test and the RTS demonstrated good fit to the data using the MTOS data set. The score therefore provides a simply calculated triage tool as well as a logistic regression model of survival using physiologic variables and is far easier to apply than the earlier Triage Index.

Other physiologic injury triage scores have been developed but all of them differ from the RTS in so far that they included anatomic and/or mechanism of injury information and are not based purely on physiologic variables. These include CRAMS (circulation, respiration, abdomen, motor, speech) [53], PHI (prehospital index) [54] and RTI (revised trauma index) [55]. Most recently, a comparison of these physiologic scoring systems using likelihood ratios and receiver operating characteristic (ROC) curve analysis found that the differences between the RTS and other instruments were small but became quite large with significantly poorer performance of the RTS when healthy extreme cases were excluded [15]. This led the authors to conclude that the widespread use of the RTS as a predictive tool of mortality should be challenged.

Trauma and Injury Severity Score (TRISS): A Model of Mortality

The Trauma and Injury Severity Score is a logistic regression model of survival developed on the MTOS data [6]. TRISS consists of the RTS, ISS and patient age dichotomized above and below 55 years of age. The logistic model predicts survival as follows: $Ps=(1/1+e^{-b})$, where e is the base of the natural logarithm and $b = b_0+b_1(RTS)+b_2(ISS)+b_3(AGE)$. The beta weights or coefficients reflect the relative importance of the component variables on survival in the representative population and are intended to represent norms. Separate coefficients were derived from a sample of 15, 754 blunt and 7,423 penetrating injury patients respectively. In both groups, patients in whom the respiratory rate or verbal component of the GCS could not be obtained were excluded from analysis because the patients were intubated. This raises some concerns regarding the generalizability of TRISS to this subset of trauma patients who may well represent the more severely injured individuals. Furthermore, the authors failed to provide many of the standard measures of model performance in the paper introducing TRISS which prohibits any objective determination of the usefulness of the model.

Outcome evaluation in TRISS methodology is performed by two complementary procedures, PRE and DEF. PRE (PREliminary outcome based evaluation) is derived by plotting RTS against ISS generating an isobar for 50% probability of survival. Survivors above the line or nonsurvivors below the line represent mathematically unexpected results worthy of peer review. DEF (DEFinitive outcome based evaluation) is a Z statistic which compares the *actual* number of survivors in a particular hospital to the predicted survival based on MTOS norms using TRISS. A Z-score of greater than 1.96 indicates significant deviation and a W statistic, which

indicates the magnitude of deviation, is then calculated. The use of this Z-score as a comparative tool is limited by the fact that a cohort of at least 800 patients is required in order to detect a 20% difference in survival rates with a power of 80% [16]. Given that few Canadian trauma centres treat more than 200-500 accident victims per year, this statistical comparison is entirely impractical [17].

A similar model of trauma survival was developed shortly after TRISS was described. ASCOT (A Severity Characterization of Trauma) [13] is similar to TRISS with two exceptions. It uses the Anatomic Profile to replace the ISS and age is now coded into four intervals instead of above and below age 55 years. The initial report of ASCOT compared it to TRISS and found sensitivity of both models identical at 99.2% with specificity of 60.9% and 63.3% for TRISS and ASCOT respectively. However, ASCOT continues to utilize the RTS and therefore is subject to the same potential limitation in generalizability to all trauma patients as the TRISS model.

Independent validation of TRISS on other data bases have almost uniformly demonstrated suboptimal performance of this model in three out of four studies [18-21]. Comparing these validation studies becomes exceedingly difficult because model performance was evaluated differently in each study. Sensitivity ranged from 34.6 - 84%, and specificity from 98.5 - 99.4%. Revision of model coefficients was reported to improve model performance in one study based on the use of the Hosmer-Lemeshow Goodness of Fit statistic but it did not report other performance characteristics such as sensitivity and specificity which could be more meaningfully

used for comparison [21]. Inclusion of comorbid illnesses into the model was recently demonstrated to improve model performance in a subpopulation of elderly patients suffering low falls but the effect of this variable was not tested in all trauma patients [36]. Similar performance problems of ASCOT were also demonstrated by many of these studies [18,20,21].

Canadian Trauma Mortality: Is TRISS a useful Model?

While the development of the TRISS model represented a major advance in the evaluation of trauma mortality and quality control assurance, the model suffers from the limitation of its component variables.The most important of these seems to center around the RTS. The potential elimination of intubated patients in whom a respiratory rate or the verbal component of the GCS cannot be obtained may limit the external validity of both the RTS and TRISS.

The relatively poor performance of TRISS in independent validation exercises published from centres in the United States raises concerns regarding the validity of applying this model to evaluate Canadian trauma victims as substantial differences may exist between these populations of people. Given that the Ontario Trauma Registry currently employs TRISS methodology as a quality control tool, it is important to evaluate the predictive performance of this model in a Canadian trauma population and to determine whether revision of coefficients of both the RTS and TRISS would further enhance performance in this population of patients.

Statement of Objectives

The objective of this thesis is to validate the TRISS Model of survival in a prospective cohort of blunt trauma victims obtained from the Ontario Trauma Registry.

Specific Objectives:

1. To develop a revised TRISS Model for blunt trauma victims with beta coefficients derived from the Ontario Trauma Registry.

2. To compare the ability of this new Ontario Trauma Registry Specific TRISS model versus the model derived from the Major Trauma Outcome Study to predict survival in Canadian blunt trauma victims and analyse their performance characteristics.

3. To evaluate the ability of the Revised Trauma Score, a component of the TRISS model, to predict survival in a cohort of blunt trauma victims obtained from the Ontario Trauma Registry.

4. To generate a TRISS model which does not include the Revised Trauma Score.

METHODS

Study Population (The Ontario Trauma Registry)

The dataset used in this study was obtained from the Ontario Trauma Registry (OTR). The OTR is a computerized database which collects information on all trauma cases throughout the province of Ontario. The registry was started in 1991, is funded by the Ontario Ministry of Health and managed by the Canadian Institute for Health Information (CIHI).

The OTR consists of three separate data sets. The **Minimal Data Set** contains demographic, diagnostic and procedural information on all admissions resulting from injury to acute care hospitals in Ontario. These admissions, which approximate 72,000 annually, are selected from the Discharge Abstract Database at CIHI and downloaded to the OTR's processing system. Selection is based on the External Cause of Injury codes within the International Classification of Disease coding system. The **Comprehensive Data Set** consists of detailed information on patients hospitalized with major trauma in participating hospitals in the province. Trauma is defined as an admission with an ISS greater than or equal to 12. A total of eleven lead trauma hospitals contribute to this data set and are provided funding and resource personnel by the Ministry of Health to accomplish this. Data collected includes age, sex, mechanism of injury, detailed descriptions of the patterns of injury including the ISS and component variables of the RTS, operative interventions, and outcome information including survival and time to hospital discharge. All data is collected by trained data analysts employed at the individual trauma centres

who followed each trauma admission until discharge or death. The data is recorded on Tri-Analytics software (™Tri-Analytics, Bel Air Md) that was then forwarded to the OTR on a monthly basis. This software employs a series of logic checks to ensure accuracy of data. Missing or inaccurate data are then reported back to the contributing centre for correction. All data analysts undergo a period of training in chart abstraction, data collection and entry as well as periodic site visits by staff from the OTR to perform double entry on randomly selected records. The third component of the OTR is the **Coroner's Data Set** which contains information on all deaths due to injury in the province recorded in the office of the Chief Coroner. A listing of variables available within the different data sets of the OTR is provided in Appendix 2.

The dataset used for this study consisted of a prospective cohort of trauma victims with ISS greater than 12 which was identified from the Comprehensive Data Set of the OTR over a 4-year period from 1991 to 1994. Patient and institutional identifiers were scrambled to ensure confidentiality by the registry staff . Data included unique patient identifier, age, sex, mechanism of injury, anatomic injury based on ICD 9-CM classification system, ISS based on the AIS-90 version, RTS and component variables of respiratory rate, systolic blood pressure, Glasgow coma scale and its component variables, comorbid illnesses based on ICD 9 -CM classification, survival status at discharge and time to hospital discharge. Additional logic checks were implemented on all TRISS variables prior to analysis to insure accuracy of the data and any inaccuracies were reported back to the OTR. Data for this analysis was maintained at the Clinical Epidemiology Unit at the Loeb Institute of The Ottawa Civic Hospital and was password protected.

Descriptive Analysis

Descriptive analyses were performed on the entire cohort which was subdivided into the following groups based on mechanism of injury: 1) blunt; 2) penetrating; 3) burns ; and, 4) mechanism unknown or not specified. The blunt trauma group was then further subdivided into all blunt trauma victims and those who had all variables necessary to perform a TRISS analysis (TRISS+). Variables analysed were age, sex, in-hospital mortality, type of anatomic injury using ICD 9-CM codes, comorbid illnesses using ICD 9-CM codes, ISS and RTS. A similar descriptive analysis was performed on the TRISS+ group randomly divided into a Development and Validation dataset for subsequent logistic regression analysis. Additional variables analysed in these groups were the total GCS as well as its component verbal, motor and eye scores, the respiratory rate and systolic blood pressure. Unless otherwise specified, all values are reported as either percentages , means ± standard deviations or medians with interquartile ranges (IQR).

Univariate Analysis of Non-TRISS Variables and Mortality

In order to determine a relationship between non-TRISS variables and mortality, univariate analysis were performed with the independent variables being comorbid illnesses and anatomic injury type and the dependent variable being mortality. Analysis was performed by Chi-square with absolute p-values reported unless otherwise stated. This analysis was performed on the Development data set of the TRISS+ group.

Multivariate analysis

Multivariate analysis using logistic regression were only performed on blunt trauma cases containing all three TRISS variables .This necessitated the exclusion of intubated patients due to the inability of verifying the accuracy of a recorded respiratory rate or the verbal component of the Glasgow Coma Scale if present. A split sample validation design was employed by randomly dividing the TRISS+ group into two approximately equal sized groups consisting of a Development data set in which model coefficients were generated and a Validation data set in which they were tested.

Step 1. Development of OTR specific Revised Trauma Score(RTSr):

The component variables of the RTS (systolic blood pressure, respiratory rate, and GCS) were entered into a logistic regression analysis modelling survival to develop new RTS coefficients. Scaling of all variables was identical to that of Champion et al [6].

Step 2. Revision of TRISS Model Coefficients:

The component TRISS variables of age (dichotomized above and below 55 years), ISS and the MTOS derived standard Revised Trauma Score (RTSs) were then forced into a logistic regression analysis modelling survival to develop an OTR-specific TRISS model with revised beta-coefficients (OTRs). Variables were scaled as in the original model of Champion et al [6]. The Ontario-specific RTS derived in Step 1 (RTSr) was then entered into the OTR-specific TRISS model in place of the standard RTS to derive a third logistic model (OTRr) in which all component variables had revised coefficients based on the OTR data (see Fig. 1).

Step 3. Model Validation:

The performance of the Ontario specific RTS model was compared to the MTOS derived RTS. Similarly, the MTOS-TRISS model was then compared to the two TRISS models developed from the OTR. The outcome for all models was in hospital survival. The ability of these models to predict survival was compared using the Hosmer-Lemeshow Goodness of Fit Test as well as by calculating their sensitivity (true positive fraction), specificity (true negative fraction) and accuracy (the proportion of correct predictions). ***Estimates of sensitivity, specificity and accuracy were calculated using a probability of survival of 50% unless otherwise stated.*** Receiver operating characteristic (ROC) curves demonstrating model performance at various levels of survival probabilities were also generated for each model by using 10% increments in predicted survival. Odds ratios predicting death were computed for each of the component RTS and TRISS variables from the beta coefficients. Odds ratios for death as opposed to survival were calculated because it was felt that these would be more clinically meaningful . No adjustments were made for multiple comparisons. Absolute p values and 95% confidence intervals are reported. All data are presented as means ± standard deviations unless otherwise stated.

Step 4. Generation of an Expanded TRISS Model

All component TRISS variables of age, ISS, Respiratory rate, Systolic Blood Pressure, and the components of the Glasgow Coma Scale: eye, verbal and motor component were entered into a forward stepwise logistic regression analysis with F-to-enter set at $p= 0.15$ The performance of this model in predicting survival was determined in a method similar to that previously outlined.

All analyses including model development and validation were performed using SAS software (™) on a Unix computer and ROC curve analysis was accomplishes using ROC Analyzer (™ ROC Analyzer version 6.0, Richmond VA) which estimates the ROC area using a non-parametric calculation based on the method described by Hanley et al [56].

