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นิพนธ์ต้นฉบับ

การพัฒนาคะแนนทำนายผลลัพธ์การทำงานในผู้ป่วยโรคหลอดเลือดสมองตีบสำหรับการวางแผนเยี่ยมบ้าน

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บทคัดย่อ

ที่มา: โรคหลอดเลือดสมองตีบเป็นสาเหตุหลักของความพิการในประเทศไทย และการวางแผนเยี่ยมบ้านเป็นสิ่งสำคัญในการเปลี่ยนแปลงผลลัพธ์ผู้ป่วย การศึกษานี้มีวัตถุประสงค์เพื่อพัฒนาโมเดลทำนายผลลัพธ์การทำงานในผู้ป่วยโรคหลอดเลือดสมองตีบโดยใช้ข้อมูลก่อนจำหน่าย ประเมินผลด้วย modified Rankin Scale (mRS) ที่ 6 เดือนหลังจำหน่าย

รูปแบบการศึกษา: การศึกษา cohort เชิงสังเกตแบบสองทิศทาง

วัสดุและวิธีการ: ศึกษาผู้ป่วย 548 ราย จากโรงพยาบาลมหาวิทยาลัยนเรศวร (มกราคม พ.ศ. 2562 - กันยายน พ.ศ. 2566) ใช้ logistic regression ในการระบุปัจจัยที่เกี่ยวข้องและพัฒนาโมเดลให้คะแนน ประเมินความแม่นยำด้วย AuROC และกราฟสอบเทียบ ทดสอบความเที่ยงภายในด้วยเทคนิค bootstrapping

ผลการศึกษา: โมเดลให้คะแนนประกอบด้วย 5 ปัจจัย ได้แก่ mRS เริ่มต้น ภาวะหัวใจเต้นผิดจังหวะ จำนวนวันนอนโรงพยาบาลมากกว่า 4 วัน NIHSS ก่อนจำหน่าย และ mRS ก่อนจำหน่าย โมเดลมีค่า AuROC 0.88 และมีความสอดคล้องกันดี ตรวจสอบความถูกต้องภายในโดยใช้เทคนิค bootstrapping ยืนยันความแข็งแกร่งของโมเดล กำหนดคะแนนตัดที่มากกว่า 4 ซึ่งเหมาะสมสำหรับระบุผู้ป่วยที่มีความเสี่ยงสูง

สรุป: โมเดลนี้ที่ใช้ข้อมูลก่อนจำหน่ายเป็นเครื่องมือที่มีประโยชน์สำหรับบุคลากรทางการแพทย์ในหน่วยปฐมภูมิ ช่วยในการวางแผนการเยี่ยมบ้านและการตัดสินใจดูแลผู้ป่วยโรคหลอดเลือดสมองตีบ

คำสำคัญ: คะแนนทำนาย หลอดเลือดสมองตีบ ความสามารถทำงานร่างกาย การวางแผนเยี่ยมบ้าน

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ORIGINAL ARTICLE

Development of a Prognostic Prediction Score for Functional Outcomes in Ischemic Stroke Patients for Home Care Planning

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ABSTRACT

Background: Ischemic stroke is a leading cause of disability in Thailand. Effective homecare planning is crucial for improving outcomes. This study aimed to develop a prognostic model to predict functional outcomes in ischemic stroke patients using pre-discharge data, with outcomes assessed by the modified Rankin Scale (mRS) at six months post-discharge.

Design: Bidirectional Observational Cohort Study

Methods: A total of 548 ischemic stroke patients from Naresuan University Hospital (January 2019 - September 2023) were studied. Logistic regression was used to identify relevant predictors and develop a scoring model. Model accuracy was assessed using AuROC and calibration plots, with internal validation performed via bootstrapping.

Results: The scoring model included five predictors: initial mRS, atrial fibrillation, hospital stay longer than four days, pre-discharge NIHSS, and pre-discharge mRS. The model achieved an AuROC of 0.88 and demonstrated good calibration. Internal validation confirmed the model's robustness. A cut-off score > 4, which demonstrated good performance, was identified as appropriate for identifying high-risk patients.

Conclusions: This prognostic model, based on pre-discharge data, provides valuable guidance for healthcare professionals in primary care, supporting home care planning for ischemic stroke patients.

