Table 3　Classification of nerve injury of the upper arm/shoulder

ICD	New classification	AIS*
S44.1 Injury of median nerve at upper arm level	Injury of median nerve at upper arm level, NFS	730499.1 Median nerve, NFS
	contusion	730402.1 contusion
	laceration	730404.2 laceration
	with motor loss	730406.2 with motor loss
S44.2 Injury of radial nerve at upper arm level	Injury of radial nerve at upper arm level, NFS	730699.1 Radial nerve, NFS
	contusion	730602.1 contusion
	laceration	730604.2 laceration
	with motor loss	730606.2 with motor loss
S44.3 Injury of axillary nerve	Injury of axillary nerve, NFS	730099.9 (.1) Nerve injury in upper extremity NFS
	contusion	730099.9 (.1)
	laceration	730099.9 (.2)
	with motor loss	730099.9 (.2)

ICD, International Classification of Diseases and Related Health Problems ; AIS, Abbreviated Injury Scale ; NSF, not further specified
*Although AIS does not have specific codes for axillary nerve injuries, the new classification system can adopt the same injury severity scores as in other nerve injuries (in brackets).

外傷についてコードを選択することとしたが，肋骨骨折・骨盤骨折については胸郭および骨盤輪を一つの解剖学的単位と考え，多発骨折を複数の単発骨折とは別の病態とする分類を採用した．Table 4に肋骨骨折と動揺胸郭の分類を示す．骨折した肋骨の本数および胸郭の安定性が重症度と関連し，AISでも骨折本数に関する情報をコードに含んでいることから，多発骨折を示すコードを残した．

骨盤骨折の例をTable 5に示す．骨盤骨折の分類方法は，ICDとAISで全く考え方が異なり，ICDでは骨折部位を記述するのに対し，AISでは重症度と関連する骨盤輪の安定性により分類する．そこで，骨盤骨折についてのみ，骨盤輪の安定性の分類と，骨折部位のコードという2通りの分類コードを含めることとした．ただし，寛骨臼骨折については，AISでも骨盤輪とは独立に記載されているので，別に分類を設けた．

新分類の具体例をTable 6に示す．例に挙げた症例は頭部の開放創，肝挫傷，骨盤骨折，肩甲骨骨折，上腕と肘の開放創があり，それぞれの新分類コードとAISとICDへの変換を示した．新分類コードの1桁目はICDと同様の解剖学的分類を，2桁目は左右を（左右別のない場合は0），3桁目は臓器分類（血管，神経，骨など），4～5桁目は臓器詳細分類（腓骨，脛骨など），6～7桁目は損傷性状を示す．前述のように，骨盤骨折では骨盤輪の安定性と骨折部位を示す2つのコードがつけられ，それぞれAISとICDに変換される．上腕と肘の開放創は，ICDでは異なるコードを使用するが，AISでは同じコード（同一分類）となる．従来通りにICDの単一の多発外傷コードを使用する場合にはT06.8（多部位のその他の明示された損傷）に変換する．

Table 4 Classification of rib fracture and flail chest

ICD	New classification	AIS
S22.3 Fracture of rib	Single rib fracture	450201.1
S22.4 Multiple fractures of ribs	Multiple rib fractures, NFS	450210.2
	two ribs	450202.2
	3 ribs	450203.3
S22.5 Flail chest	Rib fractures with flail chest, NFS	450209.3
	unilateral flail chest, NFS	450211.3
	3-5 flail ribs	450212.3
	＞5 flail ribs	450213.4
	bilateral flail chest	450214.5

ICD, International Classification of Diseases and Related Health Problems ; AIS, Abbreviated Injury Scale ; NSF, not further specified

Table 5 Classification of pelvic fracture by pelvic stability and fracture location

ICD	New classification*	AIS
	Pelvic ring stability	
	Pelvic ring fracture, posterior arch intact	856151.2
	Pelvic ring fracture, incomplete disruption of posterior arch, NFS	856161.3
	blood loss ≦20% by volume	856163.4
	blood loss ＞20% by volume	856164.5
	Pelvic ring fracture, complete disruption of posterior arch and pelvic floor, NFS	856171.4
	blood loss ≦20% by volume	856172.4
	blood loss ＞20% by volume	856173.5
	Fracture (s) and dislocation (s) †	
S32.1	Fracture of sacrum	
S32.2	Fracture of coccyx	
S32.3	Fracture of ilium	
S32.5	Fracture of pubis	
S33.2	Dislocation of sacroiliac joint	
	Dislocation of sacrococcygeal joint	
S33.4	Traumatic rupture of symphysis pubis	

ICD, International Classification of Diseases and Related Health Problems ; AIS, Abbreviated Injury Scale ; NSF, not further specified

*Two codes are selected for the new classification : one for pelvic ring stability and the other for location of fracture(s) and dislocation(s).

† Fracture of acetabulum is separately described.

Table 6　An example of coding for multiple injuries in a patient

New classification		AIS code	ICD-10 code	
Code	Description			
0110224.2	Scalp laceration, major（right）	110604.2	S01.0	T06.8
3061804.3	Liver contusion subcapsular, >50% surface area	541814.3	S36.1	
3057820.4 3157320*	Pelvic ring fracture, incomplete disruption of posterior arch blood loss ≤20% by volume with fracture of ilium（right）	856163.4	S32.3	
4154100.2	Scapula body fracture（right）	750951.2	S42.1	
4110442.1	Penetrating injury at upper arm（right） superficial	716015.1	S41.1	
5110242.1	Penetrating injury at elbow（right） superficial	716015.1	S51.0	

*A code indicating the location of the fracture.

以上のような分類方法，コーディング方法を使用することにより，ICDのS00からS99まで（Sxx.7除外），AISの1xxxxxから8xxxxxまでのコードについて，新分類からICDとAISへの変換を一義的に行うことができた．

考　察

我が国において日本外傷データバンクに参加している施設の多くは，外傷診断分類に2通りの方法を使用している[1]．ひとつは，施設内すべての患者を対象とした診療情報の管理（診療録への記載，診療報酬請求，院内データの分析など）に用いられているICDである．これは世界保健機関が死亡・疾病統計の国際比較を目的として作成した標準的分類で，現在使われているのは1990年に採択された第10回改訂（ICD-10）で，2015年の採択を目指してICD-11への改訂が進められている[6]．従来ICDは死因分類，医学研究，政策決定等に使用されてきたが，2003年から始まった診断群分類（Diagnosis Procedure Combination：DPC）による包括評価では分類にICD-10を使用し，ICDによるコーディングが収入に直結することから診療現場における診断分類の重要性が認識されるようになった[2]．

