Table 4　Area under Receiver Operating Curves & Accuracy of Models

Regresion model	AUC Derivation	Accuracy Derivation	AUC Validation	Accuracy Validation
ISS, AGE, cBP, cGCS, cRR	0.9674	93.16%	0.9670	93.69%
cISS, AGE, cBP, cGCS, cRR	0.9687	93.39%	0.9672	93.39%
cISS, cAGE, cBP, cGCS, cRR	0.9648	93.32%	0.9650	93.55%
cISS, cAGE, cBP, cGCS	0.9649	93.20%	0.9636	93.42%
cISS, cAGE, cGCS, cRR	0.9609	93.09%	0.9610	93.45%
cISS, cAGE, cGCS	0.9561	92.48%	0.9541	92.52%

AUC：aria under receiver operating characteristic curve

Table 5　Proposed Regression Model with Simplified Coefficients

Intercept	βcISS	βcAGE	βcBP	βcGCS	βcRR
−8〜−3	1	−1	1	1	1/2

$b = -8 + cISS - cAGE + cBP + cGCS + cRR/2$

$$Ps = \frac{1}{1+e^{-b}}$$

If cRR and/or cBP are/is missing, then βcRR and/or βcBP = 0.
If cRR or cBP is missing, Then intercept = −7 or −5, respectively.
If cRR and cBP are both missing, Then intercept = −3.

Regression model	AUC Derivation	Accuracy Derivation	AUC Validation	Accuracy Validation
cISS, cAGE, cBP, cGCS, cRR	0.9635	93.20%	0.9639	93.40%
cISS, cAGE, cBP, cGCS,	0.9633	93.02%	0.9622	92.84%
cISS, cAGE, cGCS, cRR	0.9599	93.08%	0.9589	92.86%
cISS, cAGE, cGCS	0.9547	92.47%	0.9522	92.54%

れらとほぼ一致していた．

本研究では，より小さい方がよりよい回帰モデルと考えられている赤池情報量基準：AIC＝−2 log(最大尤度)＋2（推定すべきパラメータ数）を用いてモデル間の適合度比較を行った[13]．その結果，ISSそのものよりcISSを説明変数とする方が，AICがより小さいモデルを得ることができた．最もAICが低かったのは，説明変数として実変数のAGEとコード化されたcISS, cBP, cGCS, cRRを用いたものであった（Table 2）．

以前の論文[4)6)]が示すように，我が国においてよりよいロジスティック回帰式を作成するためには，年齢は実変数として用いた方がよい．しかしながら，カテゴリーに分けてコード化することは，AICは若干大きくなるが，およそその年齢がわかれば，詳しい年齢がわからなくても，Psを計算できるという利点もある．年齢のみならず変数を一定の間隔をもってコード化することは，変数の正確な値がわからなくても妥当なコード化ができる可能性があり，ISSの詳細な値がわからないた

Table 6　Relationship between Coded ISS & AIS

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

ISS：Injury Severity Score
AIS：Abbreviated Injury Scale

めにPsが算出できないことを，回避できる可能性がある．Table 6に示したように，最高のAbbreviated Injury Scale（以下AIS）と同一身体部位のカテゴリーでない2番目に高いAISがわかれば，コード化されたcISSの値が決まってくる．

また，筆者は前論文[6]で，呼吸数の情報が欠損していても，ほとんど精度が下がらない生存予測式を導いたが，本研究ではさらに収縮期血圧を省いても，よい精度の生存予測式ができることを示した．Bouamraら[14]は，RTSの代わりにGCSのみを用いて精度のよい生存予測式が導けることをすでに示しているが，その代わりに性別や年齢要素をさらにカテゴリー化するなどの考慮が必要であった．本研究では，それらの説明変数を単純に式から削除しても，あまり予測精度が下がらない回帰モデルを提示することができた．

さらに，係数をTable 5のように大胆に単純化しても，ロジスティック回帰式の予測精度はあまり下がらないことが，本研究にて明らかになった．これにより，複雑な計算を行わなくても b＝logit (Survival）を得ることができ，bが正の値であれば，Psは0.5以上であると予測することができる．この式を用いれば，実際の臨床現場でもリアルタイムにおよそその生存予想をすることが，可能となる．

結　語

説明変数として連続変数としての年齢，コード化されたISSと収縮期血圧，GCSスコア，呼吸数を用いることにより，日本の鈍的外傷患者により適した生存予測ロジスティック回帰式を作成し得た．また，説明変数から呼吸数もしくは収縮期血圧を省いた回帰式でもほぼ同等の予測精度をもち，係数を単純化して使用しやすい回帰式にしても予測精度は保たれることを証明した．

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文　献

1) Boyd CR, Tolson MA, Copes WS：Evaluating trauma care：the TRISS method. Trauma Score and the Injury Severity Score. J Trauma 1987；27：370-378.
2) Champion HR, Sacco WJ, Copes WS：Injury Severity Score again. J Trauma 1995；38：94-95.
3) 小関一英：外傷治療の質の評価－Preventable trauma death と TRISS method－．日外傷会誌 1990；13：88-98.
4) 小関一英，坂本哲也，杉本勝彦，ほか：Trauma registryによって構築された日本版TRISSによる外傷重症度評価法．日外傷会誌 2001；15：310-311.
5) 小関一英：検証：trauma registry．救急医学 2006；30：533-539.
6) 木村昭夫：我が国における鈍的外傷患者の生存予測ロジスティック回帰式の検討－日本外傷データバンクの解析から－．日外傷会誌 2010；24：15-20.
7) Baker SP, O'NeillB, HaddonW, et al：The Injury Severity Score：A method for describing patients with multiple injuries and evaluating emergency care. J Trauma 1974；14：187-196.
8) Champion HR, Sacco WJ, Copes WS, et al：A revision of the trauma score. J Trauma 1989；29：623-629.
9) Teasdale GM, Jennett B：Assessment of coma and impaired consciousness：A practical scale. Lancet 1974；7872：81-84.
10) Copes WS, Champion HR, Sacco WJ, et al：Injury Severity Score revisited. J Trauma 1988；28：69-77.
11) Osler T, Baker SP, Long W：A modification of the injury severity score that both improves accuracy and simplifies scoring. J Trauma 1997；43：922-925.
12) Osler TM, Roger FB, Badger GJ, et al：A simple mathematical modification of TRISS markedly improves calibration. J Trauma 2002；53：630-634.
13) 赤池弘次，甘利俊一，北川源四郎，ほか：赤池情報量規準－モデリング・予測・知識発見－．東京：共立出版，2007.
14) Bouamra O, Wrotchford A, Hopllis S, et al：A new approach to outcome prediction in trauma：a comparison with the TRISS model. J Trauma 2006；610：701-710.

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LOGISTIC REGRESSION MODELS FOR JAPANESE BLUNT TRAUMA VICTIMS : SECOND REPORT

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The aim of this study was to identify logistic regression models that more accurately predict survival among Japanese blunt trauma (BT) victims. Furthermore, this study aimed to establish a method for estimating the probability of survival (Ps) using simplified coefficients and that could be used even when some variables are missing. Data (12,975) including Ps calculated by the TRISS method, were collected from BT patients (17,564) registered in the Japan Trauma Data Bank (JTDB, 2004～2007), and half (6,487) of the data was randomly allocated to a derivation data set, with the remaining half (6,488) allocated to a validation data set. For logistic regression analysis, age, injury severity score (ISS), Glasgow coma scale score (GCS), systolic blood pressure (BP), respiratory rate (RR), and their coded values (cISS, cBP, cGCS, cRR) were used as independent variables. For validations, areas under curves (AUCs) of receiver-operating characteristic curves were compared. The model with age, cISS, cBP, cGCS, and cRR shows the best AUC of 0.9687 in the training data and 0.9672 in the validation data. For easier calculation, we made a similar model with simplified coefficients ($b = -8 + cISS - cAGE + cBP + cGCS + cRR/2$, where $Ps = 1/1 + e^{-b}$), which showed an AUC of 0.9635 in derivation and 0.9639 in validation. Modifications of this model without cRR and/or cBP can maintained AUC>0.95. These findings indicate that this equation allows real-time assessments of Ps that can be utilized by clinicians.

Key words : JTDB, TRISS, non-penetrating trauma, ISS

Care giver supervision and child injuries: consideration of different contexts when translating knowledge into practice

Shinji Nakahara,[1] Masao Ichikawa[2]

INTRODUCTION

Accumulating evidence shows that appropriate care giver supervision can reduce child injury risk.[1–4] In an editorial, Schwebel and Kendrick[5] indicated the necessity of translating such knowledge into practice, taking into consideration cultural and societal differences. This consideration is crucial when we transfer knowledge obtained in high-income countries (HICs) to low- and middle-income countries (LMICs) with differences in culture and society, living environments, and childcare patterns.

The editorial cited a debate in this journal 13 years ago that argued a lack of evidence to call for greater parental supervision, noting the abundance of empirical evidence available today compared with the scarcity at that time.[6] The older debate between Roberts[6] and Levene[7] raised two practical issues that should be clarified in devising culturally appropriate interventions, issues that we think are still valid: how childcare responsibilities should be shared among family members and society, and how strategies should be effectively balanced between supervision and environmental approaches. Without such considerations, the necessity of greater supervision may not be translated into practice, particularly in societies where care givers, mainly mothers, are overburdened with conflicting tasks, including household chores, and are faced with hazardous environments necessitating constant vigilance to protect their children.[8–11] Mothers will have problems providing better child protection unless they have access to childcare support. Thus, in this article, we explore ways to better achieve child safety by alleviating the difficulties that care givers face in protecting children.

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Challenges in LMICs

In LMICs, parents tend to have more difficulties than their counterparts in HICs in providing appropriate child supervision. This is mainly because of poor infrastructure and insufficient public policies to support families. For example, in rural areas where access to water and fuel is poor, fetching water and firewood is a time-consuming task, causing time conflicts with childcare. In urban areas, where people are likely to live in nuclear families and relatives' support is difficult to obtain, public childcare support (eg, daycare centres) is not readily available.