Keywords: prognosis, ischemic stroke, functional outcome, home care planning

Introduction

Stroke is a leading cause of mortality and long-term disability globally.[1-2] Ischemic stroke (IS) is the most common type, and around 70% of survivors suffer from long-term consequences that affect their ability to perform activities of daily living.[3] These challenges significantly impact not only the quality of life of patients but also their families[4], highlighting the critical need for effective post-stroke care and rehabilitation interventions aimed at optimizing functional outcomes.[1]

In Thailand, home care planning after discharge plays a crucial role in promoting recovery and improving patient outcomes.[5] However, a growing shortage of healthcare providers means that not all stroke survivors receive adequate rehabilitation services. As the number of stroke patients continues to rise, it becomes increasingly difficult to ensure comprehensive care for everyone.[1,2,6,7] The prognostic tools to predict functional outcomes could be highly beneficial in addressing this challenge.[8] Such a tool could guide home care planning and help prioritize care, ensuring that resources are allocated effectively to support recovery and improve long-term outcomes for stroke patients.[9,10]

Numerous studies have focused on developing prognostic models to predict post-stroke outcomes, including well-known models like ASTRAL, DRAGON, FSV, iSCORE, PLAN, SNARL, SOAR, and THRIVE.[11-17] However, none of these models have emerged as the definitive standard for predicting outcomes in IS.[18,19] This is largely due to several limitations. First, some models, such as FSV and SOAR, are not specific to IS and are designed to predict outcomes in both ischemic and hemorrhagic stroke, or they apply only to specific treatment groups.[13,17] For example, the DRAGON model predicts functional outcomes at three months but only in patients who received rt-PA therapy.[12] Additionally, certain models, like iSCORE, PLAN, and THRIVE, focus on predicting favorable outcomes or mortality, often to identify which patients will benefit from treatment.[14,15,19] Furthermore, models like DRAGON, iSCORE, and SNARL incorporate radiological imaging from CT or MRI brain scans, which may not be universally available, especially in resource-limited settings, and require specialists to interpret stroke subtypes[12,14,16] Lastly, most models assess predictive factors only at the initial time point, typically within the first 24 hours, to forecast long-term functional outcomes. This approach can lead to inaccuracies, as the condition of stroke patients can evolve considerably beyond the initial assessment.[19]

Given these limitations, there is currently no standard prognostic score designed specifically for predicting functional outcomes in IS patients. Existing models have not been tailored to address the complexities of home care planning or adapted to the specific predictors relevant to diverse clinical settings. In response to this gap, our study aims to develop a novel prognostic score model to predict functional outcomes in IS patients. This model will incorporate predictors that are particularly relevant to our context and emphasize pre-discharge variables to enhance the accuracy and applicability of the prognostications for home care planning.

Methods

Study design

A prognostic research study with prediction score development was conducted based on a bidirectional observational cohort of patients diagnosed with IS aged ≥18 years who were admitted to Naresuan University Hospital from January 2019 to September 2023. The study initially included 559 patients who survived and received continuity of care consultations before discharge. Patients who were finally diagnosed with transient ischemic attack (TIA) before discharge (n = 8) and those lost to follow-up (n = 3) were excluded, resulting in a final sample of 548 patients. Pre-discharge data were collected, and functional outcomes were assessed six months post-discharge, as shown in Figure 1. The study protocol was approved by the Ethics Committee in Human Research at Naresuan University Institutional Review Board.

Study population

In this study, IS patients were those with a confirmed diagnosis of IS. The diagnosis was established based on clinical evaluation, imaging studies (CT and/or MRI), and confirmation using ICD-10 codes specific to IS (I63.0 to I63.9).[20,21]

Data collection and predictors

All data used in the analysis were retrieved from electronic medical records and routine con-