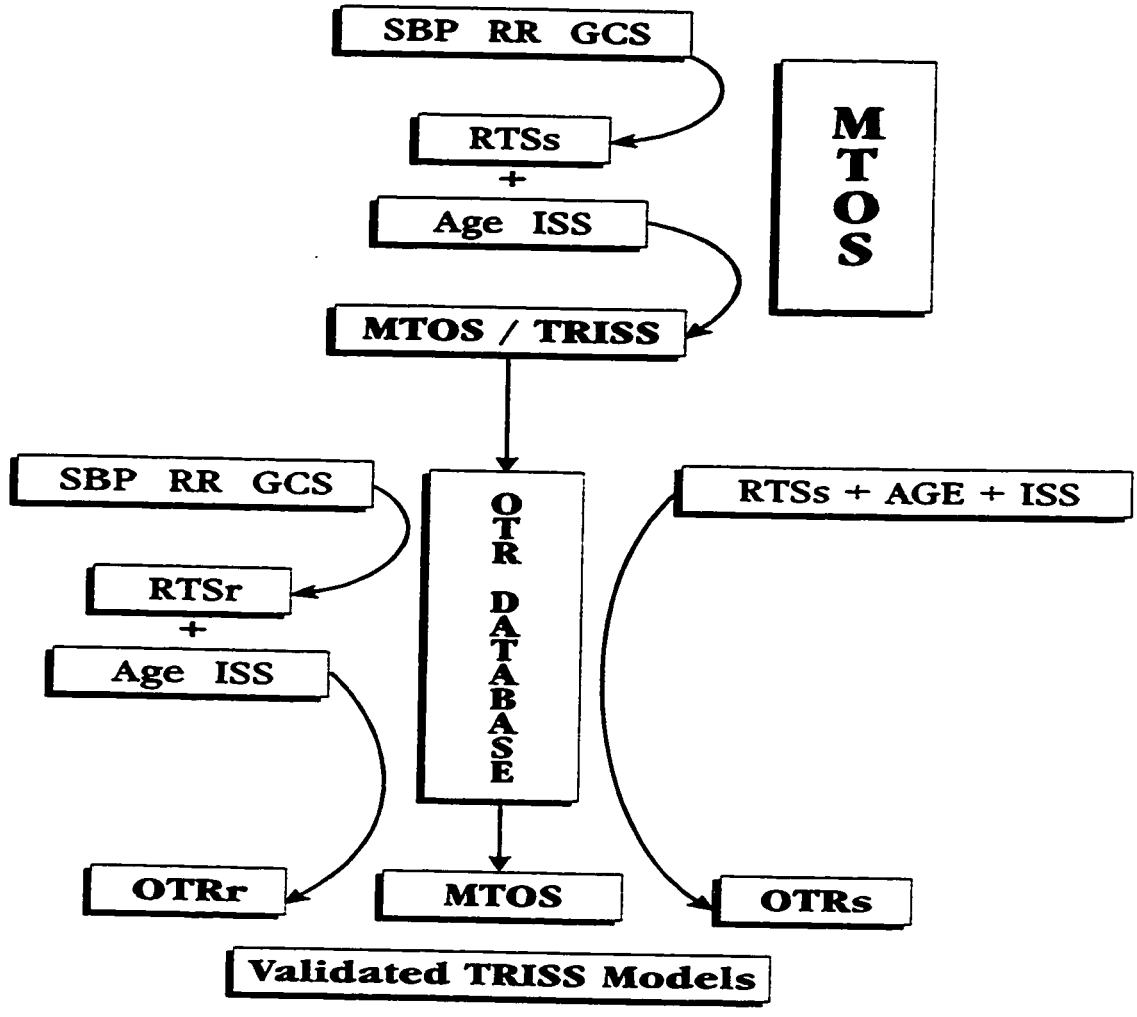


Figure 1: Development and validation of TRISS models. ***Top:*** Development of MTOS TRISS. Systolic blood pressure (SBP), respiratory rate (RR) and Glasgow Coma Scale (GCS) were entered into a logistic regression analysis of survival on the MTOS data to derive the Revised Trauma Score (RTSs). The RTSs was then entered into a similar logistic regression analysis with Age and ISS to develop TRISS. ***Bottom:*** Development of Ontario TRISS models. *Left:* Revised Trauma Score with new coefficients (RTSs) is developed on the Ontario Trauma Registry Data (OTR)data and entered into a logistic regression analysis with Age and ISS to develop a TRISS model (OTRr) with all coefficients derived from the OTR data. *Bottom Right:* All three TRISS variables including the standard Revised Trauma Score (RTSs) undergoe revision of coefficients on the OTR data to develop OTRs. All these TRISS models undergoe validation on the OTR dataset.

RESULTS

Descriptive Analysis:

The data set obtained from the Ontario Trauma Registry contained information from 9186 patients over a 4 year period of which 8442 (92%) were secondary to blunt injuries, 516 (6%) resulted from penetrating injuries, 120 (1%) from burns and 108 (1%) did not have a mechanism of injury specified. (see Table 2). Only 64% of blunt trauma cases (n=5436) contained all the component variables necessary for TRISS analysis and served as the cohort for model validation. The most common missing variable was the respiratory rate (n=1650) followed by the GCS (n=1241) and systolic blood pressure (n=115). An endotracheal tube was recorded to be present in 27.6% of patients (n=2306) in whom the respiratory rate and verbal component of the GCS were either unobtainable or the recorded value potentially inaccurate.

Those patients included in the TRISS analysis had a significantly lower mortality compared to all blunt trauma patients (7.0%: 95% CI 6.2 - 7.7 vs 15.5%: 95% CI 14.2 - 16.2) despite a similar mean age in years (39.8 ± 21.6 vs 38.8 ± 21.8), median ISS (20, IQR = 10 vs 22, IQR = 10), median RTS (7.9, IQR = 0.3 vs 7.9 IQR= 0.7) and male predominant sex distribution (70.9%: 95% CI 69.7 - 72.1 vs 70.0%: 95% CI 69.1- 70.9). The distribution of injuries by anatomic site was also similar in both groups (see Table 3) with musculoskeletal injuries being the commonest (81.7 vs 82.9%) followed by intracranial CNS injuries (51.1 vs 54.4%), internal thoracic injuries (28.3 vs 30.9%) and internal abdominal injuries (20.8 vs 22.5%) .

The TRISS+ group was randomly divided into a Development data set in which model coefficients were generated (n=2704) and a Validation data set (n=2732) in which model performance was evaluated (see Table 4). The mean age was 37.9 ± 21.8 yrs versus 39.3± 21.6 for the Development and Validation data sets respectively, with predominant male sex, varying from 70.7% (95% CI: 69.0 - 72.1) for the Development data set versus 70.2% (95% CI: 68.5 - 71.9) for the Validation data set and a survival of 6.7 (95% CI: 5.8 - 7.6) vs 7.4 (95% CI: 6.4 - 8.3). The median ISS was 20 (IQR = 10) for both groups, and the median RTS was 7.9 (IQR = 0.3) for both groups as well. The mean systolic blood pressure (SBP in mmHg) was 127.3 ± 33.6 vs 128.7 ± 30.9, and mean respiratory rate (RR in breaths per minute) was 21.1 ± 7.3 vs 21.2 ± 6.7. The distributions of the GCS and its component variables were skewed to the higher end of the scale with a median GCS of 15 (IQR = 3 and 1 for the Development and Validation data sets respectively), Motor Response =6 (IQR range 0 and 1 for Development and Validation data sets respectively), Eye Response = 4 (IQR range 0 for both data sets) and Verbal Response = 5 (IQR= 1 for both data sets).

The distribution of anatomic injuries were also similar between the Development and Validation data sets (see Table 5) with the most frequent injuries being musculoskeletal (82.5 vs 83.3%), followed by intracranial - CNS (49.7 vs 52.6%), internal thoracic (27.8 vs 28.8%), internal abdominal (20.7 vs 20.9%), vascular (3.7 vs 4.2%), spinal cord (1.0% for both sets) and other injuries (2.2 vs 2.3%).

Table 2: Descriptive analysis of demographics and TRISS variables in the Ontario Trauma Registry in the different injury subgroups. TRISS+ group contains all component variables necessary to calculate TRISS.

	Entire Cohort	Blunt (ALL)	Blunt (TRISS+)	Penetrating	Burns	Unknown
N	9186	8442	5436	516	120	108
AGE years (mean ± SD)	38.5 (21.4)	38.8 (21.8)	39.8 (21.6)	32.1 (14.2)	35.9 (19.4)	45.7 (30.5)
Sex (% Male)	71.3 (70.3, 72.2)	70.0 (69.1, 70.9)	70.9 (69.7, 72.1)	88.6 (85.9, 95.6)	78.3 (70.9, 85.7)	77.8 (70.0, 85.6)
RTS (median : IQR)	7.9 (0.7)	7.9 (0.7)	7.9 (0.3)	7.9 (0.7)	7.9 (0.3)	7.9 (1.9)
ISS (median : IQR)	22 (10)	22 (10)	20 (10)	20 (9)	25 (9)	25 (13)
Mortality (%)	16.2 (15.4, 16.9)	15.5 (14.2, 16.2)	7.0 (6.2, 7.7)	26.4 (22.6, 30.1)	23.3 (15.7, 30.8)	14.8 (8.1, 21.5)

Table 3: Distribution of Injuries by Anatomic site based on the ICD-9-CM Classification in the entire cohort as well as the blunt trauma group divided by the presence or absence of the component TRISS Variables (TRISS +ve). Values represent the percentage of patients in each group.

Injury Type	Entire Cohort	Blunt (All)	Blunt (TRISS +)
	N=9186	N=8442	N=5436
Musculo-Skeletal Fractures: (%)	78.4	81.7	82.9
CNS-Intracranial: (%)	51.3	54.4	51.1
Thoracic: (%)	31.5	30.9	28.3
Abdominal: (%)	23.0	22.5	20.8
Vascular: (%)	5.6	4.5	3.9
Spinal Cord: (%)	2.5	1.4	1.0
Other: (%)	1.8	1.9	2.2

Table 4 : Description of characteristics in TRISS+ group of blunt trauma cases in the Ontario Trauma Registry as well as the Development and Validation data sets used for TRISS model building. MR= Motor Response of Glasgow Coma Scale, VR=Verbal response of Glasgow Coma Scale and ER=Eye response of Glasgow Coma Scale.

Variable	Blunt (TRISS+) N= 5436	Development N=2704	Validation N=2732
Age years (mean ± SD)	39.8 (21.6)	37.9 (21.8)	39.3 (21.6)
Sex :%M (95% CI)	70.9 (70.5, 71.2)	70.7 (69.0, 72.1)	70.2 (68.5, 71.9)
ISS (median : IQR)	20 (10)	20 (10)	20 (10)
RTS (median : IQR)	7.9 (0.3)	7.9 (0.3)	7.9 (0.3)
SBP mmHg (mean ± SD)	128.6 (31.5)	127.3 (33.6)	128.7 (30.9)
RR breaths/min (mean ± SD)	20.3 (8.3)	21.1 (7.3)	21.2 (6.7)
GCS (median : IQR)	15 (1)	15 (3)	15 (1)
MR (median: IQR)	6 (0)	6 (0)	6 (1)
VR (median: IQR)	5 (1)	5 (1)	5 (1)
ER (median: IQR)	4 (0)	4 (0)	4 (0)
Mortality :% (95% CI)	7.0 (6.3, 7.6)	6.7 (5.8, 7.6)	7.4 (6.4, 8.3)

Table 5: Distribution of Injuries by Anatomic site based on the ICD-9-CM Classification in the TRISS+ Blunt Trauma Group subdivided into a Development and Validation data sets. Values represent the percentage of patients in each group.