To make matters worse, mothers in low-income households have to earn money, resulting in conflicts between childcare and income-generating activities. When mothers work away from home, they are compelled to leave their young children attended by older siblings or even unattended, or supervise children themselves while working if substitute care givers (eg, out-of-home daycare, babysitters or family members) are either not available or not affordable.[12 13] At times, one or both parents have to migrate to seek employment in urban cities, leaving children with a single parent, grandparents or relatives. These practices increase child injury risk.[11 14]

Hazardous environments in LMICs may necessitate higher levels of supervision to ensure child safety.[11] Living environments, especially in deprived areas, are unacceptably hazardous to children. For example, in squatter settlements on a rail line in Bangladesh, children have a high risk of train-related injuries. A newspaper reported that a young child crawled onto the railway line while her mother was collecting firewood and lost her hand under the wheels of a train.[15] In many poor households, a kerosene stove is placed at floor level for cooking in a multipurpose room because there are only one or two rooms. Mothers cook while children are playing near the stove on the floor.[16] To protect children in such hazardous environments, even a momentary lapse in supervision is not permissible.

Can parents take all the responsibility?

Given the circumstances in LMICs, simply calling for better supervision would not yield change among most poor families. They cannot convert information on the necessity for child supervision into practice without appropriate environmental modifications and support. Even if they understood the necessity of supervision, poor working mothers would still have to make the difficult choice to leave young children at home unattended, because the negative effect of not earning money is more pressing than that of not supervising children.

Some would argue that lapses in supervision resulting in child injury can be regarded as inappropriate practice, or even child abuse.[1] If so, parents must keep their children close by taking them to the workplace or forgoing out-of-home employment. At home, mothers may need to restrict children's activities to reduce injury risk.

Taking young children to workplaces (eg, construction sites, streets and agricultural sites) to meet at least the proximity requirement of supervision could negatively affect child health, including—paradoxically—an increased risk of injuries.[12 13 17] If maternal opportunities to participate in economic activities are lost, lower household income could result in a lower standard of living or lowering of a mother's self-esteem and position in the household. Restricting the outdoor physical activities of children, although possibly reducing injuries, may also predispose children to obesity and cardiovascular diseases in the future.[18]

Covering for contextual deficiencies

Although childcare and child protection are primarily parental responsibilities, the difficulties parents face in providing appropriate child supervision result from deficiencies in contextual factors, which include social support, living environments, and macroeconomic and cultural circumstances.[19] Since most of these deficiencies are beyond parental control, public policy agendas should highlight the importance of covering for such deficiencies. This requires sharing responsibilities of childcare and environmental modification to reduce hazards.

Shared responsibility between individuals and communities

Providing social support, especially childcare support, has the potential to reduce child injury risk by addressing some of these deficiencies and influencing parental supervision, child characteristics, and environmental hazards.[1 19 20] In HICs, a transition in childcare is occurring: childcare responsibilities that used to be taken predominantly by parents are largely taken by society; childcare support schemes, including out-of-home daycare, paid parental leave, subsidies for childcare, and essential child health services, are becoming governmental duties.[21] Evidence from HICs shows various benefits of such support—for example, mothers can engage in income-earning activities, and early childhood education has the potential to benefit children from disadvantaged households in terms of educational attainment leading to a reduction in inequalities. However, as the childcare support in HICs is not targeted at injury reduction, the kind of support that is effective in reducing child injuries in various settings is not well understood.

In LMICs, with hazardous living environments and prevalent time conflicts affecting mothers, out-of-home daycare could be a promising measure to reduce injuries. Trained care givers can protect children from injury in safe play areas, providing them with more opportunities for various play activities, while parents can fully engage in economic activities without concern for the care and safety of their children. Obviously, such schemes should provide better child protection than being left unattended or cared for by preteen siblings. The effect of these arrangements on injury risk is, as yet, unclear. Some study findings in HICs support the idea that public daycare reduces child injury risk, but others do not, or show no conclusive results.[22 23] Further research is needed to determine more specifically the type of support needed in various situations, who can or cannot provide appropriate support, and how to improve non-parental supervision.

An example of such interventions in LMICs is a programme in Bangladesh that provides daycare for young children, protecting them while giving mothers free time to carry out domestic chores, although its impact on child injury prevention has not yet been evaluated.[16] Villages in Bangladesh are surrounded by natural bodies of water (canals, ditches and ponds) where children bathe and play, sometimes without adult supervision.[24 25] Drowning is therefore a leading cause of death among children aged 1−17 in Bangladesh; child drowning deaths are likely to occur when children are alone or with their peers in the middle of the day when their care givers are busy with household chores.[25] In such situations, institutional supervision is a potential intervention that resource-constrained communities can afford, whereas building barriers to all natural bodies of water is not feasible.[26]

Environmental factors and their interaction with behavioural factors

Behavioural approaches and environmental modifications are complementary injury-prevention strategies.[19 27] Public child safety policies could include strategies to help care givers to adapt living environments and modify environmental factors that they cannot control. Although improving home environments is primarily the responsibility of care givers, some environmental hazards are left unmodified when care givers have insufficient knowledge about the risks, no access to necessary resources such as low-cost safety devices, or no decision-making power.[28] In such situations, home visits by health workers or community volunteers may help, as they could provide knowledge about injury risk and offer counselling about how to modify environments and gain access to necessary resources.

Local and national public policies are required to modify environmental factors that care givers cannot control. In addition, international commitment may be required, given the limited resources in LMICs. International donors should incorporate safety measures into their development programmes, including donation of proven safety technology, although current international aid seems to be focused only on economic deficiencies.[29] Various environmental modifications, such as road safety facilities and traffic calming interventions, have proved effective in reducing child injuries in HICs. However, when transferred to LMICs, close attention must be paid to country-specific contexts, such as different economic, political and cultural situations.[27 30]

We should seek the optimum balance between supervision and environmental approaches to child injury prevention because these have different effects in different settings. Environmental modification may have a greater impact than supervision in some settings, but the converse may be true in other situations; or different levels of supervision may be required to maintain child safety depending on different child behaviours and environmental hazards.[1 2 5 7 19 20] When a baby is bathed in a bathtub, no environmental measure can substitute for a care giver's vigilant attention. Fencing is a proven intervention to prevent child drowning in a swimming pool, whereas supervision can fail because of lapses in care giver attention.[31]

However, we still do not know enough about the level and type of supervision that is appropriate in different settings or the kind and extent of environmental approaches that can reduce the necessary level of supervision.[5] Without such knowledge, the only possible advice to care givers is 'always watch your children', because child injury risk that depends on different environments remains unpredictable.[3] Studies that further investigate this issue should guide policy makers to provide the necessary support and environmental modifications and care givers to use the best supervision practices for various settings.

CONCLUSIONS

We do not deny the importance of the parental role in protecting children; however, excessive emphasis on care giver responsibilities can detract attention from the need for family-supportive policies and social reforms.[32] Parents in LMICs often face more difficulties in providing appropriate childcare than their counterparts in HICs because of the contextual factors noted above. People who develop policy agendas should pay more attention to the reasons for parents' inability to provide appropriate supervision, and intervention programmes should be designed taking into account the daily experience of the targeted population through needs assessment or involvement in programme design. Sharing childcare responsibilities between individuals and societies is an example of the social reforms necessary to support parents in providing appropriate child supervision[21]; although the effects of such supportive policies on child injury still need to be properly evaluated.[16]

We still do not have adequate knowledge about the ways in which contextual factors determine parental behaviours and modify their effect on child injury risk,

Key points

- In translating into practice the knowledge that supervision can reduce child injury risk, it is necessary to consider cultural and societal differences that dictate various childcare patterns, particularly in low- and middle-income countries, given that the knowledge was obtained in high-income countries.
- Social support may help care givers to provide appropriate child supervision more readily by sharing the responsibilities of childcare and supervision between individuals and societies.
- Interventions should efficiently combine behavioural and environmental approaches.
- Future research should investigate what support is necessary in various settings and how environmental modification can change the necessary level of supervision.

nor do we fully understand how policy and environmental interventions interact with behavioural approaches. With additional research into these issues, we may some day be able to answer the questions raised by Roberts[6] and Levene[7] 13 years ago, in order to guide policy makers and care givers today.