いまひとつは，外傷に特化し，損傷形態と重症度を解剖学的に記述・分類するため，米国自動車医学振興協会によって開発されたAISである[3)4]．AISの重症度スコアをもとに，Injury Severity Score（ISS）を算出し，さらにISSと生理学的指標から外傷患者の予後予測指標であるTrauma and Injury Severity Score（TRISS）を算出する．これらの指標は外傷診療の質を評価する際の標準的方法として広く使用されていることから，日本外傷データバンクの診断分類にはAISが用いられている[1]．

このようにICDとAISは異なった目的と使用原則を持ち，お互いに代替不可能であるために，両者ともに用いた二重コーディングが行われることになった．DPCはICDコードに基づいておりAISで代用することはできないし，TRISSスコア算出にはAIS重症度スコアが必要であるから重症度情報を含まないICDで代用することはできない．コーディングには，人員と正確なコーディングのためのトレーニングやコードブックなどが必要であり，二重コーディングを行うことは人的・金銭的な負担が大きい[1)4)7]．

二重コーディングを避けるために様々な方法が試みられているが，必ずしも満足できる実用的なものとは言えない．ICDのClinical modification（ICD-CM）からAIS重症度スコアに変換するコンピュータソフトが開発されたが，ICDとAISの改訂にソフトのアップデートが追い付かないうえ，DPCにICD-CMではなくICD-10を用いている我が国では利用価値が低い[5)8]．また，ICDから直接予後予測を行う手法としてICD based injury severity score：ICISS）も開発されているが，すべてのICDコードに対して我が国独自の死亡確

率を計算するために膨大なデータが必要となり，現時点でただちにTRISSの代用となるものではない[5)7)9)].

我が国においてもICD-AIS変換表が作成されたが，以下の問題により実用に供されるには至っていない[1)]. １）１対１あるいは多対１（集約）の変換は可能であるが，１対多（分割）の変換を要する場合がある，２）対応する分類が存在しない場合がある，３）ICDでは単一コードで多発外傷を表現するため解剖学的に複数の外傷を表現するAISと対応させることができない，などである.

これまでの試みは，ICDとAISの一方から他方への変換方式で上記のような困難が存在した．コーディングを一回だけ行い，後は自動的に他の分類方式に変換するという方針を取るならば，最初のコーディングは必ずしもICDやAISを用いなくてもかまわないはずである．そこで，本研究では第３の分類としてICDとAISの中間的な新分類（以下新分類）を導入することにより直接変換で発生する問題を回避し，二重コーディングの問題を解決しうる可能性を示した．これにより予後予測指標を用いた外傷診療のアウトカム評価実施が促進されると期待できる[1)].

新分類はICDおよびAISに一義的に変換できることから，２つの利点を有する．まず，変換に際して不足する情報を補う（例えば分割を伴う変換であれば不足情報を診療録から収集する，あるいは他の利用可能な情報から推論するなど）必要がないため，単純な自動変換が行えることである．新分類コードからICDコードとAISコードを導き出す変換ソフトは複雑なアルゴリズムを必要とせず安価に作成可能である.

さらに，AISへの一義的変換が可能であることから，対応するAIS重症度スコアを新分類コードに組み込み，AISへの変換を行うことなくISSやTRISSなどのスコアを計算することも可能である．新分類作成の際，多くの場合にICDよりAISの分類粒度の方が細かいためAISの方を採用し，解剖学的分類に差異がある場合でも損傷性状の分類はAISの分類が使用可能であったことを反映して，新分類とAISの類似性は非常に高い．したがって，新分類はICDとの適合性（変換可能性）を高めたAIS改訂版とも考えることができる.

ICDの本来の利用目的は主として死因分類であったが，現在改訂中のICD-11では利用目的を疾病分類，診療報酬の算定，診療の質評価などの臨床的利用にも拡大することとされており（現時点でICD-10はDPCで利用されているがこれは本来想定されていた利用方法ではない）[6)]，臨床的利用に広く利用されているAISをICDに統合することも検討すべきではないかと考える．新分類をICD-11の19章として，あるいはICD-11CMとして組み込むことで，従来のAIS，ICD-10との変換可能性を保ちつつ，AISが持つ解剖学的外傷記述機能や重症度表現をICDの臨床的利用に活かすことができる．さらに，現在ICDで用いられている単一コードによる分類方法は，複数の病態を表現するのに情報の欠落が大きく表現の柔軟性に乏しいため，複数のコードを用いて多発外傷のみならず合併症や基礎疾患の情報を表現するといったことが求められるようになると予想される[10)11)]．このような場合にもそれぞれの外傷を記述するAISの方法論が有用となるであろう.

新分類には今後検討すべき課題がいくつかある．まず，新分類の非常に細分化された分類がコーディング作業を煩雑にしたり，新分類の習得に時間を要するなどの実用上の問題が出てこないかということである．分類粒度の違う場合は細かい方を採用し，分類境界が違う場合はすべての境界を用いた細分類を採用したことから，全体的に非常に詳細な分類になっている．例えば，上肢の解剖学的分類を，肩，上腕，肘，前腕，手首，手に細分化したため，上肢損傷の基本コード数はAISで324であるのに対して，新分類では894である．しかし，AISでもlocalizerを使用して新分類同様の細分類が可能であることから，コーディング作業上，大きな問題にはならないだろうと考えている．コード数は非常に多いが，新分類は基本的にICDとAISの組み合わせであり，ICDとAISに関する知識があれば，習得に係る労力はそれほど大きくはないであろう．しかし，ICDかAISが改訂された場合には新分類の修正も必要になり，外傷登録システムや患者データシステムの頻回の修正を要するという弱点を内在することになる.

また，ICDあるいはAISのどちらかに分類コードが存在しない場合に，新たに分類を作成し重症度スコアは同種の損傷分類と同様のものを使用した．例えば，腋窩神経損傷では他の神経損傷と同様の分類と重症度スコアを当てはめた．これらは

あくまで類推に基づくものであり，妥当性を検証する必要がある．さらに，新分類からの変換が従来のICDとAISによる分類と一致するかを，実際の外傷患者データを用いて検証することが必要である．

結　語

ICDとAISへの一義的変換が可能で，AIS同様の重症度スケールを含むことも可能な中間的新分類を作成した．これにより二重コーディングの負担解消と，外傷登録を利用した診療の質評価・改善の活発化が期待できる．さらには，ICD-11への改訂に際してAISの利点をICDに統合できる可能性があると考える．

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DEVELOPMENT OF A NEW TRAUMA CLASSIFICATION SYSTEM THAT CAN BE CONVERTED TO BOTH THE INTERNATIONAL CLASSIFICATION OF DISEASES AND RELATED HEALTH PROBLEMS AND THE ABBREVIATED INJURY SCALE