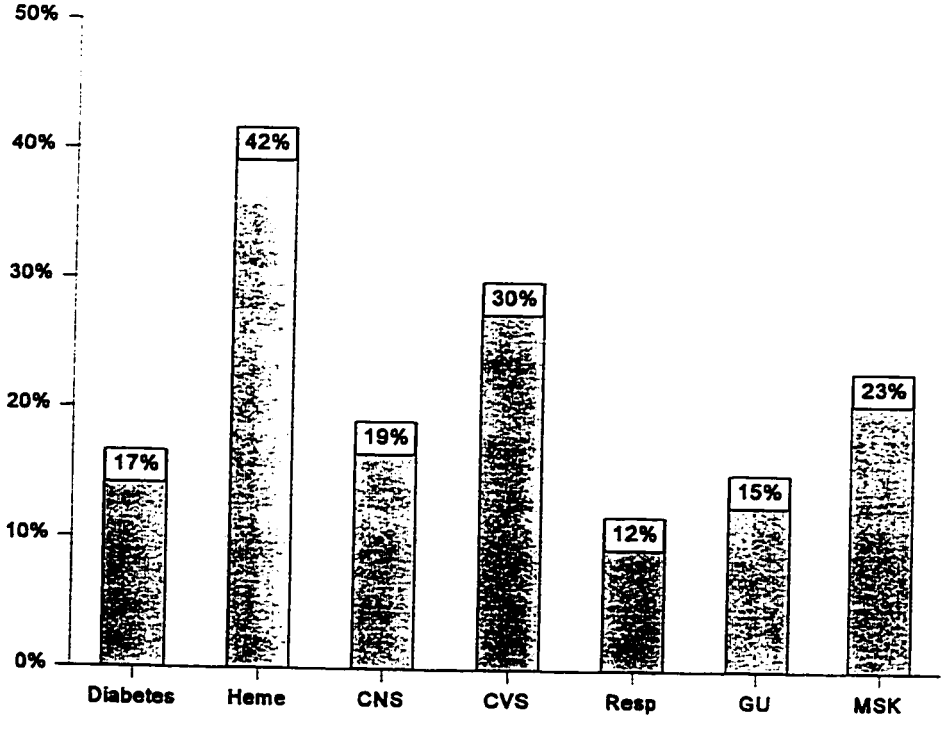
Injury	Blunt (TRISS +) N=5436	Development N=2704	Validation N=2732
Musculo-Skeletal Fractures: (%)	81.7	82.5	83.3
CNS-Intracranial: (%)	54.4	52.6	49.7
Thoracic: (%)	30.9	28.8	27.8
Abdominal: (%)	22.5	20.7	20.9
Vascular: (%)	4.5	3.7	4.2
Spinal Cord: (%)	1.4	1.0	1.0
Other: (%)	1.9	2.3	2.2

Univariate Analysis of Non-TRISS Variables

Effect of Comorbid Ilnesses on Mortality:

A comorbid illness diagnosis was entered in only 4.3% (395/9186) of the entire cohort of trauma patients obtained from the OTR. The most common comorbid illness was attributable to cardiovascular diseases (n= 117), followed by diseases of the respiratory system (n=93), central nervous system (n=84), genitourinary (n=33), Diabetes Mellitus (n=30), musculoskeletal (n=26), and hematologic(n=12) . A significant relationship existed between the type of comorbid illness present and subsequent mortality (chi-square=14.68, p=0.023) as illustrated in figure 2. Mortality was highest in those with hematologic (42%), cardiovascular (30%) and musculoskeletal (23%) diseases.

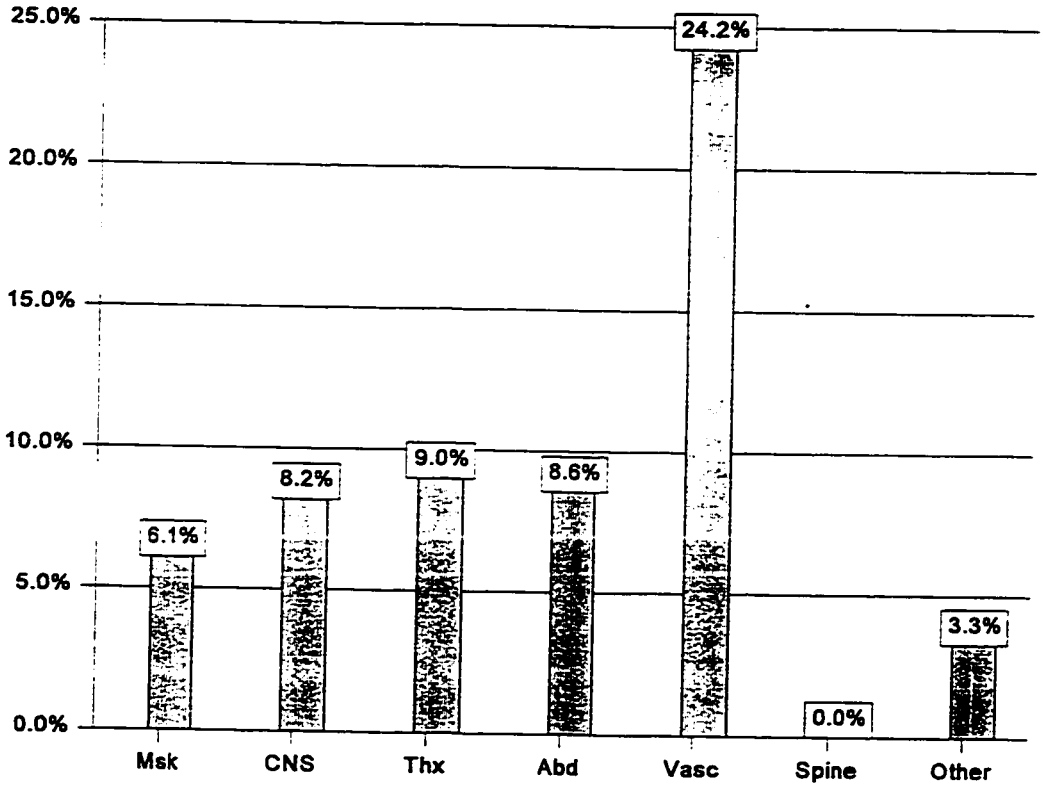
Figure 2 : Mortality (%) in Each Comorbid Category in Development Set



Effect of Anatomic Injury Type on Mortality:

The location of the anatomic injury was demonstrated to have a significant effect on survival (Chi-square = 53.4, p=0.001). Injuries to the vascular system were the most lethal (mortality 24.2%) followed by thoracic (9.0%), abdominal (8.6%), and CNS (8.2%).

Figure 3: Mortality (%) by Anatomic Injury Location in Development Set



Revised Trauma Score

Description of Models derived from MTOS and OTR:

The coefficients for the probability of survival and odds ratio of death (± 95% confidence intervals) for each component variable of the Revised Trauma Score are described in Table 6. Evaluation of the odds ratios reveals that all components of the score are significantly associated with mortality. The odds ratio of death for the OTR generated Revised Trauma Score compared to the MTOS model were 0.77 (95% CI: 0.74 - 0.81) versus 0.39 for Glasgow Coma Scale, 0.84 (95% CI: 0.71 - 0.99) versus 0.74 for Respiratory Rate, and 0.69 (95% CI: 0.56 - 0.86) versus 0.48 for Systolic Blood Pressure. The absence of previously documented or obtainable standard errors for the MTOS coefficients prevents any meaningful comparison of differences of component variables between the two models.

Table 6: Revised Trauma Score - Description of the Logistic Regression Models derived from MTOS and OTR including component variable coefficients (± SE) for probability of survival and Odds Ratios (95% confidence intervals) predicting death.

	Coefficients (± SE)		Odds Ratio (± 95% CI)	
	MTOS	OTR	MTOS	OTR
Intercept	-3.5718	-2.5369		
Glasgow Coma Scale	0.9368	0.2523 (0.0189)	0.39	0.77 (0.74, 0.81)
Systolic Blood Pressure	0.7326	0.3579 (0.1072)	0.48	0.69 (0.56, 0.86)
Respiratory Rate	0.2908	0.1773 (0.0863)	0.74	0.84 (0.71, 0.99)

Performance of MTOS and OTR derived Models

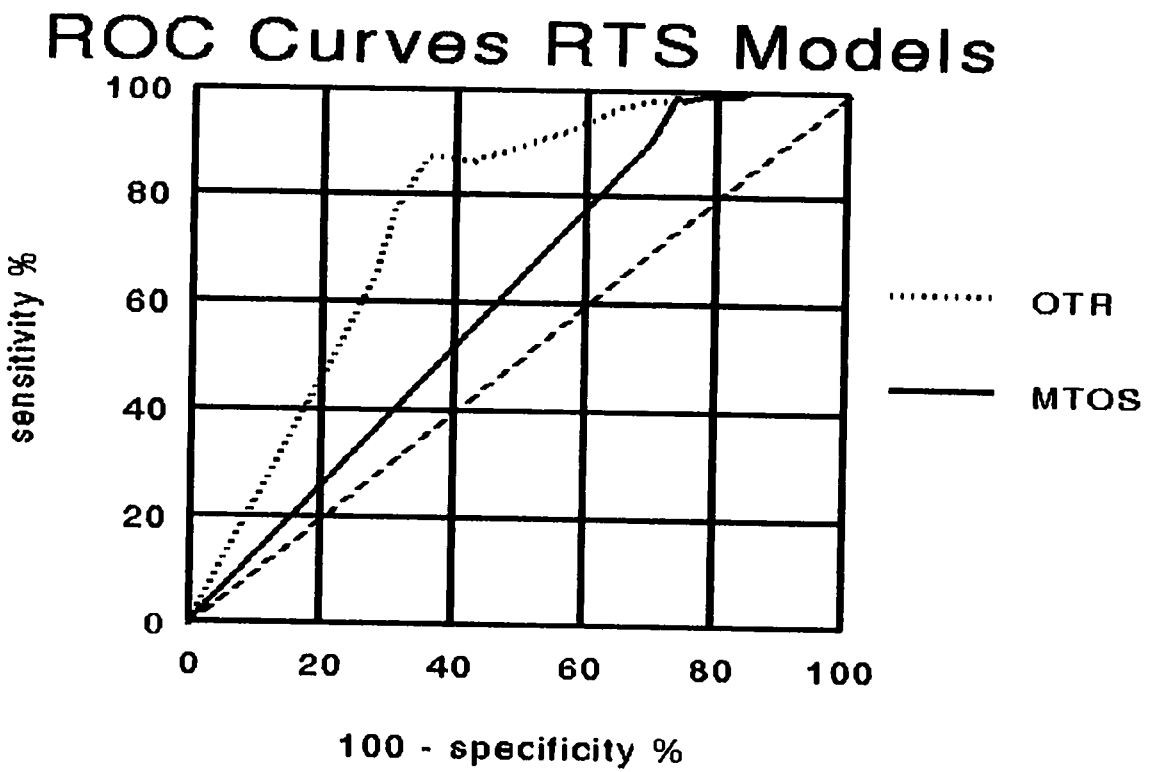
The area under the Receiver Operating Chracteristic (ROC) curves was better for the OTR derived model compared to the MTOS model (0.7154 vs 0.6014, p=0.005) . The poor discriminative ability of these models are graphically illustrated in Figure 4 where it is seen that both curves are close to 50% discriminative capability. Sensitivity was 100% (95% CI: 99.0 - 100%) for the MTOS versus 99.7% (95% CI: 98.7 - 100%) for the OTR model, Specificity was 15.9% (95% CI: 13.4 - 18.8%) for the MTOS versus 21.6% (95% CI: 18.3 - 25.5%) for the OTR model and Accuracy was 94.6% (95% CI: 93.7 -95.4%) for the MTOS versus 94.7% (95% CI: 93.9 - 95.5%) for the OTR model. Both models demonstrated poor fit to the data based on the Hosmer Lemeshow Goodness of Fit Test (see Table 7).

Table 7: Revised Trauma Score -Comparison of Performance for the MTOS and OTR Models using the Area under the Receiver Operating Chracteristic (ROC) Curve, Sensitivity , Specificity, Accuracy, and Hosmer-Lemeshow Goodness of Fit Test

	MTOS	OTR
ROC Area (SE)	0.6014 (0.0251)	0.7154§ (0.024)
Sensitivity % (95% CI)	100 (99.0, 100)	99.7 (98.7, 100)
Specificity % (95% CI)	15.9 (13.4, 18.8)	21.6 (18.3, 25.5)
Accuracy % (95% CI)	94.6 (93.7, 95.4)	94.7 (93.9, 95.5)
Hosmer-Lemeshow	> 100	34.9

§ p=0.005 Comparing OTR versus MTOS derived Revised Trauma Score

Figure 4: Receiver Operating Characteristic (ROC) Curves for The Revised Trauma Score Models



Trauma and Injury Severity Score (TRISS) Model

Description and comparison of models derived from the OTR and MTOS:

The component variables in the TRISS models derived from the OTR data were compared to the TRISS model derived from MTOS (see Table 8). The odds ratio for death with age > 55 was 9.90 (95% CI: 6.7- 14.2) for the OTRs and 9.62 (95% CI: 6.6- 14.08) for OTRr compared to 6.10 (95% CI: 6.8 - 7.7) for the MTOS/TRISS model (see Table 4). ISS is scaled continuously so the magnitude of effect appears small but remains significant with odds ratio for death 1.07 (95% CI: 1.05 - 1.08) for the OTRs and 1.06 (95% CI: 1.05,1.08) for OTRr compared to 1.09 (95% CI: 1.08 - 1.10) for the MTOS model. Finally, the RTS demonstrated a significant effect on survival with the odds of death 0.52 (95% CI: 0.46 - 0.58) for OTRs and 0.43 (95% CI: 0.36 - 0.49) for OTRr compared to 0.43 (95% CI: 0.42 - 0.46) for the MTOS model.