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REFERENCES

1. **Morrongiello BA.** Caregiver supervision and child-injury risk: I. Issues in defining and measuring supervision; II. Findings and directions for future research. *J Pediatr Psychol* 2005;**30**:536–52.
2. **Morrongiello BA,** Klemencic N, Corbett M. Interactions between child behavior patterns and parent supervision: implications for children's risk of unintentional injury. *Child Dev* 2008;**79**:627–38.
3. **Morrongiello BA,** Corbett M, Brison RJ. Identifying predictors of medically-attended injuries to young children: do child or parent behavioural attributes matter? *Inj Prev* 2009;**15**:220–5.
4. **Petrass L,** Blitvich JD, Finch CF. Parent/Caregiver supervision and child injury: a systematic review of critical dimensions for understanding this relationship. *Fam Community Health* 2009;**32**:123–35.
5. **Schwebel DC,** Kendrick D. Caregiver supervision and injury risk for young children: time to re-examine the issue. *Inj Prev* 2009;**15**:217–19.
6. **Roberts I.** Parental supervision: a popular myth. *Inj Prev* 1996;**2**:9–10.
7. **Levene S.** Is there more to parental supervision than political incorrectness? *Inj Prev* 1996;**2**:10–1.
8. **Apps P.** *Gender, time use, and models of the household.* Washington, DC: The World Bank, 2002.
9. **Ilahi N.** *The intra-household allocation of time and tasks: what have we learnt from the empirical literature? Policy research report on gender and development. Working paper no. 13.* Washington, DC: The World Bank, 2000.
10. **McGuire JS,** Popkin BM. *Helping women improve nutrition in the developing world. World Bank technical paper no. 114.* Washington, DC: The World Bank, 1990.
11. **Bartlett SN.** The problem of children's injuries in low-income countries: a review. *Health Policy Plan* 2002;**17**:1–13.
12. **Nakahara S,** Poudel KC, Lopchan M, *et al.* Availability of childcare support and nutritional status of children of non-working and working mothers in urban Nepal. *Am J Hum Biol* 2006;**18**:169–81.
13. **Ruiz-Casares M,** Heymann J. Children home alone unsupervised: modeling parental decisions and associated factors in Botswana, Mexico, and Vietnam. *Child Abuse Negl* 2009;**33**:312–23.
14. **Shen M,** Yang S, Han J, *et al.* Non-fatal injury rates among the "left-behind children" of rural China. *Inj Prev* 2009;**15**:244–7.
15. **Rahman S.** Living on the lines, chancing death: ordeals of children living by rail lines. *The Daily Star* 28 September 2005. http://www.thedailystar.net/2005/09/28/d509282501121.htm (accessed May 2010).
16. **Peden M,** Oyegbite K, Ozanne-Smith J, *et al*, eds. *World report on child injury prevention.* Geneva: World Health Organization, 2008.
17. **Hernandez P,** Zetina A, Tapia M, *et al.* Childcare needs of female street vendors in Mexico City. *Health Policy Plan* 1996;**11**:169–78.
18. **Roberts I.** Why have child pedestrian death rates fallen? *BMJ* 1993;**306**:1737–9.
19. **Peterson L,** Stern BL. Family processes and child risk for injury. *Behav Res Ther* 1997;**35**:179–90.
20. **Leininger LJ,** Ryan RM, Kalil A. Low-income mothers' social support and children's injuries. *Soc Sci Med* 2009;**68**:2113–21.
21. **United Nations Children's Fund.** *The child care transition, innocenti report card 8.* Florence: UNICEF Innocenti Research Centre, 2008.
22. **Roberts I.** Out-of-home day care and health. *Arch Dis Child* 1996;**74**:73–6.
23. **Toroyan T,** Roberts I, Oakley A, *et al.* Effectiveness of out-of-home day care for disadvantaged families: randomised controlled trial. *BMJ* 2003;**327**:906.
24. **Ahmed MK,** Rahman M, van Ginneken J. Epidemiology of child deaths due to drowning in Matlab, Bangladesh. *Int J Epidemiol* 1999;**28**:306–11.
25. **Rahman A,** Mashreky SR, Chowdhury SM, *et al.* Analysis of the childhood fatal drowning situation in Bangladesh: exploring prevention measures for low-income countries. *Inj Prev* 2009;**15**:75–9.
26. **Rahman A,** Miah AH, Mashreky SR, *et al.* Initial community response to a childhood drowning prevention programme in a rural setting in Bangladesh. *Inj Prev* 2010;**16**:21–5.
27. **Forjuoh SN.** Traffic-related injury prevention interventions for low-income countries. *Inj Control Saf Promot* 2003;**10**:109–18.
28. **Mull DS,** Agran PF, Winn DG, *et al.* Injury in children of low-income Mexican, Mexican American, and non-Hispanic white mothers in the USA: a focused ethnography. *Soc Sci Med* 2001;**52**:1081–91.
29. **Rose G.** Aid may make roads more dangerous than landmines. *BMJ* 2004;**328**:1260.
30. **Jones SJ,** Lyons RA, John A, *et al.* Traffic calming policy can reduce inequalities in child pedestrian injuries: database study. *Inj Prev* 2005;**11**:152–6.
31. **Thompson DC,** Rivara FP. Pool fencing for preventing drowning in children. *Cochrane Database Syst Rev* 2000;(2):CD001047.
32. **Silverstein LB.** Transforming the debate about child care and maternal employment. *Am Psychol* 1991 Oct;**46**:1025–32.

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Simplified Alternative to the TRISS Method for Resource-Constrained Settings

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Abstract
Background We developed simple methods of risk adjustment for evaluating the quality of injury care (predicting survival probabilities of the injured) by fully utilizing routinely collected data in injury surveillance and clinical practices. Widely used methods of risk adjustment require additional data that are difficult to collect in resource-constrained settings.
Methods We developed logistic regression models that predict survival using data obtained from 9,840 victims aged 15 years or older with blunt traumatic injuries who were registered in the Japan Trauma Data Bank, Japan's national trauma registry, between January 2004 and December 2007. The models included three predictors: age, an anatomical injury severity parameter such as a simplified severity categorization (minor, moderate, and severe) described in the *Injury Surveillance Guidelines*, and a physiological status parameter. The models' abilities to predict survival probabilities were evaluated using the area under the receiver-operating characteristic curve (AUROCC).
Results The simplified three-predictor models showed good performance with the AUROCC ranging from 0.86 to 0.94. In particular, the models with a consciousness level indicator as a physiological parameter showed a high AUROCC, ranging from 0.93 to 0.94, which was not much different from the performance of the widely used method that shows an AUROCC of 0.96.
Conclusions Simplified methods of risk adjustment that require only routinely collected data will facilitate evaluation and improvement in the quality of injury care in resource-constrained low- and middle-income countries, where injuries are a growing public health concern.

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Introduction

Injuries are a growing public health concern, killing more than 5 million people every year worldwide; more than 90% of injury deaths occur in low- and middle-income countries (LMICs) [1]. Prevention of injury deaths requires improvement in the care of the injured, as well as implementation of injury prevention measures. Quality improvement of injury treatment, including a prehospital emergency care system, is an important component in strengthening health care systems in LMICs with limited human and physical resources for injury care, as has been shown by studies based on the Guidelines for Essential Trauma Care [2–5].

Quality of care comprises three elements: structure (resources and capacities), process (how patients are treated), and outcome (survival, adverse events, or subsequent disabilities) [4]. Improvements in structure and process are intermediate steps in the pursuit of outcome improvement;

thus, outcome evaluation is a direct measurement of quality improvement. Objective comparison of injury outcomes between individuals or between hospitals requires methods of risk adjustment to control for case-mix severity.

Various risk adjustment methods have been developed: some based on the Abbreviated Injury Scale (AIS), some on physiological parameters alone, and some on the International Classification of Diseases (ICD) (Table 1) [4–7]. The AIS severity scores rate the severity of each of the sustained injuries from 1 (minor) to 6 (fatal). The Injury Severity Score (ISS) consists of the AIS severity scores for the three most severely injured body regions. The Revised Trauma Score (RTS) is a physiological score consisting of the Glasgow Coma Scale (GCS) score indicating consciousness level using three components (motor, verbal, and eye opening), respiratory rate (RR), and systolic blood pressure (SBP). The Trauma and Injury Severity Score (TRISS) is a logistic regression model that predicts survival probabilities (Ps), and comprises the ISS and RTS, age, and injury mechanisms. There is also a method based on the ICD codes, named the ICD-based Injury Severity Score (ICISS), in which the survival risk ratio (SRR) for each code is empirically derived from the data [8].

These methods seem inappropriate in resource-constrained settings owing to difficulties in collecting information. For example, TRISS is a complicated composite of several parameters including AIS severity scores and GCS scores, which may not be routinely collected. Because accurate use of the AIS and GCS requires appropriate training, collecting such information poses challenges to LMICs with additional cost [9]. Furthermore, the more parameters are required, the more frequently missing data occur. The ICISS does not require additional use of the AIS to describe injury severity; however, it does require large data sets to calculate the SRRs for each injury code, including rare ones, which is also a challenging task for LMICs, particularly those with small populations [10].

Alternative simple methods have also been developed. The Kampala Trauma Score (KTS) developed in Uganda is an example of a simplified TRISS-like scale, in which the ISS and GCS scores are replaced by the number of serious injuries with three categories and the four-point consciousness scale, respectively (Table 1) [11]. Attempts to simplify the TRISS in high-income countries (HICs) include replacing the multiple-injury scores (ISS) with the worst injury score alone, replacing the total GCS scores

Table 1 Risk adjustment methods

GlasgowComaScale(GCS) = GCSm + GCSv + GCSe

GCSm = motor component indicating best motor response, ranging from 1 (no response) to 6 (moves limb to command)

GCSv = verbal component indicating best verbal response, ranging from 1 (no response) to 5 (oriented response)

GCSe = eye component indicating eye opening response, ranging from 1 (no response) to 4 (opens spontaneously)

RevisedTraumaScore(RTS) = 0.9364 × GCS + 0.7326 × SBP + 0.2908 × RR[a]

The coefficients were derived from the Major Trauma Outcome Study (MTOS)

Injury Severity Score(ISS) = $AIS_1^2 + AIS_2^2 + AIS_3^2$

The ISS is the sum of three squared AIS severity scores in the three most severely injured anatomical body regions (out of 6 regions); 1 AIS score is derived from a single region

Trauma and Injury Severity Score (TRISS)

$\text{Logit(Ps)} = \alpha + \beta_1 \times \text{RTS} + \beta_2 \times \text{ISS} + \beta_3 \times \text{Age}$[a]

Coefficients derived from the MTOS are:

	Constant (α)	RTS (β_1)	ISS (β_2)	Age (β_3)
Blunt	−0.4499	0.8085	−0.0835	−1.7430
Penetrating	−2.5355	0.9934	−0.0651	−1.1360

ICD-based Injury Severity Score(ICISS) = $SRR_{inj1} \times SRR_{inj2} \times SRR_{inj3} \times \cdots \times SRR_{injn}$

The Survival Risk Ratio (SRR) for each code is empirically derived from the data: the number of patients who survived with a certain ICD code divided by the total number of patients with injuries. The ICISS is the product of all the SRRs in a patient: from SRR_{inj1} (SRR for injury 1) to SRR_{injn} (SRR for injury *n*)

Kampala Trauma Score(KTS) = Age + SBP + RR + AVPU + No. of serious injuries[a]

All parameters are coded: age is coded as in the TRISS; codes used in the RTS (5 points) are collapsed for SBP (4 points) and RR (3 points); The number of injuries is coded into 3 categories (nil, single, or multiple)

Source: Refs. [4, 6, 7, 11]

SBP systolic blood pressure, *RR* respiratory rate, *AIS* abbreviated injury scale, *AVPU scale* four-point consciousness scale (alert, responsive to verbal stimuli, responsive to painful stimuli, and unconscious)

[a] Age, GCS, SBP, and RR are coded

with the GCS motor component (GCSm), and developing a model with only the three parameters of age, worst injury SRR, and GCSm [12–14]. These methods perform quite well, even better than the TRISS; however, they have not fully addressed the issue of difficulties in collecting necessary information. The KTS requires five parameters, and the number of serious injuries included in the parameters may not be available in other countries; the simplified version of TRISS in HICs requires AIS severity scores, ICISS-based SRRs, or GCS scores.

Given the reality of the situations faced in LMICs, we need simplified methods based only on readily obtainable information. A study in Canada indicated that inclusion of age and a physiological parameter in the predictive models would minimize differences in the predictive ability of anatomical injury severity indicators, posing the possibility that models including the three parameters would show similar performance regardless of the types of indicators used [15]. In countries where injury surveillance has begun based on the *Injury Surveillance Guidelines* prepared by the World Health Organization, a simplified global severity indicator (minor, moderate, or severe) described in the guidelines is available [16, 17]. Simple physiological indicators can be obtained from clinical records. Therefore, we developed methods with a minimum set of parameters using easily obtainable indicators.

