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Original Contribution

Predicting hospital admission at the emergency department triage: A novel prediction model

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ABSTRACT

Background: Emergency department (ED) overcrowding is a growing international patient safety issue. A major contributor to overcrowding is long wait times for inpatient hospital admission. The objective of this study is to create a model that can predict a patient's need for hospital admission at the time of triage.
Methods: Retrospective observational study of electronic clinical records of all ED visits over ten years to a large urban hospital in Singapore. The data was randomly divided into a derivation set and a validation set. We used the derivation set to develop a logistic regression model that predicts probability of hospital admission for patients presenting to the ED. We tested the model on the validation set and evaluated the performance with receiver operating characteristic (ROC) curve analysis.
Results: A total of 1,232,016 visits were included for final analysis, of which 38.7% were admitted. Eight variables were included in the final model: age group, race, postal code, day of week, time of day, triage category, mode of arrival, and fever status. The model performed well on the validation set with an area under the curve of 0.825 (95% CI 0.824–0.827). Increasing age, increasing triage acuity, and mode of arrival via private patient transport were most predictive of the need for admission.
Conclusions: We developed a model that accurately predicts admission for patients presenting to the ED using demographic, administrative, and clinical data routinely collected at triage. Implementation of the model into the electronic health record could help reduce the burden of overcrowding.

1. Introduction

Emergency department (ED) overcrowding has been described as "the biggest impediment to the delivery of timely and adequate emergency care" worldwide [1]. It necessitates urgent attention in developed nations as rapidly aging populations increase ED utilization [2]. The strain overcrowding places on ED resources impairs access to care in the form ambulance diversion, longer times to treatment, and increased probability of patients leaving without being seen [3,4]. It also compromises quality of care. Beyond the ED doors, ED overcrowding is associated with increased inpatient mortality, length of stay, and cost for admitted patients [5]. It also has an emotional impact on patients and staff. Patient dissatisfaction also increases with prolonged wait times [6]. In turn staff morale, physician productivity, and teaching time at academic medical centers decline with increased patient volumes [7].

Causes of ED overcrowding are complex and multifactorial. Contributing factors include high patient volume, increased patient complexity and acuity, shortage of inpatient beds, and long wait times for admission from the ED to inpatient wards [7,8]. International reports have found that a primary cause is the presence of inpatients in the ED [3,9]. These patients contribute disproportionately to ambulance diversion and long wait times [3,10]. At Singapore's largest hospital, wait time from admission to ward ranges from 1 to 7.9 h on a given day. Improving flow from the ED to the admitting ward could have powerful effects on reducing overcrowding.

One solution is earlier notification to the admitting ward of an impending bed request. Advanced notice could give staff more time to prepare inpatient accommodations during delivery of emergency care. This may decrease patient wait time after emergency care has been delivered and subsequently relieve overcrowding. An admission prediction model run on all ED patients at triage could serve this purpose by

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coupling a high probability of admission to early notification of the admitting ward. Several such models have been developed with moderate to high accuracy using both logistic regression and machine learning [8,9,11-17]. These models have outperformed known independent predictors of admission such as triage acuity and nurse clinical judgment [11,15,18]. Models developed with retrospective data have had similar prospective performance [9,19]. This cost-sensitive approach has had promising performance in expediting flow and reducing wait time when applied prospectively to historical data and in a simulated hospital [9,16]. Comparisons between models derived from logistic regression and machine learning have had mixed results with no clear superior model [20-22].

To date, no model has become a widely adopted clinical tool. In order to be clinically useful, the model needs to be parsimonious and consist of variables that are readily available at triage. This limits the widespread applicability of many models which require coexisting chronic disease information or significant clinical information. Other models are not widely applicable because they are specific to a sub-population or disease. It has also been suggested that no score has been widely adopted because there is a steep tradeoff between simplicity and accuracy and no score exists that is both simple enough and accurate enough to be clinically useful [23].

In this study we aim to use routine demographic, administrative and limited clinical data readily available at triage to predict the probability of hospital admission at the time of the patient's arrival to the ED. We aim to create a more widely applicable model than extant ones by using a large and diverse population for its development and limiting variable selection to what is routinely available.

