

Predicting Hospital Admission of Patients at Triage in the Emergency Department at Lampang Hospital

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ABSTRACT

OBJECTIVE This study aims to develop a model that can help predict the likelihood of hospital admission for patients at the triage point in Lampang Hospital's Emergency Department.

METHODS The study was designed around Clinical Prediction Rules and was conducted as a retrospective cohort study using data from July 2021 to January 2022 input through the Smart ER program. Patients were categorized into two groups: admit and discharge. Statistical analysis involved both univariable and multivariable logistic regression analyses, presenting discrimination values with area under the receiver operating characteristic (AUROC), testing precision with a calibration plot, analyzing internal validation using the Bootstrapping method, and creating a risk curve to find the balanced cutoff point. The study then divided the predictions into one of three groups: Admit, Consult, and Discharge. Decision curve analysis (DCA) was performed and an application was developed and integrated into the Smart ER program for real-time analysis.

RESULTS Out of 37,474 patients screened, 18,056 were excluded leaving 19,418 patients eligible for complete case analysis. Predictors of hospital admission included age, emergency level, vital signs, mode of hospital arrival, and prominent symptoms according to criteria-based dispatch (CBD) (criteria-based dispatch). The Admission Model showed an AUROC of 0.8934 (95% CI, 0.8890-0.8980); the calibration plot demonstrated that predicted values closely matched actual observed values; internal validation using the Bootstrapping method yielded a C-statistic of 0.8920 (95% CI, 0.888-0.895); and the balanced risk curve indicated over admission at 3.8% and over discharge at 3.7%.

CONCLUSIONS The Admission Model provides high AUROC and precision values. The model's three-group division is likely to be beneficial in practical application.

KEYWORDS patient admission, clinical decision rules, models, statistical, overcrowding

INTRODUCTION

The Emergency Department (ED) at Lampang Hospital serves patients both during and outside normal working hours, handling an average of

200-250 patients per day. Each patient undergoes triage according to the Ministry of Public Health (MOPH) ED Triage principles (1) which classify emergency levels from 1 to 5. Level 1 indicates

critical conditions requiring immediate intervention to prevent death, while level 5 indicates non-urgent conditions. Triage is conducted at the professional nursing station where patients' chief complaints are recorded, vital signs measured, pain scales assessed, and patient type (trauma or non-trauma) classified. Currently, ED Lampang Hospital has implemented an Electronic Health Record system, utilizing the 'Smart ER' program to digitally store data which allows for real-time emergency medical registry analysis.

Overcrowding is a frequent issue in the ED (2-6), often exacerbated by physicians' indecisiveness regarding whether patients should be admitted or discharged (2, 3), particularly among less experienced physicians. This indecision often leads to unnecessary laboratory tests, causing delays for patients who could potentially be admitted immediately. At the ED of Lampang Hospital, this can result in delays of at least 2-3 hours in the ED.

Previous studies have highlighted the importance of several parameters in predicting hospital admissions, with a focus on vital signs such as temperature, pulse rate, blood pressure, respiration rate, and blood oxygen saturation level. Other important factors to consider include age, sex, triage levels, mode of transportation, and Glasgow Coma scale (GCS) score (7).

The 'Smart ER' program stores large amounts of data which can be analyzed using big data analytics to predict the chances of hospital admission. This tool can help guide newly graduated doctors in making more efficient admission decisions (8, 9), potentially alleviating ER overcrowding both now and in the future.

The objective of this study is to predict the likelihood of hospital admission at the triage point in Lampang Hospital's ED utilizing electronic data from the 'Smart ER' program.

METHODS

This prognostic prediction research employed a retrospective cohort design to assess the likelihood of hospital admission at the triage point in the ED of Lampang Hospital. The study setting was the triage area of the ED, where patients are initially assessed before receiving further medical services. Data were collected from the 'Smart ER' electronic program which is used for managing patient information and triage processes.

Data were retrospectively collected for all patients screened before receiving emergency room services at Lampang Hospital from July 1, 2022 to January 31, 2023 and included patients who were triaged at Lampang Hospital's ED between July 1, 2022 and January 31, 2023. Inclusion criteria consisted of all patients who underwent triage during this period and who were recorded in the 'Smart ER' system. Exclusion criteria included patients who were on intubation before triage, refused treatment, were transferred to the outpatient department, died before receiving ED services or at the ED, left without being seen by medical staff, or had incomplete data in the hospital record system.