Methods

Study design, population, and settings

We developed logistic regression models that predict the survival probabilities of injured victims on the basis of three simplified predictors—age, anatomical injury severity, and physiological status—using data derived from the Japan Trauma Data Bank (JTDB). The JTDB is Japan's national trauma registry. Participating facilities are critical care medical centers and emergency departments of tertiary care hospitals, which are equivalent to level 1 trauma centers; hospitalized patients in the participating facilities are registered [17, 18]. Because participation in the JTDB is voluntary, some facilities are participating but others are not, depending on their resource availabilities and wishes [19]. Data included in the JTDB are age, sex, injury mechanisms, type of injury (penetrating, blunt, burn, or other), physiological status at the scene and at-hospital arrival, AIS codes including severity score for all injuries, prehospital care, survival, length of ICU and hospital stay, and treatment details [17].

Study participants were patients 15 years of age or older with blunt traumatic injuries who were hospitalized and registered in the JTDB between January 2004 and December 2007. Of the eligible 16,716 participants, 12,437 had information on age, AIS severity scores, and physiological status on arrival (GCS, SBP, and RR), which are necessary to calculate TRISS-based Ps; 9,840 had outcome information (survived or not) and thus were included in the model development. We did not model the Ps of penetrating and pediatric injuries owing to the insufficient number of victims in the database. The protocol of the present study was approved by the ethics committee of St. Marianna University School of Medicine.

Models and parameters

The models developed in this study are described as:

$$\text{Logit(Ps)} = \beta_0 + \beta_1 \times \text{age} + \beta_2 \times \text{severity} + \beta_3 \times \text{physiology},$$

where β_x denotes a regression coefficient; β_0 denotes the intercept point; β_{1-3} denote coefficients for the three predictors; age indicates age; severity indicates anatomical injury severity (worst injury AIS severity scores [maxAIS], collapsed AIS severity categories, or number of serious injuries); and physiology indicates physiological status (GCS, GCSm, AVPU [four-point consciousness scale], SBP, or RR). Each model includes each of these injury severity and physiological status indicators as predictors; widely used indicators (maxAIS and GCS) were also included so that we could compare their predictive abilities with those of the simplified indicators. All indicators other than those for the maxAIS and GCSm were categorized and coded, as shown in Table 2. The coded values of age, GCS score, SBP, and RR are the same as those used in the TRISS and RTS. The coded values of the number of serious injuries are the same as those of the KTS. To compare the performance of the three-predictor models with the widely used TRISS method, the JTDB-derived TRISS model was fitted.

The maxAIS, a six-point scale, was collapsed into three categories in three ways to simulate possible variations in the usage of the simplified global injury severity categories of "minor," "moderate," and "severe" described in the *Injury Surveillance Guidelines* [16], assuming that the global severity can be judged on the basis of the severest injury (Table 2). We defined serious injuries as those with AIS severity scores of 3 or more for the number of serious injuries. The 12-point GCS score was collapsed into four categories to simulate the usage of the four-point AVPU (Alert, responsive to Verbal stimuli, responsive to Painful stimuli, and Unconscious) scale according to the report by Kobusingye and Lett that showed that the AVPU corresponded well to GCS scores [11].

Because variations or misclassifications are likely to occur in the actual classification practices using the

Table 2 Coded values of categorized indicators

Coded value	GCS score	SBP (mmHg)	RR (/min)	Age	AVPU	Collapsed Max AIS (a)	Collapsed Max AIS (b)	Collapsed Max AIS (c)	No. of serious injuries
4	13–15	>89	10–29						
3	9–12	76–89	>29		GCS 14–15				
2	6–8	50–75	6–9		GCS 11–13	AIS 1–2	AIS 1–2	AIS 1	2+
1	4–5	1–49	1–5	55+	GCS 5–10	AIS 3–4	AIS 3	AIS 2	1
0	3	0	0	0–54	GCS 3–4	AIS 5–6	AIS 4–6	AIS 3–6	0

simplified categorizations (global severity categories and the AVPU scale), simulating the use of these simplified categories just by collapsing the AIS severity scores and GCS scores is unrealistic. Therefore, we developed a model that includes as predictors a mixture of the three ways of collapsing the AIS severity scores and a mixture of the two different ways of collapsing the GCS scores to simulate the variations. For each participant, one of the three ways of collapsing the AIS and one of the two ways of collapsing the GCS scores (i.e., the AVPU scale or the GCS scores 3–5, 6–9, 10–12, and 13–15 coded from 0 to 3) were randomly selected to make mixed indicators.

Analyses

We obtained estimates for the models' regression coefficients using the maximum likelihood estimation with survival being the outcome (survival = 1; nonsurvival = 0). A 10-fold cross-validation was used to compute the predicted Ps from the model estimates. The data were randomly divided into 10 subgroups; 9 subgroups (training data sets) were used to estimate the coefficients, which were applied to the remaining subgroup (validation data set) to obtain the predicted Ps, in a round of cross-validation. This process was repeated an additional nine times. We recorded the averages of the 10 sets of coefficients. The predicted probability values were used to evaluate the models' ability to distinguish survivors from nonsurvivors and the models' goodness-of-fit (calibration). The area under the receiver-operating characteristics curve (AUROCC), which ranges from 0.5 to 1, was calculated to evaluate the discrimination ability (values nearer to 1 indicate better abilities). The Hosmer–Lemeshow (H–L) statistic was used to evaluate the calibration. The H–L statistic indicates the degree of difference between the predicted and observed numbers of survivors in each decile of predicted Ps (smaller H–L values indicate better calibration) [20]. Because of the very large sample size, we used neither statistical tests with obviously small p values nor narrow confidence intervals. Model fitting was done with SPSS version 17. To indicate how the simplified models can be easily used even without a calculator, we developed lookup tables showing Ps for each set of predictive variables (see Appendices A and B).

Results

Table 3 shows the characteristics of the study population. The majority of the 9,840 analyzed participants were male, younger than 55 years of age, and with sustained unintentional injuries due to traffic crashes or falls; 18% of them died after admission. Those with injuries of minor to moderate severity (ISS < 15) accounted for about half the study population. Most of the participants showed normal physiological status on hospital arrival.

Table 4 shows the coefficients of the tested models (averaged values from the 10-fold cross-validation), AUROCC, and H–L statistic. The TRISS model showed the best AUROCC. Among the three-predictor models, those with maxAIS and GCS scores showed a marginally better AUROCC (0.949) than did the others. Among the models with collapsed AIS severity categories or number of serious injuries, those with the GCSm or AVPU as the physiological parameter showed quite good performance, with an AUROCC ranging from 0.930 to 0.944, whereas those with BP or RR as the physiological parameter showed a lower AUROCC, ranging from 0.861 to 0.93 l. Models with the GCSm or AVPU did not differ in AUROCC; in the majority of models, those with the AVPU showed lower H–L values than did those with the GCSm. The model including mixed indicators as explained in the "Models and parameter" had an AUROCC of 0.935 and an H–L value of 51.5 (not shown in Table 4). Appendices A and B show examples of lookup tables for two models.

Discussion

The present study showed that the models using easily obtainable simple indicators showed fairly good performance in predicting Ps of blunt traumatic injuries as long as they included the three parameters of age, anatomical injury severity, and physiological status. As a physiological

Table 3 Characteristics of the eligible and analyzed participants

	Eligible (n = 16,716)		Analyzed (n = 9,840)	
	n	%	n	%
Age (years)				
15–54	8,861	53.0	5,471	55.6
55+	7,855	47.0	4,369	44.4
Sex				
F	5,312	31.8	3,003	30.5
M	11,402	68.2	6,835	69.5
Missing	2		2	
Survival				
Died	2,101	17.6	1,769	18.0
Survived	9,816	82.4	8,071	82.0
Missing	4,799		0	
Intention (cause)				
Unintentional	14,924	91.4	8,723	90.7
Self harm	1,086	6.6	695	7.2
Violence	259	1.6	170	1.8
Other	63	0.4	34	0.4
Missing	384		218	
Mechanism				
Traffic	8,766	54.2	5,454	56.7
Fall	5,956	36.8	3,344	34.8
Other	1,447	8.9	814	8.5
Missing	547		228	
Injury Severity Score				
1–8	3,018	20.4	1,790	18.2
9–14	4,723	32.0	3,051	31.0
15–25	4,035	27.3	2,822	28.7
26–45	2,427	16.4	1,731	17.6
46–75	572	3.9	446	4.5
Missing	1,941		0	
Systolic blood pressure (mmHg)				
90+	13,071	85.5	8,275	84.1
76–89	495	3.2	325	3.3
50–75	398	2.6	254	2.6
1–49	195	1.3	129	1.3
0	1,125	7.4	857	8.7
Missing	1,432		0	
Respiratory rate (min)				
10–29	10,670	77.1	7,542	76.6
30+	1,925	13.9	1,348	13.7
6–9	60	0.4	41	0.4
1–5	19	0.1	16	0.2
0	1,172	8.5	893	9.1
Missing	2,870		0	
Glasgow Coma Scale				
13–15	12,832	76.8	7,078	71.9
9–12	1,018	6.1	684	7.0
6–8	822	4.9	581	5.9
4–5	373	2.2	261	2.7
3	1,671	10.0	1,236	12.6
Time to emergency room (min)				
<30	4,343	34.1	2,974	33.7
30–59	6,868	53.9	4,793	54.4
60–89	998	7.8	693	7.9
90–119	230	1.8	151	1.7
120+	311	2.4	206	2.3
Missing	3,966		1,023	

indicator, the AVPU may be the potential candidate for actual use because it showed better discrimination ability than did SBP or RR and better calibration than did the GCSm; any type of simplified anatomical injury severity indicator showed similar abilities. These findings suggest that we can further simplify the previously developed simplified models by reducing the number of variables and replacing complicated variables with simple ones.

In under-resourced settings in LMICs, particularly in rural areas, the limited resources allow neither two separate data collection systems for two different purposes, one for injury prevention and the other for quality improvement, nor collection of additional information such as the AIS and GCS. Considerable additional cost is required to establish two systems and introduce the AIS and GCS, which require costly training, to countries where such indicators are not now in use.

Using the simplified models developed in the present study would enable the use of injury surveillance data for both injury prevention and risk adjustment in quality evaluation without significant additional cost. Many LMICs are establishing or have already established injury surveillance systems on the basis of the *Injury Surveillance Guidelines,* which are likely to include the simple global severity categorization (minor, moderate, or severe) [16, 17]. Physiological indicators routinely collected in clinical practice can be easily added to the injury surveillance. Our findings suggest that level of consciousness has better performance than hemodynamic or respiratory status. Thus, the GCS or AVPU scale should be used whenever possible as the physiological indicator in the models, and SBP or RR should be used as the second option if the consciousness level indicator is not available.