2. Methods

2.1. Study design and setting

This was a retrospective, single center, cross-sectional study of routinely collected clinical data. Institutional review board approval was obtained from Singapore Health Services. Singapore is a small, urban city state of 5.6 million people. The population is racially and ethnically diverse, composed primarily of Chinese, Indian and Malay races. It is a rapidly aging population, in line with the global trend of developed nations. The site of this study is the ED of Singapore General Hospital (SGH), a larger urban acute tertiary care hospital with over 30 clinical disciplines. SGH is the oldest and largest hospital in Singapore and houses 1600 inpatient beds. Its ED receives over 400 patients daily. Its annual patient volume exceeds 140,000 ED visits, 70,000 inpatient discharges, and 680,000 outpatient clinic visits.

2.2. Study protocol and management

The data was extracted from the hospital's Electronic Health Intelligence System (eHINTS), a data warehouse that compiles data from several databases. We masked specific patient details to ensure that data was adequately anonymized but included an identity number by which we could identify repeat visits by the same patient. Death records were drawn from the death registry and matched to the visit entries of the specific patient. Extracted data included demographic information, administrative information, and clinical information. The primary outcome of interest was admission or non-admission. An admission was defined as the physician decision to admit the patient to any inpatient discipline, including psychiatry and surgery. In Singapore this disposition decision is made by ED physicians. All other dispositions were labeled as non-admissions.

2.3. Variables

Eleven variables were selected for data analysis, including four demographic, four administrative, and three clinical. Demographic variables include age group, gender, ethnicity, and proximity of patient's home postal code to the study site. Proximity was coded as a binary variable that differentiated patients who lived closest to the study site hospital (within study site catchment) from patients who lived closer to a different hospital (outside study site catchment). In these patients preference theoretically played a role in their presentation to the study site hospital as a different hospital would have been a faster alternative. Administrative variables include day of week, shift time of presentation, mode of arrival, and whether or not the visit occurred during a public school holiday for Singaporean students. There are four public school breaks throughout the year lasting 1–4 weeks, and this variable was analyzed to determine the clinical suspicion that families bring dependent elders to the hospital during these times to enable travel. Clinical variables include triage category using the Singaporean Patient Acuity Category Score (PAC; Appendix A), fever status, and number of ED visits within the previous calendar year. The PAC system contains 4 levels, with Scale 1 representing the most acutely sick patients and Scale 4 representing non-emergent patients who are more appropriate for the primary care setting.

2.4. Statistical analysis

ED records of all patients over 21 years old who came to the study site ED during the 10-year period from January 1, 2005 and December 31, 2014 were evaluated in this study. The data was analyzed using RStudio version 1.1.383 (Boston, MA) [24]. Visits were excluded if patients were dead upon arrival, refused admission, or absconded (left the ED without or with only partial evaluation and/or treatment). After application of exclusion criteria the data was randomly divided into non-overlapping derivation (70%) and validation (30%) sets. The derivation set was used to develop the model. The model's performance was evaluated by applying it to the validation set and comparing predicted probability with actual patient outcomes.

Descriptive analysis was conducted on both the derivation and validation datasets to assure similarity. Frequency and percentage are reported for categorical data while mean and standard deviation are reported for the continuous variable. Analysis of the variance was performed with chi-square statistics on categorical variables. A two-tailed *t*-test was performed on the continuous variable. A statistically significant difference was defined as $p < 0.001$.

Univariate analysis was performed on all variables to assess their ability to independently predict admission. The largest cohort of each variable was selected as the baseline for comparison within groups. Due to the large sample size, an alpha level of 0.001 was used to determine significance.

The prediction model was built by applying stepwise logistic regression on the derivation set. For each variable, the largest cohort was used as the baseline. The modeling performance was evaluated on the validation set. It generated a probability of admission from 0 to 1 for each visit. The threshold probability of admission that optimized both sensitivity and specificity of the model was calculated and used to compare predictions to actual patient dispositions. The predictive power of the model was calculated using the area under the curve (AUC) in the receiver operating characteristic (ROC) analysis.

To further evaluate if the predicted probabilities reflect the true likelihood of admission, we have plotted the model calibration curve with “caret” package in R. We created 10 bins of the predicted probabilities of all patients in the validation set and calculated the true admission rate for each bin. Then we chose the bin midpoints and the corresponding observed admission rates to plot the calibration curve.

