A Novel Predictive Model for Intensive Care Unit Admission in Emergency Department Patients with Upper Gastrointestinal Bleeding

Jinmo Yang

The Graduate School
Yonsei University
Department of Medicine

A Novel Predictive Model for Intensive Care Unit Admission in Emergency Department Patients with Upper Gastrointestinal Bleeding

A Master's Thesis Submitted
to the Department of Medicine
and the Graduate School of Yonsei University
in partial fulfillment of the
requirements for the degree of
Master of Medical Science

Jinmo Yang

December 2024

This certifies that the Master's Thesis of Jinmo Yang is approved.

Thesis Supervisor Sung Phil, Chung

Thesis Committee Member Je Sung, You

Thesis Committee Member Jie-hyun, Kim

The Graduate School
Yonsei University
December 2024

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to my thesis supervisor, Professor Sung Phil Chung, for his invaluable guidance and support throughout this study. I am also thankful to the thesis committee professors for providing insightful feedback. Additionally, I extend my sincere appreciation to the Department of Emergency Medicine at Soonchunhyang University for their support. This research was supported by a grant through the Korea Health Industry Development Institute (KHIDI), funded by the Ministry of Health & Welfare, Republic of Korea (RS-2024-00335936). This research was also supported by the Soonchunhyang University Research Fund [grant number 2023-0058]. The authors declare that they have no conflicts of interest to disclose.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

A Novel Predictive Model for Intensive Care Unit Admission in Emergency Department Patients with Upper Gastrointestinal Bleeding

Background: Acute upper gastrointestinal bleeding (UGIB) is a critical emergency. Conventional scoring models for patients with UGIB have limitations; thus, more suitable tools for the emergency department are necessary.

Objective: We aimed to develop a new model that can identify significant predictors of intensive care unit (ICU) admission in emergency department patients with UGIB and to compare its predictive accuracy with that of existing models.

Methods: We retrospectively analyzed data from patients with UGIB treated between January 2020 and July 2022 at the emergency department of a single tertiary medical center. Using multivariable logistic regression and the area under the receiver operating characteristic curve (AUROC), we developed a new model to predict the probability of ICU admission.

Results: Among 433 patients, multiple logistic regression analysis identified sex, systolic blood pressure, diastolic blood pressure, hemoglobin level, platelet count, alanine transaminase level, and prothrombin time as significant predictors of ICU admission. Our model demonstrated superior predictive accuracy with an AUROC of 0.8539 (95% confidence interval [CI]: 0.8078–0.8999), outperforming the Glasgow–Blatchford score and AIMS65 score, which had AUROCs of 0.7598 (95% CI: 0.7067–0.8130) and 0.6930 (95% CI: 0.6324–0.7537), respectively. We implemented this model in a user-friendly calculator for clinical use.

Conclusion: We identified key predictors of ICU admission that are crucial for hemodynamic stabilization in patients with UGIB. Our model, combined with this probability calculator, will enhance clinical decision-making and patient care for UGIB in emergency settings.

Key words : Emergency Medicine; Gastrointestinal Hemorrhage; Intensive Care Units; Logistic Regression

1. INTRODUCTION

Acute upper gastrointestinal bleeding (UGIB) is a critical medical emergency.[1] Annually, approximately 50 to 150 per 100,000 adults are admitted to the emergency department (ED) with UGIB symptoms.[2] Despite advances in managing UGIB, 4% to 14% of patients experience adverse outcomes, including rebleeding or mortality.[3] In addition, hospital admissions for UGIB are associated with considerable use of healthcare resources and expenses.[4] Consequently, accurate prognostic prediction for patients presenting with UGIB in emergency settings is crucial to ensure the administration of appropriate therapeutic interventions.

Several conventional models, including the Glasgow–Blatchford score (GBS), Rockall score (RS), and AIMS65 score, have been established to assess prognosis in patients with UGIB.[5-7] The GBS assesses the need for endoscopic or other interventional procedures based on patient medical history, vital signs, and laboratory findings.[5] The RS predicts rebleeding and mortality risks according to age, shock status, and comorbidities.[6] The AIMS65 score is a tool that predicts patient mortality based on the serum albumin level, prothrombin time–international normalized ratio, changes in mental status, systolic blood pressure (SBP), and age.[7] Nonetheless, these models have limitations, including restricted applicability in high-risk patients, dependence on endoscopic findings, and variable effectiveness across different clinical settings.[5,6,8,9] In addition to conventional prediction models, various new scoring systems have been introduced to predict the prognosis of UGIB.[10-14] These scoring systems are designed to assess the requirement for emergency endoscopy,[10,11] predict mortality in patients with UGIB,[12,14] or both.[13]

In recent decades, studies into UGIB trends has shown a consistent decline in patient mortality rates according to advances in critical care, including endoscopic hemostasis techniques.[15] The results of recent studies have indicated that hemodynamic stabilization prior to urgent endoscopy may improve patient outcomes.[16,17] Specifically, a prospective study focusing on high-risk patients with acute UGIB showed no significant decrease in 30-day mortality for those receiving urgent endoscopy (within 6 h) compared with those receiving early endoscopy (6–24 h).[16] Another study showed that for hemodynamically unstable patients, efforts to prioritize the optimization of resuscitation and management of comorbidities before endoscopy can lead to lower mortality rates.[17]

An intensive care unit (ICU) is an organized system for the care of critically ill patients,

which provides intensive and specialized medical resources and multiple modalities of physiologic organ support to sustain life during a period of acute organ system insufficiency.[18] In this context, an early ICU admission decision for patients with UGIB is critical in terms of patient outcomes and appropriate arrangement of medical resources.[19] Additionally, adverse outcomes can result from under-triage of a critically ill patient with UGIB to a general ward bed and over-triage of a stable patient with UGIB to an ICU bed.[20] Therefore, the development of an appropriate tool that can determine the need for ICU admission among patients with UGIB in the ED can substantially impact medical resource allocation and patient outcomes.

