Deriving a prediction rule for short stay admission in trauma patients admitted at a major trauma centre in Australia

Michael M Dinh,[1,2] Kendall J Bein,[1] Chris M Byrne,[1,3] Belinda Gabbe,[4] Rebecca Ivers[5]

[1]Emergency Department, Royal Prince Alfred Hospital, Sydney, New South Wales, Australia
[2]Department of Trauma Services, Royal Prince Alfred Hospital, Sydney, New South Wales, Australia
[3]Division of Surgery, Royal Prince Alfred Hospital, Sydney, New South Wales, Australia
[4]Department of Epidemiology and Preventive Medicine, Monash University, Melbourne, Victoria, Australia
[5]Injury Division, The George Institute for Global Health, Sydney, New South Wales, Australia

Correspondence to
Dr Michael M Dinh, Emergency Department, Royal Prince Alfred Hospital, Missenden Road, Camperdown, Sydney, NSW 2050 Australia; Dinh.mm@gmail.com

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ABSTRACT

Introduction The aim of this study was to derive and internally validate a prediction rule for short stay admissions (SSAs) in trauma patients admitted to a major trauma centre.

Methods A retrospective study of all trauma activation patients requiring inpatient admission at a single inner city major trauma centre in Australia between 2007 and 2011 was conducted. Logistic regression was used to derive a multivariable model for the outcome of SSA (length of stay ≤2 days excluding deaths or intensive care unit admission). Model discrimination was tested using area under receiver operator characteristic curve analyses and calibration was tested using the Hosmer-Lemeshow test statistic. Validation was performed by splitting the dataset into derivation and validation datasets and further tested using bootstrap cross validation.

Results A total of 2593 patients were studied and 30% were classified as SSAs. Important independent predictors of SSA were injury severity score ≤8 (OR 7.8; 95% CI 5.0 to 11.9), Glasgow coma score 14–15 (OR 3.2; 95% CI 1.8 to 5.4), no need for operative intervention (OR 2.2; 95% CI 1.6 to 3.2) and age < 65 years. (OR 1.7; 95% CI 1.2 to 2.6). The overall model had an area under receiver operator characteristic curve of 0.84 (95% CI 0.82 to 0.87) for the derivation dataset. After bootstrap cross validation the area under the curve of the final model was 0.83 (95% CI 0.81 to 0.84).

Conclusions We report a prediction rule that could be used to establish admission criteria for a trauma short stay unit. Further studies are required to prospectively validate the prediction rule.

INTRODUCTION

Short stay admission (SSA) units have been developed over the past decade in an effort to reduce hospital overcrowding and improve patient flow.[1 2] These are distinct areas where the clinical focus is on improved access to diagnostic tests, early multidisciplinary assessment and expedited discharge planning. Patients admitted to these areas are generally stable, without complex clinical needs and with anticipated hospital length of stays of between 24 h and 48 h.[3]

A few small studies from the USA have investigated the role of short stay units in trauma patients.[4–6] In a retrospective study of 364 patients, Madsen *et al*[4] found the implementation of a unit for trauma patients to be safe with an average length of stay of around 13 h and an admission rate from the short stay unit to the ward of around 11%. Exclusion criteria for admission to the observation unit in that study included abnormal vital signs, Glasgow coma score (GCS)<14, abnormal chest radiograph or head CT and multiregion injury. Hennerman *et al*[5] evaluated 230 patients with suspected abdominal trauma and negative diagnostic peritoneal lavage who were admitted to an emergency observation ward. Eighty-one per cent of patients were discharged with no adverse outcomes reported.

Development of a prediction tool that could reliably predict the need for a SSA could assist in bed management and patient flow through trauma units at designated trauma centres. This is particularly relevant for trauma units, such as ours, where trauma patients are initially admitted under a single unit for initial management and stabilisation. In this context, decisions regarding early discharge planning directly from the trauma unit or transfer to long stay wards for ongoing care need to be made early, to avoid unnecessary delays and prolonged length of stay. We therefore sought to identify predictors of SSA in a trauma registry dataset and derive a prediction model for SSAs after trauma team activation at a single major trauma centre.