3. Results

3.1. Patient flow

Fig. 1 shows the flow of all patients presenting to the ED in our dataset. A total of 1,382,896 visits to the ED occurred in the 10-year

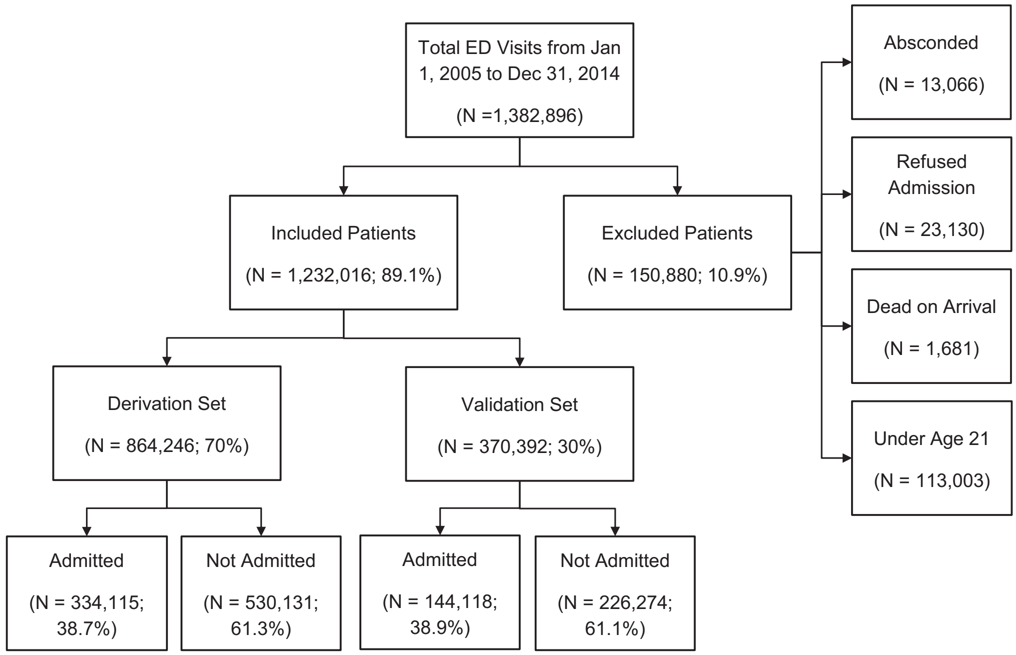

Fig. 1. Flow of patients presenting to the emergency department from January 1, 2005 – December 31, 2014 in admission prediction study (absconded refers to patients who left the ED without or with only partial assessment and/or treatment).

period between January 1, 2005 and December 31, 2014. Of these, a total of 150,880 visits were excluded because the patients absconded (13,066), refused admission (23,130), were dead on arrival (1681) or were under age 21 (113,003) leaving a remainder of 1,232,016 visits for analysis. Of remaining visits, 607,858 visits were by unique patients for an average of 2.03 visits per patient. Of these, 38.7% resulted in admission.

3.2. Baseline characteristics

Patients presenting to the ED were an average age of 51.4 years old, 53% male, and had an racial composition of 66% Chinese, 13% Indian, 12% Malay, and 9% other. A majority of patients came in the midweek (Tuesday-Thursday) during the 08:00 to 16:00 shift and were triaged as a PAC Scale 3, meaning they required "acute non-urgent treatment." Walk-ins outnumbered patients arriving by ambulance and private transport, and most lived closer to a different hospital than the study site. Table 1 shows the baseline characteristics compared between patients who were admitted and not admitted in both the derivation and validation sets. All variables except time of year in relation to school holiday period showed statistically significant differences between admitted and not admitted patient groups. The proportions of patients who were elderly, had higher triage acuity, arrived by private patient transport or government ambulance, and were febrile were significantly higher among admitted patients. Proportion of patients who were younger, lower triage category, were walk-ins, and were afebrile was significantly lower among admitted patients. The largest changes of rate of admission were seen with increasing age and triage acuity. 85.0% of PAC Scale 1 (the highest acuity) patients were admitted compared to 39.4% of Scale 2, 16.0% of Scale 3, and 1.6% of Scale 4. Old and young elderly patients were admitted at much higher rates than adult patients (73% and 62% compared to 29% respectively).