This study aimed to identify predictors of ICU admission in patients with UGIB admitted through the ED. We developed a model comprising significant predictors and its predictive accuracy was compared with that of existing models, thereby addressing the gap in the current prognostic modeling landscape.

2. METHODS

2.1. Study population

We retrospectively analyzed patients who visited the emergency center of Soonchunhyang University Hospital Bucheon, Korea between January 2020 and July 2022. All patients presented to the ED with the chief complaints of hematemesis (vomiting of blood), melena (passage of black, tarry stools), or hematochezia (passage of fresh blood per anus),[21] raising the suspicion of UGIB. The exclusion criteria were the absence of endoscopic findings, diagnosis of lower gastrointestinal bleeding, incomplete medical records, and age < 18 years.

2.2. Data collection

The electronic medical records of each patient were reviewed to obtain information regarding their medical history (e.g., hypertension and diabetes) and other data associated with UGIB, such as specific symptoms and signs (including fever, abdominal pain, syncope, and duration of symptoms). Demographic data such as age and sex were also extracted. Moreover, we obtained the vital signs of each patient, including SBP and diastolic blood pressure (DBP); laboratory test results, including complete blood count (CBC), hemoglobin (Hb) level, and platelet (Plt) count; coagulation factors, including the prothrombin time (PT); and other laboratory tests, including the alanine transaminase (ALT) level. For each patient, the AIMS65 score and GBS were determined using available data. Data were collected by board-certified emergency medicine physicians using structured data extraction forms.

The criteria for ICU admission of patients with UGIB were as follows [22]: massive bleeding requiring intubation to protect the airway before endoscopy, presentation with both hematemesis and hematochezia, active bleeding requiring emergency endoscopy, and stigmata of recent hemorrhage observed during endoscopy.

2.3. Statistical analysis

Continuous variables were analyzed using Student's t-test and the Mann–Whitney U test, and categorical variables were analyzed using the chi-square test or Fisher's exact test. Odds ratios (ORs)

and 95% confidence intervals (CIs) were derived via multivariable logistic regression modeling. A logistic regression model incorporating multiple variables was developed based on the findings of univariable analyses. The performance of each model in predicting ICU admission was determined using the area under the receiver operating characteristic curve (AUROC) with 95% CI.

The optimal cut-off value was determined using the “coords” function of the pROC package in R, which identifies the best cut-off point in terms of balancing sensitivity and specificity [23]. Based on this cut-off value, a risk probability calculator was constructed with significant variables to predict the probability of ICU admission. Statistical analyses were performed using SPSS version 26.0 (IBM Corp., Armonk, NY, USA) and R version 3.5.3 (R Foundation for Statistical Computing, Vienna, Austria).

For the machine learning validation, this study employed a Support Vector Machine (SVM) model to predict ICU admission based on various clinical variables. Based on the developed model, we selected key variables such as gender, SBP, DBP, Hb level, Plt count, ALT, PT as predictor variables, while ICU admission status served as the outcome variable. The dataset was divided into training (80%) and testing (20%) sets to evaluate the performance of the model. ICU admission probabilities were predicted on the test set, and the AUROC was calculated using the pROC package. Additionally, model performance was assessed using sensitivity, specificity, and accuracy, which were computed via the confusionMatrix() function.

2.4. Ethics approval

The study protocol was approved by the Institutional Review Board of Soonchunhyang University Hospital Bucheon (Approval No. 2024-02-013). The requirement for patient informed consent was waived due to the retrospective nature of the study. The study was conducted in accordance with the principles of the Declaration of Helsinki.

3. RESULTS

3.1. Demographics

A total of 657 patients were enrolled in this study. After applying the exclusion criteria, 433 patients were included in the analyses. The patient selection algorithm is presented in Figure 1.

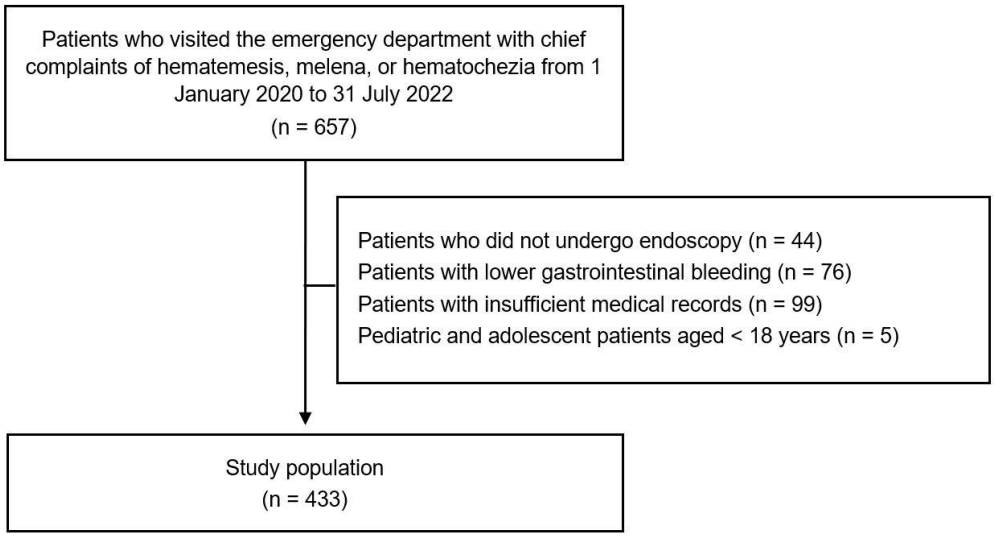

Figure 1. Patient selection algorithm

Table 1 shows the differences in variables between patients who were and were not admitted to the ICU. The initial SBP, DBP, Hb level, Plt count, PT, and ALT level were significantly different between the two groups ($p < 0.001$, Fisher's exact test). Among the demographic variables, sex was significantly different between the two groups ($p < 0.001$, chi-square test).