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In many facilities treating trauma patients, duplicate coding is performed for trauma diagnoses using two different classification systems : the International Classification of Diseases and Related Health Problems (ICD) for administrative purposes and the Abbreviated Injury Scale (AIS) for the trauma registry. As unambiguous conversion of codes between ICD and AIS is not always possible due to the different structures of the two systems, we have developed a new bridging classification system that can be used to unambiguously convert both ICD and AIS. Development of the new classification system used the following strategies to assure its compatibility with both ICD and AIS : suspension of the multiple-injury codes in ICD, adoption of the more detailed categorization when the granularity of categorizations differs between ICD and AIS, and adoption of all classification boundaries when the boundaries differ between ICD and AIS (as seen in anatomical categories of extremities). The new classification system has the potential to avoid the additional cost associated with duplicate coding, and to facilitate improved evaluation and quality of trauma care based on the trauma registry data.
Key words : injury diagnosis classification, ICD, AIS, trauma registry

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Modification of the Trauma and Injury Severity Score (TRISS) Method Provides Better Survival Prediction in Asian Blunt Trauma Victims

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Abstract

Background The objective of the present study was to identify logistic regression models with better survival prediction than the Trauma and Injury Severity Score (TRISS) method in assessing blunt trauma (BT) victims in Japan and Thailand. An additional aim was to demonstrate the feasibility of probability of survival (Ps) estimation without respiratory rate (RR) on admission, which is often missing or unreliable in Asian countries.

Methods We used BT patient data (n = 15,524) registered in the Japan Trauma Data Bank (JTDB, 2005–2008). We also extracted data on BT patients injured in the Khon Kaen District between January 2005 and December 2008 (n = 6,411) from the Khon Kaen Hospital Trauma Registry. For logistic regression analyses, we chose the Injury Severity Score (ISS), age year (AY), Glasgow Coma Scale (GCS) score, systolic blood pressure (SBP), RR, and their coded values (c) as explanatory variables, as well as the Revised Trauma Score (RTS). We estimated parameters by the method of maximum likelihood estimation, and utilized Akaike's Information Criterion (AIC), the area under the receiver operating characteristic curve (AUROCC), and accuracy for model comparison. A model having the lower AIC is considered to be the better model.

Results The AIC of the model using AY was lower than that of the model using the coded value for AY (cAY) (used by the TRISS method). The model using ISS, AY and cGCS, cSBP, and cRR instead of the RTS demonstrated the lowest AIC in both data groups. The same trend could be observed in the AUROCCs and the accuracies. In the Khon Kaen data, we found no additional reduction of the AIC in the model using the cRR variable compared to the model without cRR.

Conclusions For better prediction of Ps, the actual number of the AY should be used as an explanatory variable instead of the coded value (used by the TRISS method). The logistic regression model using the ISS, AY, and coded values of SBP, GCS, and RR estimates the best prediction. Information about RR seems to be unimportant for survival prediction in BT victims in Asian countries.

Introduction

The Trauma and Injury Severity Score (TRISS) [1, 2] is a standard method for estimating survival and is often used in evaluating the quality of trauma care. It provides the probability of survival (Ps) by the logistic regression model with the predictor variables of the Injury Severity Score (ISS) [3], Revised Trauma Score (RTS) [4], and categorized data (coded value) of age year (cAY). The formula is:

$$\text{logit(Ps)} = \text{Intercept} + \beta\text{ISS}^*\text{ISS} + \beta\text{RTS}^*\text{RTS} + \beta\text{cAY}^*\text{cAY}$$

logit is the link function of the logistic regression model and represents the natural logarithm of the odds of the probability (Ps) of a positive outcome (survival/death). The

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intercept and coefficients are determined by versions of the Abbreviated Injury Scale (AIS) [5, 6] required for ISS calculation. The RTS is calculated using the Glasgow Coma Scale (GCS) score, the systolic blood pressure (SBP), and the respiratory rate (RR). The formula is a linear equation of their coded values (c):

$$RTS = 0.9368^{*}cGCS + 0.7326^{*}cSBP + 0.2908^{*}cRR.$$

However, in our previous study [7], we demonstrated that logistic regression models with direct use of the actual AY provide a better fit than the TRISS model using the categorized (coded) AY, because a rapid increase in mortality is not observed around the AY of 55 in Japan. Moreover, a model without the RR information can be made with only a slight reduction in accuracy, and it can be feasible for Ps prediction if the RR data are missing.

This study aimed to modify the TRISS model in order to obtain better survival prediction for blunt trauma (BT) victims in Japan and Thailand, and to pursue the possibility of Ps estimation without RR information on admission.

Methods

Study design, population, and settings

We conducted a retrospective observational study to create Ps prediction models for BT victims in Japan and in Thailand. The protocol of the study was approved by the ethics committee of the National Center for Global Health and Medicine.

Once approval was obtained from the Trauma Registry Committee of the Japanese Association for the Surgery of Trauma, we used deidentified anonymous data from the JTDB [8], with which 144 Japanese hospitals have been involved since 2004. From 2005 to 2008, 25,310 patients who had suffered BT were registered in the JTDB. For analyses, we collected data on 15,524 patients without missing both outcome information on survival and information on the predictors for Ps calculation by the TRISS method using the 1990 revision of AIS (AIS90) [5].

From 2005 to 2008, 6,667 patients who had experienced BT in the Khon Kaen District in Thailand were registered in the Khon Kaen Regional Hospital Trauma Registry, where data have been collected since 1997. The hospital is one of the World Health Organization (WHO) collaborating centers for injury prevention and safety promotion, and has been providing outstanding contributions. With the permission of the hospital, we analyzed data on 6,411 patients, including items necessary for Ps calculation by the TRISS method using the 1985 version of the AIS (AIS85) [6] and information on survival at discharge.

Analyses

We performed logistic regression analyses in order to establish models. Maximum likelihood estimation was used as the method of coefficient estimation for each model. In addition to the RTS, AY, ISS, GCS, SBP, and RR, we used their coded values (cAY, cGCS, cSBP, cRR), defined in Table 1, as predictor variables. The outcome variable was survival (=1) with non-survival (=0) at discharge. We used the likelihood ratio χ^2 test for evaluating independence of variables. The statistically significant level was considered to be <0.05.