An advantage of parsimonious models with fewer parameters is that limited combinations of the parameter codes result in a limited number of Ps. This would enable the use of simple lookup tables like those shown in Appendices A and B. Survival probabilities can be obtained

Table 4 Model coefficients, discrimination abilities, and calibrations

Models	Estimates for regression coefficients				AUROCC	H–L
	Constant	Age	Anatomical Injury Severity	Physiological status		
TRISS (age, ISS, RTS)	−1.82	−1.32	−0.07	0.94	0.962	61.2
Age, MaxAIS, GCS	2.32	−0.90	−0.87	1.17	0.949	37.2
Age, MaxAIS, GCSm	1.86	−0.86	−0.98	0.89	0.947	48.6
Age, MaxAIS, SBP	3.39	−0.89	−1.49	1.35	0.941	25.7
Age, MaxAIS, RR	3.19	−0.98	−1.50	1.43	0.934	7.0
Age, cMaxAIS(a), GCSm	−3.16	−0.88	1.54	0.91	0.943	45.3
Age, cMaxAIS(a), AVPU	−1.59	−0.83	1.20	1.58	0.944	32.4
Age, cMaxAIS(a), SBP	−4.22	−0.91	2.37	1.37	0.931	14.4
Age, cMaxAIS(a), RR	−4.42	−1.00	2.35	1.44	0.924	14.2
Age, cMaxAIS(b), GCSm	−2.81	−0.83	1.43	0.94	0.943	28.1
Age, cMaxAIS(b), AVPU	−1.28	−0.78	1.12	1.63	0.942	32.4
Age, cMaxAIS(b), SBP	−3.33	−0.79	1.97	1.35	0.920	42.7
Age, cMaxAIS(b), RR	−3.62	−0.88	2.03	1.44	0.913	22.7
Age, cMaxAIS(c), GCSm	−2.66	−0.84	2.48	1.00	0.930	64.7
Age, cMaxAIS(c), AVPU	−1.14	−0.79	2.16	1.73	0.934	29.7
Age, cMaxAIS(c), SBP	−2.82	−0.79	2.77	1.38	0.869	29.7
Age, cMaxAIS(c), RR	−3.05	−0.87	2.92	1.46	0.861	32.6
Age, No of injuries, GCSm	−0.56	−1.03	−1.30	0.97	0.936	64.4
Age, No of injuries, AVPU	0.64	−0.96	−1.12	1.68	0.941	36.0
Age, No of injuries, SBP	−0.68	−0.97	−1.23	1.29	0.888	55.6
Age, No of injuries, RR	−0.69	−1.08	−1.40	1.38	0.884	56.5

AUROCC area under receiver-operating characteristic curve, *H–L* Hosmer–Lemeshow statistic, *ISS* injury severity score, *RTS* revised trauma score, *MaxAIS* worst injury AIS severity score, *GCS* Glasgow Coma Scale score, *GCSm* GCS motor component, *cMaxAIS* collapsed MaxAIS into three categories, *AVPU* four-point consciousness scale (alert, responsive to verbal stimuli, responsive to painful stimuli, and unconscious)

Age, GCS, cMaxAIS(a–c), SBP, RR, and AVPU were coded as shown in Table 2

quickly from such tables. However, if many parameters are used, the lookup tables will become large and complicated; thus, software to calculate the Ps may be required.

Furthermore, using fewer parameters can reduce the magnitude of the problems associated with missing data [21]. Scales like TRISS that require many parameters suffer from frequency of missing data. In the present study, 26% of the eligible participants were missing some of the information necessary to calculate TRISS-Ps. Even in HICs, it is not infrequent to find data missing in a trauma registry or in patient records in a tertiary care hospital [22, 23].

Some limitations of the present study should be noted. We used simulated simplified indicators to test the models instead of data actually collected on simple global injury severity, number of serious injuries, or the AVPU scale, because these were not available in the JTDB data. The good performance of the tested models might have resulted from the fact that the simulated indicators were derived by collapsing the AIS severity scores and GCS scores. This possibility, however, is unlikely. The different ways of collapsing the AIS severity scores yielded similar results; simulated variations or misclassifications in the actual utilization of the simplified indicators by mixing different ways of collapsing the AIS severity scores and the GCS scores also made marginal differences.

Another limitation is the lack of representativeness in the data in two ways. First, owing to missing data, only 59% of the eligible cases were analyzed. The differences in characteristics between the total eligible participants and the analyzed participants were small. (We did not perform statistical testing because the large sample size would make very small differences statistically significant.) Second, because participating in the JTDB is voluntary, the registered data might have overrepresented well-staffed facilities that are likely to participate [19]. Quality of care might be different between well-staffed and understaffed facilities.

Although we showed the potential usefulness of the simplified models, it should be noted that we should validate them with data actually collected in LMICs and, even more important, further studies should estimate the coefficients of the models for each country [24, 25]. The coefficients estimated in the present study based on

Japanese data may not apply to other countries with different situations (e.g., emergency care and transportation systems). Therefore, the lookup tables shown in Appendices A and B should be considered as a reference, and the development of country-specific tables is recommended.

Furthermore, given the different country-specific situations such as extremely long transportation time in LMICs (up to several hours in remote areas) [26], model modification may be necessary. In the present study, we did not include such factors because our primary purpose was to simplify the standard methods, which do not include a time factor (the relative contribution of a time factor to outcome prediction is small when using data collected in HICs) [27]. In addition, extrapolation of modeling based on short transportation time to situations with longer transportation times is inappropriate. Such model modification, if necessary, should be based on the data obtained in LMICs.

Finally, we could not test the models for pediatric and penetrating injuries owing to the insufficient number of such injuries in the JTDB. As the TRISS method shows, however, the same model (combination of parameters) may apply to both blunt and penetrating injuries, or to both adult and pediatric injuries, with different coefficients [28]. Further studies are also needed to validate the models and estimate coefficients for pediatric and penetrating injuries.

Conclusions

We developed simple models to predict survival probability for the purpose of risk adjustment in care quality evaluation with a performance level that is not very inferior to widely used models such as TRISS or models with worst injury severities. Our models do not require AIS severity scores or GCS scores, which are difficult to collect in resource-constrained settings. Although validation of the models from data actually collected in LMICs is needed, the findings open up the possibility of existing or emerging injury surveillance systems, which are designed for injury prevention, being also used for quality improvement activities.

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Conflict of interest none

Appendix

See Tables 5 and 6.

Table 5 Probability of survival chart by age, injury severity, and AVPU

	AVPU			
	A	V	P	U
Age ≥ 55 years				
Severity (cMaxAIS[c])				
Minor (MaxAIS = 1)	0.999	0.997	0.984	0.916
Moderate (MaxAIS = 2)	0.996	0.976	0.876	0.556
Severe (MaxAIS = 3–6)	0.963	0.823	0.451	0.127
Age < 55 years				
Severity (cMaxAIS[c])				
Minor (MaxAIS = 1)	1.000	0.999	0.993	0.960
Moderate (MaxAIS = 2)	0.998	0.989	0.940	0.734
Severe (MaxAIS = 3–6)	0.983	0.911	0.644	0.242

Model: Logit (Ps) = −1.14 − 0.79 × age + 2.16 × severity + 1.73 × AVPU

Table 6 Probability of survival chart by age, number of severe injuries, and AVPU

	AVPU			
	A	V	P	U
Age≥ 55 years				
No. of severe injuries				
0	0.991	0.954	0.794	0.420
1	0.973	0.871	0.559	0.192
2+	0.922	0.689	0.293	0.072
Age < 55 years				
No. of severe injuries				
0	0.997	0.982	0.910	0.655
1	0.990	0.947	0.768	0.383
2+	0.969	0.853	0.521	0.169

Model: Logit (Ps) = 0.64 − 0.96 × age − 1.12 × no. of injury + 1.68 × AVPU

References

1. WHO. Disease and injury regional estimates for 2004. Available at: http://www.who.int/healthinfo/global_burden_disease/estimates_regional/en/index.html. Accessed 15 September 2010
2. Mock C, Lormand JD, Goosen J et al. (2004) Guidelines for Essential Trauma Care, World Health Organization, Geneva
3. Mock C, Nguyen S, Quansah R et al (2006) Evaluation of trauma care capabilities in four countries using the WHO-IATSIC Guidelines for Essential Trauma Care. World J Surg 30:946–956
4. Mock C, Juillard C, Brundage S et al (eds) (2009) Guidelines for Trauma Quality Improvement Programmes. World Health Organization, Geneva
5. Nakahara S, Saint S, Sann S et al (2009) Evaluation of trauma care resources in health centers and referral hospitals in Cambodia. World J Surg 33:874–885