METHODS

Design

This was a study using trauma registry data from a single major trauma centre. Data on all trauma presentations to this hospital were collected prospectively by a single trained data manager (SR).

Setting

An inner city major trauma centre in New South Wales, Australia with around 700 trauma team activations per annum. The direct catchment area of the hospital serves around 850 000 people of the inner west and central business district of the city of Sydney. All trauma patients are initially admitted under the trauma service until discharge or transfer of care to the most appropriate subspecialty unit. There is currently no short stay unit for injured patients at this institution.

Study population

Data were obtained for all adult (age≥15 years) trauma activations in the emergency department (ED) who were admitted as inpatients to the hospital between 2007 and 2011. Exclusion criteria were the absence of vital signs on arrival or discharge from the ED. Patients with missing length of stay data or vital signs, or who were still inpatients on 31 December 2011 were also excluded. The need for trauma team activation was based on a previously validated two-tiered trauma activation protocol and meets current American College of Surgeons Committee on Trauma benchmarks for triage performance.[7] All patients were initially assessed and managed in the ED. Any patients requiring admission after trauma team activation were admitted under the trauma surgeon on call with a tertiary survey performed within 24 h to determine the most appropriate inpatient specialty team and disposition from hospital.

Primary outcome

Patients with SSA were defined as those with an admission length of stay 48 h or less, who survived and did not require intensive care unit admission.

Variables abstracted

The hospital trauma data registry routinely collected demographic details (age, sex), clinical variables (vital signs on arrival to ED, GCS on arrival, mechanism of injury), injury diagnoses (abbreviated injury scale, injury severity scores (ISS)) and outcomes (length of stay and inhospital death) for all trauma activation patients since 2007. These were linked by name, medical record number and date of presentation to the hospital medical records department to obtain International Classification of Diseases 10th revision, Australian Modification (ICD-10AM) coded diagnoses for medical and mental health condition. Patients were classified as having a significant medical comorbidity if an ICD-10AM diagnostic code included in the Charlson comorbidity index[8] (including dementia, cancer, diabetes, congestive cardiac failure, acute myocardial infarction, liver failure, renal disease, peptic ulcer disease, connective tissue disorders, chronic lung disease) was recorded for their admission. Patients with ICD diagnostic codes that included any non-organic psychiatric diagnoses (F20.0–F99.0) were classified as having a mental health disorder. These included all mood, personality and schizophrenia related disorders.

Injured body regions were classified by Abbreviated Injury Scale (AIS) regions[9](head, face, neck, spine/vertebral column, chest, abdomen, lower limb including pelvic injuries) and upper limb. Injuries classified in the 'external' region, such as burns (which were routinely transferred to a specialist burns hospital) were excluded from analyses. Age was categorised into elderly (age≥65 years) and non-elderly, based on previous work.[10] Normal vital signs were defined as the presence of all of the following in a given patient: 50 beats per minute ≤pulse rate ≤110 beats per minute, 90 mm Hg≤systolic blood pressure ≤180 mm Hg and 10 breaths per minute ≤respiratory rate ≤24 breaths per minute according to the current clinical emergency response system criteria used at this hospital. Any operative procedures performed while an inpatient, including orthopaedic procedures, were recorded. Demographic details such as marital status (married and living with spouse vs other) and preferred language at home (English vs non-English) were obtained from admission records.

Statistical analysis

Univariate analyses using χ^2 tests for categorical data and Wilcoxon rank sum tests for non-parametric continuous data were performed to compare baseline characteristics between short stay patients and non-short stay patients and screen for potential predictors of SSA. Using statistical software (SAS V.9.3 SAS Institute, Cary, Illinois, USA) the entire dataset was then randomly divided in a 1:1 ratio into derivation and validation datasets. A multivariable logistic regression model was used to develop a prediction model from the derivation dataset.