This study utilized a range of determinants (independent variables) derived from real-time electronic data captured through the 'Smart ER' program at Lampang Hospital. Variables included gender, age, presenting symptoms (criteria based dispatch, CBD), triage level, time of hospital arrival, referral source, vital signs (blood pressure, pulse rate, respiratory rate, temperature, GCS), pain scale, patient type (trauma, non-trauma), and shift timings. The primary outcome variable was the likelihood of hospital admission.

Data were extracted from the 'Smart ER' program and exported to Excel for preliminary cleaning. Statistical analysis was conducted using STATA® version 18. The study used a "complete case analysis" approach, avoiding data imputation. Patient characteristics were compared using exact probability tests for categorical variables and the Student's t-test or Wilcoxon rank sum test for continuous variables. Multivariable logistic regression was employed to analyze predictors of hospital admission, with the model's discrimination ability assessed using the area under the receiver operating characteristic (AUROC) curve. Model validity was tested using calibration plots and internal validation through bootstrapping. Decision curve analysis and a risk curve were also utilized to enhance the clinical applicability of the predictive model.

The sample size was calculated using Dr. Richard D. Riley's method (10) as suggested in modern clinical epidemiology, considering a C-statistic of 0.8, 20 parameters, an admission prevalence of 41.42%, and a shrinkage factor of 0.99, resulting in a minimum required sample size of 6,738. To

account for potential missing data, a 30% buffer increased the total required sample size to approximately 10,000 cases.

Ethical considerations

The study maintained strict patient confidentiality by anonymizing personal identifiers such as name, hospital ID, and national ID number. Ethics approval was secured from the Lampang Hospital Ethical Research Committee (approval No. 074/66).

Definition

The CBD (11) for sorting and prioritizing emergency patient care as established by the Thai Emergency Medicine Foundation in 2013 includes:

- Code 1: Abdominal/back/pelvic and groin pain
- Code 2: Anaphylaxis/allergic reactions
- Code 3: Animal bites
- Code 4: Bleeding (non-traumatic)
- Code 5: Breathing difficulties
- Code 6: Cardiac arrest
- Code 7: Chest pain/cardiac pain
- Code 8: Chocking
- Code 9: Diabetes
- Code 10: Environmental hazard
- Code 11: Unassigned
- Code 12: Headache/neck pain
- Code 13: Psychiatric/behavioral issues
- Code 14: Drug overdose/poisoning
- Code 15: Obstetric/gynecological emergencies
- Code 16: Seizures
- Code 17: General Illness/Weakness (Non-specific)/Others
- Code 18: Weak Limbs/difficulty speaking/facial droop (stroke)
- Code 19: Unconscious/unresponsive/transient loss of consciousness
- Code 20: Pediatric/emergency pediatric care
- Code 21: Assault/injury
- Code 22: Burns - thermal/electrical/chemical
- Code 23: Drowning/water-related injuries
- Code 24: Motor vehicle accidents
- Code 25: Medical staff alert/vital signs abnormalities

Hospital staff shifts

- Morning Shift: from 08:00 to 15:59
- Afternoon Shift: from 16:00 to 23:59
- Night Shift: from 00:00 to 07:59

Patient admission

Patients requiring hospitalization for at least 24 hours.

RESULTS

During the study period, 37,474 patients were screened for eligibility at the ED of Lampang Hospital. Of these, 17,344 were excluded: 712 based on intubation before triage, 39 died before arrival, 40 died in ER, 289 left against medical advice, 1,831 were referred to outpatient services, 71 refused treatment and 15,074 had incomplete data. Consequently, a total of 19,418 cases were included in the complete case analysis (Figure 1).

Although the initial sample size calculation indicated a need for 10,000 cases, data from 19,418 patients were collected to enhance robustness, increase statistical power, account for missing data, and ensure greater generalizability.

The study population consisted primarily of females, making up 59% of the total, with an average age of 49.9 ± 0.2 years. Approximately half of the medical services were provided during the afternoon shift and two-thirds of the cases were non-trauma related. Over one-third of the patients were triaged as level 3 (Table 1).