Table 1. Baseline characteristics of patients in the study

Variable	Total (n = 433)	Non-ICU (n = 324)	ICU (n = 109)	*p*-value
Demography				

Variable	Total (n = 433)	Non-ICU (n = 324)	ICU (n = 109)	*p*-value
Age (years)	61.04 ± 16.31	61.01 ± 16.95	61.14 ± 14.31	0.94
BMI (kg/m^2)	23.83 ± 14.00	24.36 ± 16.02	22.26 ± 3.58	**0.0289**
Sex				
Female	125 (28.87%)	109 (33.64%)	16 (14.68%)	**< 0.001**
Male	308 (71.13%)	215 (66.36%)	93 (85.32%)	
Hypertension	175 (40.42%)	132 (40.74%)	43 (39.45%)	0.9007
Diabetes	113 (26.10%)	81 (25.00%)	32 (29.36%)	0.4412
Laboratory tests				
WBC count (×10^3/μL)	10.21 ± 4.89	9.77 ± 4.05	11.53 ± 6.64	**0.0101**
Hb (g/L)	9.37 ± 2.89	9.78 ± 2.96	8.18 ± 2.31	**< 0.001**
Plt count (×10^9/L)	221.1 ± 138.05	240.82 ± 144.75	162.48 ± 94.5	**< 0.001**
Albumin (g/L)	3.38 ± 0.62	3.53 ± 0.57	2.95 ± 0.56	**< 0.001**
Glucose (mg/dL)	170.72 ± 85.06	164.48 ± 79.28	189.28 ± 98.39	**0.0183**
BUN (mg/dL)	37.7 ± 25.79	36.52 ± 25.66	41.2 ± 25.97	0.1041
Creatinine (mmol/L)	1.57 ± 1.99	1.57 ± 2.06	1.54 ± 1.76	0.8733
Total bilirubin (mg/dL)	1.11 ± 1.30	0.95 ± 1.03	1.57 ± 1.82	**< 0.001**
AST (IU/L)	46.21 ± 102.15	32.93 ± 60.42	85.69 ± 169.46	**0.0019**
ALT (IU/L)	35.46 ± 54.82	27.39 ± 27.61	59.46 ± 94.69	**< 0.001**
LDH (IU/L)	464.06 ± 372.42	417.44 ± 241.73	602.55 ± 595.12	**0.0028**
hs-CRP (mg/dL)	1.36 ± 3.07	1.24 ± 3.02	1.73 ± 3.19	0.1561
PT (s)	15.01 ± 4.21	14.05 ± 2.17	17.83 ± 6.76	**< 0.001**
aPTT (s)	34.25 ± 7.64	33.43 ± 6.36	36.64 ± 10.20	**0.0025**
pH	7.37 ± 0.07	7.37 ± 0.06	7.37 ± 0.08	0.6103

Variable	Total (n = 433)	Non-ICU (n = 324)	ICU (n = 109)	*p*-value
Base excess (mmol/L)	−1.07 ± 5.50	−0.5 ± 4.65	−2.73 ± 7.21	**0.003**
Lactic acid (mmol/L)	2.89 ± 2.50	2.42 ± 1.67	4.29 ± 3.73	**< 0.001**
Duration of UGIB	2.28 ± 2.73	2.42 ± 2.99	1.88 ± 1.71	**0.0213**
Vital signs				
SBP (mmHg)	118.39 ± 26.47	122.81 ± 25.51	105.23 ± 24.94	**< 0.001**
DBP (mmHg)	74.04 ± 17.13	75.59 ± 17.45	69.46 ± 15.32	**< 0.001**
HR (beats/min)	94.75 ± 19.82	94.27 ± 19.14	96.16 ± 21.73	0.4212
RR (breaths/min)	19.8 ± 1.20	19.79 ± 1.22	19.83 ± 1.14	0.7285
BT (℃)	36.65 ± 0.55	36.65 ± 0.52	36.63 ± 0.61	0.6895
SpO_2 (%)	97.51 ± 1.91	97.63 ± 1.87	97.17 ± 2.00	**0.0398**
GCS score	14.78 ± 1.02	14.77 ± 1.06	14.82 ± 0.86	0.637
Symptoms and Signs				
Fever	5 (1.15%)	3 (0.93%)	2 (1.83%)	0.8025
Abdominal pain	61 (14.09%)	51 (15.74%)	10 (9.17%)	0.1222
Syncope	12 (2.77%)	10 (3.09%)	2 (1.83%)	0.7254

Continuous variables are presented as means ± standard deviations, and categorical variables are presented as n (%) of patients. p-values were computed by t-tests for continuous variables and the chi-squared test for categorical variables, as appropriate. Bold values denote statistical significance ($p < 0.05$).

SBP, systolic blood pressure; DBP, diastolic blood pressure; HR, heart rate; RR, respiratory rate; BT, body temperature; SpO2, pulse oxygen saturation; GCS, Glasgow Coma Scale; BMI, body mass index; WBC white blood cell; Hb, hemoglobin; Plt, platelet; BUN, blood urea nitrogen; ALT, alanine transaminase; AST, aspartate transaminase; LDH, lactate dehydrogenase; hs-CRP, high-sensitivity C-reactive protein; PT, prothrombin time; aPTT, activated partial thromboplastin time

3.2. Logistic regression model

Univariable analyses identified 16 statistically significant factors (Table 2).