3.3. Univariate statistical analysis

Table 2 shows demographic, administrative and clinical variables compared between patients who were and were not admitted. All variables except day of the week and time of year in relation to school holiday were independent predictors of admission. Demographically, patients who were over age 65, female, Chinese, and who lived closest to the study site hospital were more likely to be admitted than baseline. Patients who were Indian, Malay, or other races were less likely to be admitted than baseline. Administratively, patients who arrived by private patient transport or government ambulance were more likely to be admitted than walk-ins. Patients who came from 16:00 to 24:00 were marginally more likely to be admitted than patients who came from 08:00 to 16:00, and patients who came from 24:00 to 08:00 were less likely to be admitted. Clinically, patients who were triaged as PAC Scale 1 or Scale 2 were much more likely to be admitted than the baseline of Scale 3, and patients triaged as Scale 4 were much less likely to be admitted. Patients who were febrile were more likely to be admitted. Number of ED visits in the previous calendar year was marginally higher among admitted patients.

3.4. Admission prediction model

All variables except time of year in relation to school holiday were used to create the stepwise regression model. Although day of week was not statistically significant in univariable analysis we included it because clinical judgment suggests it is predictive. Gender and number of ED visits in the past year were eliminated during the stepwise variable selection. The final model contains eight variables: age, race, postal code, shift time, day of week, arrival mode, triage category, and fever. Table 3 shows multivariable analysis with corresponding adjusted odds ratio and 95% confidence interval (CI). The strongest predictors of admission were increasing age, increasing triage category, and mode of arrival via private patient transport. The odds ratio (OR) was 28.6 for Scale 1 and 7.3 for Scale 2 patients. The OR was 3.2 for old elderly and 2.4 for young elderly. Patients who arrived by private patient transport were more likely to be admitted than walk-ins, while patients who arrived by government ambulance were less likely.

3.5. Predictive model performance

The model shows good discriminatory power on predicting hospital admissions (Fig. 2). When applied to the validation set, the model achieved an AUC of 0.825 (95% CI: 0.824–0.827). The optimal threshold probability for classification of "admitted" was 0.425. This maximized

Table 1
Descriptive analysis of all patients included in derivation and validation sets.

