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Construction and Validation of a Machine Learning-Based Risk Prediction Model for Recurrent Upper Gastrointestinal Bleeding in Patients with Liver Cirrhosis: A Prospective Study

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Abstract

Background

Upper gastrointestinal bleeding (UGIB) is a common and life-threatening complication of liver cirrhosis, with a substantial risk of recurrence despite secondary prevention. Identifying high-risk patients is essential for individualized management. Therefore, this study aimed to construct and validate a machine learning-based predictive model for UGIB recurrence in patients with liver cirrhosis, enabling accurate identification of high-risk individuals and supporting personalized management.

Methods

This prospective cohort study included 653 cirrhotic patients with UGIB, comprising 505 patients in the modeling cohort and 148 in the external validation cohort. Independent predictors were identified by univariate and multivariable logistic regression analyses. Four models, including logistic regression, random forest, support vector machine, and k-nearest neighbor, were developed and compared. Model performance was assessed by discrimination, calibration, and clinical utility.

Results

UGIB recurrence rates were 24.16% and 23.65% in the modeling and external validation cohorts, respectively. Six independent predictors were identified: age, chronic disease history, bleeding recurrence risk perception score, white blood cell count, platelet count, and serum albumin level. The logistic regression model showed the best performance, with AUCs of 0.862 (95% CI: 0.796–0.928) in internal validation and 0.827 (95% CI: 0.747–0.907) in external validation. Decision curve analysis demonstrated superior clinical benefit.

Conclusion

This validated model provides an accurate tool for predicting UGIB recurrence risk in cirrhotic patients and supports individualized risk stratification and management. An interactive web-based nomogram is available at https://yuceliexiantu.shinyapps.io/UGIB_Nomogram/.

1. Introduction

Liver cirrhosis (LC) is a common chronic liver disease and a major global health burden. Epidemiological evidence indicates that cirrhosis is currently the 11th leading cause of death worldwide, accounting for approximately 2 million deaths annually[1]. Upper gastrointestinal bleeding (UGIB) is one of the most common and life-threatening complications of cirrhosis[2], characterized by acute onset, rapid disease

progression, high recurrence, and high mortality. Despite successful hemostatic treatment, the rebleeding rate may reach 60% within 1–2 years and the mortality rate may be as high as 33% in the absence of appropriate secondary prophylaxis[3]. Recurrent bleeding not only results in frequent hospitalizations but also accelerates hepatic decompensation, reducing the 5-year survival rate to below 50% and substantially compromising patient survival[4]. Therefore, early identification of patients at high risk of recurrent bleeding and implementation of risk-stratified, individualized interventions are essential for improving long-term outcomes in patients with cirrhosis.

In recent years, several scoring systems and prediction models have been proposed to assess the risk of recurrent UGIB. The Rockall, Glasgow-Blatchford, and AIMS65 scores are widely used in clinical practice; however, these scoring systems were developed for the general population with gastrointestinal bleeding rather than specifically for patients with cirrhosis. Although the Child-Pugh classification and the Model for End-stage Liver Disease score are commonly used to evaluate disease severity and prognosis in cirrhotic patients, their ability to predict rebleeding remains limited[5–6].

Regarding prediction models, Wang et al[7]demonstrated in a single-center retrospective cohort study that the MELD-Na score outperformed the MELD and Child-Pugh scores in predicting rebleeding after endoscopic hemostasis for esophageal variceal bleeding in patients with cirrhosis. However, this study focused on comparisons among existing scoring systems rather than developing a novel multivariable prediction model, and the absence of independent external validation limited its generalizability. Deng et al[8]developed a machine learning model based on residual variables to predict major bleeding in critically ill patients with UGIB and compared its performance with conventional scoring systems. Nevertheless, because the study population was not limited to patients with cirrhosis, the applicability of the model to cirrhotic patients remains uncertain. Zhan et al[9] integrated multidomain clinical variables to establish a prediction model for esophagogastric variceal rebleeding after endoscopic therapy in patients with cirrhosis and demonstrated satisfactory generalizability through external validation. However, the retrospective design may have introduced selection and information bias, and different machine learning algorithms were not systematically compared. Liu et al[10] developed an Extreme Gradient Boosting model incorporating laboratory parameters, liver stiffness measurements, and imaging findings to predict esophageal variceal rebleeding in patients with hepatitis B-related cirrhosis. Although this model provided a more comprehensive assessment of rebleeding risk, it was also based on a retrospective study without independent external validation, limiting its clinical applicability.