Table 2. Univariable logistic regression

Variable	Univariable model		
	OR	(95% CI)	*p*-value
Sex (male)	1.584	(1.584–5.473)	**< 0.001**
SBP (mmHg)	0.972	(0.961–0.982)	**< 0.001**
DBP (mmHg)	0.978	(0.963–0.992)	**0.003**
SpO_2 (%)	0.860	(0.768–0.963)	**0.009**
WBC count ($\times 10^3/\mu L$)	1.067	(1.022–1.116)	**0.003**
Hb (g/L)	0.792	(0.722–0.865)	**< 0.001**
Plt ($\times 10^9/L$)	0.992	(0.989–0.995)	**< 0.001**
Albumin (g/L)	0.180	(0.110–0.284)	**< 0.001**
Glucose (mg/dL)	1.004	(1.002–1.007)	**0.002**
Total bilirubin (mg/dL)	1.449	(1.206–1.779)	**< 0.001**
AST (IU/L)	1.006	(1.003–1.009)	**< 0.001**
ALT (IU/L)	1.013	(1.008–1.019)	**< 0.001**
LDH (IU/L)	1.001	(1.001–1.002)	**< 0.001**
PT (s)	1.509	(1.356–1.698)	**< 0.001**
Base excess (mmol/L)	0.911	(0.863–0.959)	**< 0.001**
Lactic acid (mmol/L)	1.336	(1.209–1.491)	**< 0.001**

OR, odds ratio; CI, confidence interval; SBP, systolic blood pressure; DBP, diastolic blood pressure; SpO2, pulse oxygen saturation; WBC, white blood cell; Hb, hemoglobin; Plt, platelet; ALT, alanine transaminase; AST, aspartate transaminase; LDH, lactate dehydrogenase; PT, prothrombin time

After multivariable logistic regression analysis, seven independent variables were selected. The ORs with 95% CIs and *p*-values for these variables were as follows: sex (OR = 4.277, 95% CI [1.954–10.217], p < 0.001), SBP (OR = 0.956, 95% CI [0.934–0.977], p < 0.001), DBP (OR = 1.040, 95% CI [1.008–1.074], p = 0.015), Hb level (OR = 0.784, 95% CI [0.687–0.887], p < 0.001), Plt count (OR = 0.996, 95% CI [0.992–0.999], p = 0.014), ALT level (OR = 1.010, 95% CI [1.003–1.017], p

= 0.006), and PT (OR = 1.279, 95% CI [1.136–1.461], p < 0.001). The process for final model selection is detailed in Table 3.

Table 3. Multivariable logistic regression

Variable	Multivariable model 1			Final model		
	OR	**(95% CI)**	***p*-value**	**OR**	**(95% CI)**	***p*-value**
Sex (male)	5.114	(2.116–13.765)	**< 0.001**	4.277	(1.954–10.217)	**< 0.001**
SBP (mmHg)	0.961	(0.937–0.984)	**< 0.001**	0.956	(0.934–0.977)	**< 0.001**
DBP (mmHg)	1.040	(1.004–1.079)	**0.031**	1.040	(1.008–1.074)	**0.015**
SpO_2 (%)	0.882	(0.752–1.029)	0.114			
WBC count ($\times 10^3/\mu L$)	1.048	(0.978–1.124)	0.188			
Hb (g/L)	0.787	(0.670–0.917)	**0.003**	0.784	(0.687–0.887)	**< 0.001**
Plt ($\times 10^9$/L)	0.994	(0.990–0.998)	**0.008**	0.996	(0.992–0.999)	**0.014**
Albumin (g/L)	0.863	(0.425–1.749)	0.682			
Glucose (mg/dL)	1.002	(0.998–1.005)	0.342			
Total bilirubin (mg/dL)	1.056	(0.760–1.431)	0.727			
AST (IU/L)	0.998	(0.994–1.002)	0.368			
ALT (IU/L)	1.009	(1.002–1.018)	**0.027**	1.010	(1.003–1.017)	**0.006**
LDH (IU/L)	1.001	(1.000–1.002)	0.051			
PT (s)	1.261	(1.111–1.456)	**< 0.001**	1.279	(1.136–1.461)	**< 0.001**
Base excess (mmol/L)	0.994	(0.938–1.049)	0.835			
Lactic acid (mmol/L)	0.953	(0.823–1.114)	0.534			

Multivariable model 1 includes variables with statistical significance in the univariable analyses. Multivariable model 2 (the final model) includes only the variables that remained significant in Multivariable model 1.

OR, odds ratio; CI, confidence interval; SBP, systolic blood pressure; DBP, diastolic blood pressure;

SpO2, pulse oxygen saturation; WBC, white blood cell; Hb, hemoglobin; Plt, platelet; ALT, alanine transaminase; AST, aspartate transaminase; LDH, lactate dehydrogenase; PT, prothrombin time

The AUROC of the final model was 0.8539, with a 95% CI of 0.8078–0.8999; in contrast, the AUROCs of the GBS and AIMS65 score were 0.7598 and 0.6930, respectively. The AUROC and 95% CI for each method are shown in Figure 2 and Table 4.