Variables	Derivation set				Validation set			
	Total Patients (n = 864,246; 70.00%)	Admitted Patients (n = 334,115; 38.66%)	Not Admitted Patients (n = 530,131; 61.34%)	*p*-value	Total Patients (n = 370,392; 30.00%)	Admitted Patients (n = 144,118; 38.91%)	Not Admitted Patients (n = 226,274; 61.09%)	p-value
Age, n(%)[a]				<0.001				<0.001
Adult (21–64)	621,436 (71.90)	180,989 (54.17)	440,447 (83.08)		265,443 (71.67)	77,885 (54.04)	187,558 (82.89)	
Young elderly (65–84)	211,479 (24.47)	130,170 (38.96)	81,309 (15.34)		91,208 (24.62)	56,129 (38.95)	35,079 (15.50)	
Old elderly (85+)	31,331 (3.63)	22,956 (6.87)	8375 (1.58)		13,741 (3.71)	10,104 (7.01)	3637 (1.61)	
Gender, n(%)[a]				<0.001				<0.001
Female	407,609 (47.16)	161,340 (48.29)	246,269 (46.45)		175,025 (47.25)	69,560 (48.27)	105,465 (46.61)	
Male	456,616 (52.83)	172,767 (51.71)	283,849 (53.54)		195,359 (52.74)	74,555 (51.73)	120,804 (53.39)	
Day of week, n(%)[a]				<0.001				<0.001
Monday	142,776 (16.52)	55,868 (16.72)	86,908 (16.39)		61,444 (16.59)	24,210 (16.80)	37,234 (16.46)	
Midweek	369,284 (42.73)	145,463 (43.54)	223,821 (42.22)		157,781 (42.60)	62,512 (43.38)	95,269 (42.10)	
Friday	119,278 (13.80)	46,572 (13.94)	72,706 (13.71)		51,262 (13.84)	20,143 (13.98)	31,119 (13.75)	
Weekend	232,908 (26.95)	86,212 (25.80)	146,696 (27.67)		99,905 (26.97)	37,253 (25.85)	62,652 (27.69)	
Triage category, n(%)[a,1]				<0.001				<0.001
Scale 1	78,539 (9.09)	66,778 (19.99)	11,761 (2.22)		33,983 (9.17)	29,055 (20.16)	4928 (2.18)	
Scale 2	320,623 (37.10)	193,028 (57.77)	127,595 (24.07)		137,480 (37.12)	83,058 (57.63)	54,422 (24.05)	
Scale 3	464,227 (53.71)	74,295 (22.24)	389,932 (73.55)		198,561 (53.61)	31,997 (22.20)	166,564 (73.61)	
Scale 4	857 (0.10)	14 (0.00)	843 (0.16)		368 (0.10)	8 (0.01)	360 (0.16)	
Race, n(%)[a]				<0.001				<0.001
Other Races	77,301 (8.94)	18,899 (5.66)	58,402 (11.02)		32,996 (8.91)	8119 (5.63)	24,877 (10.99)	
Chinese	571,424 (66.12)	237,000 (70.93)	334,424 (63.08)		245,124 (66.18)	102,452 (71.09)	142,672 (63.05)	
Indian	113,039 (13.08)	37,370 (11.18)	75,669 (14.27)		48,885 (13.20)	16,150 (11.21)	32,735 (14.47)	
Malay	102,449 (11.85)	40,829 (12.22)	61,620 (11.62)		43,369 (11.71)	17,389 (12.07)	25,980 (11.48)	
Shift Time, n(%)[a]				<0.001				<0.001
24:00 to 08:00	116,772 (13.51)	42,465 (12.71)	74,307 (14.02)		50,100 (13.53)	18,325 (12.72)	31,775 (14.04)	
16:00 to 24:00	319,458 (36.96)	125,511 (37.57)	193,947 (36.58)		136,899 (36.96)	54,162 (37.58)	82,737 (36.56)	
08:00 to 16:00	428,016 (49.52)	166,139 (49.73)	261,877 (49.40)		183,393 (49.51)	71,631 (49.70)	111,762 (49.39)	
Mode of Arrival, n(%)[a]				<0.001				<0.001
Private patient Transport	37,448 (4.33)	30,831 (9.23)	6617 (1.25)		16,104 (4.35)	13,250 (9.19)	2854 (1.26)	
Walk-In	753,500 (87.19)	263,210 (78.78)	490,290 (92.48)		322,487 (87.07)	113,277 (78.60)	209,210 (92.46)	
Government ambulance	73,298 (8.48)	40,074 (11.99)	33,224 (6.27)		31,801 (8.59)	17,591 (12.21)	14,210 (6.28)	
Time of year, n(%)[2]				0.503				0.083
Holiday	218,115 (25.24)	84,191 (25.20)	133,924 (25.26)		93,668 (25.29)	36,222 (25.13)	57,446 (25.39)	
Not holiday	646,131 (74.76)	249,924 (74.80)	396,207 (74.74)		276,724 (74.71)	107,896 (74.87)	168,828 (74.61)	
Postal code, n(%)[a,3]				<0.001				<0.001
Outside catchment	620,709 (71.82)	243,149 (72.77)	377,560 (71.22)		265,910 (71.79)	104,727 (72.67)	161,183 (71.23)	
In catchment	221,122 (25.59)	87,794 (26.28)	133,328 (25.15)		94,892 (25.62)	38,048 (26.40)	56,844 (25.12)	
Fever status, n (%)[a]				<0.001				<0.001
Afebrile	740,108 (85.64)	276,741 (82.83)	463,367 (87.41)		317,760 (85.79)	119,819 (83.14)	197,941 (87.48)	
Febrile	124,138 (14.36)	57,374 (17.17)	66,764 (12.59)		52,632 (14.21)	24,299 (16.86)	28,333 (12.52)	
Number of prior ED visits, mean (SD)[a]	0.92 (4.80)	1.05 (3.09)	0.84 (5.62)	<0.001	0.91 (4.59)	1.05 (3.13)	0.83 (5.32)	<0.001

ED: Emergency Department; 1 = Triage category per Patient Acuity Category, see appendix; 2 = Holiday refers to the four annual public school holiday breaks; 3 = Catchment refers to geographical area in which study site is the closest hospital.
[a] Refers to significant difference.

Table 2
Univariable analysis of demographic, administrative, and clinical variables of patients admitted versus not admitted to the hospital at time of emergency department triage.