Table 8 : TRISS - Description of the Logistic Regression Models derived from MTOS and OTR including component variable coefficients (± SE) predicting survival and Odds Ratios (95% confidence intervals) predicting death.

	Coefficient (± SE)			Odds Ratio for Death (95% CI)		
	MTOS [1]	OTRs [2]	OTRr [3]	MTOS	OTRs	OTRr
Intercept	-0.4843 (0.3507)	0.8075 (0.4803)	0.4759 (0.4820)			
AGE>55	-1.8084 (0.2318)	-2.2879 (0.1957)	-2.2669 (0.1953)	6.10 (4.8, 7.7)	9.90 (6.7, 14.2)	9.62 (6.6, 14.08)
ISS	-0.0848 (0.0071)	-0.0662 (0.0081)	-0.0657 (0.0081)	1.09 (1.08, 1.10)	1.07 (1.05,1.08)	1.06 (1.05,1.08)
RTS	0.8234 (0.0485)	0.6492 (0.0558)	0.8609 (0.0702)	0.43 (0.42, 0.46)	0.52 (0.46,0.58)	0.43 (0.36, 0.49)

1. Major Trauma Outcome Study (MTOS) TRISS model.
2. Ontario Trauma Registry (OTR) specific TRISS model using the standard Revised Trauma Score (OTRs).
3. Ontario Trauma Registry (OTR) specific TRISS model using the revised RTS (OTRr).

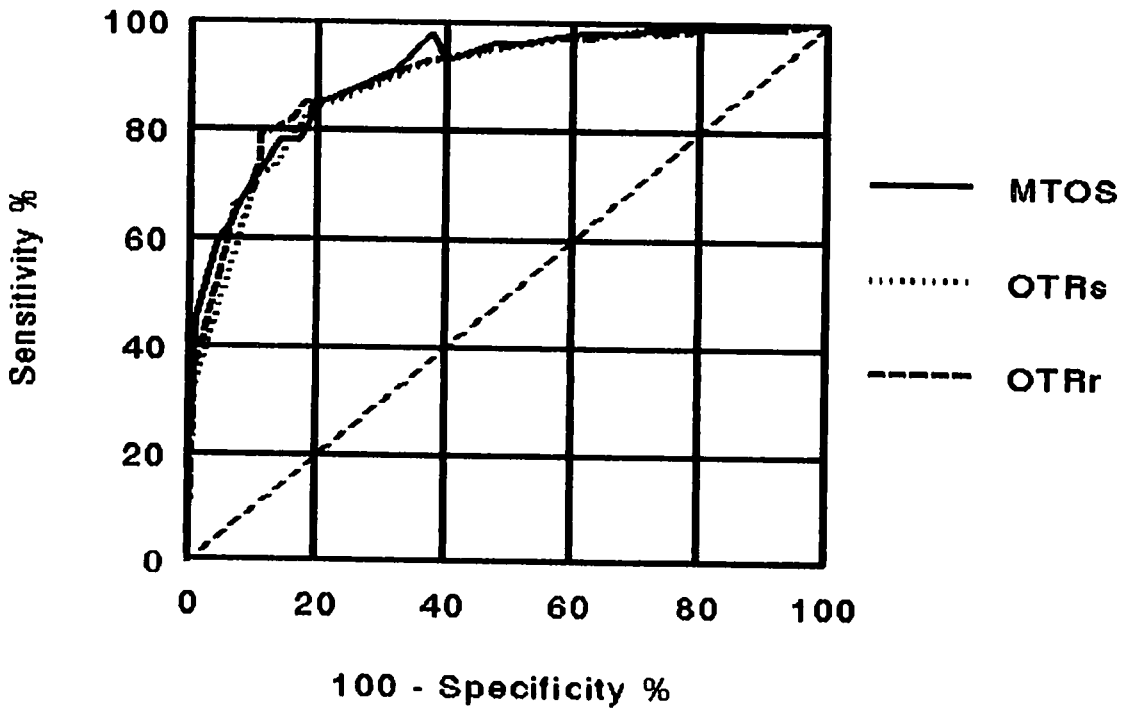
Performance of MTOS and OTR derived Models

The MTOS/TRISS model showed a poor fit to the data based on the Hosmer-Lemeshow Goodness of Fit test (HL=25.62) while both the Ontario Trauma Registry Specific Models showed a similarly good fit (OTRs model: HL=11.42; OTRr model: HL= 13.81: see Table 9) . Despite the poor fit of the MTOS/TRISS model on the Ontario database based on the Hosmer-Lemeshow Statistic, all three models showed virtually identical discriminative ability with areas under the ROC Curves of 0.91 ± 0.01 for the MTOS model , 0.89 ± 0.01 for the OTRs and 0.90 ± 0.01 for the OTRr model. The ROC curves are graphically indistinguishable from each other (see Figure 5). Similarly the sensitivities were 98.4% (95% CI: 97.5 - 99.4%) for the MTOS model, 99.1% (95% CI: 98.1 - 100%) for OTRs and 99.2% (95% CI: 98.0 - 100%) for the OTRr. Accuracy was 94.3% for all three models. The specificity of the MTOS model was 35.2% (95% CI: 30.0 - 41.4%) and this differed from the specificity of the OTRs model of 24.4% (95% CI: 20.6 - 28.9%) but did not differ from that of the OTRr model which was 26.7% (95% CI: 22.6 - 31.6%).

Table 9: TRISS - Comparison of Performance for the MTOS and OTR Models using the Area under the Receiver Operating Chracteristic (ROC) Curve, Sensitivity , Specificity, Accuracy, and Hosmer-Lemeshow Goodness of Fit Test.

	MTOS	OTRs	OTRr
ROC Area (SE)	0.91 (0.01)	0.89 (0.01)	0.90 (0.01)
Sensitivity % (95% CI)	98.4 (97.5, 99.4)	99.1 (98.1, 100)	99.2 (98.0, 100)
Specificity % (95% CI)	35.2 (30.0, 41.4)	24.4 (20.6, 28.9)	26.7 (22.6, 31.6)
Accuracy % (95% CI)	94.3 (93.5, 95.2)	94.3 (93.4, 95.1)	94.3 (93.5, 95.2)
Hosmer-Lemeshow	25.62	11.42	13.81

Figure 5: Receiver Operating Characteristic(ROC) Curves of the Three TRISS Models



An Expanded TRISS Model :

Forward stepwise logistic regression analysis entering all component variables of TRISS and the RTS produced a model consisting of age (greater or less than 55 years), ISS, SBP, RR, Motor Response (MR) and Verbal Response (VR) of the Glasgow Coma Scale (see Table 10). The odds ratio for death with Age > 55 was 9.62 (95% CI: 6.5 - 14.2), ISS = 1.07 (1.05 - 1.08), SBP = 0.76 (95% CI: 0.60 - 0.96), RR = 0.82 (95% CI: 0.68 - 0.99), MR= 0.72 (95% CI: 0.62 - 0.85), VR= 0.73 (95% CI: 0.73 - 0.85).

The performance characteristics of this model are similar to those described for TRISS with a sensitivity of 98.9% (95% CI: 97.8 - 100), specificity of 31.4% (95% CI: 26.9 - 36.5), accuracy of 93.8% (95% CI: 92.8 - 94.7), ROC Area = 0.82 (SE=0.02), and Hosmer Lemeshow Goodness of Fit Statistic = 9.72.

Table 10: Expanded TRISS Model derived by Stepwise Logistic Regression on OTR Development Set. Includes model variables with coefficients (± SE) and odds ratios for death (95% CI). MR= Motor response and VR= Verbal response of the Glasgow Coma Scale.

	Intercept	AGE > 55	ISS	SBP	RR	BMR	BVR
Coefficient (± SE)	0.7090 (0.5224)	-2.2661 (0.2010)	-0.0654 (0.008)	0.2729 (0.1194)	1.218 (1.004)	1.376 (1.171)	0.3140 (0.077)
Odds Ratio (95% CI)		9.62 (6.5, 14.2)	1.07 (1.05, 1.08)	0.76 (0.60, 0.85)	0.82 (0.68, 0.99)	0.72 (0.62, 0.85)	0.73 (0.63, 0.85)

DISCUSSION:

The Use of Trauma Severity Scores:

The development of trauma and injury severity scores subserve several important needs. First is the necessity to describe severity of injury in a standardized quantifiable manner. This provides a common language by which individual trauma cases can be classified, enables clinicians to identify high risk cases and allows populations of trauma patients to be described for the purposes of clinical trials. More complex models, such as those derived by logistic regression analysis, can be used to test hypotheses regarding the relationship of certain independent variables to the dependent variable of interest. Thus, the strength of association between certain risk factors and mortality can be tested while controlling for confounding by other variables. Finally, such scores can also model and predict outcome. TRISS was developed as a comprehensive description of injury by incorporating age, an anatomic index of injury severity (ISS) and a physiologic index (RTS). The other exceedingly important purpose of this model is to predict survival in trauma patients in order to facilitate quality assurance in trauma centres.

Criteria for Optimal Model Performance:

Criteria to evaluate the clinical usefulness and accuracy of probability models could not be found in the published literature. Instead, the following criteria will be applied to determine whether TRISS represents a useful and acceptable model of trauma.

1. **Face Validity of Component Variables** - Simply stated, it must be apparent to all who utilize the model that the components variables employed make sense, are known to characterize illness severity and are related to outcome in some meaningful way.

2. **External Validity** - A model which is externally valid must be generalizable to the target population in which the predictive model will be applied. This requires that the model is developed on a cohort that is representative of the desired target population. Accordingly, strict criteria need to be explicitly and reproducibly defined as to who is included and excluded in the course of model development and these eligibility criteria should be consistent with the ultimate goals of the model. Investigators who subsequently validate the model on a separate and independent group of people need to confirm comparability between their study sample and the one in which the model was derived. The only available means of accomplishing this is by determining if the characteristics between study groups appear similar.

3. **Parsimony**- The model should be constructed to be as simple as possible thereby constituting a parsimonious model. There are several components that characterize simplicity in a statistical model. Clearly, the more variables entered into a statistical model to explain a particular outcome, the more accurate that model will be. One potentially deleterious

consequence of this the development of multicollinearity within the model [57]. Multicollinearity refers to inclusion of variables which are correlated with one another. The result is that the coefficients and standard errors for these variables become extremely large and the resulting odds ratios are inaccurate. Consequently, the ideal model should include as few variables as possible that adequately describe the outcome of interest.

4. **Accuracy**- Evaluation of model accuracy has been subdivided into assessment of calibration and discrimination. Each of these parameters has several strengths and limitations.

Calibration, in a general sense, is described as how well the model fits the data set. The most commonly used test for this is the Hosmer-Lemeshow Goodness of Fit Statistic (H-L statistic) [58]. The H-L statistic measures the extent to which the frequency of observed survivors and non-survivors agree with the model's predicted frequencies over the entire range of survival probabilities thereby providing an index of reliability in making accurate predictions in patient sets. It has been argued that if poor calibration to a dataset is indicated by the H-L statistic [59], then further assessments of discriminative ability are meaningless. The H-L statistic divides the study population into ten groups of increasing probability of survival and sums the differences of observed and predicted deaths by calculating a chi-square statistic. A value greater than 15.5 corresponds to a p-value less than 0.05 and indicates a significant deviation between expected and observed; hence, a poor fit. One of the principal limitations of this statistical test is that it is

highly dependent on sample size. If the sample is large enough the H-L statistic may show poor fit of the model even if the discrepancies are minimal and clinically irrelevant. Conversely, if the sample size is small, the model may show good fit despite major difficulties.