For model selection, we used Akaike's Information Criterion (AIC) [9], defined as:

$$AIC = -2^{*}\log(\text{maximum likelihood}) + 2^{*}(\text{number of adjusted parameters}).$$

Table 1 Demographics of each data set and distribution of variables

	Coded value	JTDB data	Khon Kaen data
Number		15,524	6,411
Gender (male %)		69.2	74.1
Age (years) mean (SD)		48.5 (23.2)	31.6 (18.9)
<55	0	55.0%	87.6%
≧55	1	45.0%	12.4%
RTS mean (SD)		6.78 (2.13)	7.47 (1.08)
SBP			
>89 mmHg	4	86.3%	95.9%
76–89 mmHg	3	3.2%	1.6%
59–75 mmHg	2	2.4%	1.1%
1–49 mmHg	1	1.3%	0.2%
No pulse	0	6.8%	1.2%
GCS score			
13–15	4	73.8%	89.4%
9–12	3	7.3%	3.0%
6–8	2	5.9%	4.6%
4–5	1	2.2%	1.1%
<4	0	10.8%	1.9%
RR			
10–29/min	4	77.9%	92.1%
>29/min	3	14.3%	0.2%
6–9/min	2	0.4%	0.02%
1–5/min	1	0.2%	0.2%
0/min	0	7.2%	7.5%
ISS mean (SD)		17.9 (13.6)	9.5 (10.1)
Survival (%)		85.0	95.9

JTDB Japan Trauma Data Bank, *ISS* Injury Severity Score, *RTS* Revised Trauma Score, *SBP* systolic blood pressure, *GCS* Glasgow Coma Scale score, *RR* respiratory rate

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The AIC was used to identify the model that best explains the data with a minimum of free parameters. The model having the lower AIC is considered to be the better model.

We compared the area under the receiver operating characteristic curve (AUROCC) (which distinguishes between survival and non-survival, and varies between 0.5 and 1 [1 = perfect discrimination]), and accuracy (the proportions of survivors with Ps $\geq$ 0.5 and proportions of non-survivors with Ps < 0.5) among the models.

The JMP 9.0 (SAS Institute Inc., Cary, NC) and SAS 9.1 (SAS Institute Inc., Cary, NC) software packages were used for statistical analyses.

Results

Table 1 shows the demographics of each data set, including the distributions of predictor variables and the proportions of survivors. The JTDB seems to have data of older and more severely injured BT patients than the Khon Kaen Trauma Registry. The proportions of patients whose RRs were more than 29/min or 6–9/min were quite low in the Khon Kaen data.

The survival proportion of younger patients (AY < 55, cAY = 0) was 88.13%, which was slightly higher than the survival proportion (81.25%) of the older patients (AY $\geq$ 55, cAY = 1) in the JTDB data. In the Khon Kaen data, the difference can hardly be recognized between the survival proportion (95.86%) of the older patients (AY $\geq$ 55, cAY = 1) and the survival proportion (95.92%) of the younger patients (AY < 55, cAY = 0).

Table 2 shows the AIC of each model. The AIC of the model using AY was lower than that of the model using cAY (used by the TRISS method). In both data groups, the model using ISS, AY and cGCS, cSBP, and cRR instead of the RTS demonstrated the lowest AIC, 4,305 and 1,105, respectively. In the Khon Kaen data, no additional reduction of the AIC was shown in the model with the cRR variable compared with the model without cRR.

The estimated coefficients of the logistic regression models derived from the JTDB data are shown with the original TRISS coefficients in Table 3. As discussed in previous reports [10], each coefficient of cSBP, cGCS, and cRR on the TRISS line of the table is obtained by multiplying by the coefficient of RTS, namely 0.8085, in the TRISS equation using the AIS90. All estimated coefficients were significant. However, the intercept of the model using the ISS, AY, cSBP, and cGCS was not significant.

Table 2 AIC for each model

Regression model	AIC Japan	AIC Khon Kaen
ISS, RTS, cAY	4,372	1,120
ISS, RTS, AY	4,305	1,109
ISS, AY, cSBP, cGCS, cRR	4,305	1,105
ISS, AY, cSBP, cGCS	4,347	1,105

Regression models are represented by their predictor variables

AY age year, *cAY* coded value of AY, *cSBP* coded value of systolic blood pressure, *cGCS* coded value of Glasgow Coma Scale score, *cRR* coded value of respiratory rate

Table 3 Coefficients of logistic regression models of Japanese data

Regression model	Intercept	βISS	βRTS	βAY	βcAY	βcSBP	βcGCS	βcRR
TRISS (AIS90)	−0.4499	−0.0835	0.8085	×	−1.743	0.5923	0.7574	0.2351
ISS, RTS, cAY	−1.9502*	−0.0679*	1.0096*	×	−1.492*	×	×	×
	(0.1812)	(0.00310)	(0.024)		(0.086)			
	[115.85]	[479.6]	[1,723]		[297.6]			
ISS, RTS, AY	−0.76266*	−0.0710*	1.0256*	−0.0379*	×	×	×	×
	(0.2011)	(0.00316)	(0.024)	(0.00198)				
	[14.38]	[504.7]	[1,718]	[367.1]				
ISS, AY, cSBP, cGCS, cRR	−1.0723*	−0.0711*	×	−0.0383*	×	0.7370*	0.9318*	0.4243*
	(0.2616)	(0.00317)		(0.00199)		(0.0496)	(0.0281)	(0.0604)
	[16.79]	[502.2]		[369.9]		[221.2]	[1096.9]	[49.3]
ISS, AY, cSBP, cGCS	−0.3375	−0.0707*	×	−0.0369*	×	0.9017*	0.9814*	×
	(0.2059)	(0.00314)		(0.00196)		(0.0410)	(0.0273)	
	[2.69]	[508.6]		[354.4]		[483.3]	[1,290]	

Regression models are represented by their predictor variables

β regression coefficients

AIS abbreviated injury scale, *ISS* Injury Severity Score, *RTS* Revised Trauma Score, *AY* age year, *cAY* coded value of AY, *cSBP* coded value of systolic blood pressure, *cGCS* coded value of Glasgow Coma Scale score, *cRR* coded value of respiratory rate

* $p < 0.05$ (standard error) [χ^2 value]

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The estimated coefficients of the logistic regression models derived from the Khon Kaen data are shown with the original TRISS coefficients in Table 4. Each coefficient of cSBP, cGCS, and cRR is obtained by multiplying by 0.9544, that is, the coefficient of RTS of the TRISS equation using the AIS85. The variable of cRR had a very low χ^2 value, and was not significant ($p = 0.06$). The intercepts of the models using ISS, AY, cSBP, and cGCS with or without cRR were not significant.

All models, including the models without the cRR variables, had AUROCCs > 0.95 in both data sets (Table 5). The model using AY, ISS, and RTS provided better AUROCC than the model with the variables of cAY, ISS, and RTS in both groups of data.