	OR (95% CI)	p-Value
Age[a]		
Adult (baseline)		
Young elderly (65–84)	3.90 (3.86–3.94)	<0.001
Old elderly (85+)	6.67 (6.50–6.84)	<0.001
Gender[a]		
Male (baseline)		
Female	1.08 (1.07–1.09)	<0.001
Day of week		
Midweek (baseline)		
Monday	0.99 (0.98–1.00)	0.0868
Friday	0.99 (0.97–1.00)	0.0868
Weekend	0.90 (0.89–0.91)	0.0868
Triage category[a,1]		
Scale 3 (baseline)		
Scale 1	29.80 (29.18–30.44)	<0.001
Scale 2	7.94 (7.86–8.02)	<0.001
Scale 4	0.09 (0.05–0.14)	<0.001
Race[a]		
Chinese (baseline)		
Other races	0.46 (0.45–0.46)	<0.001
Indian	0.70 (0.69–0.71)	<0.001
Malay	0.93 (0.92–0.95)	<0.001
Shift time[a]		
08:00 to 16:00 (baseline)		
24:00 to 08:00	0.90 (0.89–0.91)	<0.001
16:00 to 24:00	1.02 (1.01–1.03)	<0.001
Mode of arrival[a]		
Walk-in (baseline)		
Private transport	8.68 (8.45–8.92)	<0.001
Government ambulance	2.25 (2.21–2.28)	<0.001
Time of year[2]		
Not holiday (baseline)		
Holiday	1.00 (0.99–1.01)	0.503
Postal code[a,3]		
Outside catchment (baseline)		
In catchment	1.02 (1.01–1.03)	<0.001
Fever status[a]		
Afebrile (baseline)		
Febrile	1.44 (1.42–1.46)	<0.001
Prior ED visits[a]	1.01 (1.01–1.01)	<0.001

ED: Emergency department; 1 = Triage category per Patient Acuity Category, see appendix; 2 = Holiday refers to the four annual public school holiday breaks; 3 = Catchment refers to geographical area in which the study site is the closest hospital.
[a] Denotes clinical significance.

both sensitivity (0.775; 95% CI: 0.772–0.777) and specificity (0.748; 95% CI: 0.746–0.750). Positive predictive value (PPV) was 0.830 (95% CI: 0.828–0.831) and negative predictive value (NPV) was 0.677 (95% CI: 0.674–0.679). Furthermore, the calibration curve of our prediction model is illustrated in Fig. 3 where the predicted probabilities of admission are almost identical to the observed probabilities of admission.

4. Discussion

In this study, we developed a model predicting inpatient hospital admission for patients presenting to the ED using eight easily obtained variables. Our model has a good predictive performance with an AUC of 0.825 (95% CI: 0.824–0.827). The results suggest the possibility of building a reliable admission prediction model from basic demographic, administrative and limited clinical information as a useful tool for hospital bed management. Our model compares well to other similar logistic regression models predicting admission at triage for all-comers to the ED. Cameron et al. developed a model in Glasgow with an AUC of 0.877 [17]. The significant variables included were triage category (Manchester Triage System), age, National Early Warning Score, arrival by ambulance, referral source, and admission within the last year. This model performed better than triage nurse predictions [15]. Similarly to our model, this model's applicability is limited by the use of a regional triage system. Additionally, this model requires more clinical

Table 3
Odds ratios of covariates selected to be part of the admission prediction model following stepwise elimination logistic regression.

Variable	OR (95% CI)	*P*-Values
Shift[a]		
24:00 to 08:00	1.19 (1.17–1.21)	<0.001
16:00 to 24:00	1.18 (1.16–1.20)	<0.001
Age[a]		
Young elderly (65–84)	2.44 (2.41–2.47)	<0.001
Old elderly (85 and above)	3.24 (3.15–3.34)	<0.001
Race[a]		
Indian	0.89 (0.87–0.90)	<0.001
Malay	1.10 (1.08–1.12)	<0.001
Other races	0.72 (0.70–0.73)	<0.001
Mode of arrival[a]		
Private transport	2.11 (2.04–2.17)	<0.001
Government ambulance	0.86 (0.85–0.88)	<0.001
Postal code[a]		
In catchment	0.90 (0.89–0.92)	<0.001
Triage[a,1]		
Scale 1	28.60 (27.96–29.26)	<0.001
Scale 2	7.31 (7.23–7.40)	<0.001
Scale 4	0.14 (0.08–0.22)	<0.001
Fever status[a]		
Febrile	2.72 (2.68–2.76)	<0.001
Day of week[a]		
Monday	1.02 (1.00–1.03)	0.0454
Friday	0.97 (0.96–0.99)	<0.001
Weekend	0.92 (0.90–0.93)	<0.001

ED: Emergency department; 1 = Triage category per Patient Acuity Category, see appendix.
[a] Denotes clinical significance.

information in the form of a National Early Warning Score [25]. This model could not be applied to our data for comparison because we do not have the clinical data necessary to calculate either variable.