Model discrimination is further assessed by calculations of accuracy, misclassification rates, as well as sensitivity, specificity and receiver operating characteristic (ROC) curve analysis [56,60-62]. Accuracy and misclassification rates are misleading in the sense that they depend on the prevalence of the outcome in the study population [62]. Accuracy estimates, derived by the sum of all the correct classifications over the total number of cases, assumes that the summation of the correct predictions of a rare event such as death with the correct predictions of a frequent event such as survival results in a single figure that estimates an instrument's performance. This assumption is problematic because identification of survivors will often be exceedingly accurate due to the high prevalence of that outcome. Simply stated, given that mortality in the OTR cohort is 7%, TRISS would have an accuracy of 93% by simply identifying all cases as survivors. The effect of prevalence is reduced in estimates of sensitivity and specificity because these parameters evaluate an instrument's performance in two separate populations [62]. Sensitivity is the true positive fraction in the population with a positive outcome, while specificity is the true negative fraction in the population with a negative outcome. However, this is accomplished by forsaking our ability to summarize how a model performs in the population of survivors and nonsurvivors together. Moreover, it is by convention that the decision rule employed (and commonly reported in the literature) uses a cut point for survival probability of 50%. Those

cases with estimated survival probability of > 50% are classified as survivors and those with estimated probability of survival < 50% are classified as nonsurvivors. Clearly, this can result in the loss of information. ROC curve area analysis has the advantage that the estimates are comprised of the model's true positive fraction (sensitivity) and true negative fraction (specificity) and consequently are less dependent on disease prevalence than accuracy and misclassification rates while still providing an overall summary of how the model performs in the entire population [56,62]. Moreover, there is information gain, as opposed to loss, because the model performance is tested at varying decision threshold cut points ranging from survival probability of 0 to 1.

The perfect predictive model would have a H-L statistic < 15.5, sensitivity and specificity of 100%, and an ROC area of 1.0. The preceding argument would support the contention that ROC area is the optimal method of assessing and comparing the discriminative capability of the model. However, it can be argued that specificity in a model derived to predict mortality so that the "appropriateness" of that death can be scrutinized is equally as important. For the purposes of TRISS modelling which predicts probability of survival, poor specificity means that the true negative fraction (the number of correctly identified deaths) is low while the false negative fraction (the number of deaths not identified by the model) is high. Given that the primary purpose of the quality assessment process in trauma is to determine whether traumatic death was preventable, then having a larger number of observed deaths to those predicted by the model raises serious concerns about the quality of care.

Comparison of MTOS and OTR Databases

A statistical model can be derived which will predict an event in a given data set with great accuracy. The true usefulness of the model is apparent only when it can be applied to other databases without unacceptable deterioration in performance. The MTOS database was created to be large enough and contain a sufficient number of specialized trauma care facilities in order to be representative of the standard of trauma care in North America. TRISS was subsequently developed to predict and compare outcomes in trauma databases to the MTOS. In order for this thesis analysis to validate the TRISS model on a Canadian trauma data set it would be necessary to compare the demographic and injury characteristics of the MTOS and the OTR groups in some descriptive manner.

It has been speculated that trauma is different in Canada compared to the United states [17]. One author has estimated that the risk to Canadian drivers is 50% greater per mile driven [2]. The reported incidence of violent crimes and penetrating injuries is less [2]. Canada has a small population distributed over a wider geographic area prolonging transportation times to specialized trauma centres [2,17]. The organization of regionalised trauma centres in Canada has only developed since the late 1980's while these systems have been in effect within the United States for the past two decades [43]. The establishment in Canadian cities of trained and certified paramedic ambulance crews who could provide on site treatment and stabilization of trauma victims is well behind what exists in most major urban centres within the United States. These

differences would lead one to expect that a TRISS model with MTOS norms would perform quite differently on a population of Canadian trauma victims.

Contrary to such expectations, the OTR trauma cohort demonstrated many similarities to MTOS. In both cases the majority of victims were young and of the male sex. There was a greater proportion of blunt trauma in the OTR compared to MTOS (92% vs 75% respectively). The mean RTS in MTOS was 7.1 and the average ISS was 12.8 (standard deviations are not provided) [5] in the blunt trauma group compared to a mean RTS of 7.2 (SD=1.5) and average ISS of 25.1 (SD=11.3) in the OTR data set. Despite the fact that the anatomic injury severity based on the ISS is somewhat higher in the Canadian trauma data set the overall mortality in both cohorts remains comparable (16.8% vs 15.5%; MTOS vs OTR respectively).

The vast majority (81.7%) of blunt trauma victims within the OTR were found to have fractures of the musculoskeletal system and over half (54.4%) suffered from some degree of head injury which is consistent with a blunt mechanism of origin. Injuries to the vascular system were the most lethal (mortality 24.2%) compared to other body regions where the mortality ranged from 3.3 - 9.0%. It should be noted that this assessment of the distribution of anatomic injuries is based on ICD9-CM classification system which unlike AIS does not provide severity coding for anatomic injuries. Although AIS coding was available in the data set, a detailed description of AIS coding and severity was not the main focus of analysis. Rather, the intention was to

characterize the distribution of anatomic injuries in the OTR patients at all levels of injury severity in a particular body region. MTOS makes no attempt to provide such a simple characterization of anatomic injury in their cohort [5]. Indeed, none of the studies evaluating TRISS or the ISS provide a similar descriptive analysis. Rather, they focus on the predictive usefulness of AIS injuries of different grades. Such an analysis will be the focus of future research where ISS and component AIS grades will be compared to other anatomic scoring systems in the OTR.

While these comparisons suggest that the two data sets are similar with respect to the characteristics of the blunt trauma victims, one must be cautious about accepting this conclusion unequivocally. Substantial differences are still likely to exist between Canadian and US trauma centres based on the quality and organization of both prehospital and inhospital care. However, the similarity in demographics, injury severity and overall mortality would lead one to anticipate similar predictive abilities of TRISS in MTOS and OTR.

Comorbidities

The hypothesis that comorbid illnesses may have a significant impact on mortality following trauma comes from the APACHE Score which is a statistical model of mortality in critically ill patients [31]. Studies of comorbid illnesses focusing on chronic health conditions

which were present prior to the accident, are hampered by differing definitions between studies, varying study designs and problems with reporting biases [32-35]. Analysis on the OTR revealed that while a comorbid illness diagnosis was uncommon (present in only 4.3% of the entire OTR), it did exhibit a significant association with mortality. Mortality was greatest in those with hematologic disease, cardiovascular and musculoskeletal illnesses. Inclusion of this variable in the TRISS model was not performed in this analysis for two reasons. First, there were serious concerns with regards to the uniformity of reporting of comorbid illnesses by the contributing centres. An informal poll conducted by the author revealed that in most centres a comorbid illness diagnosis was entered *only* if the reviewer believed that this factor had a significant influence on morbidity or mortality. This selection bias would serve to inflate the magnitude of any effect that comorbid illnesses would have on mortality. Secondly, the relative rarity of comorbid illnesses in this population, given that trauma primarily occurs in young people, means that the magnitude of association between these conditions and mortality would have to be substantial in order to serve as a useful addition to the TRISS model. However, it is conceivable that the selection bias already discussed has underestimated the extent to which comorbid illness are present in this population of trauma victims. This current state of affairs with the quality of comorbid data in the OTR precluded any further assessment of this issue for at the present time.

Several trauma studies have specifically examined the effect of preexisting disease, independent of age on the risk of dying following trauma. Using a case-control design, Morris et al [32] compared the prevalence of comorbid illnesses in trauma survivors compared to

nonsurvivors while controlling for the effects of age and ISS using logistic regression. The prevalence of one or more comorbid illnesses was 8.8% and the odds ratio of death was 1.3. Unfortunately, this study was performed using a large administrative dataset and serious concerns were expressed by the authors with regards to the potential for misclassification and selection bias, particularly in view of other reports about serious under reporting in medical records [63]. In a prospective study, using reproducible operational definitions a comorbid illness diagnosis was found to be present in 16% of patients with a significant almost threefold effect on mortality (9.2% vs 3.2%, $p<0.0001$) [35].

Given these encouraging preliminary results, two subsequent studies sought to determine whether the inclusion of this variable improved the predictive performance of TRISS. Hannan et al [33] demonstrated that the performance of both ASCOT and TRISS were improved by the inclusion of comorbid illnesses based on the H-L statistic and ROC curve analysis. Unfortunately, this effect was only evaluated in people who suffered low falls and the demographics of this population, being predominantly older (75% greater than 65 years of age) and female, differed significantly from the general population of trauma patients. Finally, in a study using a subpopulation of MTOS patients in whom data on comorbid illnesses were collected prospectively using operational definitions, Sacco et al [34] demonstrated that the mortality of those who had comorbid illnesses differed significantly from that predicted for them based on ASCOT analysis. However, because these comorbid illnesses occurred in only 6.8% of their cohort, they doubted that inclusion of this variable would substantially alter the predictive

performance of either TRISS or ASCOT.

The issue of whether or not comorbid illnesses have a significant enough effect on mortality in the Ontario trauma population to be included in a statistical model remains largely unresolved. Answering this question would necessitate a committed effort on the part of the registry study and contributing hospitals to prospectively record a comorbid illness diagnosis on all trauma admissions prior to the knowledge of survival or morbidity outcomes, and based on reproducible operational definitions. Sample size calculations for a prospective cohort study based on a conservative estimate of 4.8% for the prevalence of comorbid illness, a 15% mortality rate, a minimal odds ratio worth detecting of 1.5, power of 80% and alpha error of 5% result in an estimated 3,000 patients required to complete such a study. Only at that point could the variable be added to the existing TRISS model to assess the effect on the performance of the model in predicting mortality in the OTR.

Evaluation of the Revised Trauma Score

The Revised Trauma Score was primarily developed by Champion and colleagues as a simple, statistically developed physiologic score which could triage trauma patients at the scene of injury [8]. This triage tool would allow a determination of whether the trauma victim was injured severely enough to warrant transfer to a specialized trauma facility . It also had the

additional advantage of providing a probability of survival following injury based purely on a few key variables which were deemed clinically relevant. Because this score was generated by logistic regression analysis on a subset of the MTOS database and represented an improvement over earlier scoring systems, it has been considered state of the art and has been widely adopted as the most commonly used physiologic score of injury severity.

The supremacy of the RTS is affirmed by the fact that only a single paper has been published since its development which has attempted to validate the ability of this score to independently predict survival in a population of trauma patients not derived from MTOS. Lett et al [15] used ROC curve and likelihood ratio analysis as a means of comparing RTS to other physiologic injury severity scores such as CRAMS [53] and PHI [54] using a non-MTOS database. In an effort to tease out differences between models he performed analyses on the entire data set, as well as separate subgroup analysis excluding patients with a low and high probability of survival based on the actual score values themselves. The RTS performed with an ROC area of 0.9665 (SE = 0.0052) which was similar to that of CRAM (0.9960, SE=0.0014) and PHI (0.9873, SE=0.0028). However, when the extremes of the population were excluded the performance of the RTS decreased to (0.8334, SE=0.0193). This deterioration was more pronounced than that of the other physiologic scores. It was subsequently concluded that the RTS was the weakest of all physiologic trauma severity indices despite its wide popularity.

The authors' conclusions can be challenged on several aspects. First, they did not consider training the RTS variables on their own data set in order to develop new beta-coefficients. Instead they used those published in the original report. This could have a significant bearing on the interpretation of their results as they do not provide a sufficiently detailed description of their study population in order to assess how similar it was with MTOS. It is therefore conceivable that revision of coefficients could have augmented model performance. Secondly, while the exclusion of extreme cases representing easily identified survivors and nonsurvivors produces a more challenging task for the scoring models, this likely represents little practical advantage as it is not the method in which the models will generally be applied. Finally, despite the potential benefits of ROC and likelihood ratio analysis, it would have been useful to have other parameters such as sensitivity, specificity and Hosmer-Lemeshow Goodness of Fit Statistic in order to compare model performance to the current study as well as the original report.

The evaluation of RTS in this thesis analysis is unique in so far that it is the first time that updated coefficients were derived for this model since its inception. We anticipated an improvement in the RTS performance in view of the reported improvement that revision of TRISS model coefficients produced in TRISS performance during a previous independent validation exercise [21]. Furthermore, a detailed analysis of the role the component variables played in predicting mortality within the model was possible by conversion of model coefficients to odds ratios for death. Finally, model performance was fully characterized by providing an

assessment of calibration using the H-L statistic and discrimination using ROC curve analysis as well as sensitivity and specificity at a cut point of 50% probability of survival more standardly reported in other studies.

When the component variables of the RTS were run through a logistic regression analysis on the Ontario data set there were some marked differences in their weighting compared to the standard RTS model derived from MTOS. Unfortunately, a statistical comparison of these beta coefficients between the MTOS-RTS and OTR-RTS is not possible because the standard errors are not published for the RTS derived from MTOS. In personal communication with the authors and the statistician directly involved in development of this model it was determined that these standard errors are not available. However, several conclusions can be made. All RTS variables demonstrate a significant relationship to survival in both models, but the magnitude of effect is weaker in the OTR developed model. The variables most strongly associated with survival in the OTR model is systolic blood pressure followed by Glasgow Coma Scale. Systolic blood pressure exhibited an odds ratio of death of 0.69 which means that for each interval fall in systolic blood pressure the odds of death increase by 31%. Alternatively, Glasgow Coma Scale was the strongest variable associated with survival in the MTOS model (odds ratio for death= 0.39) followed by systolic blood pressure (odds ratio for death= 0.48). Respiratory rate was the weakest variable in both models. The upper boundary of the confidence interval in the OTR model was within 1% of the null value of 1.0. This suggests that model performance might not be substantially changed by excluding respiratory rate as a component.