Discussion

Tables 3 and 4 reveal that the χ^2 value of cAY is much smaller than that of AY. Therefore, categorization (coding) of AY with a cut-off value of 55 reduces the amount of information and the discriminative abilities in both countries. This seems to be due to no obvious increase in mortality above the AY of 55 in the registry data of both Japan and Thailand, unlike that seen in the Major Trauma Outcome Study (MTOS) of the United States, from which the TRISS model was derived [1, 2]. Thus, we recommend the use of AY instead of cAY as a predictor variable in Asian countries. From the results of their M-statistic score calculation, Fujita et al. [11] concluded that the trauma population of a particular trauma center in Tokyo that has been participating in the JTDB differed significantly from that of the MTOS. Fujita et al. pointed out that modified TRISS coefficients should be adapted for outcome assessment based on the location of the injured population.

Our previous study [7] revealed that information on RR was missing in up to 18.8% of the JTDB data (2004–2007). In applying the model using only ISS, AY, cSBP, and cGCS, the Ps could be estimated in 38.1% of the patient data from which Ps was not calculated by the TRISS method. The model had sufficiently high discriminative ability (AUROCC = 0.923). Bouamra et al. [12] reported that a successful model (AUROCC = 0.947) using only GCS instead of RTS dramatically reduced the number of missing cases in the United Kingdom. However the equation of Bouamra et al. was more complicated than that of the TRISS method. Our recent study [13] demonstrated that simpler models using cGCS or cSBP with cAY and maximum AIS (or its coded value) showed high AUROCCs of >0.94, which seems to be suitable in more resource-constrained countries.

We found no additional reduction of the AIC in the model using cRR than the model without cRR in the Khon Kaen data. Moreover, multivariate analysis failed to show cRR as an independent predictor variable (Table 4). Information bias about collecting RR data might exist in

Table 4 Coefficients of logistic regression models of Khon Kaen data

Regression model	Intercept	βISS	βRTS	βAY	βcAY	βcSBP	βcGCS	βcRR
TRISS (AIS 85)	−1.2470	−0.0768	0.9544	×	−1.9052	0.6992	0.8941	0.2775
ISS, RTS, cAY	−0.7241	−0.0710*	0.8128*	×	−0.583*	×	×	×
	(0.3502)	(0.00548)	(0.0487)		(0.2509)			
	[4.27]	[168.2]	[278.5]		[5.40]			
ISS, RTS, AY	−0.2377*	−0.0707*	0.8215*	−0.0184*	×	×	×	×
	(0.3741)	(0.00550)	(0.0489)	(0.00463)				
	[0.4038]	[165.3]	[281.8]	[15.74]]				
ISS, AY, cSBP, cGCS, cRR	−0.1130	−0.0710*	×	−0.0177*	×	0.4458*	0.9669*	0.0960
	(0.4738)	(0.00562)		(0.00469)		(0.1019)	(0.0828)	(0.0606)
	[0.0569]	[159.8]		[14.29]		[19.13]	[136.4]	[2.515]
ISS, AY, cSBP, cGCS	−0.1565	−0.0731*	×	−0.0174*	×	0.4392*	1.0525*	×
	(0.4747)	(0.00546)		(0.00469)		(1.843)	(282.4)	
	[0.1087]	[179.0]		[13.80]		[18.43]	[282.4]	

Regression models are represented by their predictor variables

β regression coefficients

AUROCC area under receiver-operating characteristic curve, *AIS* abbreviated injury scale, *ISS* Injury Severity Score, *RTS* Revised Trauma Score, *AY* age year, *cAY* coded value of AY, *cSBP* coded value of systolic blood pressure, *cGCS* coded value of Glasgow Coma Scale score, *cRR* coded value of respiratory rate

* $p < 0.05$ (standard error) [χ^2 value]

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Table 5 AUROCC and accuracy of models

Regression model	AUROCC Japan	Accuracy Japan (%)	AUROCC Khon Kaen	Accuracy Khon Kaen (%)
TRISS (USA)	0.9625	92.74	0.9628	96.33
ISS, RTS, cAY	0.9598	94.16	0.9657	96.60
ISS, RTS, AY	0.9624	94.38	0.9666	96.56
ISS, AY, cSBP, cGCS, cRR	0.9624	94.37	0.9667	96.66
ISS, AY, cSBP, cGCS	0.9617	94.25	0.9667	93.77

Regression models are represented by their predictor variables

AUROCC area under receiver-operating characteristic curve, *AIS* abbreviated injury scale, *ISS* Injury Severity Score, *RTS* Revised Trauma Score, *AY* age year, *cAY* coded value of AY, *cSBP* coded value of systolic blood pressure, *cGCS* coded value of Glasgow Coma Scale score, *cRR* coded value of respiratory rate

the Khon Kaen Trauma Registry, because the proportions of patients whose RR was >29/min or 6–9/min were quite small (Table 1). Thus, utilization of the model without cRR is recommended. In the model without cRR, the intercept can be zero for simplification because it was not statistically significant (Tables 3 and 4).

Finally, we should mention the limitations of the present study. Because of large amount of missing data for the TRISS predictors and outcome in the JTDB data, we could develop the models using 61.3% from registered BT patients. Recently, Tohira et al. [14] revealed that only 58.2% of the registered data of the JTDB from 2004 to 2008 had sufficient data on the TRISS Ps estimation and outcome, and that statistically significant differences existed in mean AY (74.8 vs. 51.2), in mean RTS (6.90 vs. 6.68), and in mean ISS (15.1 vs. 17.3) between outcome missing data and non-outcome missing data. They pointed out that selection bias may exist in research outputs gained from the extracted data from the JTDB by excluding patients with missing outcome and the TRISS predictors. However, we could demonstrate almost the same results with the Khon Kaen Trauma Registry data, which are substantially different from the JTDB in AY, RTS, and ISS. Thus, the assumable selection bias might not be important for interpretation of the results. At present, the tendency of the logistic regression models revealed in this study is observed only in the JTDB and the Khon Kaen Trauma Registry in Thailand. For generalization, our results must be verified by data from other Asian countries.

The JTDB has been using the AIS 90 [5], and The Khom Kaen trauma registry has been using the AIS 85 [6]. Both of these are out of date and insufficient for contemporary coding of injuries. Japan and Thailand has been preparing for utilization of AIS 2005 update 2008 [15], but implementation of nationwide coding under that version is not realized in either country. In the future, we should conduct this kind of research once again under the newest measure for quality assurance of our results.

Conclusions

For better prediction of Ps, the real number of AY should be used as a predictor variable instead of the coded value of AY in the TRISS method. The logistic regression model with the predictor variables of ISS, AY, and the coded value of SBP, GCS, and RR estimates the best prediction.