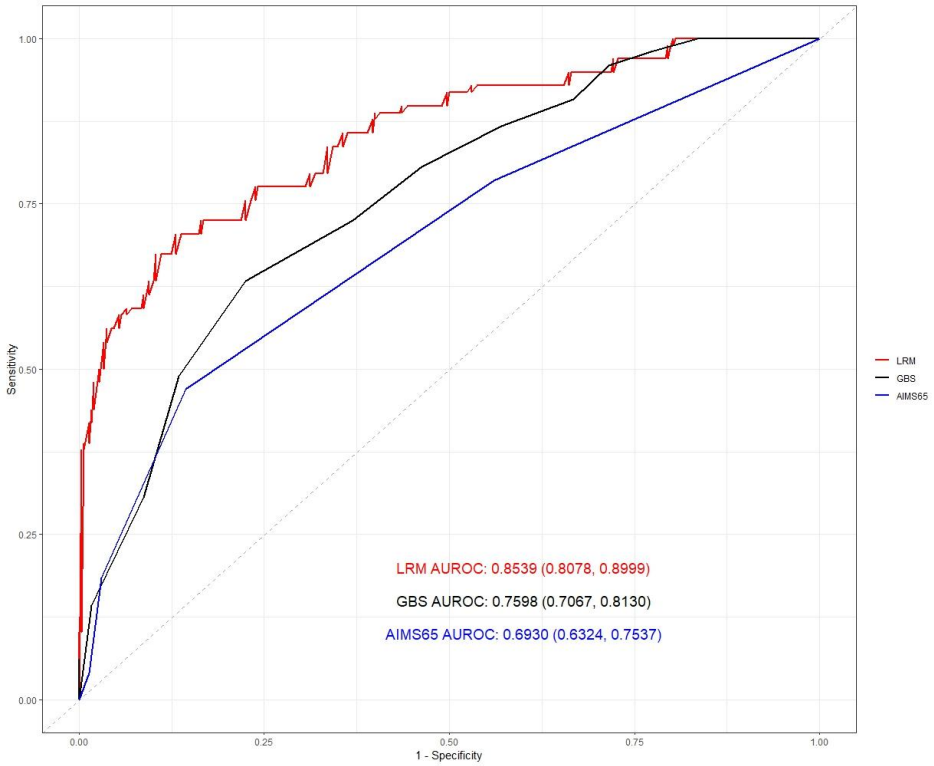

Figure 2. AUROCs and 95% confidence intervals of different prognostic models
AUROC, area under the receiver operating characteristic curve; LRM, logistic regression model; GBS, Glasgow–Blatchford score

Table 4. Prediction performance for the final model compared with GBS and AIMS65 score

	AUROC	95% CI	Accuracy	Sensitivity	Specificity	PPV	NPV
Final model	0.8539	0.8078–	0.8283	0.7041	0.8691	0.6389	0.8993

	AUROC	95% CI	Accuracy	Sensitivity	Specificity	PPV	NPV
GBS	0.7598	0.8999 0.7067– 0.8130	0.7399	0.6327	0.7752	0.4806	0.8652
AIMS65 score	0.6930	0.6324– 0.7537	0.7601	0.4694	0.8557	0.5169	0.8306

AUROC, area under the receiver operating characteristic curve; CI, confidence interval; PPV, positive predictive value; NPV, negative predictive value; GBS, Glasgow–Blatchford score; SVM, Support Vector Machine

We developed the following equation to calculate the probability of ICU admission according to the final multiple logistic regression model:

$$logit(P) = \beta_0 + \beta_1 \times Sex + \beta_2 \times SBP + \beta_3 \times DBP + \beta_4 \times Hb + \beta_5 \times Plt + \beta_6 \times ALT + \beta_7 \times PT$$

$$P = \frac{exp^{logit(P)}}{1 + exp^{logit(P)}}$$

The intercept and regression coefficients (β) for the equation are presented in Table 5.

Table 5. Intercept and regression coefficients (β) for the final model

Variable	**Beta**
Intercept	−1.0925
Sex[a]	1.4533
SBP (mmHg)	−0.0450
DBP (mmHg)	0.0393
Hb (g/L)	−0.2440
Plt count ($\times 10^9$/L)	−0.0043
ALT (IU/L)	0.0098
PT (s)	0.2461

[a]Female sex is the reference.

Based on receiver operating characteristic curve analysis, we obtained the optimal cut-off

value for predicting ICU admission, maximizing the sum of sensitivity and specificity. The cut-off value was 0.3459, indicating that a probability of ≥0.3459 suggests a high likelihood of ICU admission. To facilitate clinical application, we developed a calculator that simplifies computation of the ICU admission probability (Figure 3).

ICU admission probability calculator v1.0/2024

Use this section to calculate score for each patient

Sex (Male)	0
SBP (mmHg)	90
DBP (mmHg)	60
Hb (g/L)	6.5
Plt (10^9/L)	81
ALT (IU/L)	126
PT (s)	15.2
Total Score	0.2530318

$$logit(P) = \beta_0 + \beta_1 \times Sex + \beta_2 \times SBP + \beta_3 \times DBP + \beta_4 \times Hb + \beta_5 \times Plt + \beta_6 \times ALT + \beta_7 \times PT$$

$$P = \frac{exp^{logit(P)}}{1 + exp^{logit(P)}}$$

Use this section to calculate ICU admission probability for each patient

predicted ICU Adm probability	0.5629226	High

Figure 3. ICU admission probability calculator

3.3. Machine learning validation

The performance of the SVM model showed an overall accuracy of 91.03% (95% CI: 82.38% to 96.32%), demonstrating strong predictive capabilities. The model exhibited a high sensitivity of 98.31%. However, the specificity was lower, at 68.42%, which suggests some degree of misclassification among non-ICU admission cases. The positive predictive value (PPV) was 90.63%, while the negative predictive value (NPV) was 92.86%. These results highlight the robustness and good overall performance of the model, particularly in terms of sensitivity and overall accuracy. The AUROC and 95% CI for SVM model are shown in Figure 4 and Table 6.