Therefore, this prospective study aimed to systematically integrate multidimensional variables, including demographic characteristics, laboratory parameters, lifestyle factors, and psychosocial factors, to develop and externally validate a prediction model for recurrent UGIB in patients with liver cirrhosis. The ultimate goal was to facilitate early identification and risk stratification of patients at high risk of recurrent bleeding and to provide evidence for individualized follow-up and intervention strategies.

2. Methods

2.1 Study design and participants

A convenience sampling method was used to recruit patients with liver cirrhosis and UGIB who were hospitalized in a tertiary care hospital between August and November 2025 as the training cohort. Patients with UGIB admitted to another tertiary care hospital during the same period were included as the external validation cohort. All patients were followed for 6 months after discharge to determine whether rebleeding events occurred.The inclusion criteria were as follows: (1) age ≥ 18 years; (2) diagnosis of liver cirrhosis according to the clinical practice guidelines for the diagnosis and treatment of cirrhosis[11], accompanied by UGIB; (3) normal cognitive and communication abilities and the ability to independently complete questionnaires; and (4) provision of informed consent and voluntary participation in the study.The exclusion criteria were as follows: (1) presence of malignant tumors or dysfunction of major organs, including the liver and kidneys; and (2) voluntary withdrawal during follow-up or inability to complete the survey.

The sample size was calculated using the events per variable method for clinical prediction models[12]. This method requires at least 10 outcome events per predictor variable. Based on previous studies, the recurrence rate of UGIB in patients with liver cirrhosis was estimated to be approximately 22%[9]. Assuming that 6–8 variables would be included in the final prediction model, the training cohort was randomly divided into training and internal validation sets at a ratio of 7:3. Considering a 10% invalid sample rate, the required sample size for the training cohort was calculated as follows:10 × 7 ÷ 22% ÷ 0.7 ÷ (1 − 10%) = 505 cases. According to the sample size calculation method for external validation of prediction models recommended by PROBAST[13], the minimum sample size for external validation studies should be ≥ 100 cases. Therefore, 148 patients were ultimately included in the external validation cohort.This study was approved by the Ethics Committee of the participating institution.

2.2 Definition of Bleeding Recurrence

Bleeding recurrence was defined according to the Baveno IV consensus criteria[14]. Specifically, after successful treatment of the initial bleeding episode and achievement of hemostasis and clinical stabilization, recurrence was defined as the reappearance of clinical bleeding manifestations, including hematemesis or melena, accompanied by a decrease in hemoglobin levels, increased transfusion requirements, or other evidence suggestive of active bleeding. For patients suspected of rebleeding, endoscopic examination was performed to confirm the bleeding source, and confirmed cases were considered recurrence events.

2.3 Data Collection Instruments

2.3.1 Risk Factor Questionnaire for UGIB Recurrence in Patients with Liver Cirrhosis

A self-developed questionnaire was used to collect risk factors associated with UGIB recurrence. The questionnaire consisted of four dimensions with a total of 30 predictors:(1) General characteristics: age,

sex, education level, occupation, employment status, marital status, residence area, average monthly income, medical payment method, history of chronic diseases, smoking history, and drinking history; (2) Disease-related characteristics: Child-Pugh classification, type of cirrhosis etiology, duration of cirrhosis, and number of previous bleeding recurrence episodes; (3) Dietary habits: dietary preference and dietary pattern; (4) Laboratory parameters: red blood cell count(RBC), white blood cell count(WBC), platelet count(PLT), hemoglobin(Hb), total bilirubin(TBILI), albumin(ALB), Serum sodium(Na), aminotransferase (ALT), aspartate aminotransferase (AST), prothrombin time (PT), activated partial thromboplastin time (APTT) and international normalized ratio (INR).All laboratory parameters were obtained from the first examination during hospitalization. For continuous variables, the initial measurement values were used.