Univariable and multivariable logistic regression analyses identified several predictors of hospital admission, including age, respiratory rate, pulse rate, blood oxygen level, temperature, GCS score, triage levels 1–3, and modes of transportation (e.g., referral, relatives, ALS, BLS, stretcher, wheelchair). Non-trauma patients and CBD codes 1, 4, 5, 7, 9, 10, 12–25 were also significant predictors (Table 2)

The admission model (see: supplementary materials) showed excellent performance with an AUROC of 0.8934. (95% CI, 0.8890–0.8980) (Figure 2). A calibration plot indicated high accuracy (E:O = 1.000) (Figure 3). Internal validation using bootstrapping confirmed the model's robustness with a C-statistic of 0.8920 and minimal shrinkage, indicating reliability when applied to other datasets (Table 3).

Risk curve analysis (Figure 4) identified optimal cutoff points for the probabilities of admission, leading to practical recommendations for patient management based on the chance of admission. The optimal cutoff points are at log odds = -1.1 and 0.45, corresponding to probabilities of admission of 25% and 60%, respectively. The calculated

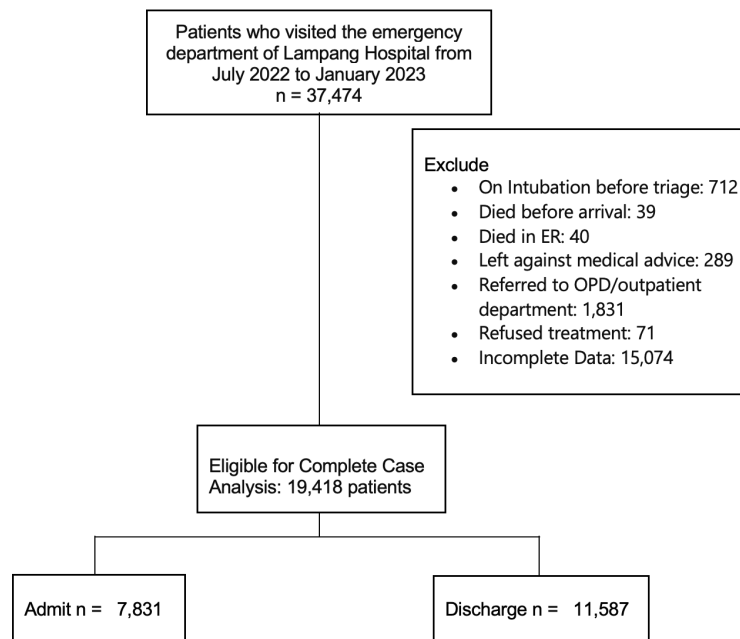


Figure 1. Outcome flowchart

percentages are used as follows (Table 4) 1) 0–25%: Can be discharged (false positive rate 3.8%, 2) 25%–60%: Consider consultation with an emergency medicine physician, 3) 60%–100%: Can be admitted (false positive rate 3.7%).

Decision curve analysis demonstrated that the admission model outperforms standard clinical judgment, showing substantial benefits from an admission prevalence of 10% and above. This study had a high prevalence of admission at 40.3%, indicating significant benefits (Figure 5).

DISCUSSION

The study identified critical predictors of hospital admission in the emergency setting, including age, respiratory rate, blood oxygen level, temperature, and GCS scores. These findings align with previous research by Kishore et al., which also highlighted the significance of these variables in predicting hospital admissions (12). Moreover, also in agreement other studies, patients triaged at levels 1–3 and those arriving via hospital transport such as referrals or emergency medical services (EMS) or by stretcher were more likely to be admitted (13–18).

Our study's methodology and the use of big data significantly contributed to the robustness of our findings. By nearly doubling the pre-calculated sample size needed and employing a complete case analysis, the data's reliability exceeded

that typically achievable through methods that permit data imputation (19). The minimal amount of missing data and the predominance of clinical variables helped ensure comprehensive coverage and high validity of the study results (20).

The Admission Model's high AUROC values (0.8934) and accuracy further validate its effectiveness in clinical settings, outperforming traditional clinical judgment. These results are similar to those reported in other studies (21–24) in the region, which reported AUROC values ranging from 0.630 to 0.878, demonstrating the model's superior predictive capability.