The RTS demonstrated a poorer performance in predicting trauma mortality than was anticipated regardless of whether model coefficients from MTOS or the OTR were employed. Both models exhibited poor fit to the data based on the H-L statistic. The accuracy of both models was exceedingly high (94.5 - 94.9%), primarily as a result of the high sensitivity (99.7 - 100%) which in turn was due to the large proportion of survivors in the cohort (93% survival). The specificity, which in this case represents the models' ability to predict death, was exceedingly poor and this was most marked in the MTOS model (MTOS=15.9%, OTR= 21.6%).

Calculation of the area under the ROC curves for the models demonstrated better performance of the OTR derived compared to the standard MTOS (0.7154 versus 0.6014, respectively), but both values are considerably lower than the one previously reported by Lett et al (0.9665) [15]. Only the H-L statistic is provided to characterize RTS performance in the original paper by Champion et al [8] and that value was 13.9 which represents a good fit. It is unclear why the performance of RTS in this analysis is far below the previous report of Lett et al [15] and further comparisons between these two studies are hampered by the fact that little data is available in that paper to describe their population. However, the fact that the mortality in their group of 3, 000 patients was 4.7% which is lower than our observed mortality of 7.0% (95%CI: 6.2, 7.7) suggests that other substantial differences in our study cohort may account for the discrepancy in the ROC performance of this trauma score.

In addition to the poor performance demonstrated by the RTS in independently predicting mortality, there are several theoretical and practical concerns which threaten the validity and generalizability of this score and any subsequent model such as TRISS into which it is incorporated.

One of the concerns regarding the validity of the RTS revolves around the fact that the physiologic response of a trauma victim to the stress of injury is dynamic and ever changing whereas a single recorded value for each of the components of the RTS represents only a momentary snapshot in time. Such difficulty does not exist for either age or the anatomic distribution of injury because these factors are more or less static during the post traumatic course of the illness.

The RTS was originally developed as a triage tool, the purpose of which was to aid paramedic teams in the decision to transfer an injury victim to a specialized trauma hospital. Accordingly, physiologic values may be recorded at the scene of the accident. However, when the score is utilized as a component of the TRISS model then its physiologic values are to be recorded on arrival at the receiving hospital. While there has occasionally been confusion as to the correct time to record these physiologic variables [6,8,64], the originators of TRISS are clear that

these values are to be recorded on arrival to hospital and this is the policy adopted by the OTR [50]. To understand the rational for this approach we must remind ourselves of the fact that when the RTS is used within the TRISS model its primary purpose changes from that of a triage tool to one of quality control. If a patient arrives without evidence of cardiovascular shock then that person would be expected to survive. If that individual subsequently dies then concerns must be raised about the adequacy of their in hospital care. Such cases would then be individually reviewed to determine whether or not that death was preventable.

It is entirely possible that using the first physiologic variables recorded on arrival may not adequately reflect the homeostatic state of the trauma victim. For instance, a person intoxicated with alcohol may demonstrate a low Glasgow Coma Scale at the time of arrival resulting in a spuriously high mortality prediction for that individual because the depressed level of consciousness is presumed to be secondary to head injury. When the sedating effect of the alcohol wears off that individual would then become a survivor not predicted by the model. This can represent a significant problem since it has been estimated that alcohol consumption may be involved in as many as 25% to 52% of motor vehicle accidents [2]. Similarly, clinicians are keenly aware of the fact that although some patients arrive with poor physiologic values, there are a substantial number who are normal on arrival but exhibit rapid deterioration over the ensuing hour. This may occur because young people who are hemorrhaging have remarkable abilities to maintain pulse and blood pressure despite being in a state of physiologic shock. It is only by observing the changes in the response of these variables over time during the initial early period

of assessment and resuscitation in the trauma emergency room that a true picture of that person's physiologic status becomes apparent. So while level of consciousness, blood pressure and respiratory rate on arrival to hospital are important parameters, there are substantial pitfalls in assuming that these adequately characterize injury severity from a physiologic point of view.

In addition to these problems with regard to the validity of the RTS, there are several issues surrounding the practicalities of obtaining accurately recorded values. This raises concerns about the introduction of measurement bias and the subsequent generalizability of the RTS model. Many trauma victims must undergo intubation of their trachea with an artificial tube prior to hospital arrival either because they required assistance to breath or because they were at risk of aspirating their own vomit down their airway. These intubated patients present considerable difficulty in determining the correct value for respiratory rate and verbal component of the Glasgow Coma Scale. There exists no consensus of how to deal with this problem [65]. One commonly employed method is to estimate what the observer believes that value to be based on the values of the other components of the GCS. Clearly, such an approach lacks objectivity and reliability. Another approach is to provide the summed values of the motor and eye component of the GCS and add a "T" indicating intubation. The precise interpretation of such a recording for the purposes of analysis remains unresolved. The approach chosen by the originators of the RTS, and subsequently TRISS, is to exclude patients intubated on arrival from any analysis [6]. However, the fact that a clinician or paramedic decided to intubate a trauma patient implies that the individual was considered to be extremely physiologically unstable. It can be anticipated that

can be anticipated that exclusion of such cases would result in a group of people who were less severely injured and less likely to die. This analysis shows that when intubated patients are excluded from RTS or TRISS analysis, the mortality of blunt trauma victims significantly drops from 15.5% to 7.0%. Consequently, the RTS, and any model which incorporates it, excludes some of the most severely injured patients from analysis because of the inability to accurately obtain two variables in all trauma victims. This fatal flaw represents a major drawback in the modelling of trauma mortality for any model which incorporates the RTS including both TRISS and ASCOT.

Evaluation of TRISS

This analysis of TRISS involved evaluation of three models. The first was the TRISS model with coefficients derived from the MTOS database. This is the model currently used by the OTR. The second model derived coefficients for each of the three TRISS variables but continued to use the MTOS coefficients for the component variables of the RTS. The final model was developed by obtaining OTR specific coefficients for the RTS and then incorporating this into a logistic regression model where all variables contained coefficients derived from the OTR data set. This final step has been omitted in the two prior papers describing revised TRISS coefficients [21,59] as each used the MTOS derived RTS. If revision of model coefficients were to improve model performance, then one would anticipate that this would be further enhanced by deriving data specific coefficients for the component variables of the RTS.

The relationship of each of the three component TRISS variables to survival was assessed by comparison of their odds ratio of death. This revealed that each of the three TRISS variables demonstrated a significant relationship to death.

The relationship between increasing age and trauma mortality is clearly significant in the OTR data set. Those patients 55 years of age and older had an odds of death which was 6.10 to 9.62 times greater than younger individuals. While the odds ratios were larger in the OTR derived models compared to the MTOS model, all confidence intervals overlapped indicating that they were not statistically different. The importance of age as a risk factor in trauma mortality is well supported. Earlier epidemiologic studies have documented an increased risk of mortality in those 65 yrs of age or older and this effect persists after stratification by injury severity using the ISS [29,30]. Furthermore, it has also been observed that elder patients with good physiologic status still had poor outcomes compared to their younger counterparts[29]. The primary reason behind this effect is likely related to an inability of the elderly to withstand major physiologic disturbances as a consequence of trauma and shock. Several studies have demonstrated a survival benefit for patients developing a hyperdynamic response and generating supranormal oxygen delivery and consumption after sepsis and major operations [66,67] and more recent work indicates a similar survival benefit of this response in trauma [68]. Elderly patients typically lack reserve in many physiologic systems . Diminished physiologic function in the elderly is identified by a decrease in cardiac index, pulmonary compliance, renal function, and the ability to handle fluid challenges and regulate fluid balance [69]. Even in the absence of

coronary artery disease, the cardiac pump function in the elderly may be reduced by as much as 50% [69]. Precedent for the importance of age in predictive models of mortality come from the critical care literature where disease severity classification systems derived by logistic regression analysis such as the APACHE versions II [70] and III [71] as well as the MPM [72] model all incorporate age as a powerful predictor of death.

The ISS also exhibited a strong association with survival in this analysis although the magnitude of effect appears less than the other two variables. This is accounted for by the fact that ISS is modelled continuously. Therefore, an odds ratio of 1.06 indicates a 6% increase in the odds of death for every unit increase in ISS, confirming the important role of this anatomic injury severity score in predicting mortality. The odds ratio ranged from 1.06 to 1.09 and did not differ between the three models.

Despite the previous observation that the RTS as a logistic regression model predicting mortality performs rather poorly based on the H-L statistic and ROC curve analysis, it is clear that this physiologic score does exhibit a strong association to mortality when included in the TRISS model based on assessment of odds ratios for death which ranged from 0.43 to 052. Given that the RTS in the TRISS model is scaled continuously as is the ISS, it would appear that this physiologic score has a far stronger association with outcome then the anatomic injury score. However, one must be cautious about accepting such a conclusion in view of the fact that the

range in values for ISS (1 - 75) is far greater than that of the RTS (0 - 12). This undoubtedly has an influence on the magnitude of the odds ratios and comparison between differently scaled variables becomes exceedingly difficult to interpret.

The ability of TRISS to predict mortality in the Ontario Trauma registry was evaluated by determining the sensitivity, specificity, accuracy, area under the ROC curve and the Hosmer-Lemeshow Goodness of Fit statistic. Although revision of model beta coefficients improved the Hosmer -Lemeshow Goodness of Fit statistic for both models developed on the Ontario data set, it did not affect the discriminant ability of any of the three TRISS models. Sensitivity (the ability to identify survivors) ranged from 94.9% to 95.6%, overall accuracy was 94.3% and ROC area ranged from 0.89 to 0.91. However, specificity of the model (ability to identify nonsurvivors) was markedly poor with values ranging from 24.4% to 35.2%. Comparison of these findings with that of previous validation reports [18-21] is hampered by the use of different performance characteristics in each of these studies. Most recently Champion et al [59] showed that revision of TRISS coefficients on an updated MTOS database resulted in a specificity of 99.1%, sensitivity of 64.3%, ROC area of 0.91 and a HL statistic of 30.7 which was not significantly better than the model with the original coefficients [6]. The mortality in this most recent study from these authors was 9.7%. A similar revision of ASCOT performed in this same study resulted in improved performance leading the authors to conclude that TRISS was inferior to ASCOT even after revision of model. In two papers from the Institute for Trauma and Emergency Care (ITEC) group [19,20] the performance of TRISS using the standard beta coefficients was characterized by a

sensitivity of 34.6% and a specificity of 99.4% with an overall mortality in their cohort of 6.8%. The most recent paper from this group reported that revision of TRISS coefficients on the ITEC database improved the HL statistic to 6.3 from 41.7 for the standard TRISS coefficients but they did not provide other performance parameters [21]. It is essential to point out that these previous studies invariably report higher specificities than sensitivities which is exactly opposite to the current findings. This observation is readily explained by the fact that the model predicts probability of survival and yet the previous papers indicate in their methods that calculations were performed as if the model calculated probability of death.

Several conclusions can be drawn from the results of this thesis analysis. First, development of OTR specific coefficients did result in better calibration of the model based on the H-L statistic. However, regardless of the improved calibration, discriminant ability was similar for the TRISS model developed from MTOS and those trained on the Ontario data set. Despite satisfactory discriminant ability based on summary measures such as the ROC area, the poor specificity highlights limited ability to accurately classify deaths which is worse in this study then previous validation reports. It can therefore be concluded that the TRISS model showed superior ability to predict survivors but poor ability to predict deaths in our trauma population. This performance was little affected by revision of model coefficients.

Is TRISS a Satisfactory Model of Trauma Mortality?:

Formulating an answer to this question requires revisiting the criteria presented for a satisfactory model laid out earlier in this discussion and determining whether or not the model satisfies these criteria. Despite major concerns expressed in previous papers about the limitations of the ISS in TRISS [13,19,59] the current analysis identifies the Revised Trauma Score as the major weakness of TRISS and any other model which incorporates the score such as ASCOT. First and foremost is the issue of generalizability. The inability to obtain accurate values for the RTS in intubated patients results in TRISS being applicable only to those trauma victims who are less severely injured and excludes a very important group from analysis. This poor generalizability must be seen to represent the most critical inadequacy of the TRISS model.