2.3.2 Risk Perception Scale for UGIB Recurrence in Patients with Liver Cirrhosis

The risk perception scale developed by Zhu Xinying[15]was used to assess patients' perceptions regarding UGIB recurrence risk. The scale consists of four dimensions: perceived likelihood of recurrence, perceived severity of recurrence consequences, perceived risk factors for recurrence, and perceived self-efficacy, with a total of 32 items. Higher scores in the last three dimensions indicate greater awareness of UGIB recurrence risk. The overall Cronbach's α coefficient of the scale was 0.957.

2.3.3 Social Support Rating Scale

The Social Support Rating Scale, developed by Xiao Shuiyuan[16] based on the characteristics of the Chinese population, was used to evaluate individual social support status. The scale includes three dimensions: objective support, subjective support, and utilization of social support, consisting of 10 items. A four-point scoring system was used, with higher scores indicating better social support. The overall Cronbach's α coefficient was 0.896.

2.4 Data Collection and Quality Control

Baseline data were collected after patients' conditions stabilized during hospitalization. Data collectors received standardized training to minimize inaccuracies caused by differences in communication methods during questionnaire administration. Questionnaires were completed independently by participants whenever possible. For participants with difficulties in writing, reading, or comprehension, trained investigators read each item aloud and recorded responses according to participants' verbal answers. All collected data were independently reviewed and entered by two researchers to ensure accuracy.

2.5 Statistical Analysis

Statistical analyses were performed using SPSS version 26.0. Continuous variables with non-normal distributions were expressed as median *M (P25, P75)*, and comparisons between groups were performed using the Mann–Whitney U test. Categorical variables were presented as frequencies and percentages (%), and comparisons between groups were conducted using the chi-square test.

R software version 4.4.3 was used for model development and evaluation. The training cohort was randomly divided into training and internal validation sets at a ratio of 7:3. The training set was used for univariate analysis, variable selection, and construction of four predictive models. The performance of the four models was evaluated using the internal validation set and an independent external validation cohort. The optimal predictive model was ultimately selected based on comprehensive performance evaluation.

3. Results

3.1 Participant Selection

According to the predefined inclusion and exclusion criteria, patients with liver cirrhosis complicated by upper gastrointestinal bleeding admitted to two tertiary care hospitals were screened. In the training cohort, 542 patients were initially assessed for eligibility, and 505 patients were ultimately included and randomly assigned to the training set and internal validation set at a ratio of 7:3. In the external validation cohort, 159 patients were initially screened, and 148 patients were finally included. The detailed participant selection process is shown in Fig. 1.

3.2 Baseline Characteristics of the Included Participants

A total of 653 patients were included in the final analysis, comprising 505 patients in the training cohort and 148 patients in the external validation cohort. The distribution of demographic characteristics, clinical characteristics, and laboratory parameters was generally comparable among the training set, internal validation set, and external validation cohort, indicating good representativeness and comparability among the datasets. The baseline characteristics of participants in each group are presented in Appendix A.

3.3 Univariate and Multivariable Logistic Regression Analyses of UGIB Recurrence in Patients with Liver Cirrhosis

Using the occurrence of UGIB recurrence in patients from the training set as the dependent variable, univariate analyses were performed to evaluate candidate variables, including demographic characteristics, laboratory parameters, and psychosocial factors. Variables with statistical significance in the univariate analysis ($P < 0.05$) were subsequently entered into multivariable logistic regression analysis.