Kim et al. also developed a model in Australia with a relatively low accuracy of 72% as determined by adding true positive and true negative results [26]. Significant predictors of admission were patient age, initial presenting symptoms or diagnosis, triage category (Australian Triage Scale), mode of arrival, existence of an outside referral, time of day of arrival, day of the week, whether or not blood tests were ordered and the extent of the abnormality of the blood test. The utility of this score is constrained by the need to wait for blood tests, which only improved

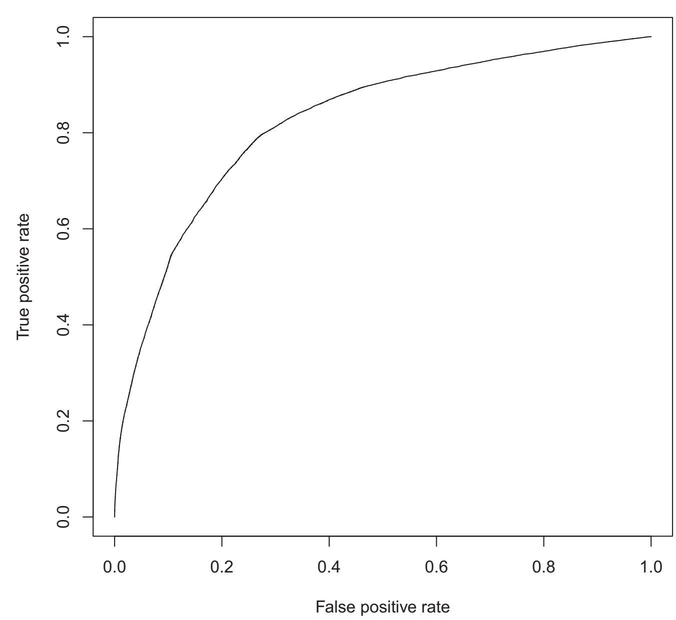

Fig. 2. Receiver operating characteristic (ROC) curve of hospital admission prediction model assigned to validation set (area under the curve [AUC] = 0.825; 95% confidence interval [CI] 0.824–0.827).

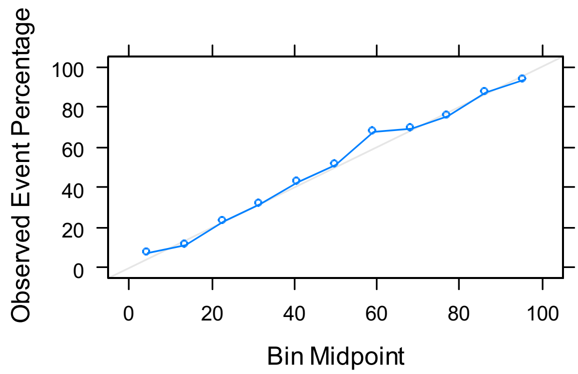

Fig. 3. Calibration plot of the admission prediction model. The calibration curve was generated using "caret" package in R version 3.2.3 (R Foundation, Vienna, Austria).

the accuracy of the score by 3%. This supports the non-inclusion of blood tests into our model. Kim et al. found that their score compared similarly to triage nurse predictions.

Sun et al. also developed a model to predict hospital admission for all-comers to the ED in Singapore. The AUC value was 0.849 and the variables predictive of admission were older age, Chinese ethnicity, arrival by ambulance, higher triage score (PAC), prior ED attendance in the past three months, and the existence of certain chronic disease (diabetes, hypertension, or dyslipidemia). Our model is notably different from this because it does not require information on chronic conditions. This information may sometimes be readily available in the small country of Singapore with a centralized health care database, but chronic condition information is typically not available at triage in larger countries with decentralized databases. In our goal to create a more translatable model we did not include this information. Our study is also much larger and therefore our model is expected to be more applicable to different populations.

A major strength of our model is the size of the data set used for its development. This is among the largest data sets used to build an admission prediction model. Because Singapore's population is so diverse, this includes an exceptional array of genetic and behavioral diversity. Another advantage of our model is its simplicity. It contains only eight easily obtained variables. The model is simple enough to be incorporated into the electronic health record to calculate a probability at time of triage.