Information about RR seems to be less important for BT victims in Asian countries than in the United States, where the TRISS method was developed. The logistic regression model without cRR can provide the Ps with almost the same discriminative ability as the model that uses RR.

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Conflict of interest None.

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The development of simple survival prediction models for blunt trauma victims treated at Asian emergency centers

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Abstract

Background: For real-time assessment of the probability of survival (Ps) of blunt trauma victims at emergency centers, this study aimed to establish regression models for estimating Ps using simplified coefficients.

Methods: The data of 10,210 blunt trauma patients not missing both the binary outcome data about survival and the data necessary for Ps calculation by The Trauma and Injury Severity Score (TRISS) method were extracted from the Japan Trauma Data Bank (2004-2007) and analyzed. Half (5,113) of the data was allocated to a derivation data set, with the other half (5,097) allocated to a validation data set. The data of 6,407 blunt trauma victims from the trauma registry of Khon Kaen Regional Hospital in Thailand were analyzed for validation. The logistic regression models included age, the Injury Severity Score (ISS), the Glasgow Coma Scale score (GCS), systolic blood pressure (SBP), respiratory rate (RR), and their coded values (cAGE, 0-1; cISS, 0-4; cSBP, 0-4; cGCS, 0-4; cRR, 0-4) as predictor variables. The coefficients were simplified by rounding off after the decimal point or choosing 0.5 if the coefficients varied across 0.5. The area under the receiver-operating characteristic curve (AUROCC) was calculated for each model to measure discriminant ability.

Results: A group of formulas (log (Ps/1-Ps) = logit (Ps) = -9 + cISS - cAGE + cSBP + cGCS + cRR/2, where -9 becomes -7 if the predictor variable of cRR or cISS is missing) was developed. Using these formulas, the AUROCCs were between 0.950 and 0.964. When these models were applied to the Khon Kean data, their AUROCCs were greater than 0.91.

Conclusion: These equations allow physicians to perform real-time assessments of survival by easy mental calculations at Asian emergency centers, which are overcrowded with blunt injury victims of traffic accidents.

Background

The Trauma and Injury Severity Score (TRISS) [1,2] is a standard method for estimating survival and is often used to evaluate the quality of trauma care. However, it requires the Injury Severity Score (ISS) [3], the Revised Trauma Score (RTS) [4] calculated based on the Glasgow Coma Scale score (GCS), the systolic blood pressure (SBP), the respiratory rate (RR), and the categorically coded value of age (cAGE). The formulas are:

Probability of survival (Ps) = 1/(1 + e-b),
where b = - 0.4499 - 0.0835*ISS + 0.8085*RTS -1.743*cAGE [2]
RTS = 0.9368*cGCS + 0.7326*cSBP + 0.2908*cRR [4]

Collecting all of this information and performing such complex calculations are not feasible in the clinical setting at emergency centers. For clinicians, especially emergency physicians, it is hoped that a way to predict survival of trauma victims more easily without a significant decrease in accuracy could be developed.

This study aimed to establish regression models for quick assessment of Ps for blunt trauma (BT) victims based on simplified coefficients that could be used even when the variable of RR or the variable of ISS is missing. The former is frequently missing in the trauma registry data of Japan [5], and the latter is rarely determined during the early stage of trauma management in most cases.

Methods

Study design, population, and settings

A retrospective observational study was conducted to create Ps prediction models with simple coefficients for BT victims in Japan and Thailand.

Once approval was obtained from the trauma registry committee of the Japanese Association for the Surgery of Trauma, deidentified, anonymous data from the Japan Trauma Data Bank (JTDB), with which 144 Japanese hospitals have been involved since 2004, were used [6].

Data (10,210) that were not missing both outcome data about survival and the predictors necessary for Ps calculation by the TRISS method were collected from BT patients (17,564) registered in the JTDB from 2004 to 2007. Half (5,113) of the data was randomly allocated to a derivation data set, with the remaining half (5,097) allocated to a validation data set.

Table 1 Coded (categorized) values

Coded value	GCS score	Systolic blood pressure (SBP mmHg)	Respiratory rate (RR / min)	Age	ISS
4	13-15	>89	10-29		16>
3	9-12	76-89	>29		24-16
2	6-8	50-75	6-9		40-25
1	4-7	1-49	1-5	>55	65-41
0	<4	No pulse	0	0-55	>65

ISS: Injury Severity Score
GCS: Glasgow Coma Scale

For international validation, with the permission of the hospital, the proposed equations were applied to 6,409 of 6,667 BT patients injured in the Khon Kaen District in Thailand between January 2005 and December 2008 and collected in the Khon Kaen Regional Hospital Trauma Registry, where data have been collected since 1997. This hospital is one of the World Health Organization (WHO) collaborating centers for injury prevention and safety promotion. The data of two patients were excluded because they were erroneous.

The independent variable was survival (survival=1; non-survival=0). Age, the ISS, the GCS, SBP, RR, and their coded values (cAGE, cISS, cSBP, cGCS, cRR), defined in Table 1, were used as predictor variables. The GCS, SBP, RR, and age were coded according to the RTS [4] and the TRISS method [1,2]. For ISS categorization to cISS, recursive partitioning, which is an exploratory technique to split a dataset into increasingly homogeneous subgroups having the greatest difference between the groups at each stage, was conducted with reference to previous literature [7,8].

Table 2 Distribution of Variables

		Derivation Data	Validation Data	Khon Kaen Data
Number		5113	5097	6409
cAGE	0	58.0%	58.5%	87.6%
	1	42.0%	41.5%	12.4%
RTS		7.8 [6.9, 7.8]	7.8 [6.9, 7.8]	7.8 [7.8, 7.8]
cBP	4	85.0%	85.3%	95.9%
	3	3.2%	3.4%	1.6%
	2	2.6%	2.6%	1.1%
	1	1.3%	1.1%	0.2%
	0	7.9%	7.6%	1.2%
cGCS	4	72.4%	73.4%	89.4%
	3	7.5%	7.0%	3.0%
	2	6.1%	5.9%	4.6%
	1	2.6%	2.6%	1.1%
	0	11.4%	11.1%	1.9%
cRR	4	76.0%	76.8%	92.1%
	3	15.0%	14.8%	0.2%
	2	0.4%	0.4%	0.0%
	1	0.2%	0.1%	0.2%
	0	8.4%	7.9%	7.5%
ISS		17.6 ±14.2	17.4 ±14.0	9.5 ±10.1
cISS	4	51.1%	51.0%	83.2%
	3	21.2%	22.3%	6.9%
	2	20.4%	19.7%	7.4%
	1	5.3%	5.2%	2.3%
	0	2.0%	1.8%	0.2%
Survival		82.1%	83.1%	95.9%

cAGE, coded value of age; RTS, the Revised Trauma Score shown by median [IQR]; cBP, coded value of systolic blood pressure; cGCS, coded value of the Glasgow Coma Scale score; cRR, coded value of respiratory rate; ISS, the Injury Severity Score shown by mean ± standard deviation; cISS, coded value of the Injury Severity Score

Analyses

Logistic regression analyses were applied to establish the models. The maximum likelihood estimation was used as the method of coefficient estimation for each model.