All variables were considered as a priori predictors. Individual AIS body regions and mechanisms of injury were entered into the model as indicator variables. The final model was selected using a stepwise selection algorithm with variable entry and selection criteria $p<0.05$. Receiver operator characteristic curves were plotted and the area under the curve (AUC) was used to assess overall discrimination, the ability of the model to correctly classify a patient with or without SSA. The Hosmer-Lemeshow statistic was used to test calibration, defined as how well the predicted probability correlates with the observed probability of SSA across deciles of risk. All clinically relevant first-order interactions between age, medical comorbidity, mental health and body regions were tested using interaction terms. The model was further tested with bootstrap validation using 500 resampling simulations to obtain an estimate of mean AUC and overall optimism of the final model. Optimism is a measure of expected difference in model performance after resampling and is an indicator of overfitting. β Coefficients of model predictors were used to derive risk scores using a previously described methodology and sensitivities and specificities calculated at relevant score cut-offs.[11]

Ethics

The study was approved by the Sydney Local Health District Research Ethics Committee (Royal Prince Alfred Hospital (RPAH) zone).

RESULTS

Study population

A total of 2608 eligible cases were identified from the trauma registry. Fifteen cases (0.6%) had missing data relating to length of stay or vital signs and were excluded leaving 2593 cases for analysis. The mean (SD) age was 45 (20) years and 71% were male. Thirty per cent of patients were classified as SSAs. Patients with an ISS>15 comprised 28% of the study population and the overall inhospital death rate was 3%. The most common mechanisms of injury were falls (33%), motor vehicle crashes (15%) and pedestrians (14%). Penetrating injury accounted for 10% of patients. Baseline characteristics of derivation and validation datasets are shown in table 1.

Univariate analysis of SSAs

Age≥65 years was found to be associated with increased proportion of SSA compared with age <65 years, whereas other demographic variables were not associated with SSA (table 2). Other variables positively or negatively associated with SSA included ISS≤8, medical comorbidities, operative intervention, mental health diagnosis, normal vital signs and GCS 14 or 15. Penetrating injury, cyclist and motor vehicle crash mechanisms were significantly associated with SSA whereas falls were associated with non-SSAs. The only body region injury associated with increased SSA was the upper limb.

Prediction model derivation and validation

After logistic regression with stepwise selection, age≥65 years (OR 1.73; 95% CI 1.15 to 2.59, p=0.01), ISS≤8 (OR 7.73; 95% CI 5.03 to 11.87, p<0.001), GCS 14–15 (OR 3.16; 95% CI 1.83 to 5.43, p<0.001) and no operation performed (OR 2.26; 95% CI 1.61 to 3.15, p<0.001) were found to be the most important predictors of SSA. Chest injury, lower limb injury and spine/vertebral column injury were found to incrementally decrease the probability of SSA (table 3). The AUC of

Table 1 Baseline characteristics in derivation and validation datasets.

	Derivation dataset N=1306	Validation dataset N=1287
Age, years (median IQR)	42 (28,63)	42 (27,59)
Age≥65 years (%)	276 (21)	276 (21)
Male (%)	930 (71)	905 (70)
English (%)	1000 (77)	988 (77)
Married (%)	436 (33)	397 (31)
Medical comorbidity (%)	153 (12)	168 (13)
Mental health (%)	350 (27)	319 (25)
GCS 14–15 (%)	1078 (83)	1062 (83)
SBP (mean, sd) mm Hg	130 (22)	129 (22)
RR (mean, sd) bpm	19 (5)	19 (5)
PR (mean, sd) bpm	87 (19)	86 (19)
Normal vital signs (%)	988 (76)	1015 (79)
ISS (median, IQR)	5 (4,17)	5 (4,17)
ISS≤8 (%)	789 (60)	817 (63)
Penetrating (%)	144 (11)	123 (10)
Falls	432 (33)	439 (34)
MVC (%)	176 (13)	200 (16)
MBC (%)	127 (10)	109 (8)
Cyclist (%)	79 (6)	73 (6)
Pedestrian (%)	178 (14)	172 (13)
ICU admission (%)	361 (28)	332 (26)
Inhospital mortality (%)	39 (3)	42 (3)
Length of stay (median, IQR) days	4 (2,10)	4 (2,10)
Short stay admission (%)	387 (30)	389 (30)