The validity of the components of the model have also been questioned. While age is undoubtedly a key contributor to survival following trauma, there is less confidence in ISS and the RTS. The argument has been put forth in this thesis that although all component variables of the RTS appear to be a valid clinical description of physiologic status following injury, there is great risk in assuming that a single set of values recorded immediately on arrival to hospital adequately reflects whether or not that individual is demonstrating signs of cardiovascular shock. With respect to ISS, although it demonstrates a strong association with survival in this and other studies [7,11,12] it does not provide a complete anatomic description of all injuries. The exclusion of all but the most severe injury in any body region, the diversity of injury severity combinations

and injury locations which produce the same ISS value and the equal weighting given each region all contribute to substantial heterogeneity within any given ISS.

The criteria of parsimony is also violated by inclusion of the RTS in the TRISS model. Correct coefficients for the component variables of RTS must first be derived using standard logistic regression analysis resulting in an equation with an intercept. Calculation of the score for inclusion into TRISS requires multiplying coefficients derived in the preceding step by the coded values for the component variables and summing them without including the intercept. This value for the RTS is then multiplied by a coefficient derived from the TRISS analysis. Clearly, there are ample opportunities for computational or programming errors and it is entirely unclear what the mathematical effect of running the same variables through two different sorts of regression analysis has on the performance of the final model.

Finally, the issue of accuracy must be addressed. While the calibration of TRISS and discriminant ability based on ROC area indicate the model performs with reasonable accuracy, there must be concern over the poor specificity of this model which indicates a suboptimal ability to accurately classify deaths. Given that one of the principle purposes of the model is to provide a quality control tool this represents an important limitation because trauma deaths are precisely the group of patients who require close scrutiny in order to determine whether or not their deaths were preventable.

Generation of Exploded TRISS Model

Subsequent to the preceding validation exercise on TRISS and the limitations imposed upon it by including the RTS, an attempt was made to rid the model of the RTS as a component while continuing to incorporate many of the important physiologic variables that it contains. All component variables of the TRISS model including, age, ISS, SBP, RR, and components of the GCS (eye, motor and verbal responses) were entered as separate variables into a forward stepwise logistic regression analysis on the development set of the TRISS cohort. By doing so, it was hoped that the potential complexity of having a logistic regression model within a logistic regression model (RTS as a component of TRISS), could be removed without sacrificing the important predictive effect of the physiologic variables. It was also hoped that some of the more troublesome variables excluding the intubated patient, namely RR and the verbal component of the GCS (VR) might be removed from the model.

Interestingly, the final model derived from this regression analysis included almost all TRISS variables except the best eye response of the GCS. The exploded model demonstrated similar discriminative performance based on estimates of sensitivity, specificity, accuracy and ROC area but a better fit to the data set based on the H-L statistic. While all component variables demonstrated a significant association to survival within the model based on odds ratio estimates it can be seen in Table 9 that the confidence limits for the odds ratio of respiratory rate almost include the null value of 1.0 (OR=0.82: 95% CI 0.68 - 0.99). This would suggest that this

variable could be removed from the model without substantially sacrificing predictive accuracy. Unfortunately, this still leaves the verbal response of the GCS in the model which results in persistent difficulty in applying the model to intubated patients.

Generalizability of the model to intubated patients could be obtained by eliminating respiratory rate and the verbal response of the GCS. This would result in a model consisting of age, ISS, systolic blood pressure and the motor response of the GCS. Such a model has already been described by Offner et al [73]. In this study the authors noted that TRISS could not be applied to 25% of their patients because of intubation and this resulted in a difference in overall mortality between the target group and those who could undergo TRISS analysis. This led them to create a revision of TRISS which consists of Age (+/- 55 yrs), ISS and the best motor response of the GCS. This "TRISS-Like" model demonstrated similar performance characteristics to the standard TRISS with the additional advantage that it could easily be applied to intubated patients. Despite this remarkable advantage, their discovery has received little recognition in the literature and the model has never been independently validated. In light of the arguments against the use of the Revised Trauma Score provided in this thesis there is great need for further studies to be done on this TRISS model for intubated patients.

***Limitations in further model building*:**

The proposal for this thesis stated that an attempt would be made to include comorbidities as a component of TRISS in order to determine whether this would enhance model performance. Unfortunately, concerns about missing information and other potential reporting biases with this variable in the OTR data set precluded any meaningful analysis using comorbidity. This issue will be re-examined in the future since more rigorous data collection has been instituted by the Ontario Trauma Registry.

It was also proposed that if suboptimal model performance was identified then subgroup analysis would be performed in order to identify groups in which model performance substantially differed. However, re-evaluation of this approach led to skepticism as to its usefulness. Morise et al [74] demonstrated that the accuracy of a logistic regression model is degraded when it is transported to populations with outcome prevalence different from that of the population used to derive the model. Consequently, if TRISS performance was found to change significantly in certain subgroups of the trauma population, it would be unclear whether this was due to factors beyond the model accounting for differing mortality in that subgroup or due to the fact that TRISS was not invariant to changes in mortality rate. This approach could only be applied once the behaviour of TRISS to changes in mortality prevalence was determined.

Concerns: Potential Sources of Bias:

Patient Selection Bias

The importance of patient selection bias is related to the fact that if databases such as MTOS are used to predict outcomes for individuals selected by substantially different criteria, then the resulting predictions may not be properly calibrated, which means they may systematically overestimate or underestimate the actual risk.

The issue of selection bias with regards to the inapplicability of TRISS to intubated patients has already been discussed and represents one of the most severe limitations of the model by reducing it's generalizability to all trauma victims. However, other forms of selection bias may also have occurred.

Review of the selection criteria for MTOS indicate that they were fairly broad and ill-defined having included either all hospital admissions due to trauma or all injured patients admitted to intensive care during their hospital stay [5]. Similarly, the validation exercises performed on the Institute for Trauma and Emergency Care [19-21] included all trauma admissions to three Level I and five non-trauma hospitals. In contrast, the Ontario data included only those

trauma victims with an injury severity characterized by an ISS > 16 to 11 Level I trauma centres. This may partially serve to explain the differences in performance of TRISS observed in this study compared to previous validation reports.

Lead Time Bias:

For a model to reliably predict the outcome of a clinical disease process such as injury, it should be applied to each individual at a similar point in time from the onset of the injury. Thus, all physiologic variables in TRISS are standardly collected as the first set of vital signs on arrival to hospital. Unfortunately, there may be varying periods of pre-hospital time between individuals. This can be accounted for by delays in transport as a result of geographic distance, poor road conditions, delays in ambulance response times or difficulty extracting the victim from the scene (ie., when the "jaws of life' are used to free an individual from a severely deformed vehicle). Some individuals may have received therapeutic interventions such as administration of intravenous fluids, intubation of their airways or other treatments which could alter their status on arrival to the trauma centre. Furthermore, regionalization of trauma care means that a proportion of victims are initially stabilized at a non-trauma hospital prior to transportation to one of the Level I centres. Consequently, the assumption that the patients physiologic status on admission to a trauma centre is the initial phase of the injury process is violated.

The best solution to this dilemma is to obtain data on physiologic status of victims immediately at the scene of the accident. The greatest obstacle rests with the fact that there is no standardized system of prehospital paramedic care in the province of Ontario by which accurate prehospital data can be obtained. Hopefully, this situation will improve with ongoing efforts to better pre-hospital care through training and certification of paramedic teams in many urban centres.

Concerns about Data Quality:

The OTR is a primarily administrative database which was developed to provide comprehensive, accurate and timely information about injury in the province of Ontario. The purpose of this was to provide a scientific basis to facilitate injury prevention programs and allow evaluation of the impact of preventive measures and legislative changes. This information would aid in decisions about resource allocation and could also serve as a quality control tool thereby contributing to improvements in trauma patient outcomes.

While the advisory committee of the registry were cognisant of the research potential for the data, it was not primarily developed as a scientific tool. Previous reports have raised concerns about the accuracy of data in large administrative data sets [63]. In order for the data to be released for this thesis analysis the OTR scrambled hospital and patient identifiers in order to insure

confidentiality. This eliminated any mechanism by which accuracy of the data elements could be determined. An audit performed by the medical advisory committee of the registry of all cases from June 1991 to June 1994 revealed that 16.1% of all files in the registry had incorrect data entry [75]. This was largely attributed to intra- and inter-hospital inconsistencies in data entry procedures employed by the data analysts. The audit corrected those errors and took steps to enforce standardized methodologies for data collection and entries. Nevertheless, it is impossible to determine the rate of error present in this data set. Several logic checks were employed in SAS programming to include ranges for coded variables. A little over 1,000 entries were discovered by SAS analysis to have all component variables for the calculation of RTS but the value for the RTS was missing. Correct values were calculated and these cases were used in analysis. Other cases with missing data were excluded from analysis in attempt to maintain data accuracy. This selection bias may limit the validity of conclusions reached in this study.

Another concern with regard to the quality of the data is the completeness of many of the data elements. Cases with missing values may clearly have a variety of reasons as to why they are missing and may introduce selection bias into an evaluation of outcome. This also raises difficulties in exploratory model building when attempting to provide an improvement in predictive capability. For instance, while physiologic variables are supposed to be collected at the scene of the accident, anywhere from 40.8 - 80.8% of cases are missing one or more key physiologic variables necessary for analysis [76]. This severely restricts ability to derive a valid model based on other key variables.

SUMMARY and CONCLUSIONS:

In this thesis the ability of the TRISS model and its component Revised Trauma Score to characterize mortality in a Canadian trauma population have been evaluated. This revealed that the generalizability of TRISS is severely limited by the use of the Revised Trauma Score which prohibited the inclusion of patients who were intubated because of the inability to obtain several key variables. The exclusion of these cases reduced the overall mortality of the cohort by 50%. While the overall accuracy of both TRISS and RTS were greater than 90%, the specificity of both models was exceedingly poor. This indicates that these models are strong in identifying survivors but weak in identifying mortalities. The overall performance of the RTS was by far the worse of the two. The poor generalizability of TRISS due to inclusion of component variables of the RTS, the poor independent performance of the RTS in predicting mortality and the complexity of having a logistic regression model (RTS) within another logistic regression model argues strongly for exclusion of RTS as a component variable of TRISS. Nevertheless, inclusion of physiologic variables in a trauma model of mortality carries much face validity and indeed all component physiologic variables showed a significant relationship with mortality. Rather than discarding the RTS entirely, its component variables as well as age and ISS were entered into a stepwise logistic regression analysis. This expanded TRISS model has the advantage of not including a logistic regression model with its own component beta weights without sacrificing accuracy in classifying survivors. Unfortunately, this model still includes variables which would prohibit analysis of intubated patients. It does however, bear striking similarity to a published model called TRISS-Like. This model consists of age, ISS, systolic blood pressure and the motor

component of the GCS. Despite the fact that this model is clearly far more generalizable than TRISS it has achieved no attention in subsequent validation studies The focus of future work needs to identify a more broadly applicable trauma mortality model with improved specificity.

FUTURE RESEARCH:

1) To validate the TRISS-Like model consisting of Age, ISS and Motor Response of the GCS on the OTR.

2) To compare the predictive capability of ISS and Anatomic Profile (AP) and evaluate the effect of inclusion of AP in the TRISS-Like model.

3) To determine whether TRISS and TRISS-Like demonstrate different performance characteristics with systematic changes in the prevalence of mortality and examine mathematical equations which might correct for this.

4) Poor specificity identified for TRISS (and potentially for TRISS-Like) will be further evaluated by characterizing and comparing those mortalities correctly and incorrectly classified by the models.

5) A more rigorous analysis of comorbidities will be undertaken by prospectively collecting comorbid illness diagnosis based on agreed operational definitions on a prospective cohort of all consecutive trauma admissions recorded in the OTR.

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APPENDICES

APPENDIX I

History of the Ontario Trauma Registry

1. HISTORY OF THE ONTARIO TRAUMA REGISTRY

In the mid 1980's in Ontario, the Ministry of Health in conjunction with the Emergency Health Services Advisory Committee, developed guidelines for the designation of lead hospitals and the development of regional trauma networks. Little reliable population based data were available to define the scope and distribution of injured patients in Ontario. Because of these concerns, the Trauma Association of Canada and the Ontario Ministry of Health joined in an effort to establish a provincial database, the Ontario Trauma Patient Registry.

A Task Force first met in 1988 to advise the Ministry of Health regarding the establishment and implementation of a comprehensive registry of patients injured in the province of Ontario.

The Ontario Trauma Patient Registry Task Force, chaired by Dr. David Wesson of the Hospital for Sick Children in Toronto, was struck by the Ontario Ministry of Health to examine the feasibility and methodology of establishing a provincial injury Registry. Dr. Peter Lane, from Victoria Hospital in London, served as consultant to the Task Force which included broad representation from across the province.