6. Champion HR (2002) Trauma scoring. Scand J Surg 91:12–22
7. Senkowski CK, McKenney MG (1999) Trauma scoring systems: a review. J Am Coll Surg 189:491–503
8. Osler T, Rutledge R, Deis J et al (1996) ICISS: an international classification of disease-9 based injury severity score. J Trauma 41:380–386
9. Kim Y, Jung KY, Kim CY et al (2000) Validation of the International Classification of Diseases 10th Edition-based Injury Severity Score (ICISS). J Trauma 48:280–285
10. Cryer C (2006) Severity of injury measures and descriptive epidemiology. Inj Prev 12:67–68
11. Kobusingye OC, Lett RR (2000) Hospital-based trauma registries in Uganda. J Trauma 48:498–502
12. Healey C, Osler TM, Rogers FB et al (2003) Improving the Glasgow Coma Scale score: motor score alone is a better predictor. J Trauma 54:671–678
13. Kilgo PD, Osler TM, Meredith W (2003) The worst injury predicts mortality outcome the best: rethinking the role of multiple injuries in trauma outcome scoring. J Trauma 55:599–606
14. Kilgo PD, Meredith JW, Osler TM (2006) Incorporating recent advances to make the TRISS approach universally available. J Trauma 60:1002–1008
15. Moore L, Lavoie A, Le Sage N et al (2008) Consensus or data-derived anatomic injury severity scoring? J Trauma 64:420–426
16. Holder Y, Peden M, Krug E et al (eds) (2001) Injury Surveillance Guidelines. World Health Organization, Geneva
17. Nakahara S, Jayatilleke AU, Ichikawa M et al (2008) Feasibility of standardized injury surveillance and reporting: a comparison of data from four Asian nations. Inj Prev 14:106–112
18. Japan Trauma Care and Research (2008) Japan Trauma Data Bank Report 2004–2007. http://www.jtcr-jatec.org/traumabank/dataroom/data/JTDB04-07eng.pdf. Accessed 15 September 2010
19. Ichikawa M, Nakahara S, Wakai S (2005) Factors related to participation in the Japan Trauma Data Bank. J Jpn Assoc Acute Med 16:552–556
20. Hosmer DW, Lemeshow S (2000) Applied logistic regression, 2nd edn. Wiley, New York
21. Kimura A (2010) Logistic regression models for Japanese blunt trauma victims: second report. J Jpn Assoc Surg Trauma 24:321–326
22. Kimura A (2010) Logistic regression models for Japanese blunt trauma victims. J Jpn Assoc Surg Trauma 24:15–20
23. Nakahara S, Taira Y, Takahashi M et al. (2008) Extracting information from free-texts in computerized medical records of traffic injury patients admitted to a critical care medical center in Japan. In: Proceedings of the 11th international conference on human and computers, November 20–23, Nagaoka, Japan, pp 215–220
24. Zafar H, Rehmani R, Raja AJ et al (2002) Registry based trauma outcome: perspective of a developing country. Emerg Med J 19:391–394
25. Lane PL, Doig G, Mikrogianakis A et al (1996) An evaluation of Ontario trauma outcomes and the development of regional norms for Trauma and Injury Severity Score (TRISS) analysis. J Trauma 41:731–734
26. Nakahara S, Saint S, Sann S et al (2010) Exploring referral systems for injured patients in low-income countries: a case study from Cambodia. Health Policy Plan 25:319–327
27. DiRusso SM, Sullivan T, Holly C et al (2000) An artificial neural network as a model for prediction of survival in trauma patients: validation for a regional trauma area. J Trauma 49:212–220
28. Schluter PJ, Nathens A, Neal ML et al (2010) Trauma and Injury Severity Score (TRISS) coefficients 2009 revision. J Trauma 68:761–770

Revision of the International Classification of Diseases to include standardized descriptions of multiple injuries and injury severity

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Introduction

The International Classification of Diseases (ICD) is widely used as a source of mortality statistics. However, two major difficulties arise when recording, presenting and analysing injury data using this diagnosis classification. First, due to the absence of standardized methods for describing multiple injuries, they are described in various ways in mortality and morbidity statistics. For example, designating the most severe injuries as the primary injuries or categorizing multiple injuries as such without further details.[1] Second, an increasing need to describe injury severity for case-mix groups has led to the introduction of various additional severity-scoring methods, as the ICD itself, as a diagnosis classification for mortality, does not consider severity. To avoid the costs of additional severity scoring, methods have been developed to convert administrative ICD-based diagnosis codes into severity scores using computer software or to calculate survival probability for each diagnosis code from patient data. However, these approaches have respective disadvantages due to the need to track software updates or the need for large data sets to calculate the probabilities.[2]

The World Health Organization[3] is currently advocating revision of the ICD to expand upon its largely administrative applications and allow more clinical uses. This provides an opportunity to address the issues associated with describing multiple pathologies and scoring the severity of injury data, which are also relevant to other non-injury diseases. In addition, a few low-income countries do not use the ICD or severity scores, even in the absence of vital registrations depending on periodical surveys,[5] thus the revision process should facilitate their adoption of standardized methods. Here we discuss how the revised ICD system could standardize the description of multiple injuries to provide accurate statistics, incorporate severity scores to avoid additional resource input, and facilitate utilization in countries where it is not currently in use.

Describing multiple injuries

For mortality statistics, the one-dimensional principle of the ICD allows only one underlying cause of death to be selected and coded. The multi-dimensional phenomenon of multiple injury is thus usually reduced either to a single code reflecting the primary (most severe) injury or to one of a few multiple-injury codes, based upon an arbitrary decision.[1,4] Selecting the primary injury when filling in death certificates, or the underlying cause from among several injuries reported in death certificates, is also an arbitrary practice that reflects the certifier's or coder's perception of which pathology is the most important. Choosing just one code results in a loss of information on the other, unselected, pathologies, so the resultant statistics underestimate the significance of each injury and inadequately depict the interactions between them.[1] The limited number of multiple-injury codes included in the ICD cannot cover all possible patterns. For example, codes T00–T07 indicate injuries involving multiple body regions while S codes also include multiple injuries in the same body regions, (e.g. S52.7 indicates "multiple fractures of the forearm"). This arbitrariness, due to a lack of standardization, also applies to the presentation and analysis of morbidity statistics,[1] although not to the way that they are recorded because clinical modifications of the ICD require the coding of each injury, thereby superseding the multiple-injury codes.

The shortcomings of one-dimensional coding have led some countries to introduce multiple coding systems for mortality statistics, in which all causes mentioned on a death certificate are coded and reported.[4] It would be preferable to omit the multiple-injury codes from the revised ICD, and to code and record all injuries separately. This would allow all patients with a certain injury to be counted, even when it is not the primary injury, which is not the case with one-dimensional underlying-cause (or primary-injury) coding.[1] When presenting data on multiple injuries, instead of simply listing all injuries sustained, it might be preferable to use two-dimensional coding that reflects the important attributes of the nature of the injury and the affected body region to characterize an individual's injuries.

Proposed methods to describe multiple injuries while presenting statistics in a standardized way include the multiple injury profile, which combines information on the anatomy and the nature of the injury, using a body-region by injury-nature matrix.[1] Each injury falls into one of the cells in the matrix. The multiple injury profile can summarize all of the individual injuries in one patient using cell combinations. The granularity of the categorizations used in the matrix can be changed by subdividing or collapsing the categories as needed. An abridged version of the matrix can be used as a shortlist in countries where the full list of the ICD is not used. By contrast, the matrix can be used as a supplement, in conjunction with listing all of the injuries to give complete descriptions in countries where multiple coding is done.

Multiple coding using standardized methods of presenting multiple pathologies, if applied to the whole ICD, would allow more accurate descriptions of each pathology and the interactions both

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Table 1. **Methods for scoring severity of injuries**[a]

Severity scores	Definition	Characteristics	Required resources
Abbreviated injury scale (AIS)	An injury categorization with severity scores assigned to each injury category. Injuries are rated from 1 (minor) to 6 (fatal).	– Not designed for survival prediction. – Determined based on expert consensus.	– Duplicate coding or computer software (ICDMAP) to obtain AIS severity scores from ICD codes.
Injury severity score (ISS)	Indicates overall severity for a patient with multiple injuries. ISS is a sum of the square of the highest AIS severity scores of the three most severely injured body regions (from a choice of six body regions). $ISS = AIS_1^2 + AIS_2^2 + AIS_3^2$	– Does not consider physiological parameters. – Equal weighting given to each body region. – Does not account for multiple injuries in the same body region.	– AIS severity score
Revised trauma score (RTS)	Consists of physiological parameters independent of anatomical injury scores. $RTS = 0.9364 \times GCS + 0.7326 \times SBP + 0.2908 \times RR^b$	– Physiological parameters are time-sensitive.	– Patient data and statistical software to calculate country-specific coefficients.
Trauma and injury severity score (TRISS)	A combination of an anatomical measure (ISS), physiological measure (RTS) and patient ability to withstand injury severity (age) by type of injury (blunt/penetrating). Probability of survival (Ps) is determined using a logistic regression model. $\text{Logit (Ps)} = \beta_0 + \beta_1 \times RTS + \beta_2 \times ISS + \beta_3 \times age^b$	– Widely used in outcome studies because of its good predictive ability.	– Availability of AIS severity score. – Patient data and statistical software to calculate country-specific coefficients. – Computer software to calculate the score because of its mathematical complexity.
ICD-based injury severity score (ICISS)	A multiplicative prediction model with an assumption that all injuries contribute to the overall severity. The SRR for each code is empirically derived from the patient data. To obtain ICISS, SRRs of all injuries are multiplied. $ICISS = SRR_{inj1} \times SRR_{inj2} \times SRR_{inj3} \times SRR_{injn}$	– Directly derived from ICD or ICD-CM codes. – Predictive ability is equal to, or better than, that of the TRISS.	– Large patient data set. – Computer software might be required to calculate each patient's score due to large number of codes
Matrix-based method	In a body-region by injury-nature matrix (such as the Barell matrix), the proportions of survival and approximated AIS score are calculated based on data for each cell. These values are used in the same way as ICISS and AIS-based indices.	– Relatively easy to handle due to diminished number of categories compared with other methods.	– Patient data set (not necessarily a large one) and statistical software to calculate country-specific values. – AIS severity score if approximated severity scores are determined.

GCS, Glasgow Coma Score; ICD, International Classification of Diseases; ICD-CM, International Classification of Diseases-Clinical Modification; RR, respiratory rate; SBP, systolic blood pressure; SRR, survival risk ratio.

[a] This is not a comprehensive list of injury scores, but rather shows typical and popular indices to indicate their relationships with the ICD codes and required resources.

[b] Coded values are used for Glasgow Coma Score, systolic blood pressure, respiratory rate and age.

within and between specific types of injury or internal cause.[3,4] This would also help to clarify how underlying ailments contribute to the impact of injuries in ageing societies.

Describing injury severity

Various methods have been developed to score injury severity (Table 1).[5] The abbreviated injury scale (AIS) describes the anatomical injury severity using consensus-based scores determined by experts. The revised trauma score (RTS) is based on physiological parameters independent of injury diagnoses. The injury severity score (ISS) consists of the square of the highest AIS scores in the three most severely injured body regions. The trauma and injury severity score (TRISS) predicts survival probabilities using logistic regression modelling that employs the ISS, RTS, age and injury mechanism as predictors. AIS-based methods, such as TRISS, are widely used because of their suitability and accuracy based on ample research findings. However, duplicate coding for injury diagnosis and severity carries additional costs in terms of human resources and training requirements to ensure accuracy, which is unaffordable in resource-constrained settings.[2]

To avoid the additional costs associated with duplicate coding, attempts have been made to assign a severity score to each ICD-based diagnosis. One successful example is a method that derives AIS severity scores from ICD-9 codes using computer software (ICDMAP).[2] Although this is a validated tool, it also carries additional costs, albeit smaller ones than those associated with duplicate coding, and it notably fails to update using newer versions of the ICD and AIS, resulting in variability in the versions used in case-mix grouping methods.[2]

Another example is the ICD-based injury severity score (ICISS), which assigns an empirically derived severity score to each ICD code.[2,5] Survival probabilities, called survival risk ratios (SRRs), are calculated for each code based on patient data (Table 1). The ICISS is a promising measure that performs as well as, or better than, AIS-based methods; however, it has some shortcomings that might hinder its use in low-income countries, particularly those with small populations. Large data sets are required to avoid large fluctuations occurring in the SRRs for rare injuries. Also, SRRs might differ across countries and over time, depending on health-care systems and improvements in treatment, thereby requiring countries to calculate and update their own data sets.[2]

Whereas code conversion and the ICISS operate outside the ICD framework and do not modify the diagnosis codes, an alternative approach would be to integrate consensus-based severity scores into the ICD. The revised ICD is expected to have wider coverage, including morbidity statistics and case-mix groupings.[3] Integrating an AIS system into the revised ICD as a clinical modification or expansion would remove the need for duplicate coding or code conversion (and associated software updates). This would be facilitated by recent improvements in the compatibility between the ICD and the AIS.