Critically, the present study also carefully considered the balance between risks of over-discharge and excessive admission. The defined cutoff points were optimized to maintain false positive rates below 5%, which is essential for minimizing potential harm in clinical practice (25, 26). Over-admission, typically influenced by non-clinical factors such as relatives' preferences or specialist referrals, and over-discharge, particularly concerning for patients with chronic conditions who might manage at home, were notably low (27, 28).

The primary limitation of this research lies in its derivation of the admission model, which, while robust, represents only the initial stage in the development of Clinical Prediction Rules. The lack of external validation is a significant gap that

Table 1. Baseline characteristics of patients who visited emergency department, Lampang Hospital

Characteristics	Total (n=19,418)	Admission (n=7,831)	Discharge (n=11,587)	p-value
Female	11,457	4,582	6,875	0.070
Age (years), mean±SD	49.9±0.2	57.2±0.2	44.5±0.2	<0.001
Mean arterial pressure (mmHg), mean±SD	98.0±0.1	97.9±0.2	98.1±0.1	0.511
Respiratory rate (breaths per minute), mean±SD	20.3±0.02	21.4±0.10	19.5±0.00	<0.001
Pulse rate (beat/min), mean±SD	90.1±0.1	91.7±0.2	88.9±0.2	<0.001
SpO ₂ (%), mean±SD	97.5±0.02	96.9±0.05	97.8±0.02	<0.001
Temperature (degree celsius), mean±SD	36.7±0.0	36.9±0.0	36.6±0.0	<0.001
Glasgow Coma score (sum), [min, max]	15 [3, 15]	15 [3, 15]	15 [6,15]	<0.001
Pain scale	2.3±0.02	2.1±0.03	2.4±0.03	<0.001
Shift, n (%)				<0.001
Morning (08:00 to 15:59)	7,091 (36.5)	3,035 (38.8)	4,056 (35.0)	
Afternoon (16:00 to 23:59)	9,679 (49.9)	3,709 (47.4)	5,970 (51.5)	
Night (00:00 to 07:59)	2,648 (13.6)	1,087 (13.8)	1,561 (13.5)	
Triage, n (%)				<0.001
Level 1	1,108 (5.7)	1,046 (13.4)	63 (0.5)	
Level 2	5,924 (30.5)	3,751 (47.9)	2,173 (18.8)	
Level 3	7,915 (40.8)	2,917 (37.2)	4,998 (43.1)	
Level 4	3,750 (19.3)	122 (1.4)	3,638 (31.4)	
Level 5	720 (3.7)	5 (0.1)	715 (6.2)	
Type, n (%)				<0.001
Trauma	6,653 (34.3)	2,270 (29.0)	4,383 (37.8)	
Non-trauma	12,765 (65.7)	5,561 (71.0)	7,204 (62.2)	
CBD, n (%)				<0.001
1. Abdominal/back/pelvic and groin pain	3,699 (19.1)	1,346 (17.2)	2,353 (20.3)	
2. Anaphylaxis/allergic reactions	209 (1.1)	14 (0.2)	195 (1.7)	
3. Animal bites	992 (5.1)	29 (0.4)	963 (8.3)	
4. Bleeding (nontraumatic)	205 (1.1)	135 (1.7)	70 (0.6)	
5. Breathing difficulties	1,332 (6.9)	943 (12.0)	389 (3.4)	
6. Cardiac arrest	12 (0.1)	5 (0.1)	7 (0.1)	
7. Chest pain/cardiac pain	843 (4.3)	363 (4.6)	480 (4.1)	
8. Chocking	15 (0.1)	5 (0.1)	10 (0.1)	
9. Diabetes	41 (0.2)	35 (0.4)	6 (0.1)	
10. Environmental hazard	97 (0.5)	29 (0.4)	68 (0.6)	
11. Unassigned	0 (0.0)	0 (0.0)	0 (0.0)	
12. Headache/neck pain	800 (4.1)	153 (2.0)	647 (5.6)	
13. Psychiatric behavioral issues	98 (0.5)	53 (0.7)	45 (0.4)	
14. Drug overdose/poisoning	61 (0.3)	48 (0.6)	13 (0.1)	
15. Obstetric/gynecological emergencies	75 (0.4)	38 (0.5)	37 (0.3)	
16. Seizures	263 (1.4)	247 (3.2)	16 (0.1)	
17. General illness/weakness (non-specific)/others	4,459 (23.0)	1,752 (22.4)	2,707 (23.4)	
18. Weak limbs/difficulty speak-ing/facial droop (stroke)	382 (2.0)	334 (4.3)	48 (0.4)	
19. Unconscious/ unresponsive/ transient loss of consciousness	137 (0.7)	85 (1.1)	52 (0.4)	
20. Pediatric/emergency pediatric care	276 (1.4)	62 (0.8)	214 (1.8)	
21. Assault/injury	220 (1.1)	67 (0.9)	153 (1.3)	
22. Burns thermal/ electrical /chemical	54 (0.3)	25 (0.3)	29 (0.3)	
23. Drowning/water-related injuries	14 (0.1)	6 (0.1)	8 (0.1)	
24. Motor vehicle accidents	3,380 (17.4)	1,213 (15.5)	2,167 (18.7)	
25. Medical staff alert/vital signs abnormalities	1,754 (9.0)	844 (10.8)	910 (7.9)	