For model selection, Akaike's Information Criterion (AIC) [9], -2log (maximum likelihood) +2 (number of adjusted parameters), was used. The model having the lower AIC is considered to be better fitting. The area under the receiver-operating characteristic curve (AUROCC), which distinguishes between survival and non-survival, and varies between 0.5 (=no discrimination) and 1 (=perfect discrimination), of each model was also measured.

The coefficients were simplified by rounding off after the decimal point or choosing 0.5 if it was nearer to the coefficients than 0 or 1.

The JMP 9.0 (SAS Institute Inc.) and SAS 9.1 (SAS Institute Inc.) software packages were used for statistical analyses.

The protocol of the present study was approved by the Ethics Committee of the National Center for Global Health and Medicine.

Results

Distributions of predictor variables and the proportion of survivors of each data set are shown in Table 2. The characteristics were substantially different between the Khon Kaen data and the JTDB data, in which both the derivation data and the validation data were similar.

Table 3 AIC for each Model

Predictor variables of each regression model	AIC
TRISS	1988
ISS, RTS, cAGE	**1788**
ISS, cAGE, cBP, cGCS, cRR	**1791**
cISS, cAGE, cBP, cGCS, cRR	**1732**
cISS, cAGE, cBP, cGCS	**1748**
cISS, cAGE, cGCS, cRR	**1819**
cISS, cBP, cGCS, cRR	**1846**
cISS, cBP, cGCS,	**1854**
cAGE, cBP, cGCS, cRR	**1987**
cAGE, cBP, cGCS	2000
cISS, cAGE, cGCS	2101
cISS, cAGE, cBP, cRR	2017
cISS, cAGE, cBP	2024

AUROCC, The area under the receiver-operating characteristic curve; cAGE, coded value of age; RTS, the Revised Trauma Score; cBP, coded value of systolic blood pressure; cGCS, coded value of the Glasgow Coma Scale score; cRR, coded value of respiratory rate; ISS, the Injury Severity Score; cISS, coded value of the Injury Severity Score

The AIC and the AUROCC of each model are shown in Table 3. Over the set of models, the model with cISS, cAGE, cSBP, cGCS, and cRR as predictor variables showed the smallest AIC (1732), which was even smaller than the AIC for the model using ISS, RTS, and cAGE. Initially, six models that used only coded values and had lower AICs than that of the original TRISS model (1988) were selected for simplification. Then, the two models that had a higher AUROCC than the TRISS model and one model that does not require cISS were selected.

Table 4 Coefficients of Logistic Regression Models

Models with predictor variables	Intercept	β(c)ISS	βRTS	βcAGE	βcGCS	βcBP	βcRR
Original TRISS	-0.4499	-0.0835	0.8085	-1.743	0.7574	0.5923	0.2351
ISS, RTS, cAGE	-1.7162* (0.279) [37.8]	-0.0675* (0.005) [181]	0.9301* (0.0368) [639]	-1.439* (0.137) [111]	*	*	*
ISS, cAGE, cSBP, cGCS, cRR	-1.8646 (0.340) [30.2]	-0.0678* (0.0050) [181]	*	-1.452* (0.137) [112]	0.846* (0.047) [328]	0.670* (0.077) [75.8]	0.346* (0.090) [14.9]
cISS, cAGE, cSBP, cGCS, cRR	-6.281* (0.335) [351]	**1.058*** (0.070) [227]	*	**-1.404*** (0.137) [104]	**0.777*** (0.047) [267]	**0.718*** (0.077) [87.5]	**0.370*** (0.090) [17.0]
cISS, cAGE, cSBP, cGCS	-5.734* (0.283) [410]	**1.038*** (0.069) [225]	*	**-1.348*** (0.136) [98.8]	**0.841*** (0.045) [345]	**0.889*** (0.063) [202]	×
cAGE, cSBP, cGCS, cRR	-4.663* (0.357) [170]	×	*	**-1.328*** (0.129) [105]	**1.025*** (0.044) [540]	**0.843*** (0.077) [122]	**0.349*** (0.094) [13.7]

Bx, regression coefficients; *, p<0.001; (standard error); [likelihood ratio chi-square value]; PVs, predictor variables; cAGE, coded value of age; RTS, the Revised Trauma Score; cBP, coded value of systolic blood pressure; cGCS, coded value of the Glasgow Coma Scale score; cRR, coded value of respiratory rate; ISS, the Injury Severity Score; cISS, coded value of the Injury Severity Score

The estimated coefficients of the logistic regression models derived from the training data are shown with the original TRISS coefficients in Table 4. Each coefficient of cSBP, cGCS, and cRR on the TRISS line of the table was obtained from each coefficient of the RTS (0.7326, 0.9368 and 0.2908, respectively) multiplied by the coefficient of the RTS (0.8085) of the TRISS method using the 1990 version of AIS [2]. All estimated coefficients were significant.

The coefficients of cISS, cAGE, cSBP, and cGCS in Table 4 were rounded off after the decimal point, and the coefficient of cRR was regarded as 0.5.

The three developed models were as follows:

logit (Ps) = intercept +β= - 9 + cISS - cAGE+ cSBP + cGCS + cRR/2,

logit (Ps) = intercept +β= - 7 + cISS - cAGE+ cSBP + cGCS,

logit (Ps) = intercept +β= - 7 - cAGE+ cSBP + cGCS + cRR/2,

where logit (Ps) = log (Ps/1-Ps)

As for the intercept of each model, the nearest integer (-7 or -9) to -β, where actual survival proportions just crossed 50% in the derivation data set, namely logit (Ps = 0.5) = 0, was chosen (Table 5).