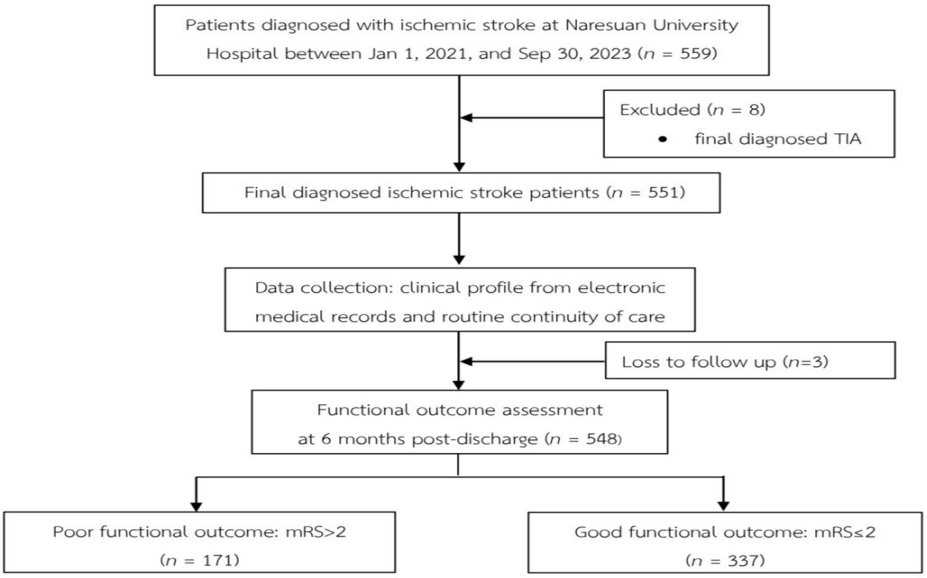

Figure 1. Study flow diagram of patient cohort

tinuity of care consultation forms for patients with IS. Baseline clinical characteristics collected included age, sex, initial NIHSS score, initial mRS score, previous history of stroke, smoking and drinking status, comorbidities, laboratory investigations, and receipt of rtPA. Pre-discharge data comprised pre-discharge NIHSS and mRS scores, number of home medications, length of hospital stay, and caregiver status. These data were collected before the patient's discharge to ensure comprehensive information for analysis. For any missing data, we planned to use Multiple Imputation by Chained Equations (MICE) to handle the gaps and ensure the robustness of our findings.

Assessment of functional outcomes

Functional outcomes were assessed using the Modified Rankin Scale (mRS), a standard tool in stroke research that measures mobility and disability.[22] The mRS scores range from 0 to 6, with a score of 2 or lower generally indicating good functional outcomes and the ability to manage daily activities independently, while a score above 2 suggests a need for assistance with daily activities. A score of 6 indicates death.[23,24] In this study, functional outcomes were evaluated at six months post-discharge, as the mRS typically stabilizes after three months, providing a reliable measure of long-term recovery.[25] This timing ensures a comprehensive assessment of the patient's functional status beyond the immediate post-discharge period.

Study size estimation

The sample size estimation for this study followed TRIPOD guidelines.[26] Based on previous data on post-stroke mRS outcomes, we estimated a minimum of 114 events needed to develop a multivariable prediction model[27], considering an expected AuROC of 0.70, five predictors, and a 25% incidence of poor outcomes. Consequently, a total of 456 IS patients were required for the study.

Statistical analysis

Continuous variables were summarized using mean and standard deviation, and categorical variables as frequency and percentage. The independent t-test was used for normally distributed continuous variables, while the Wilcoxon rank-sum test was applied for non-normal distributions. Categorical variables were compared using Fisher's exact test. Univariable logistic regression assessed the unadjusted effects of predictors on poor functional outcomes. All analyses were performed with Stata 17, considering a $p < 0.05$ as statistically significant.

Model development

In developing the model, predictors with significant p-values from univariable logistic regression were included in a multivariable logistic regression to establish the full model. Clinically

important predictors, even if not statistically significant, were also considered, and models were compared using Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to identify the optimal final model. A stepwise backward elimination approach was applied to remove non-significant predictors, with decisions guided by odds ratios, statistical significance, and the impact on the AuROC. After refining the model, the variance inflation factor (VIF) was evaluated to assess multicollinearity among the predictors in the final model. The remaining predictors' regression coefficients were then used to generate a weighted score. Each coefficient was normalized by dividing it by the smallest coefficient, and the resulting values were rounded to the nearest integer. The predictor with the smallest coefficient was assigned a score of one, and the cumulative score for each individual was calculated to evaluate the model's predictive performance for poor functional outcomes.

Test of score performance and internal validation

The performance of the derived score was assessed in terms of discrimination, calibration, and clinical utility. Discrimination was evaluated using the AuROC. Calibration was assessed with a calibration curve and the Hosmer-Lemeshow goodness-of-fit (HL-GOF) test. The clinical utility of the score was determined through decision curve analysis (DCA), which calculates the net benefit of using the score to classify patients across a range of clinically relevant threshold probabilities, comparing this approach to the default strategies of treating all patients or none. Internal validation was conducted using a bootstrap re-sampling procedure with 1,000 replicates to evaluate the model's optimism.

Score classification

Scores were categorized into low and high-risk groups for clinical applicability, with cut-off points selected based on group-specific likelihood ratios (LR) for poor functional outcomes. Lower cut-off points minimized LRs for the low-risk group, while higher points maximized them for the high-risk group. The predictive ability of each category was assessed using positive likelihood ratios (LHR+), with values less than 1 indicating lower odds and greater than 1 suggesting higher odds of poor outcomes. Diagnostic performance was evaluated through sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and overall accuracy.