English, preferred language spoken at home; GCS, Glasgow coma score; ICU, intensive care unit; ISS, injury severity score; Married, married and living with spouse; MBC, motor bike crash; MVC, motor-vehicle crash; SBP, systolic blood pressure; PR, pulse rate; RR, respiratory rate; Short stay admission, length of stay ≤2 days and survived and not requiring ICU.

the derivation dataset was 0.84 (95% CI 0.82 to 0.87) and the Hosmer-Lemeshow test statistic was 7.50 (p=0.43). Calibration of the model was plotted in figure 2 and shows good calibration until the highest probability decile (85%) where the calibration was reduced. The AUC for the validation dataset was 0.79 (95% CI 0.76 to 0.82) (figure 1). Using bootstrap cross validation, the mean estimate for AUC of the final model was 0.83 (95% CI 0.81 to 0.84) indicating moderately good discrimination. Optimism of the model after cross validation was 0.004. The optimal point on the receiver operator characteristic curve corresponded to a risk score cut-off of six points or more with a sensitivity of 83%, specificity of 66%, negative predictive value of 90% and positive predictive value of 51%. According to the probability function curve (figure 3) a risk score between 7 and 8 gave an estimated probability of SSA of 50%.

DISCUSSION

The present study was conducted to ascertain predictors of SSA in a group of trauma patients, and develop a prediction tool that could be used by clinicians and bed managers to triage appropriate patients from the trauma unit after appropriate initial assessment and diagnostic investigation. Based on our findings, eligibility criteria in trauma patients would include patients with an ISS≤8, normal vital signs (systolic blood pressure, respiratory rate and pulse rate), GCS of 14 or 15, who do not require operative intervention. The final model had moderately good overall discrimination and calibration with an AUC of 0.83 after cross validation.

Predicting length of stay has important implications, not just for benchmarking quality of care,[12 13] but to improve operational efficiency[14] and streamline transitions of care between acute care services, rehabilitation and primary care services.

Table 2 Comparison of short stay admission (SSA) patients versus non-SSA patients with respect to baseline and injury characteristics

	SSA N=776	Non-SSA N=1817	Significance
Age≥65 years (%)	93 (12)	459 (25)	<0.001
Male (%)	554 (71)	1281 (71)	0.74
Married (%)	236 (30)	597 (33)	0.22
English (%)	603 (78)	1385 (76)	0.41
Medical comorbidity (%)	44 (6)	277 (15)	<0.001
Mental health (%)	125 (16)	544 (30)	<0.001
GCS 14–15 (%)	736 (95)	1404 (77)	<0.001
Normal vitals (%)	668 (87)	1335 (74)	<0.001
ISS≤8 (%)	709 (91)	897 (49)	<0.001
Penetrating	111 (14)	156 (9)	<0.001
Falls (%)	209 (27)	662 (36)	<0.001
MVC (%)	134 (17)	242 (13)	0.01
MBC	64 (8)	172 (9)	0.32
Cyclist (%)	63 (8)	89 (5)	0.001
Assault (%)	114 (14)	245 (13)	0.42
Body regions (%)			
Head	241 (31)	871 (48)	<0.001
Face	132 (17)	411 (23)	0.001
Neck	14 (2)	41 (2)	0.46
Chest	122 (16)	471 (26)	<0.001
Abdomen	55 (7)	215 (12)	0.003
Upper limb	305 (39)	595 (33)	0.001
Lower limb	158 (20)	724 (40)	<0.001
Operation (%)	264 (34)	873 (48)	<0.001

English, preferred language spoken at home; GCS, Glasgow coma score; ISS, injury severity score; Married, married and living with spouse; MBC, motor bike crash; MVC, motor-vehicle crash; Operation, any operative procedure during inpatient admission; PR, pulse rate; RR, respiratory rate; SBP, systolic blood pressure.