None of the above-mentioned severity-scoring methods can be used in countries where a shortlist of ICD codes is required. The matrix-based approach can, however, be applied if the predominant AIS severity scores (because more than one code can fall in one cell) or ICISS-type survival probabilities are determined for each of the matrix cells based on empirical data.[6] Assigning a consensus-based approximate severity score to each cell is also possible. This abridged method, with diminished diagnosis categories and the flexibility to handle both AIS-type and ICISS-type indices, can be used to create a short morbidity list with severity scores for resource-constrained settings.

Conclusion

The ICD revision process presents a good opportunity to standardize the description of multiple injuries and injury severities regardless of resource availabilities. We suggest that the revised ICD should have a multiple coding framework for individual pathologies, deactivating multiple-injury codes, so as to consider the significance of each injury or pathology and their interactions. The ICD should also incorporate consensus-based severity scores in its clinical modifications, so that case-mix groupings can be considered in resource-constrained settings without requiring duplicate coding or code-conversion software, while data-derived severity indices can be employed in less constrained settings. Matrix-based methods should also be considered, as they provide a simple basis for multiple injury description and case-mix groupings using fewer categories, making them suitable for countries where a shortlist of ICD codes is needed. ■

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References

1. Aharonson-Daniel L, Giveon A, Peleg K. Gaps in injury statistics: multiple injury profiles reveal them and provide a comprehensive account. *Inj Prev* 2005;11:197–200. doi:10.1136/ip.2005.008227 PMID:16081744
2. Cryer C. Severity of injury measures and descriptive epidemiology. *Inj Prev* 2006;12:67–8. doi:10.1136/ip.2006.011668 PMID:16595417
3. *WHO business plan for classifications: building blocks of health information.* Geneva: World Health Organization; 2005. Available from: http://www.who.int/entity/classifications/BuisinessPlan.pdf [accessed 24 January 2011].
4. Goldacre MJ, Duncan ME, Cook-Mozaffari P, Griffith M. Trends in mortality rates comparing underlying-cause and multiple-cause coding in an English population 1979-1998. *J Public Health Med* 2003;25:249–53. doi:10.1093/pubmed/fdg058 PMID:14575203
5. Chawda MN, Hildebrand F, Pape HC, Giannoudis PV. Predicting outcome after multiple trauma: which scoring system? *Injury* 2004;35:347–58. doi:10.1016/S0020-1383(03)00140-2 PMID:15037369
6. Clark DE, Ahmad S. Estimating injury severity using the Barell matrix. *Inj Prev* 2006;12:111–6. doi:10.1136/ip.2005.010058 PMID:16595426

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Effects of high-profile collisions on drink-driving penalties and alcohol-related crashes in Japan

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ABSTRACT

Background Japanese road traffic law was amended in 2002 and 2007 to increase the penalties for drink-driving in response to media coverage, publicity campaigns, and debates following high-profile alcohol-related motor-vehicle crashes in 1999 and 2006.

Objective To test the hypothesis that the proportion of crashes involving drink-driving started to decline before the law amendments, because of changes in social norms and driver behaviour after the high-profile crashes.

Methods In order to assess the impact of the cases in 1999 and 2006, time-series analyses were used to examine the trends in the proportion of crashes involving drink-driving, and whether there were abrupt changes in the level or slope at the expected time points, using monthly police data for the period between January 1995 and December 2008.

Results In 1999, the proportion of alcohol-related fatal crashes in which the driver had a blood alcohol concentration (BAC) ≥0.5 mg/ml started to decline with a slope change of −0.09 percentage points per month (95% CI −0.15 to −0.03) but no level change, whereas there were no changes for drivers with a BAC <0.5. In 2006, the trends for drivers with a BAC ≥0.5 or <0.5 showed significant level declines of −3.1 (−5.0 to −1.2) and −1.7 (−2.5 to −0.9) percentage points, respectively, but no slope changes.

Conclusions Media coverage of high-profile crashes, and subsequent publicity campaigns and debates might have altered social norms and driver behaviour, reducing the proportion of alcohol-related crashes before the introduction of more severe penalties for drink-driving.

Drink-driving is one of the leading causes of motor vehicle crashes worldwide. The magnitude of the problem varies greatly among countries: the proportion of road traffic deaths involving alcohol consumption exceeds 50% in some, whereas others have succeeded in reducing this to less than 10%.[1] Understanding the experiences of successful countries could benefit those that still have a growing drink-driving problem.

Japan has considerably reduced the number of alcohol-related crashes during the past decade: fatal crashes involving drink-driving decreased from 1276 in the year 2000 to 292 in 2009, while fatal crashes not involving drink-driving decreased from 6554 to 4056; injury crashes (including fatal ones) involving drink-driving decreased from 26 280 to 5725, while injury crashes not involving drink-driving decreased from 859 414 to 691 016. Previous studies attributed this successful reduction to amendments of the road traffic law made in June 2002 and in September 2007[2–4]: the former comprised a 5–6-fold increase in fines for drink-driving, a lowering of the punishable limit for blood alcohol concentration (BAC) from 0.5 mg/ml to 0.3 mg/ml, and increases of the licence suspension/revocation periods; the latter involved an approximately twofold increase of fines. A study using time-series analyses revealed an abrupt decrease in the levels of crash rates per vehicle-km-travelled in June 2002.[4]

The strict and rapid imposition of severe penalties, and a lowering of the BAC limit, have been shown to reduce alcohol-related crashes effectively, if imposed with certainty and swiftness.[5–9] However, law amendments alone cannot achieve long-lasting success, because without changes in social norms, people will not accept stricter statutes or comply with them in the long run.[10–12] Previous experience in Japan illustrates the short-term effects of imposing tougher penalties in isolation: changing the penalty for heavy drink-driving from licence suspension to licence revocation in 1978 only reduced alcohol-related crashes temporarily.[13]

The toughening of penalties has often been preceded by high-profile crashes that were vigorously covered by the news media, raising a public debate.[11 14–16] The two law amendments in Japan were stimulated by preceding high-profile cases in 1999 and in 2006, in which young children were killed, prompting calls for more severe penalties for drink-driving.[17–20] Pre-legislative events, including media coverage of the tragic details of the crashes and grass-root activities, could have played an agenda-setting role, attracting public attention and facilitating changes in social norms and attitudes towards drink-driving that led to changes in driver behaviour.[10 21]

To date, few studies have investigated pre-legislative changes in driver behaviour. Reports from the United States indicated various declining trends in crashes that were likely to involve drink-driving declined before law amendments were made.[11 14 22] However, these studies either defined the starting point of the changes as the dates when publicity campaigns were launched or grass-root organizations were founded, rather than considering the occurrence of high-profile cases, or they arbitrarily specified a time point one year before the law was implemented.

We hypothesised that the news coverage of high-profile cases might have initiated societal changes even before law amendments imposed more severe penalties and, specifically, that alcohol-related crashes in Japan started to decline immediately after the crashes in 1999 and 2006. The present study tested this hypothesis using interrupted time-series analyses, which examined the time trends of alcohol-related crashes with respect to the high-profile crashes, with the aim of drawing lessons from the Japanese experience that could help to achieve a sustained decline in drink-driving worldwide.

BACKGROUND

There was sustained media coverage of high-profile cases in 1999 and 2000, and of subsequent developments (table 1).[18 20] The offenders in these cases received light sentences for negligence in their criminal trials, after which the victims' parents collected signatures on a petition calling for more severe punishments for such drivers. Consequently, in 2001, the Criminal Law was amended to impose a maximum term of imprisonment of 20 years for dangerous driving resulting in death. In 2002, the maximum fine for driving under the influence of alcohol (DUI) was increased from 50 000 yen to 300 000 yen; this was further increased to 500 000 yen in 2007. In November 2004, the penalty for refusing to undergo breath testing was equalised to that for DUI, in response to an increase in refusal. In the 2006 crash, the offender was a local government employee. Following the incident, the media condemned the government for its employer liability and raised a debate about drink-driving.[17 19]

The fine for DUI is the most relevant penalty in this context. In theory, there is the potential for imprisonment or prosecution for driving while intoxicated (DWI), which is defined as being heavily drunk based on police officer observations, and carries heavier penalties (the current maximum fine is 1 000 000 yen), but in practice these measures are rarely applied.[13 23] To accelerate the judicial process and to assure consistency when imposing fines, summary procedures are taken whenever the offenders agree (with the exception of cases involving serious injuries or deaths); offenders need not appear in court and the sentences are determined based on documentation alone. Driving with a positive BAC that is under the punishable limit (currently 0.3 mg/ml) is illegal. Drivers with a BAC below the limit are stopped from further driving if identified at checkpoints. Crashes involving drivers with a detectable BAC below the punishable limit are recorded as alcohol-related crashes.

METHODS

Design

We assessed the impact of high-profile crashes and law amendments on the trends of alcohol-related fatal motor-vehicle crashes and all road crashes involving injuries, for different BAC levels using a quasi-experimental design and interrupted time-series analyses, in which the high-profile crashes were expected to be points of interruption or abrupt trend change.[24] The unit of analysis was vehicle crashes involving injuries, rather than injuries or deaths. Motor vehicles included four-wheeled vehicles and motorcycles. Fatal crashes were defined as those that involved at least one death within 24 h of the collision.