Results

Baseline characteristics between groups are presented in Table 1. Missing data were imputed using the MICE method, with no significant differences found post-imputation (see supplementary material). The complete imputed dataset was used for analysis, and significant predictors are detailed in Table 2. Smoking and alcohol consumption were excluded due to incomplete data.

Model development

All significant predictors from the univariable analysis were included in the multivariable analysis, as illustrated in Table 2. The model was subsequently reduced using a stepwise approach, as described in the methods section. Five predictors were identified as independent predictors of poor functional outcomes in the multivariable logistic regression: initial mRS, atrial fibrillation (AF), length of hospital stay, discharge NIHSS, and discharge mRS. The tolerance of the covariates in the final model ranged between 0.56 and 0.98, with a mean VIF of 1.44. The AuROC for the final model was 0.87 (95%CI: 0.84-0.91). The HL-GOF yielded a p-value of 0.302, indicating a good fit. The AIC was 445.32, and the BIC was 475.47. Additional details on the selection of the optimal model are provided in the supplementary materials.

Score transformation

Each predictor in the multivariable model was assigned a specific score derived from the logistic regression coefficients, as detailed in Table 3. The scoring scheme produced a total score ranging from 0 to 15. There was a significant difference in the average scores between patients with poor and good functional outcomes, with mean scores of 7.35 ± 2.72 and 2.78 ± 2.54, respectively ($p < 0.001$). The crude score demonstrated discriminative ability with an AuROC of 0.88 (95%CI:, 0.84-0.91) (Figure 2a). Calibration was assessed using a calibration plot and the HL-GOF, which yielded a p-value of 0.289. The calibration plot indicated that the predicted probability of poor functional outcomes increased with higher scores, demonstrating a high level of

Table 1. Baseline characteristics and functional outcomes at 6 months for ischemic stroke patients

Characteristic	Missing data n (%)	Functional outcome n (%)		p-value
		Poor functional outcome (mRS >2) 171 (31.20)	Good functional outcome (mRS ≤2) 337 (68.80)	
Patient profile				
Age (years) mean±SD	0 (0)	71.56±12.42	62.79±13.99	<0.001[a]
Sex n (%)	0 (0)			
Female		91 (29.35)	219 (70.65)	0.307
Male		80 (33.61)	158 (66.39)	
Time from onset >4.5 hours n (%)	0 (0)	106 (33.65)	209 (66.35)	0.162
Initial NIHSS median, IQR	33 (6.02)	6, 4-12	3, 1-5	<0.001[b]
<7 (mild)		83 (20.65)	319 (79.35)	<0.001[c]
8-15 (moderate)		45 (56.96)	34 (43.04)	
>15 (severe)		26 (76.47)	8 (23.53)	
Initial mRS mean±SD	8 (1.45)	4.09±0.99	2.67±1.22	<0.001[a]
≤2		9 (5.73)	148 (94.27)	<0.001[c]
>2		161 (42.04)	222 (57.96)	
BMI (kg/m^2) mean±SD	0 (0)	23.15±4.27	24.37±4.14	0.002[a]
Smoking status n (%)	0 (0)			
Never		158 (33.91)	308 (66.09)	<0.001[c]
Current		13 (15.85)	69 (84.15)	
Alcohol drinking n (%)	0 (0)			
Never		157 (33.98)	305 (66.02)	<0.001[c]
Current		14 (16.28)	72 (83.72)	
Co-morbidity n (%)				
Old CVA	0 (0)	75 (42.37)	102 (57.63)	<0.001[c]
Diabetes mellitus	0 (0)	57 (34.13)	110 (65.87)	0.367
Hypertension	0 (0)	134 (35.45)	244 (64.55)	<0.001[c]
Dyslipidemia	0 (0)	99 (34.86)	185 (65.14)	0.065
Myocardial infraction	0 (0)	42 (50.60)	41 (49.40)	<0.001[c]
Atrial fibrillation	0 (0)	45 (67.16)	126 (26.20)	<0.001[c]
Congestive heart failure	0 (0)	7 (30.43)	16 (69.57)	1.000
Chronic kidney disease stage 4-5	0 (0)	12 (29.27)	29 (70.73)	0.862
Cancer	0 (0)	13 (43.33)	17 (56.67)	0.157
Laboratory investigation mean±SD				
Hemoglobin	0 (0)	12.20±2.11	12.66±2.10	0.018[a]
FBS	0 (0)	121.33±43.05	114.74±49.17	0.132
HbA1C	14 (2.55)	6.35±1.79	6.24±1.71	0.485
Cholesterol	12 (2.19)	159.30±48.86	175.27±104.69	0.062
Triglyceride	13 (2.37)	117.18±56.77	130.42±109.76	0.145
HDL	13 (2.37)	44.01±12.56	45.84±14.45	0.160
LDL	13 (2.37)	92.62±43.42	97.76±42.91	0.204
Albumin	81 (14.78)	3.65±0.57	3.94±0.49	<0.001[a]
Creatinine	0 (0)	1.22±1.04	1.17±1.06	0.568
Treatment profile				
rtPA received n (%)	0 (0)	8 (28.57)	20 (71.43)	0.837
Number of medications median (IQR)	0 (0)	7 (4-9)	5 (3-8)	<0.001[b]
No caregiver	0 (0)	7 (33.33)	14 (66.67)	0.814
Hospital stays (days) median (IQR)	0 (0)	5 (4-9)	4 (3-5)	<0.001[b]
Discharge NIHSS median (IQR)	34 (6.20)	6 (3-10)	2 (1-4)	<0.001[b]
<7 (mild)		81 (19.33)	338 (80.67)	<0.001[c]
7-15 (moderate)		60 (75.00)	20 (25.00)	
>15 (severe)		14 (93.33)	1 (6.67)	
Discharge mRS median (IQR)	21 (3.83)	4 (3-5)	2 (1-3)	<0.001[b]
≤2		18 (6.77)	248 (93.23)	<0.001[c]
>2		147 (56.32)	114 (43.68)	