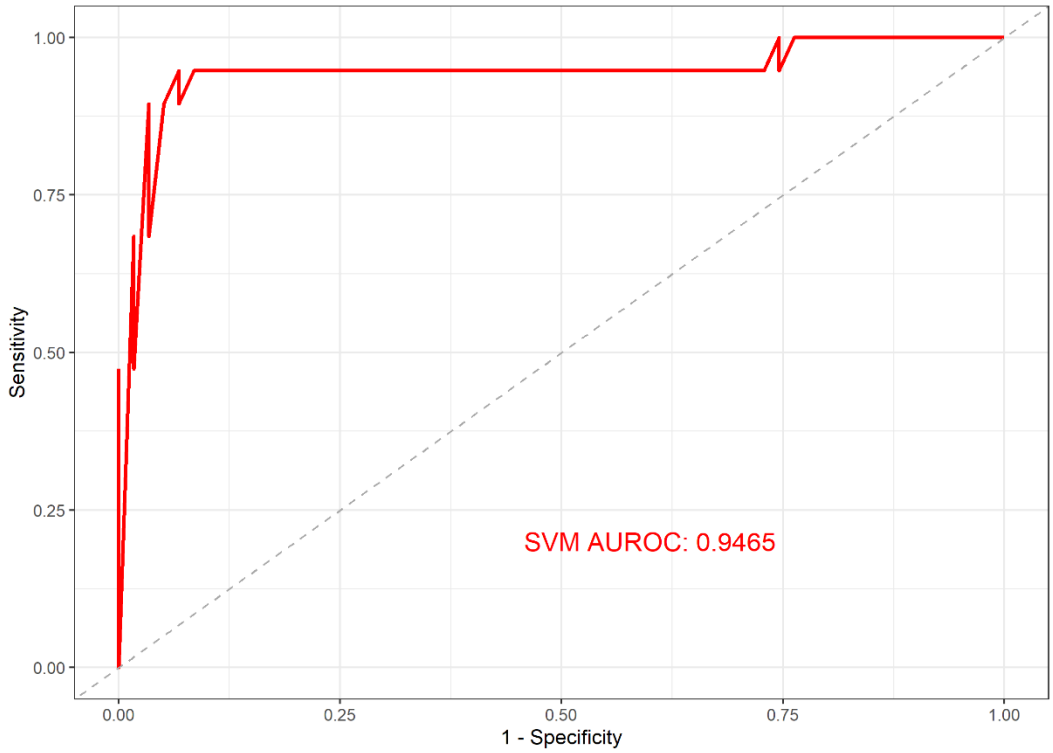

Figure 4. AUROC of SVM model

AUROC, area under the receiver operating characteristic curve; SVM, Support Vector Machine

Table 6. Prediction performance of SVM

	AUROC	95% CI	Accuracy	Sensitivity	Specificity	PPV	NPV
SVM	0.9465	0.8238–0.9632	0.9103	0.9831	0.6842	0.9063	0.9286

AUROC, area under the receiver operating characteristic curve; CI, confidence interval; PPV, positive predictive value; NPV, negative predictive value; GBS, Glasgow–Blatchford score; SVM, Support Vector Machine

4. DISCUSSION

This study identified specific factors, including a demographic characteristic (sex), two vital signs (SBP and DBP), and several laboratory results (Hb level, Plt count, ALT level, and PT), to predict ICU admission in patients with UGIB. Based on these findings, we developed a new equation for use in the ED, simplifying the computation of the ICU admission probability. The AUROC of our model for ICU admission prediction (0.8739) was higher than those of the GBS and AIMS65 scores. Additionally, our model showed higher accuracy than the other models.

Hb levels and blood pressure were significant factors in our model, consistent with those of previous studies.[5,10,11,13] Previous studies incorporated Hb levels and SBP as categorical variables within the scoring system;[10,11,13] these constitute risk factors when their values fall below specific thresholds. The likelihood of ICU admission increased as Hb levels and SBP decreased and DBP increased. This could be due to the physiological compensatory mechanisms in hypovolemic shock, such as increases in heart rate and peripheral vascular resistance, to maintain DBP. Additionally, factors such as aging-related aortic stiffness, which raises pulse pressure and disrupts the linear relationship between SBP and DBP, may have contributed.[24] Further studies with larger sample sizes are necessary to confirm these findings.

This study identified Plt count and ALT level as novel predictive factors for ICU admission in patients with UGIB. Lower Plt counts and higher ALT levels were associated with a higher likelihood of ICU admission. Platelets play a crucial role in primary hemostasis; bleeding tendencies due to reduced Plt function typically manifest in the mucous membranes, including the gastrointestinal tract.[25] Many patients show a significant decrease in the Plt count during their initial days in the ICU.[26] Comorbidities in severely ill patients affect Plt homeostasis, making thrombocytopenia common in critically ill patients in the ICU.[27]

Liver dysfunction is observed in approximately 60–80% of ICU patients[28] and plays a significant role in the ICU patient's morbidity and mortality.[29] Our study included patients with UGIB of various causes not limited to liver disease complications and found that an elevated ALT level was significantly predictive of ICU admission. The liver plays a crucial role in hemostasis by producing all clotting factors except von Willebrand factor.[30] Therefore, increased ALT levels, a primary screening tool for liver damage, is relevant because it may exacerbate the

bleeding tendency in patients with UGIB. Similarly, increases in PT caused by liver disease, vitamin K deficiency, warfarin therapy, and disseminated intravascular coagulation, all of which induce a bleeding tendency,[31] can exacerbate UGIB severity.

This study revealed that male sex was a predictive factor for ICU admission in patients with UGIB. Several studies on UGIB outcomes have shown no significant difference based on sex.[32,33] In contrast, an analysis of large populations showed that the 30-day mortality rate associated with UGIB was significantly higher in men.[34] Another study revealed higher incidences of serious UGIB and perforation in men.[35] Considering the higher prevalence of variceal bleeding in men, with a greater risk of mortality than other causes of UGIB,[1] male sex should be considered a positive predictive factor for a poor prognosis in patients with UGIB. However, further prospective studies are required to confirm this hypothesis.

Recent scoring systems for patients with UGIB have focused on determining the importance of endoscopic interventions.[10,11,13] However, some studies suggest that hemodynamic stabilization before endoscopy is crucial for improving patient outcomes.[16,17] Therefore, from an ED perspective, early determination of the need for ICU admission to stabilize hemodynamic characteristics may have a greater impact on patient outcomes than urgent endoscopic intervention. To the best of our knowledge, this is the first study to identify the factors influencing ICU admission in patients with UGIB admitted via the ED. Furthermore, based on our findings, we developed a probability calculator to support clinical decision-making on ICU admission.

The ICU admission probability calculator developed in this study had several advantages. While previous scoring models used predetermined cut-off values for factor scoring, our model incorporates measurement values into its calculations, generating more precise outcomes for borderline values. Furthermore, to facilitate clinical application, we developed a calculator that simplified the process, Improving its clinical accessibility. The model design, based on data obtained from ED patients, highlights its potential value in real-world applications, particularly in acute settings where rapid decision-making is crucial. This approach enhances the accuracy of the ICU admission probability and supports healthcare professionals in delivering timely and appropriate care.