Due to the simplicity and good performance of our model, we are proposing incorporating it into the electronic medical record. The probability of admission could be calculated for every patient at ED triage and patients above the threshold identified as a "likely to admit". For these patients, a notification could be sent to admitting hospital wards for early preparation. Of note, our model is designed for administrative use only. Therefore, the model is not intended to be an alternative to physician judgment and should not be used to determine whether or not to admit a patient.

Our data analysis yielded several notable findings. It is unsurprising that the most significant predictors of admission are increasing triage category, increasing age group, and presence of fever. This aligns with clinical perception that more acute, older patients with abnormal vitals are more likely to require admission. Interestingly, several observations contradicted general clinical assumptions. Arrival by ambulance is thought to be an indicator of increased patient acuity as it is the fastest way to get to the hospital. Private transportation is intended for less acute problems as vehicles are not required to be equipped with resuscitation equipment. However, we found that patients who arrived by private transportation were most likely to be admitted, while those who arrived by ambulance were least likely. This illustrates a gap in the utilization of emergency ambulances, possibly due to a lack of public education regarding use of emergency medical services (EMS). Another explanation is that patients are utilizing private transportation over government ambulances to exercise their preference for the study site hospital, as it is Singapore's oldest and largest. The policy of Singapore's government ambulance system is to bring patients to the closest ED, while patient choice directs private transportation. This explanation is supported by another unexpected observation of this study: most patients who came to the study site hospital lived closer to a different hospital. If these patients had called EMS from home, they would not have been brought to the study site. Furthermore, these patients who lived further were more likely to be admitted. This indicates that patients who are choosing to travel to the study site rather than a closer hospital are actually sick, but their preferences for the hospital are over-riding their perceived illness severity. Future work could identify patient perceptions that contribute to their hospital preference. However, in our study some patients may have been brought to the ED from places other than their homes such as their places of work.

It is noted that our analysis does not find that patients who come to the ED during a school holiday are any more likely to be admitted than those attending during the school year. This variable was analyzed to evaluate whether the phenomenon of families "dropping off" care-dependent elders at the ED in hopes of admission during optimal travel times was real or perceived among ED providers. The data suggests it is merely perceived.

4.1. Limitations

There were several limitations of this study. Firstly variables included in this study are representative of what is available in the extracted data set. It is not inclusive of all information readily available at triage, such as initial vitals, chief complaint, and type of injury, among others. Variables that have been significant in other models that were not extracted into our data set included ED visit or hospital admission in the preceding three months, existence of a referral, initial vitals, and chief complaint. Secondly one of the variables used is the PAC, a regional triage system. This is decided by triage nurses based on patients' initial symptoms and vital signs. Triage systems differ geographically and limit the applicability of the study. Thirdly the measurement method for some variables such as fever may have changed over 10 years, which could potentially impact model building. Lastly this is a single-site study which may limit the accuracy of the model when applied to other populations. It may only be applicable to the specific working practices of this site. More work is needed to validate this model using data from other hospital settings.

5. Conclusions

We developed an admission prediction model for all patients presenting to the ED at triage using eight routinely collected variables. Our score performed well with an AUC of 0.825. This compares well to similar models, but our model requires less clinical information and is therefore more rapidly and easily calculated. Our model was also developed using a very large database in an ethnically diverse country which likely would yield similar performance across different populations. To make the score as broadly applicable as possible future work should replace regional triage classification with more objective variables. Ideally this would include initial vitals. Future work should also test the prospective performance of the model by incorporating it into the electronic health record to determine likelihood of admission for patients at ED triage. Predictions could be compared to actual patient outcomes to further assess the validity of the model.

Conflict of interest

None.

Appendix A. Patient acuity categorization in Singapore

Explanation table of patient acuity categorization in Singapore designated by triage nurses at the time of patient's registration at the ED using patient's presenting complaint and vital signs.

	Condition	Requirements
Scale 1	Either already in a state of cardiovascular collapse or in imminent danger of collapse	Maximum allocation of staff and equipment resources for initial management
Scale 2	Ill and non-ambulant and in various forms of severe distress. Appear to be in a stable state on initial exam and not in danger of imminent collapse	Early attention but likely trolley-based
Scale 3	Acute mild to moderate symptoms	Non-urgent acute treatment
Scale 4	Non-emergent. More appropriately managed in a primary health care setting	No immediate treatment

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