[a], independent t-test for continuous variables with normal distribution; [b], Mann-Whitney U test for continuous variables with non-normal distribution and c, Fisher's exact probability test for categorical variables. Significant $p < 0.05$
n (%), number (percentage); IQR, interquartile range; mRS, Modified Rankin Scale; SD, standard deviation; NIHSS, National Institutes of Health Stroke Scale, BMI: body mass index; Old CVA, old cerebrovascular accident; FBS, fasting blood sugar; HbA1C, hemoglobin A1c; HDL, high-density lipoprotein; LDL, low-density lipoprotein; rtPA, recombinant tissue plasminogen activator

Table 2. Odds ratios and 95% confidence intervals (95%CI) for predictors of poor functional outcome in univariable and multivariable logistic regression

Predictors	Univariable analysis			Multivariable analysis		
	OR	95%CI	p-value	OR	95%CI	p-value
Age (years)						
≤60	1	Ref.	-	1	Ref.	-
>60	2.02	1.33-3.08	0.001	1.56	0.86-2.83	0.147
Initial NIHSS						
<7	1	Ref.	-	1	Ref.	-
7-15	6.14	3.85-9.81	<0.001	0.80	0.38-1.66	0.547
>15	12.77	5.57-29.22	<0.001	0.73	0.19-2.79	0.651
Initial mRS						
≤2	1	Ref.	-	1	Ref.	-
>2	11.63	5.76-23.48	<0.001	2.45	1.03-5.81	0.043
BMI (kg/m^2)						
Normal (18.5-22.99)	1	Ref.	-	1	Ref.	-
Underweight (<18.5)	2.26	1.14-4.48	0.020	0.98	0.36-2.63	0.968
Overweight (23-24.99)	0.96	0.58-1.56	0.862	0.92	0.47-1.78	0.794
Obesity (≥25)	0.79	0.51-1.23	0.302	0.99	0.55-1.78	0.976
Old CVA						
No	1	Ref.	-	1	Ref.	-
Yes	2.11	1.44-3.07	<0.001	1.55	0.93-2.63	0.093
Hypertension						
No	1	Ref.	-	1	Ref.	-
Yes	1.97	1.30-3.01	0.002	1.18	0.66-2.14	0.569
Myocardia infraction						
No	1	Ref.	-	1	Ref.	-
Yes	0.98	0.51-1.46	<0.001	1.23	0.61-2.46	0.557
Atrial fibrillation						
No	1	Ref.	-	1	Ref.	-
Yes	5.76	3.33-9.98	<0.001	2.79	1.28-6.08	0.010
Albumin (g/dl)						
<3.5	2.46	1.54-3.93	<0.001	1.45	0.75-2.82	0.267
≥3.5	1	Ref.	-	1	Ref.	-
Hospital stays (days)						
≤4 days	1	Ref.	-	1	Ref.	-
>4 days	3.95	2.70-5.78	<0.001	1.76	1.05-2.95	0.031
Number of home medications						
≤4	1	Ref.	-	1	Ref.	-
>4	1.77	1.22-2.55	0.003	1.07	0.63-1.84	0.789
Discharge NIHSS						
<7	1	Ref.	-	1	Ref.	-
7-15	14.69	8.55-25.22	<0.001	5.12	2.36-11.12	<0.001
>15	59.17	7.67-456.23	<0.001	17.10	1.50-194.49	0.022
Discharge mRS						
<2	1	Ref.	-	1	Ref.	-
≥2	17.77	10.38-30.41	<0.001	6.56	3.47-12.42	<0.001

OR: odds ratio, 95% CI: 95% confidence interval, NIHSS: National Institutes of Health Stroke Scale, mRS: Modified Rankin Scale, BMI: body mass index, CVA: cerebrovascular accident, AF: atrial fibrillation, Ref.: reference, g/dL: grams per deciliter

agreement between actual and predicted risks (Figure 2b).