CBD, criteria-based dispatch; GCS, Glasgow Coma Scale scores

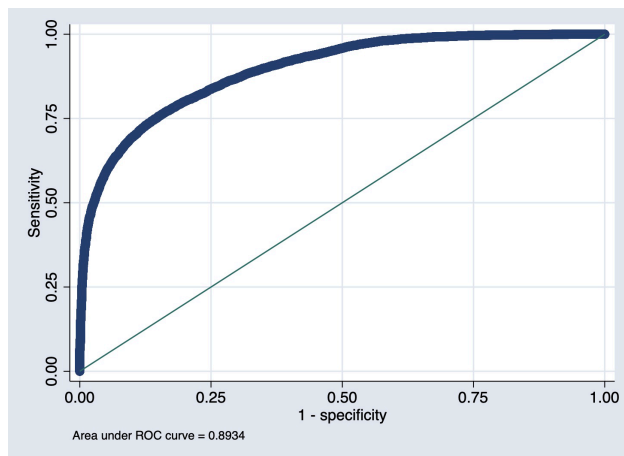
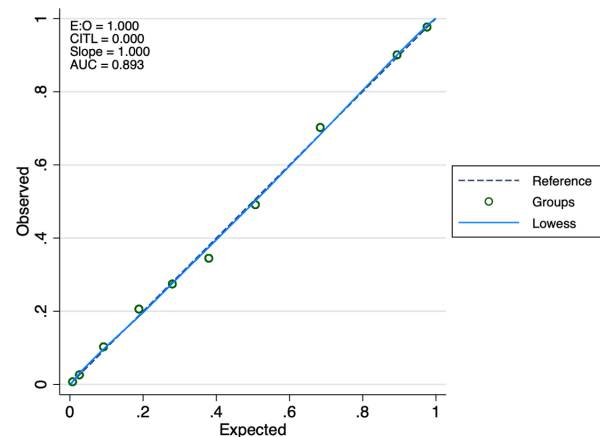
Table 2. Univariable and Multivariable logistic regression