Table 5 β value and Actual Survival Percentage in the Derivation Data

β	cISS−cAGE+ cSBP+cGCS+cRR/2 Survival (%)	cISS−cAGE + cSBP+cGCS Survival (%)	−cAGE+cSBP+ cGCS+cRR/2 Survival (%)
-1			
0			
1			
2	0	0	0
3	1.7	11.8	30
4	14	19.7	28
5	30	26.8	33.8
6	32.4	40.3	47.6
<u>7</u>	28.8	**51.5**	**66.5**
8	38.3	75.3	82.7
<u>9</u>	**58.3**	88.5	96.5
10	78.7	96.7	99.5
11	91.4	98.6	
12	96.1	99.9	
13	98.5		
14	99.9		

If only one variable cannot be obtained, then a zero value is given for the missing predictor variable in each equation. Actual survivals just crossed 50% around the nearest integer value of β (7 or 9)

cAGE: coded value of age, cBP: coded value of systolic blood pressure, cGCS: coded value of the Glasgow Coma Scale score, cRR: coded value of respiratory rate, cISS: coded value of the Injury Severity Score

For all models, including the models with missing variables, the AUROCCs were greater than 0.95 (Table 6). The same results were also shown for the Japanese validation data.

The AUROCCs of each model, applied to the data of the Khon Kaen Trauma Center in Thailand, are also shown in Table 6. The two models with cISS, cAGE, cSBP, cGCS as predictor variables showed AUROCCs greater than 0.96, almost the same as that of the TRISS model. For the model without cISS, the AUROCC was even greater than 0.91.

Discussion

The TRISS [1,2] method is the most popular method of survival estimation. However, it is not a suitable tool for quick assessment of survival probability in the clinical setting, because it requires complicated calculations using the ISS, for which precise coding of the Abbreviated Injury Scale (AIS) [10] is required, and the RTS, which also has complex coefficients for cGCS, cSBP, and cRR. Therefore, we tried to simplify Ps prediction without a significant decrease in accuracy for clinical rather than for administrative uses. Without substantial loss in the AUROCC compared with the original TRISS, the present study showed that logit (Ps) can be obtained even with a marked simplification of variables and intercepts (Table 6), sufficient to enable its mental calculation. In any case where logit (Ps) is greater than 0, by easy mental calculation it provides for quick determination as to whether the Ps is greater than 0.5, which is considered the lower limit for decision making about unexpected trauma death.

Table 6 Proposed Regression Models with Simplified Coefficients

Logit (Ps) of each model	AUROCC JTDB derivation data	AUROCC JTDB validation data	AUROCC Khon Kaen registry data
-9 + cISS - cAGE + cSBP + cGCS + cRR/2	0.9635	0.964	0.9619
-7 + cISS - cAGE + cSBP + cGCS	0.9633	0.9622	0.9601
-7 + cAGE + cSBP + cGCS + cRR/2	0.9503	0.9524	0.9115

AUROCC, The area under the receiver-operating characteristic curve; cAGE, coded value of age; cBP, coded value of systolic blood pressure; cGCS, coded value of the Glasgow Coma Scale score; cRR, coded value of respiratory rate; cISS, coded value of the Injury Severity Score

In addition to a recent report [11], the present study also directly used cSBP, cGCS, and cRR as predictor variables instead of the RTS. The ISS was coded based on our recent paper [7], and predictive models using the cISS were successfully constructed. Some of these models showed even smaller AICs or larger AUROCCs than those of the models using the ISS (Table 3). An important benefit of using the cISS instead of the ISS is that we can determine the cISS even without the information of the third most severe AIS score, which is sometimes lacking in physicians' records, as shown in Table 7, which was constructed with reference to Copes et al. [7]. This shows that, by dividing all variables into categories with adequate intervals, it is possible to perform valid coding in cases where only an approximate value, not the exact value of ISS, is known.

Table 7 Relationship between Coded ISS and Most Severe Abbreviated Injury Scale (AIS)

Coded ISS	ISS Interval	**Most severe AIS** / <u>2nd most severe AIS</u> Included
4	<16	**3**
3	16-24	**4**
2	25-40	**5** or **4** & <u>3</u>
1	41-65	Two **5** or **5** & <u>4</u>
0	>65	Two **5** & <u>4</u> or Three **5** or **6**

ISS: the Injury Severity Score

Moreover, it was also shown that even if the cISS is undetermined, Ps calculation is nevertheless possible using just the age and vital sign factors, with only a slight decline in the AUROCC. This means that it is possible to predict Ps with high accuracy even for initial assessment at emergency centers in cases of undetermined anatomical severity. If a quick reference chart of Ps like Table 8 is prepared and kept in the pocket of physicians with Tables 1 and 7, Ps can be predicted without a computer. It can be used for hospital triage during initial management in case of a large number of BT victims, especially in multiple traffic or railroad accidents.

In Japan, RR information is frequently deficient [5], but with the regression equation presented in this study, even without information on cRR, only a slight decline in AUROCC is seen. As shown in Table 4, cRR had the lowest chi-square value in each model. This indicates that, based on their experience, Japanese surgeons or emergency physicians appear to have realized that RR is a less important indicator for survival in BT patients. From the results of Table 6, RR also seems to be unimportant in Thailand, because the models without cRR showed only a slight decline in the AUROCC. The deficiency that most increases the AIC and reduces

Table 8　Probability of Survival (Ps) Chart

b1–3	<-3	-2.5	-2	-1.5	-1	-0.5	0	0.5	1	1.5	2	2.5	>3
Ps	<0.05	0.08	0.12	0.18	0.27	0.38	0.5	0.62	0.73	0.82	0.88	0.92	0.95

Ps = 1/(1 + e-b1~3)
b1 = -9 + cISS - cAGE + cSBP + cGCS + cRR/2
b2 = -7 + cISS - cAGE + cSBP) + cGCS
b3 = -7 - cAGE + cSBP + cGCS + cRR/2

The AUROCC is cGCS (Table 3), which had the highest chi-square value in each model (Table 4). Thus, the level of consciousness is the most important factor at the time of survival prediction. The importance of information on consciousness level was also proven in a different way in our recent paper [12]

The present study had a few limitations that might have biased the results. Because of missing data related to survival and the predictors, the Ps calculation of the TRISS could be done in only 58% of 17,564 BT patients registered in the JTDB. Tohira et al. [13] pointed out that significant differences existed in age, RTS, and ISS between outcome-missing data and non-outcome-missing data, and that selection bias may exist in research outputs gained from the extracted data from the JTDB by excluding patients with missing outcomes and the TRISS predictors. Thus, it seems to be of great worth to validate the developed models with the Khon Kaen trauma registry data, which are substantially different from the JTDB data in age, RTS, and ISS. At present, the simplified models in this study have been validated only with the Japan Trauma Registry data and the Khon Kaen Trauma Registry data in Thailand. If the results of the present study can be verified with other data from around the world, especially from middle-income countries where traffic injuries are rapidly increasing [14], it will be of greater use internationally.

Conclusion

The proposed, simplified equations allow quick assessments of Ps by simple mental calculation, which should prove useful at Asian emergency centers overcrowded with traffic accident victims suffering from blunt trauma.

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