Score categorization

The crude score model was categorized into two risk subcategories for clinical applicability, as detailed in Table 4. This categorization was based on the calibration plot, which depicted the relationship between the probability of a poor functional outcome and the score distribu-

Table 3. Prognostic factors and risk score derivation using multivariable logistic regression coefficients

Predictors	mOR	95%CI	p-value	Coefficients	Score
Initial mRS					
≤2	1	Ref.	-	-	0
>2	2.89	1.25-6.66	0.013	1.06	2
Atrial fibrillation					
No	1	Ref.	-	-	0
yes	3.41	1.66-7.04	0.001	1.22	2
Hospital stays (days)					
≤4	1	Ref.	-	-	0
>4	1.81	1.11-2.94	0.017	0.59	1
discharge NIHSS					
<7 (mild)	1	Ref.	-	-	0
7-15 (moderate)	4.52	2.47-8.29	<0.001	1.51	3
>15 (severe)	12.73	1.59-101.96	0.017	2.54	4
discharge mRS					
≤2	1	Ref.	-	-	0
>2	6.25	3.39-11.52	<0.001	1.83	3

mOR, multivariable odds ratio; 95%CI, 95% confidence interval; mRS, Modified Rankin Scale; AF, atrial fibrillation; NIHSS, National Institutes of Health Stroke Scale; Ref., reference

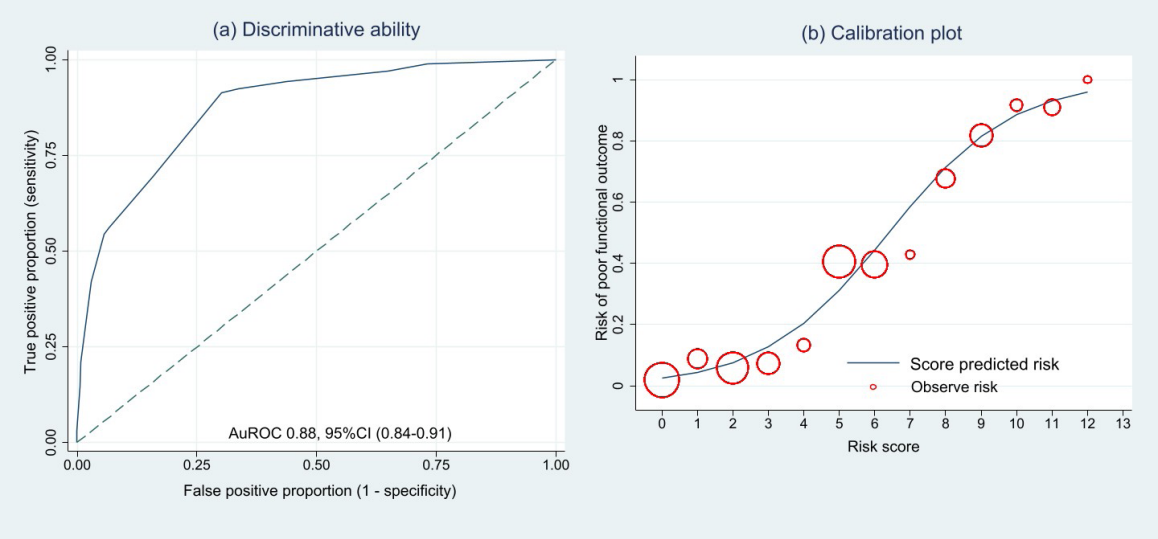

Figure 2. (a) The ROC curve of the crude score demonstrates the model's discriminative ability, with an AuROC of 0.88 (95% CI: 0.84-0.91), (b) The calibration plot illustrates the alignment between predicted and observed risks

Table 4. Score categorization and the likelihood ratio of functional outcome at 6 months after ischemic stroke