Data

We obtained monthly police data on the number of vehicle crashes involving injuries across the whole country during the period between January 1995 and December 2008 from the Institute for Traffic Accident Research and Data Analysis. The data included information on the alcohol consumption of the driver who was considered most responsible for each crash (one driver per collision) based either on breath testing or, in its absence (due to severe injuries, escape, or refusal by the driver), a police investigation. The BAC level was categorised as follows: '≥0.5 mg/ml', '0.5> BAC >0 mg/ml', 'untested but alcohol consumption detected', 'no evidence of alcohol consumption', or 'no information'.

Table 1 High-profile crashes and consequences between 1999 and 2007

Date	Events and interventions
28 Nov 1999	A high-profile crash in which two young children (aged 1 and 3 years) died in a post-crash vehicle fire caused by a heavily drunken truck driver on a highway in Tokyo
9 Apr 2000	A high-profile crash in which two college students were killed in a collision caused by a drunken and unlicensed driver speeding in an unregistered and uninsured car
24 Nov 2000	The parents of the victims of the crashes collected the signatures of 160 000 people on a petition calling for more severe punishment for dangerous driving resulting in death, and submitted them to the Japanese Minister of Justice (MoJ)
22 Oct 2001	Petitions signed by a sum total of 370 000 individuals were submitted to the MoJ
25 Dec 2001	An amendment of the criminal law increased the maximum penalty for driving resulting in death, from a 5-year term of imprisonment for negligence resulting in death to a 15-year term of imprisonment, applicable only in cases of extremely dangerous driving, resulting in a maximum term of 20 years in combination with other offences (Criminal Law Article 208)
1 Jun 2002	Amendments of the Road Traffic Law: an increase of the maximum penalty for drink-driving from a 2-year term of imprisonment or a fine of 100 000 yen for driving while intoxicated (DWI) and a 3-month term of imprisonment or a 50 000 yen fine for driving under the influence of alcohol (DUI), to a 3-year term of imprisonment or a fine of 500 000 yen and a 1-year term of imprisonment or a fine of 300 000 yen, respectively*; a lowering of the blood alcohol concentration (BAC) limit for punishment from 0.5 mg/ml to 0.3 mg/ml (or from 0.25 mg/l to 0.15 mg/l by breath test); an elongation of the period of licence suspension from 30 days to 90 days for first offenders for DUI (those with a previous conviction for any violation may receive a longer period of suspension or revocation)†; and an elongation of the disqualification period before the reissue of a licence after its revocation from 1 to 2 years†
1 Nov 2004	An increase of the maximum penalty for refusal to undergo a breath test from 50 000 yen to 300 000 yen (ie, the same penalty as for DUI)
1 Jan 2005	An increase of the maximum penalty for dangerous driving resulting in death to a 20-year term of imprisonment (up to 30 years in combination with other offences)
25 Aug 2006	A high-profile crash in which three young children (aged 1, 2, and 3 years) died when a vehicle fell from a bridge into water after a collision that was caused by a drunken government employee
12 Jun 2007	An extension of the coverage of Criminal Law Article 208 to include motorcycles
19 Sep 2007	Amendments of the Road Traffic Law: an increase of the maximum penalty for drink-driving to a 5-year term of imprisonment or a fine of 1 000 000 yen for DWI and a 3-year term of imprisonment or a fine of 500 000 yen for DUI; an extension of the same penalties to those who provide the offender with a vehicle; and an extension of culpability to those serving alcoholic beverages and to other passengers in the motor vehicle with maximum penalties of a 3-year term of imprisonment or a fine of 500 000 yen when the driver is charged with DWI and a 2-year term of imprisonment or a fine of 300 000 yen when the driver is charged with DUI

*Prison sentences are rarely given to offenders for DUI or DWI alone, and first offenders usually receive fines of 60–70% of the maximum amount allowed by the law.
†The decision as to whether a licence is suspended or revoked, and the length of the suspension and disqualification periods before the reissue of a licence, are determined based on the number of accumulated penalty points.

Variables and analyses

In the analysis, monthly data on the proportions of crashes involving drink-driving by the most responsible driver was the dependent variable. We used proportions instead of absolute numbers or rates, in order to control for factors affecting the crash occurrence; this meant that our models did not need to include factors such as vehicle-km-travelled, petrol prices, or unemployment rates. We considered per capita alcohol consumption as an intermediate factor between changes in social norms and drink-driving, which should not be included in the models. In fact, monthly data on the potential confounding factors, including alcohol consumption and police-enforcement activities, were mostly unavailable.

The proportions were calculated for fatal crashes and all crashes involving injuries, based on the BAC level (≥0.5, <0.5, or untested); the denominators of these proportions did not include cases with no information on alcohol consumption, although they were separately analysed to determine any changes in the pattern of under-reporting due to a lack of information. A first-order autoregressive model was fitted based on residual autocorrelation judged graphically through an autocorrelation function plot and a partial autocorrelation function plot. Linear trends, dummy variables for events, interaction terms between events and the time after the events, and sine and cosine functions for seasonal patterns (the only significant terms for seasonality) were included in the time-series regression model as follows[25]:

$$P_t = \beta_0 + \beta_1 t + \sum_{i=1}^{5} \beta_{2i}E_{it} + \sum_{i=1}^{5} \beta_{3i}E_{it}(t-t_i) + \sum_{k=1}^{6} [\beta_{4k}\sin(\frac{2k\pi t}{12}) + \beta_{5k}\cos(\frac{2k\pi t}{12})] + \varepsilon_t$$

Here, P_t denotes the monthly proportions (percentages) of crashes involving drink-driving, t denotes the time period (ranging from t=1 for January 1995 to t=168 for December 2008), β_0 denotes the intercept, β denotes the regression coefficients, E_{it} denotes the pre-event and post-event periods of the i-th event (E_{it}=0 for the pre-event period and E_{it}=1 for the post-event period), $(t-t_i)$ denotes the time after the i-th events, k is assigned a value between 1 (for annual seasonality) and 6 (for 2-month seasonality), and ε_t is the error term. The abrupt changes (discontinuity) in the levels of the series between the pre-event and post-event periods were estimated using the term $\beta_{2i}E_{it}$. β_1 indicated the slope of the baseline trend before the first event, and the slope changes in trends between two periods were estimated using $\beta_{3i}E_{it}(t-t_i)$ for interactions between the events and the time periods. For example, the first event was the high-profile crash in November 1999, and E_{1t}=0 until November 1999, E_{1t}=1 from December 1999 and t_1=59 (November 1999).

The model included the following events: the high-profile crash in 1999, the strengthened penalties for drink-driving in 2002, the increased fine for refusing a breath test in 2004, the high-profile crash in 2006, and the further strengthening of penalties for drink-driving in 2007. The change in criminal law in December 2001 was not included in the model because of the relatively short time period between this and the law amendment made in June 2002. The increase in the penalties for test refusal made in November 2004 was included, in order to determine its influence (table 1). SPSS V.17 was used for statistical analyses.

RESULTS

Of the 9227 fatal crashes and 723 687 crashes involving injuries in 1995, 15.5% and 3.1%, respectively, involved drink-driving. These numbers decreased to 4654 and 723 520, respectively, in 2008, with 6.6% and 0.9% involving drink-driving. Drivers who were untested but were revealed to have been drink-driving accounted for 2.4% of fatal crashes and 0.2% of all crashes involving injuries in 1995, and for 0.7% and 0.04%, respectively, in 2008. Cases lacking information on driver alcohol consumption accounted for 2.5% of the fatal crashes and 0.2% of all crashes involving injuries in 1995, and for 1.2% and 0.1%, respectively, in 2008.

Figure 1 shows the monthly proportions of fatal crashes and injury crashes involving drink-driving by the level of BAC (≥0.5 or <0.5). Table 2 shows the results of the time-series analyses for the three groups based on the level of BAC (≥0.5, <0.5, and untested). For fatal crashes, there were no significant level changes in the proportions of all of the groups after the crash in 1999; by contrast, the groups with BAC ≥0.5 and <0.5 showed significant level changes in the proportions of −1.9 (95% CI −3.3 to −0.5) and −0.9 (95% CI −1.4 to −0.3) percentage points, unlike the untested group, after the law amendment in 2002.

All three groups showed significant level changes after the crash in 2006: −3.1 (95% CI −5.0 to −1.2), −1.7 (95% CI −2.5 to −0.9), and −1.1 (95% CI −1.9 to −0.3) percentage points, respectively. Only the group with BAC ≥0.5 showed a significant level change of −2.0 (95% CI −3.9 to −0.1) percentage points after the law amendment in 2007. In 1999, those with BAC ≥0.5 showed a significant slope change of −0.09 percentage points per month (95% CI −0.15 to −0.03), and the untested group showed a change of 0.03 (95% CI 0.01 to 0.05) percentage points per month, whereas those with BAC <0.5 showed no significant slope change. In 2002, those with BAC <0.5 and the untested group showed significant slope changes of −0.04 (95% CI −0.07 to −0.004) and −0.06 (95% CI −0.09 to −0.02) percentage points per month. Those with BAC <0.5 showed a significant slope change of 0.06 (95% CI 0.01 to 0.10) percentage points per month, after the increase of the fine for test refusal in 2004.

In all crashes involving injuries, all three groups showed significant level changes: 0.14 (95% CI 0.05 to 0.23), 0.20 (95% CI 0.14 to 0.27), and 0.16 (95% CI 0.11 to 0.21) percentage points, respectively, in 1999; those with BAC <0.5 and the untested group showed significant level changes of −0.33 (95% CI −0.40 to −0.25) and −0.08 (95% CI −0.13 to −0.02) percentage points, respectively, in 2002, whereas those with BAC ≥0.5 did not. All of the groups showed significant level changes: −0.23 (95% CI −0.37 to −0.09), −0.15 (95% CI −0.26 to −0.05), and −0.07 (95% CI −0.14 to −0.01) percentage points, respectively, in 2006. Those with BAC ≥0.5 showed a significant slope change of −0.007 (95% CI −0.012 to −0.003) percentage points per month in 1999. The untested group showed a significant slope change of −0.004 (95% CI −0.008 to −0.001) percentage points per month in 2002.

The proportion of those with no information on alcohol consumption among the fatal crashes showed a significant slope change of −0.058 (95% CI −0.10 to −0.01) percentage points per month in 2002 (data not shown). Among all crashes involving injuries, this group showed a significant level change of 0.03 (95% CI 0.002 to 0.06) percentage points in 1999, and a significant slope change of −0.002 (−0.004 to −0.001) percentage points per month in 2002.

DISCUSSION

The present study identified significant abrupt declines in alcohol-related crashes after two high-profile crashes as well as after law amendments; the onset of the changes coincided with