Table 3 Final prediction model after stepwise selection

	β coefficient	OR	SE	95% CI	p Value	Risk score
Age≤65 years	0.55	1.73	0.21	1.15 to 2.59	0.01	1
GCS 14–15	1.15	3.16	0.28	1.83 to 5.44	<0.001	2
Normal vital signs	0.62	1.86	0.20	1.25 to 2.76	0.002	1
No operation performed	0.81	2.24	0.17	1.62 to 3.15	<0.001	1.5
ISS≤8	2.04	7.75	0.22	5.02 to 11.90	<0.001	4
Mental health	−0.81	0.45	0.20	0.30 to 0.65	<0.001	−1.5
Penetrating	0.59	1.80	0.25	1.10 to 2.94	0.02	1
Pedestrian	−0.49	0.62	0.24	0.38 to 0.99	0.045	−1
Falls	−0.66	0.52	0.19	0.36 to 0.75	<0.001	−1
Chest	−0.87	0.42	0.21	0.28 to 0.64	<0.001	−2
Spine/vertebral column	−0.80	0.45	0.25	0.28 to 0.73	0.001	−1.5
Lower limb	−1.26	0.28	0.18	0.20 to 0.40	<0.001	−2

Intercept β coefficient −1.828; Hosmer-Lemeshow test statistic p=0.48; OR—adjusted OR; GCS, Glasgow Coma Score; Normal vital signs, all of the following parameters met: systolic blood pressure 90–180 mm Hg, pulse 50–110 beats per minute and respiratory rate 10–24 breaths per minute

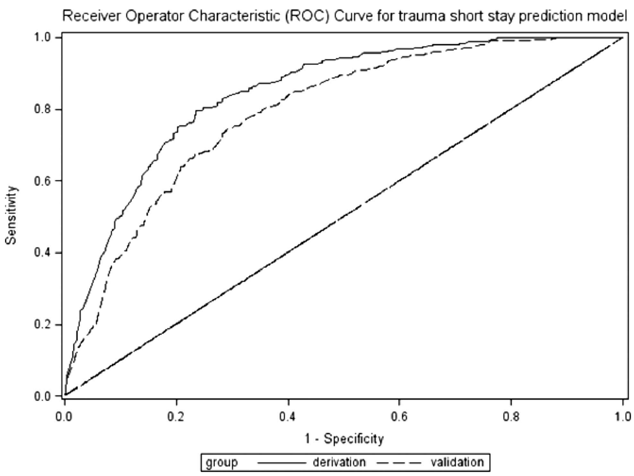

Figure 1 Receiver operator characteristic curve for derivation and validation datasets—derivation area under curve (AUC) 0.84; 95% CI 0.82 to 0.87, validation AUC 0.79; 95% CI 0.77 to 0.82.

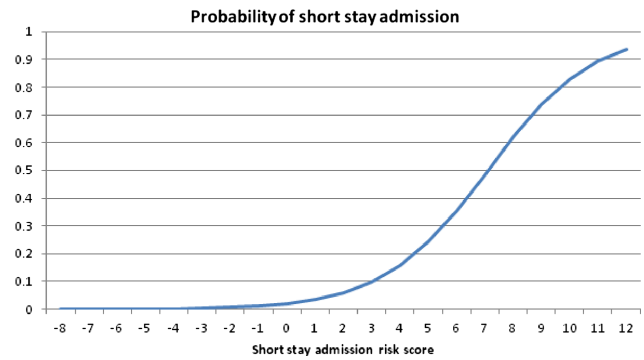

Figure 3 Probability of short stay admission as a function of risk scores.

Trauma patients predicted to have SSA may be eligible for expedited discharge planning and community based early discharge programmes. Currently all literature regarding short stay units in Australia involves medical admission units[1–3] with no eligibility criteria developed to date for surgical patients in general or trauma patients with minor injuries.

A number of observations about the prediction model should be made. The ISS and need for operative intervention are not typically known at the time of patient presentation. These variables are usually determined within 24 h of admission, at the time of tertiary survey, when the patient has been admitted to the trauma unit and all injuries and ongoing clinical needs are defined. Even if the exact ISS cannot be calculated by trauma clinicians within 24 h of admission, an ISS≤8 can be thought of conceptually by the absence of any severe injuries (such as intracranial haemorrhage, solid organ injury or severe chest injury) and the presence of minor injuries in no more than two body regions. The risk tool would therefore be useful in the context of trauma admitting units where clinicians need to decide which patients can be safely observed and discharged within the next 24 h and those who need transfer to ongoing care. To further define the clinical utility of this prediction model, prospective evaluation and comparison with clinician prediction is required. A study of emergency physicians' ability to predict length of stay after admission found that around 35% of predictions were correct.[15] Predictors of SSA in that study included age <65, normal oxygenation and self referral. Application of a decision rule in conjunction with clinician expertise is therefore likely to assist and improve decision making regarding short stay unit admission.