Parameter	Univariable logistic regression			Multivariable logistic regression		
	uOR	95% CI	p-value	mOR	95% CI	p-value
Female	1.02	1.01-1.03	0.502	1.01	1.03	0.500
Age (years)	1.03	1.03-1.03	<0.001	1.02	1.02-1.02	<0.001
Mean arterial pressure (mmHg)	0.99	1.00-1.00	0.511	1.00	0.99-1.00	0.002
Respiratory rate (breaths per minute)	1.24	1.23-1.26	<0.001	1.09	1.07-1.10	<0.001
Pulse rate (beat/min)	1.01	1.01-1.01	<0.001	1.00	1.00-1.00	0.002
SpO ₂ (%)	0.90	0.89-0.91	<0.001	0.98	0.97-1.00	0.020
Temperature (degree celsius)	1.43	1.39-1.49	<0.001	1.26	1.19-1.33	<0.001
Glasgow Coma score (sum)	0.58	0.55-0.62	<0.001	0.84	0.79-0.91	<0.001
Pain Scale	0.96	0.95-0.97	<0.001	1.00	0.98-1.01	0.889
Shift						
Morning	1.20	1.13-1.28	<0.001	1.05	0.96- 1.15	0.299
Afternoon	(Ref)	(Ref)	(Ref)	(Ref)	(Ref)	(Ref)
Night	1.12	1.03-1.22	0.011	1.04	0.93-1.17	0.488
Triage						
Level 1	2374.25	950.36-5931.50	<0.001	142.40	55.85- 363.08	<0.001
Level 2	246.84	102.27-595.81	<0.001	35.12	14.38-85.74	<0.001
Level 3	83.46	34.59-201.37	<0.001	17.25	7.09-42.00	<0.001
Level 4	4.40	1.79-10.82	0.001	2.05	0.83-5.07	0.120
Level 5	(Ref)	(Ref)	(Ref)	(Ref)	(Ref)	(Ref)
Carrier						
Refer	136.06	111.42-166.14	<0.001	25.44	20.31-31.87	<0.001
Relative	4.22	3.72-4.78	<0.001	1.52	1.30-1.76	<0.001
ALS	45.26	34.12-60.05	<0.001	4.35	3.08-6.14	<0.001
BLS	14.09	12.16-26.32	<0.001	2.38	1.97-2.88	<0.001
Citizen	5.01	2.38-10.55	<0.001	1.15	0.44-3.01	0.772
FR	19.00	12.48-28.90	<0.001	2.46	1.54-3.93	<0.001
Friend	1.81	1.43-2.31	<0.001	1.26	0.95-1.66	0.113
Other	12.06	7.87-18.49	<0.001	2.81	1.66-4.77	<0.001
By yourself	(Ref)	(Ref)	(Ref)	(Ref)	(Ref)	(Ref)
Transfer						
Relative	4.19	3.10-5.66	<0.001	1.78	1.22-2.60	0.003
Stretcher	13.40	12.26-14.65	<0.001	2.35	2.08-2.66	<0.001
Carry	9.58	4.90-18.72	<0.001	3.78	1.61-8.92	0.002
Walk	(Ref)	(Ref)	(Ref)	(Ref)	(Ref)	(Ref)
Wheelchair	3.51	3.14-3.91	<0.001	1.43	1.25-1.64	<0.001
Type						
Trauma	(Ref)	(Ref)	(Ref)	(Ref)	(Ref)	(Ref)
Non-trauma	1.49	1.40-1.59	<0.001	0.55	0.39-0.79	0.001
CBD						
1. Abdominal/back/pelvic and groin pain	19.00	13.05- 27.64	<0.001	5.20	2.90-9.33	<0.001
2. Anaphylaxis/allergic reactions	2.38	1.24-4.60	0.009	1.13	0.51-2.54	0.763
3. Animal bites	(Ref)	(Ref)	(Ref)	(Ref)	(Ref)	(Ref)
4. Bleeding (nontraumatic)	64.04	40.07-102.35	<0.001	12.14	6.16-23.91	<0.001
5. Breathing difficulties	80.50	54.62- 118.64	<0.001	4.77	2.61-8.71	<0.001
6. Cardiac arrest	23.72	7.10- 79.19	<0.001	3.73	0.93-15.04	0.064
7. Chest pain/cardiac pain	25.11	16.94-37.23	<0.001	3.36	1.84-6.13	<0.001
8. Chocking	16.60	5.34- 51.67	<0.001	1.07	0.21-5.52	0.939
9. Diabetes	193.71	75.55-496.64	<0.001	18.7	6.06-57.68	<0.001
10. Environmental hazard	14.16	8.01- 25.05	<0.001	4.89	2.22-10.80	<0.001
11. Unassigned	NA	NA	NA	NA	NA	NA
12. Headache/neck pain	7.85	5.22-11.82	<0.001	2.51	1.37-4.61	0.003
13. Psychiatric behavioral issues	39.11	22.73- 67.28	<0.001	10.89	5.11-23.22	<0.001
14. Drug overdose /poisoning	122.61	59.95-250.77	<0.001	39.10	16.77-91.16	<0.001
15. Obstetric/gynecological emergencies	34.10	19.01- 61.17	<0.001	11.45	5.18-25.33	<0.001
16. Seizures	512.63	274.07-958.85	<0.001	46.81	21.26-103.04	<0.001
17. General Illness/weakness (non-specific)/ others	24.49	14.78- 31.25	<0.001	5.10	2.85-9.11	<0.001

Table 2. Univariable and Multivariable logistic regression (continued)