In this study, a machine learning model was employed to evaluate the predictive performance of the developed logistic regression model for ICU admission in patients with UGIB. The model demonstrated strong performance, reinforcing the robustness of the logistic regression

model. The high sensitivity of 98.31% indicates that the model effectively identifies patients requiring ICU care, which is essential for improving patient outcomes in emergency settings. However, the specificity was relatively lower, at 68.42%, indicating potential misclassification of patients who do not require ICU admission. This suggests the need for further refinement, particularly in enhancing the ability of model to accurately identify non-ICU patients. Future studies with larger datasets could help improve the specificity and overall predictive performance.

This study has several limitations. First, because this was a single-center retrospective study, external validation is required to confirm the reliability of the results. Second, delays in ICU admission or patient transfers may have occurred because of ICU overcrowding, leading to statistical bias. Additionally, although typical criteria for ICU admission were used, variations may have occurred based on ICU availability and the judgment of the on-site medical staff. Therefore, the use of a prospective study design with standardized ICU admission criteria is warranted in future studies. Finally, the direct comparison of our model with other models focusing on mortality prediction was limited. Future studies to address these gaps, including prospective multicenter studies and external validations, will enhance the reliability and applicability of our findings.

5. CONCLUSION

In conclusion, this study identified significant predictors of ICU admission in patients with UGIB, an aspect of care that is crucial for hemodynamic stabilization. Our model, combined with the probability calculator, will enhance clinical decision-making and patient care for UGIB in emergency settings.

References

1. Van Leerdam ME. Epidemiology of acute upper gastrointestinal bleeding. Best Pract Res Clin Gastroenterol 2008;22(2):209-24.

2. Rockall T, Logan RF, Devlin HB, Northfield TC. Incidence of and mortality from acute upper gastrointestinal haemorrhage in the United Kingdom. BMJ 1995;311(6999):222-6.

3. Coskun F, Topeli A, Sivri BJ. Patients admitted to the emergency room with upper gastrointestinal bleeding: factors influencing recurrence or death. Adv Ther 2005;22:453-61.

4. Parker DR, Luo X, Jalbert JJ, Assaf AR, Rosen AK, Cofield SS, et al. Impact of upper and lower gastrointestinal blood loss on healthcare utilization and costs: a systematic review. J Med Econ 2011;14(3):279-87.

5. Blatchford O, Murray WR, Blatchford MJ. A risk score to predict need for treatment for upper gastrointestinal haemorrhage. Lancet 2000;356(9238):1318-21.

6. Rockall T, Logan RF, Devlin HB, Northfield TC. Risk assessment after acute upper gastrointestinal haemorrhage. Gut 1996;38(3):316.

7. Saltzman JR, Tabak YP, Hyett BH, Sun X, Travis AC, Johannes RS, et al. A simple risk score accurately predicts in-hospital mortality, length of stay, and cost in acute upper GI bleeding. Gastrointest Endosc 2011;74(6):1215-24.

8. Yaka E, Yılmaz S, Özgür Doğan N, Pekdemir M. Comparison of the Glasgow-Blatchford and AIMS65 scoring systems for risk stratification in upper gastrointestinal bleeding in the emergency department. Acad Emerg Med 2015;22(1):22-30.

9. Budimir I, Gradišer M, Nikolić M, Baršić N, Ljubičić N, Kralj D, et al. Glasgow Blatchford, pre-endoscopic Rockall and AIMS65 scores show no difference in predicting rebleeding rate and mortality in variceal bleeding. Scand J Gastroenterol 2016;51(11):1375-9.

10. Iino C, Mikami T, Igarashi T, Aihara T, Ishii K, Sakamoto J, et al. Evaluation of scoring models for identifying the need for therapeutic intervention of upper gastrointestinal bleeding: a new prediction score model for Japanese patients. Dig Endosc 2016;28(7):714-21.

11. Sasaki Y, Hirasawa K, Tsuchihashi T, Nakamura T, Nakamura H, Matsuhashi N, et al. Prediction of the need for emergency endoscopic treatment for upper gastrointestinal bleeding and new score model: a retrospective study. BMC Gastroenterol 2022;22(1):337.

12. Matsuhashi T, Hatta W, Hikichi T, Fukuda S, Mikami T, Tatsuta T, et al. A simple

prediction score for in-hospital mortality in patients with nonvariceal upper gastrointestinal bleeding. J Gastroenterol 2021;56(8):758-68.

13. Redondo-Cerezo E, Vadillo-Calles F, Stanley AJ, Laursen S, Laine L, Dalton HR, et al. MAP (ASH): A new scoring system for the prediction of intervention and mortality in upper gastrointestinal bleeding. J Gastroenterol Hepatol 2020;35(1):82-9.

14. Laursen SB, Oakland K, Laine L, Bieber V, Marmo R, Redondo-Cerezo E, et al. ABC score: a new risk score that accurately predicts mortality in acute upper and lower gastrointestinal bleeding: an international multicentre study. Gut 2021;70(4):707-16.

15. Wuerth BA, Rockey DC. Changing epidemiology of upper gastrointestinal hemorrhage in the last decade: a nationwide analysis. Dig Dis Sci 2018;63:1286-93.

16. Lau JY, Yu Y, Tang RSY, Chan HCH, Yip HC, Chan SM, et al. Timing of endoscopy for acute upper gastrointestinal bleeding. N Engl J Med 2020;382(14):1299-308.

17. Laursen SB, Leontiadis GI, Stanley AJ, Møller MH, Hansen JM, Schaffalitzky de Muckadell OB. Relationship between timing of endoscopy and mortality in patients with peptic ulcer bleeding: a nationwide cohort study. Gastrointest Endosc 2017;85(5):936-44.e3.