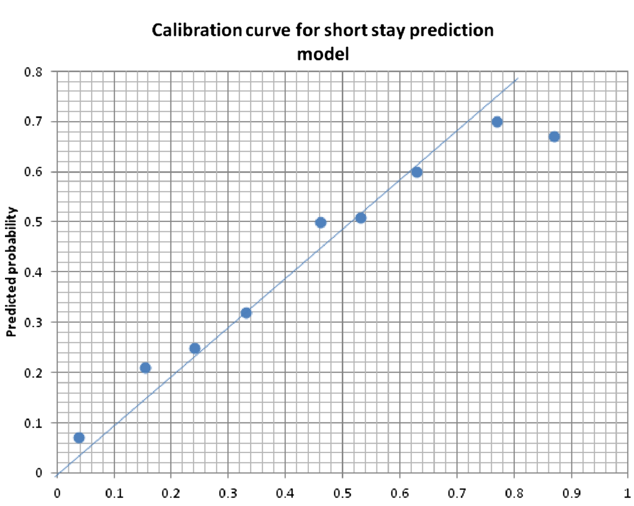

Figure 2 Calibration curve for short stay prediction model. Diagonal line indicates perfect (1:1) calibration between predicted and observed probabilities.

Mental health diagnoses were found to be predictive for non-SSA. Although many studies have looked at the impact of trauma on subsequent mental health, few studies have examined the impact of pre-existing mental health diagnoses on hospital resource use and cost after acute trauma. A study from San Francisco using medical records and registry data found similar rates of mental health diagnoses in cases of unintentional injury.[16] These authors also found that patients with mental health diagnoses had longer lengths of stay and repeat admissions for injury.[17]

The presence of penetrating injuries, most of which were stabbing-related, was found to increase the odds of SSAs. These findings are consistent with a recent trend toward non-operative management of penetrating torso injury without obvious indications for surgical exploration.[18 19] In this dataset, 30% of patients sustaining penetrating injury did not have operative intervention and the median length of stay in these patients was 2 days (IQR 1–4).

There are a number of acknowledged limitations to this study. The use of registry and medical record data relies on the accuracy of coding, which in turn relies on the completeness of clinical documentation. However the data were collected prospectively and information abstracted from standardised trauma admission forms. It is unlikely that designing a prospective study from the outset would have substantially improved the quality of data collected. The list of medical comorbid diagnoses was limited to those present in the Charlson comorbidity index[12] which is intended to predict longer-term mortality in the general population. The absence of medical comorbidities was not found to be predictive for SSA over and above their injury profile, contrary to previous studies looking at length of stay and comorbidities in general medical patients.[20] Increasing number of medical comorbidities would be expected to decrease the probability of SSA in hospitalised patients but we only used the presence of any medical comorbidity as a binary categorical variable.

Mental health diagnoses used in this study included all major diagnostic categories, including mood disorders, schizophrenia and personality disorders that were coded from the medical record. It is possible that mental health diagnoses were under-reported but the proportion of patients with mental health diagnostic codes was consistent with recent population estimates in Australia.[21] The findings need to be validated in an external dataset before being applied in other settings.[22 23] Differences in admission practices and population characteristics at other trauma centres will reduce the external validity of the described model. However the same methodology reported here could be applied to develop customised eligibility criteria for SSA at other centres.

In conclusion, we have developed and internally validated a model to predict the need for short stay hospital admission in a group of trauma patients. This may be used to refine eligibility criteria for entry into a short stay ward or an observation ward designed to expedite the discharge planning process in trauma patients.

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Contributors MMD—study design, data analysis and manuscript preparation; KJB—data analysis and manuscript preparation; CMB—manuscript review; BG—manuscript review, statistical support; RI—study supervisor and manuscript review.

Competing interests None.

Ethics approval Sydney Local Health District Human Research Ethics Committee.

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