Parameter	Univariable logistic regression			Multivariable logistic regression		
	uOR	95% CI	p-value	mOR	95% CI	p-value
CBD						
18. Weak limbs/difficulty speaking/facial droop (stroke)	231.06	143.34-372.47	<0.001	22.41	11.42-44.01	<0.001
19. Unconscious/ unresponsive/ transient loss of consciousness	54.28	32.74-89.99	<0.001	4.86	2.41-9.82	<0.001
20. Pediatric/emergency pediatric care	9.62	6.04-15.32	<0.001	5.85	2.97-11.51	<0.001
21. Assault/injury	14.54	9.11-23.22	<0.001	6.24	3.40-11.45	<0.001
22. Burns thermal/ electrical /chemical	28.62	14.94-54.84	<0.001	12.89	5.26-31.54	<0.001
23. Drowning/water-related injuries	24.91	8.12-76.42	<0.001	6.14	1.14-33.21	0.035
24. Motor vehicle accidents	28.59	12.76-27.07	<0.001	5.55	3.46-8.90	<0.001
25. Medical staff alert/vital signs abnormalities	30.80	21.04-45.09	<0.001	7.06	4.35-11.47	<0.001

ALS, advanced life support; BLS, basic life support; CBD, criteria-based dispatch; FR, first responder, NA; not applicable

**Figure 2.** Area under the receiver operating characteristic (AUROC)**Figure 3.** Calibration plot**Table 3.** Bootstrapping method internal validation

	Apparent	95% CI	Bootstrap	95% CI
Brier scaled	47.0		46.7	
C-statistic	0.8934	0.8890-0.8980	0.8920	0.8880-0.8950
E:O ratio	1.000		1.001	0.990-1.015
CITL	0.000	-0.039-0.039	-0.001	-0.045-0.037
Slope	1.000	0.970-1.030	0.990	0.964-1.021

Bootstrap shrinkage = 0.990; CITL, Calibration-in-the-large

Table 4. Percent of prediction compare true admit and true discharge

Decision	Percent of prediction	True admit (%)	True discharge (%)	Total (%)
Discharge	0-25%	748 (3.8)	7373 (38.0)	8,115 (41.8)
Consult	>25%-60%	2,198 (11.3)	3,488 (18.0)	5,686 (29.3)
Admission	>60%-100%	4,891 (25.2)	726 (3.7)	5,617 (28.9)
Total		7831 (40.3)	11,587 (59.7)	19,418 (100.0)

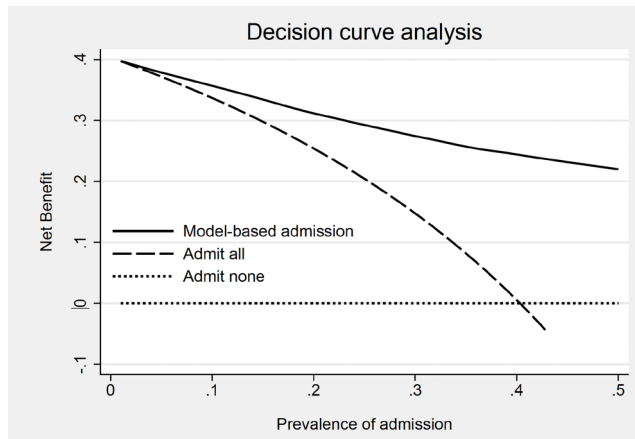


Figure 4. Decision analysis

future work must address. Incorporating temporal and geographical validations can enhance the model's applicability and reliability across different settings and over time (29). However, there has been no external validation, nor has the model been implemented in clinical practice, and no comparable studies have previously been conducted in Thailand.

The focus of our study is to enhance the triage decision-making process by predicting the likelihood of hospital admission at the initial triage point using real-time electronic data. This focus was chosen to address the immediate need for improving both the accuracy and efficiency of initial triage decisions in the ED. While revisits and mortality among released patients are not specifically addressed in our study, we acknowledge that they have important consequences for patient safety and the standard of care. Patients who return to the ED frequently have untreated or deteriorating illnesses. For that reason, to avoid unfavorable outcomes, admission decisions should be carefully considered.