Probability categories	Score (total = 15)	Poor functional outcome: mRS >2 (n=171)		Good functional outcome: mRS ≤2 (n=377)		LHR+	95%CI	p-value
		n	%	n	%			
Low	≤4	15	5.40	263	94.60	0.13	0.08-0.20	<0.001
High	>4	156	57.78	114	42.22	3.02	2.57-3.54	<0.001
Mean±SD	-	7.35	(±2.72)	2.78	(±2.54)			<0.001

mmRS, Modified Rankin Scale; LHR+, positive likelihood ratio; 95%CI, 95% confidence interval; SD, standard deviation

The statistical tests: a, independent t-test for continuous variables with normal distribution; and b, Fisher's exact probability test for categorical variables, Significant p < 0.05

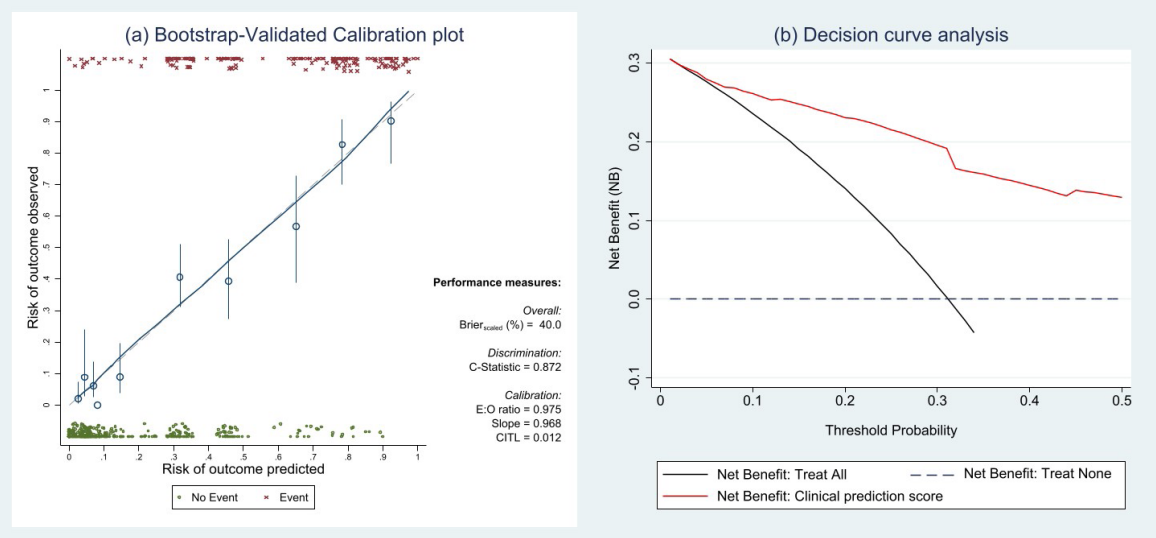

Figure 3: (a) The bootstrap-validated calibration plot shows the predicted versus observed risk of poor functional outcomes, with a C-statistic of 0.872. (b) The decision curve analysis illustrates the net benefit of the clinical prediction model compared to treating all or none, demonstrating clinical utility.

tion. The cut-off score was determined to be 4. Patients with scores ranging from 0 to 4 were categorized as low risk, while those with scores from 4 to 15 were categorized as high risk.

In the high-risk group, the positive likelihood ratio (LR+) was 3.02 (95%CI:, 2.57-3.54). In the low-risk group, the positive LR+ was 0.13 (95%CI:, 0.08-0.20). There was no overlap between the likelihood ratios of each category, indicating the discriminative ability of the categorized score. After categorizing the scores, the AuROC dropped to 0.80 (95%CI:, 0.77-0.83), which still indicates acceptable performance.

The diagnostic performance of the score categorization, using a cut-off >4 to predict poor functional outcomes, was evaluated as follows: sensitivity was 91.2% (95%CI:, 85.9-95.0%), specificity was 69.8% (95%CI:, 64.9-74.4%), positive predictive value (PPV) was 57.8% (95%CI:, 51.6-63.7%), negative predictive value (NPV) was 94.6% (95%CI:, 91.3-96.9%), and overall accuracy was 76.46%.

Internal validation and clinical usefulness

Internal validation using the bootstrap technique was performed to assess the performance of our predictive model for poor functional outcomes. The bootstrap-validated calibration plot indicates that the model is well-calibrated, with a Calibration-in-the-Large (CITL) of 0.012, signifying minimal deviation between predicted and observed risks on average. The model's discrimination ability, as indicated by the C-statistic, remained robust with a slight drop to 0.872 (95%CI:, 0.841-0.904) after bootstrapping, demonstrating excellent predictive accuracy. The shrinkage factor was estimated to be 0.968 (95%CI:, 0.800-1.143), indicating minimal overfitting and confirming the model's stability and reliability (Figure 3a). DCA revealed that the net benefit (NB) of our risk score model is consistently greater across a wide range of threshold probabilities compared to the default strategies of treating all patients or treating none (Figure 3b).