In June 1989, Health Minister Elinor Caplan announced improvements to access in emergency and trauma services including the establishment of an Ontario Trauma Registry.

The principal goal of the Ontario Trauma Registry (OTR) according to the Task Force report would be to provide comprehensive, accurate and timely information about injury in the province of Ontario. This would be accomplished through the provision of a provincial database which will identify, describe, and quantify traumatic injury and death in the province of Ontario including risk factors and type of injury. This would provide, for the first time, a scientific basis to facilitate injury prevention programs and would allow evaluation of the impact of preventive measures and legislative changes. In addition, the database would substantially aid in resource allocation decisions and would contribute toward a reduction in the cost of trauma both in human and fiscal terms. Finally, the Registry would serve as a quality assurance tool and would contribute to improvements in trauma patient care and outcome.

The Task Force recommended that:

1. the Ontario Trauma Patient Registry be implemented

2. a system of unique patient identifiers be introduced in the province of Ontario

3. the Ontario Trauma Patient Registry comprise two levels of detail - the Minimal and Comprehensive Data Sets

The Minimal Data Set would include information on all patients admitted to acute care hospitals in the province as a result of injury. The Comprehensive Data Set would include more detailed information on severe injuries and fatalities from the specialized lead/trauma hospitals and the Coroner's Office

4. the Ontario Trauma Patient Registry be operated by a Registry Office, with a Director and appropriate support staff. It was further recommended that the Registry be managed by a steering committee reporting to the Deputy Minister of Health and that this steering committee include representation from physicians and surgeons involved in trauma care in different regions of the province, the Ontario Hospital Association, the Trauma Association of Canada, HMRI (now CIHI), and the Ministry of Health

5. the development of Regional Trauma Networks and lead hospital designation in the province include a requirement for participation in the registry, and that lead hospitals be provided with appropriate funding to ensure such participation

6. regular reports be provided to participating hospitals, including provincial, regional, and hospital based data

7. HMRI data base serve, on a limited trial basis, as the principal data source for the Minimal Data Set

8. Tri-Analytics, Inc. be contracted, on a limited trial basis of no longer than two years, to provide software, analyze data, ad produce reports for the comprehensive registry

9. that all hospitals in the province be required to submit discharge data to HMRI utilizing ICD-9 CM coding (ICD 10 when available).

The Ministry of Health accepted the recommendations of the Task Force Report received March 1990 and convened the multidisciplinary Trauma Registry Advisory Committee (TRAC) in June 1990 to advise on the implementation of the OTR. Members include representatives from the Ministry of Health Emergency Health Services and Public Health Branches, Ministry of Labour, Ministry of Transportation, CIHI, epidemiologists, trauma care providers, health records administrators, the Office of the Chief Coroner, the Trauma Association of Canada and Health Canada.

The TRAC Subcommittee on the Evaluation of Trauma Registry Software submitted their final report in July 1991 recommending the trauma registry software packages COLLECTOR and TRI-CODE from Tri-Analytics, Inc. for the Comprehensive Data Set. Dedicated lead/trauma hospital staff use this software to abstract and submit data to the Ontario Trauma Registry Office.

The Ontario Trauma Registry (OTR), funded by the Ontario Ministry of Health, was established in May 1992. Funding was provided by the Ministry of Health to the lead/trauma hospitals to establish the necessary infrastructure for data collection and purchase of hardware and specialized software based on recommendations from TRAC.

The current implementation of the Registry is based on the data elements, data collection procedures, report formats, and management procedures determined by the Task Force and TRAC.

Ontario Trauma Registry

The Registry was originally located at HMRI, a non-government, national health care information organization collecting patient discharge information on approximately 85% of all acute care hospital discharges in Canada. HMRI merged in February 1994 with the MIS Group and specific health information programs from Health Canada and Statistics Canada to become the Canadian Institute for Health Information (CIHI). CIHI continues to be the home of the Registry.

The primary Users of the Ontario Trauma Registry include participating hospitals, the members of the Trauma Registry Advisory Committee (TRAC) and Area Emergency Health Services (EHS) Committees. The Area EHS Committees are part of regional planning networks made up of committees at the provincial, regional and local levels involving health care planners, providers and consumers in emergency health initiatives.

The Ontario Trauma Registry receives ad hoc requests for injury data from hospitals, governments, universities, consultants, physicians, head injury and spinal cord injury associations, safe cycling groups, health departments and injury prevention coalitions.

APPENDIX II

Comprehensive Data Set Elements of

Ontario Trauma Registry

The Comprehensive Data Set data elements have been summarized into the following groups:

1. Identifying data elements
2. Demographic data elements
3. Injury related data elements
4. Prehospital/transport data elements
5. Clinical data elements
6. Hospital care data elements
7. Operating room data elements
8. Outcome data elements
9. Motor vehicle crash data elements
10. Follow up data elements
11. Readmission data elements
12. Miscellaneous data elements

1. IDENTIFYING DATA ELEMENTS	
Data Element	**Components**
Address - patient and legal next of kin	Street address, city, province, postal code
Campus number	
Chart number	
Health Number (Ontario)	
Health Number (Other than Ontario)	
Institution number (lead/trauma hospital)	
Name - patient and legal next of kin	Surname, first name, middle name (middle name of legal next of kin not collected as of April 1, 1995)
Trauma number (assigned to patient by hospital)	

2. DEMOGRAPHIC DATA ELEMENTS	
Data Element	**Components**
Age	
Date of birth	
Language spoken (patient and legal next of kin)	
Occupation for work related injury	
Province of residence	
Relationship of legal next of kin to patient	
Residence code	
Sex	

3. INJURY RELATED DATA ELEMENTS	
Data Element	**Components**
Abbreviated Injury Scale (AIS) Code	
AIS Version	
Approximated time of injury (added April 1, 1995)	
International Classification of Diseases (ICD) External Cause of Injury Codes (E Codes)	Primary, secondary and tertiary
Cause of injury text description	
Activity causing sports and recreational injury	
Sports and recreational injury text description	
Was extrication required?	
If extrication required, extrication time	
Geocode of incident location	
Incident date and time	
Province of incident (if out of province)	
Injury text descriptions (up to 27 injuries)	

3. INJURY RELATED DATA ELEMENTS (continued)	
Data Element	**Components**
Injury type (primary)	
Intentionality	
Injury Severity Score (ISS)	
Maximum Abbreviated Injury Scale (MAIS) (a calculated field for each of 6 body regions)	
Place of injury	Primary, secondary, tertiary
Place of injury text description	
Predot Code (AIS Coding System - up to 27 codes)	
TRISS	
Was injury work related?	

4. PREHOSPITAL/TRANSPORT DATA ELEMENTS	
Data Element	**Components**
Dates and times at scene	Call received, dispatched, arrived at scene, arrived at patient, departed from scene
Institution numbers patient transferred to	Primary, secondary, second secondary, lead/trauma hospital
Modes of transport (up to 3 providers)	From scene, from primary hospital, from secondary hospital
Nonoperative procedures	Scene
Number of qualified personnel in transport (up to 3 providers)	From scene, from primary hospital, from secondary hospital
Prehospital number (up to 3 providers)	From scene, from primary hospital, from secondary hospital
Prehospital time (calculated)	
Is runsheet available? (up to 3 providers)	From scene, from primary hospital, from secondary hospital
Scene time (calculated)	
Transport service for land ambulance (up to 3 providers; as of April 1, 1995)	From scene, from primary hospital, from secondary hospital

5. CLINICAL DATA ELEMENTS	
Data Element	**Components**
Blood Alcohol Concentration (BAC - mm/L)	Primary hospital, secondary hospital, lead/trauma hospital
Glasgow Coma Scale components: eye opening, motor response, verbal response, total	Scene, primary hospital, secondary hospital, lead/trauma hospital
Heart rate	Scene, primary hospital, secondary hospital, lead/trauma hospital
Intracranial Pressure (ICP) monitoring days	Primary hospital, secondary hospital, lead/trauma hospital
Was the patient intubated?	Primary hospital, secondary hospital, lead/trauma hospital
Were paralytic agents in effect?	Scene, primary hospital, secondary hospital, lead/trauma hospital
Pediatric Trauma Score	Primary hospital, secondary hospital, lead/trauma hospital
Respiration rate (unassisted)	Scene, primary hospital, secondary hospital, lead/trauma hospital
Revised Trauma Score	Scene, primary hospital, secondary hospital, lead/trauma hospital
Systolic blood pressure	Scene, primary hospital, secondary hospital, lead/trauma hospital
Temperature	Primary hospital, secondary hospital, lead/trauma hospital
Ventilator days	Primary hospital, secondary hospital, lead/trauma hospital
Weight (pediatric patients as of April 1, 1995)	

6. HOSPITAL CARE DATA ELEMENTS	
Data Element	**Components**
Admitting Service (lead/trauma hospital)	
Comorbidities	
Complications	
CT Scan locations	Primary hospital, secondary hospital, lead/trauma hospital
Date of admission to lead/trauma hospital	
Date and time of arrival	Primary hospital, secondary hospital, lead/trauma hospital, lead/trauma hospital ED
Date and time of departure	From primary hospital, secondary hospital, lead/trauma hospital ED

6. HOSPITAL CARE DATA ELEMENTS (continued)	
Data Element	**Components**
Direct admission to service (patient bypasses ED)	
ED Physician lead/trauma hospital (not transmitted to OTR)	
Nonoperative procedures	Primary hospital, secondary hospital, lead/trauma hospital
Number of Intravenous Therapy (IV) sites	Primary hospital, secondary hospital, lead/trauma hospital
Post ED destination	
Post OR destination	
Referring physician (not transmitted to OTR)	
Service transfers (up to 6 transfers)	Type of service, date admitted, date discharged, length of stay
Special Care Units (SCU) (up to 5 SCUs)	Type of SCU, date admitted, date discharged, length of stay
Trauma team activated (lead/trauma hospital)	
Trauma team leader (not transmitted to OTR)	

7. OPERATING ROOM DATA ELEMENTS	
OR data is collected for: Primary Hospital (up to 5 visits) Secondary Hospital (up to 5 visits) Lead/Trauma Hospital (up to 10 visits)	
Data Element	**Components**
OR visits - dates	
OR visits - elapsed time	
OR visits - finish time	
OR visits - number of	
OR visits - procedures	
OR visits - services performing procedures	
OR visits - start time	

8. OUTCOME DATA ELEMENTS	
Data Element	**Components**
Alternative Level of Care (ALC):	
Number of ALC days	
Reasons for ALC days	
Was ALC from completed?	
Date patient ready for ALC	
Was Coroner notified of death?	
Date and time of discharge or death	
Discharge disposition	
Glasgow Outcome Scale	
Institution name discharged to outside of Ontario	
Institution name discharged to outside of Canada	
Institution number discharged to within Ontario	
Length of stay (lead/trauma hospital)	
MORE involvement with organ donation (not collected as of April 1, 1995)	
Was family approached re organ donation?	
List of organs donated	
Were organs donated?	
Place of death	
Was post mortem examination done?	
Was post mortem report received?	
RANCHOS at discharge	
Separation status	

9. MOTOR VEHICLE CRASH DATA ELEMENTS	
Data Element	**Components**
Motor Vehicle Crash report number	
Collision detail	
Ejected from vehicle	
Distance ejected (meters)	
Impact location	
Impact type	
Police Force	
Police Force Division	
Position in vehicle	
Protective devices	
Vehicle type	

10. FOLLOW UP DATA ELEMENTS	
Data Element	**Components**
FIM Components (Functional Independence Measure)	At Discharge, At Follow Up
FIM Total Score	At Discharge, At Follow Up
FIM Type (adult or pediatric)	At Discharge, At Follow Up
Was FIM taken from chart at discharge?	
Follow Up: Were there admissions related to injury in the 6 months post discharge?	
Follow Up: Contact	
Follow Up: Date	
Follow Up: Institution number admitted to	

10. FOLLOW UP DATA ELEMENTS (continued)	
Data Element	**Components**
Follow Up: Level of employment	
Follow Up: Level of study	
Follow Up: Percent of previous income	
Follow Up: Was therapy received after discharge?	
Follow Up: Therapy type	

11. READMISSION DATA ELEMENTS	
Data Element	**Components**
Is this admission a readmission?	
Number of readmissions	

12. MISCELLANEOUS DATA ELEMENTS	
Data Element	**Components**
Memo fields	Demographic, Follow Up, Injury, Lead/Trauma Hospital, Lead/Trauma Hospital Care, Nursing, Outcome, Primary Hospital, Quality Assurance, Readmission, Scene, Secondary Hospital, System
American College of Surgeon (ACS) audit filters (not transmitted to OTR)	
Overflow field used for special studies