The exclusion of 15,074 patients due to incomplete data is acknowledged as a limitation; however, the impact on the study's findings may have been minimal given the large remaining sample size of 19,418 patients. This substantial dataset helps maintain the robustness and generalizability of our results despite the exclusions. The reasons for data incompleteness included operational issues and variations in documentation records. To address this limitation, we chose a complete case analysis approach to ensure the robustness of our predictive model. Future re-

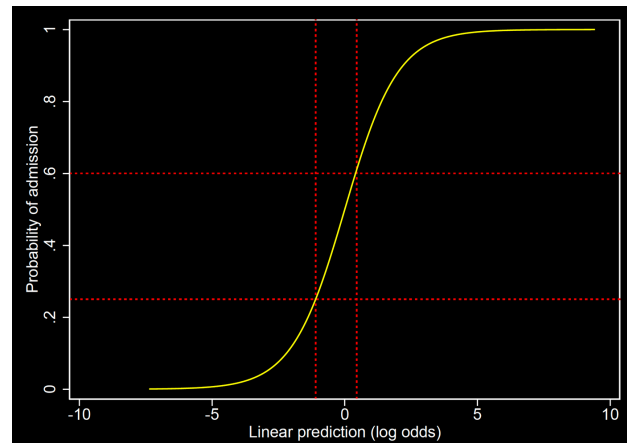


Figure 5. Risk curve

search should focus on enhancing data collection methods and developing strategies for effectively integrating incomplete datasets to minimize potential biases and to improve the comprehensiveness of research outcomes.

CONCLUSIONS

The hospital admission prediction model developed in this study demonstrated strong accuracy, with an AUROC of 0.8934. Key predictors include age, vital signs, and mode of arrival. The three-group cutoff system-discharge, consult, and admit-proved practical for real-time decision-making in the ED. While the model shows promise, external validation is necessary to confirm its broader applicability.

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CONFLICT OF INTEREST

There were no conflicts of interest regarding the publication of this paper.

ADDITIONAL INFORMATION

Supplementary materials

The following supporting information can be downloaded at: [Appendix file](#)

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Appendix

Admission Model

Sum of Log Odds (Linear combination)= $-4.241326 + (3.981628 * [(age/100) - 0.4958559069]) + (-2.215531 * [(age/100)^2 - 2.458730804]) + (-0.0052393 * (map - 98.00504686)) + (0.00403 * (pr - 90.07482748)) + (-2.121562 * [(rr/10)^2 - 0.2430246143]) + (-12.51323 * (((rr/10)^2) * \ln(rr) - 0.1718904041)) + (-0.0185235 * [spo2 - 97.45890411]) + (0.2323003 * [temp - 36.72641364]) + (-0.171473 * [gcs_sum - 14.79519003]) + (0.0023636 * [pain - 2.285250798]) + (-0.0078924 * shift_morning) + (-0.482765 * shift_noon) + (4.952123 * triage_esi1) + (3.533679 * triage_esi2) + (2.85074 * triage_esi3) + (0.7189496 * triage_esi4) + (0.2100244 * carrier_2_friend + citizen) + (0.3701199 * carrier_3_relative) + (0.8076558 * carrier_4_bls, refer) + (1.41694 * carrier_5_als) + (3.189861 * carrier_6_refer) + (0.7382427 * transfer_2_relative, carry) + (0.3750932 * transfer_3_wheel) + (0.8891516 * transfer_4_stretcher) + (-0.5363155 * type_nontrauma) + (-1.409562 * CBD_2) + (-1.474398 * CBD_3) + (0.9828423 * CBD_4) + (0.0089316 * CBD_5) + (-0.2241017 * CBD_6) + (-0.3171437 * CBD_7) + (-1.422221 * CBD_8) + (1.465532 * CBD_9) + (0.0789443 * CBD_10) + (0.908997 * CBD_13(12)) + (2.26813 * CBD_14(13)) + (0.9204234 * CBD_15(14)) + (2.332658 * CBD_16(15)) + (0.1096822 * CBD_17(16)) + (1.616454 * CBD_18(17)) + (0.0795744 * CBD_19(18)) + (0.5049024 * CBD_20(19)) + (0.3416289 * CBD_21(20)) + (1.077244 * CBD_22(21)) + (0.3703078 * CBD_23(22)) + (0.2622904 * CBD_24(23)) + (0.4994029 * CBD_25(24))$

Odds = $\exp(\text{Sum of Log Odds})$

Probability = $\text{Odds} / (1 + \text{Odds})$