18. Marshall JC, Bosco L, Adhikari NK, Connolly B, Diaz JV, Dorman T, et al. What is an intensive care unit? A report of the task force of the World Federation of Societies of Intensive and Critical Care Medicine. J Crit Care 2017;37:270-6.

19. Mathews KS, Durst MS, Vargas-Torres C, Olson AD, Mazumdar M, Richardson LD. Effect of emergency department and ICU occupancy on admission decisions and outcomes for critically ill patients. Crit Care Med 2018;46(5):720-7.

20. Haas NL, Medlin RP Jr, Cranford JA, Tsuchida RE, Nicholson A, Boyd C, et al. An emergency department-based intensive care unit is associated with decreased hospital length of stay for upper gastrointestinal bleeding. Am J Emerg Med 2021;50:173-7.

21. Walker HK, Hall WD, Hurst JW. Clinical methods: the history, physical, and laboratory examinations. 3rd ed. Boston: Butterworths; 1990. Chapter 85.

22. Kankaria AG, Fleischer DE. The critical care management of nonvariceal upper gastrointestinal bleeding. Crit Care Clin 1995;11(2):347-68.

23. Robin X, Turck N, Hainard A, Tiberti N, Lisacek F, Sanchez JC, et al. pROC: an open-source package for R and S+ to analyze and compare ROC curves. BMC Bioinformatics 2011;12:1-8.

24. Steppan J, Barodka V, Berkowitz DE, Nyhan D. Vascular stiffness and increased pulse pressure in the aging cardiovascular system. Cardiol Res Pract 2011;2011:263585.

25. Lassila R. Platelet function tests in bleeding disorders. Semin Thromb Hemost 2016;42(3):185-90.

26. Akca S, Haji-Michael P, De Mendonça A, Suter P, Levi M, Vincent JL. Time course of platelet counts in critically ill patients. Crit Care Med. 2002;30(4):753-756.

27. Greinacher A, Selleng K. Thrombocytopenia in the intensive care unit patient. Hematology Am Soc Hematol Educ Program. 2010;2010(1):135-143.

28. Koch A, Streetz K, Tischendorf J, Trautwein C, Tacke F. Abnormal liver function tests in the intensive care unit. Med Klin Intensivmed Notfmed. 2013;108(7):599-608.

29. Soultati AA, Dourakis SP. JAog. Liver dysfunction in the intensive care unit. Ann Gastroenterol. 2005;18(1):35-45.

30. Kujovich JL. Coagulopathy in liver disease: a balancing act. Hematology Am Soc Hematol Educ Program 2015;2015(1):243-9.

31. Tripodi A, Caldwell SH, Hoffman M, Trotter JF, Sanyal AJ. The prothrombin time test as a measure of bleeding risk and prognosis in liver disease. Aliment Pharmacol Ther 2007;26(2):141-8.

32. Miilunpohja S, Jyrkkä J, Karkkainen JM, Kastarinen H, Heikkinen M, Paajanen H, et al. Long-term mortality and causes of death in endoscopically verified upper gastrointestinal bleeding: comparison of bleeding patients and population controls. Scand J Gastroenterol 2017;52(11):1211-8.

33. Kim JJ, Sheibani S, Park S, Buxbaum J, Laine L. Causes of bleeding and outcomes in patients hospitalized with upper gastrointestinal bleeding. J Clin Gastroenterol 2014;48(2):113-8.

34. Button L, Roberts SE, Evans PA, Goldacre MJ, Akbari A, Dsilva R, et al. Hospitalized incidence and case fatality for upper gastrointestinal bleeding from 1999 to 2007: a record linkage study. Aliment Pharmacol Ther 2011;33(1):64-76.

35. Hernández-Díaz S, Rodríguez LAG. Incidence of serious upper gastrointestinal bleeding/perforation in the general population: Review of epidemiologic studies. J Clin Epidemiol 2002;55(2):157-63.

Abstract in Korean

응급실 상부 위장관 출혈 환자의 중환자실 입실 예측을 위한 새로운 모델 개발

상부 위장관 출혈은 중대한 응급 질환이다. 상부 위장관 출혈 환자를 위한 기존의 모델들은 각각의 한계가 있어 응급실에서 사용할 수 있는 더 적합한 도구가 필요하다. 본 연구의 목적은 응급실에 내원한 상부 위장관 출혈 환자에서 중환자실 입실 예측에 중요한 예측 변수를 식별하고, 그 예측 정확도를 기존 모델과 비교하는 것이다. 2020년 1월부터 2022년 7월까지 단일 3차 의료기관 응급실을 통해 치료받은 상부 위장관 출혈 환자 데이터를 후향적으로 분석하였다. 로지스틱 회귀분석과 수신자 조작 특성 곡선 하 영역(AUROC)을 사용하여 중환자실 입원의 가능성을 예측하는 새로운 모델을 개발하였다. 총 433명의 환자를 대상으로 한 로지스틱 회귀 분석에서 성별, 수축기 혈압, 이완기 혈압, 혈색소 수치, 혈소판 수치, 알라닌아미노전이효소 수치, 프로트롬빈 시간이 중환자실 입원의 중요한 예측 변수로 확인되었다. 우리의 모델은 AUROC 0.8539 (95% 신뢰 구간: 0.8078-0.8999)로, 기존의 Glasgow-Blatchford 점수(AUROC 0.7598, 95% CI: 0.7067-0.8130) 및 AIMS65 점수(AUROC 0.6930, 95% CI: 0.6324-0.7537)보다 우수한 예측 정확도를 보였다. 우리는 임상에서 쉽게 사용할 수 있는 계산기로 이 모델을 구현하였다. 결론적으로, 상부 위장관 출혈 환자의 혈역학적 안정화에 중요한 중환자실 입원 예측 변수를 확인하였으며, 이 모델과 계산기는 응급실 내 임상 의사결정 및 환자 관리에 도움을 줄 것이다.

핵심되는 말 : 응급의학, 위장관 출혈, 중환자실, 로지스틱 회귀 분석