Discussion

In this study, we developed a novel prognostic scoring model to predict poor functional outcomes in IS patients using pre-discharge data from our cohort. Our model incorporates five significant predictors: initial mRS, AF, hospital stay longer than four days, pre-discharge NIHSS, and pre-discharge mRS. It demonstrated excellent predictive accuracy, with an AuROC of 0.88, indicating strong discriminative ability. The strategically determined cut-off score of >4 balances sensitivity and specificity, effectively identifying high-risk patients requiring more intensive post-discharge support.

The inclusion of initial mRS as a predictor reflects the patient's pre-stroke status and aligns with established stroke prognostic models. It serves as a critical marker of baseline functional ability prior to the stroke, aiding in recovery pre-

dictions.[28] AF is another significant predictor associated with poor stroke prognosis and increased risks of recurrent ischemic and hemorrhagic strokes due to anticoagulation therapy.[29] By incorporating AF, our model enhances home care planning, ensuring patients receive necessary support for managing stroke recurrence and treatment complications.[30] Length of hospital stay reflects post-stroke complications. In Thailand, the average IS admission duration is approximately 3-4 days, with extended stays often indicating complications such as severe disability or caregiver unpreparedness.[4,5,31] These patients require more intensive home care programs and regular visits to manage complications effectively. Our model's inclusion of pre-discharge NIHSS and mRS is unique, as many models focus only on initial assessments.[14,32] Discharge status provides a more accurate reflection of the patient's condition and quality of care received.[33] By incorporating pre-discharge data, our model better informs home care planning, allowing tailored care strategies based on recovery trajectories.[19]

Determining an appropriate cut-off point for our scoring model was challenging. Our analysis revealed that cut-offs of 3 and 4 yielded nearly identical diagnostic indices; however, clinical criteria, particularly the NIHSS score, are critical for guiding care planning. Patients with moderate NIHSS scores typically require acute inpatient rehabilitation, while those with high scores necessitate long-term skilled care.[34,35] Ultimately, we selected a cut-off of 4, effectively capturing high-risk patients and ensuring a comprehensive approach to care.

Compared to existing prognostic models such as DRAGON and iSCORE, our model offers several advantages. Primarily, it relies on routine clinical data that are easily accessible in most healthcare settings, including resource-limited environments where advanced imaging or complex diagnostic tools may not be readily available.[12, 14,18,19] This broader applicability ensures that the model can be utilized in primary care facilities in developing countries and other settings with limited resources. Additionally, by focusing on pre-discharge data, our model captures the patient's evolving condition throughout their hospital stay, enhancing the precision of long-term outcome predictions. This focus on a dynamic assessment period, rather than just acute-phase data, strengthens the model's ability to forecast post-discharge outcomes.[15,18,19]

Despite its strengths, our prognostic scoring model has limitations. This study was conducted using data from a single center, which may limit the generalizability of the findings to other populations or healthcare settings. Although internal validation using bootstrapping enhances the model's reliability, external validation in larger and more diverse populations is essential to confirm its applicability across various settings.[36]- Additionally, while the model focuses on easily accessible clinical data, it does not include advanced imaging or biomarkers, which may further enhance predictive accuracy but are not always available in resource-limited settings.[2] Furthermore, this model was specifically designed for IS patients, and its performance in other types of stroke, such as hemorrhagic stroke, remains untested. Future research should address these limitations and evaluate the model's broader applicability.

Conclusion

In conclusion, the newly developed prognostic scoring model, which integrates pre-discharge data, proves to be a valuable tool for healthcare professionals, particularly in primary care settings. With a high predictive accuracy this model facilitates effective home care planning and decision-making for IS patients. By focusing on readily available clinical data, the model offers practical advantages for managing patient outcomes and optimizing resource allocation. Further validation in diverse populations and exploration of additional data sources are recommended to enhance the model's applicability and generalizability.

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Highlights

1. Pre-discharge-based model: a new prognostic score was developed using pre-discharge data to predict 6-month functional outcomes in ischemic stroke patients.

2. Strong performance: the model includes 5 routine clinical predictors and demonstrated excellent accuracy (AuROC = 0.88) with good calibration and internal validation.

3. Practical and applicable: the score is simple, requires no imaging, and is suitable for home care planning in primary care and low-resource settings.

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