The results demonstrated that age, history of chronic diseases, bleeding recurrence risk perception score, white blood cell count, platelet count, and serum albumin level were independent predictors of UGIB recurrence in patients with liver cirrhosis (all $P < 0.05$). The detailed results are shown in Table 1.

Table 1
Univariate and Multivariable logistic regression analyses of risk factors associated with UGIB recurrence in patients with liver cirrhosis based on the training cohort

Variable	N=354	Univariate analysis		Multivariable analysis	
		Statistical values	P-value	OR(95%CI)	P-value
Age		14.285	<0.001		<0.001
<60	168			1	
≥ 60	186			2.959(1.598,5.482)	
Occupation		10.065	0.018		0.099
Farmer	122			1	
Intellectuals	16			3.183(0.889,11.398)	0.075
Workers	67			1.447(0.622,3.364)	0.391
Other	149			0.748(0.385,1.454)	0.392
Chronic Diseases		8.757	0.003		0.010
None	195			1	
Yes	159			2.261(1.200,3.890)	
Liver Function Grading		9.337	0.009		0.348
Grade A	140			1	
Grade B	105			1.785(0.794,4.015)	0.161
Grade C	109			1.533(0.722,3.253)	0.266
Number of relapses		12.109	0.002		0.164
0 times	162			1	
1 times	128			1.031(0.500,2.127)	0.934
≥ 2 times	64			2.029(0.898,4.585)	0.089
Risk Perception	74(66,92)	-2.965	0.003	0.966(0.949,0.984)	<0.001
WBC	5.06(3.17,7.80)	-3.284	0.001	1.084(1.018,1.155)	0.012
PLT	101(68,136)	-2.840	0.005	0.990(0.984,0.996)	<0.001
ALB	34.25(29.3,41.4)	-4.449	<0.001	0.944(0.911,0.978)	0.001

Variable	N=354	Univariate analysis		Multivariable analysis	
		Statistical values	P-value	OR(95%CI)	P-value
ALT	36(21,68.5)	-2.663	0.008	1.004(1.000,1.009)	0.062
PT	14(12.8,17.2)	-2.295	0.022	0.998(0.972,1.024)	0.862
APTT	35.45(30.08,45.30)	-2.069	0.039	1.012(0.992,1.032)	0.233

3.4 Construction and Validation of the Prediction Models for UGIB Recurrence

Based on the six independent predictors identified by multivariable logistic regression analysis, four prediction models, including logistic regression, random forest, support vector machine, and k-nearest neighbor, were developed to predict UGIB recurrence in patients with liver cirrhosis. The classification performance of the four models was first evaluated using confusion matrix analysis in both the internal and external validation cohorts (Table 2). The results showed that the four models exhibited different classification capabilities. In the internal validation cohort, the LR model achieved an accuracy of 0.795, precision of 0.905, recall of 0.819, and F1 score of 0.860. In the external validation cohort, the LR model maintained stable performance, with an accuracy of 0.791, precision of 0.880, recall of 0.841, and F1 score of 0.859. Although the SVM model showed higher recall values in both validation cohorts, the LR model demonstrated a more balanced performance across multiple classification metrics.

ROC curves were subsequently generated, and the AUC values were calculated to assess the discriminative ability of the four prediction models. In the internal validation cohort (Fig. 2a), the AUC values of the LR, RF, SVM, and KNN models were 0.862, 0.804, 0.822, and 0.834, respectively. The LR model achieved the highest AUC, indicating superior discrimination ability compared with the other three models. Similar results were observed in the external validation cohort (Fig. 2b), where the AUC values of LR, RF, SVM, and KNN were 0.827, 0.712, 0.760, and 0.748, respectively. These findings demonstrated that the LR model maintained the best discriminative performance and robustness during external validation.

DCA was further performed to evaluate the clinical utility of the four models (Fig. 3). In both internal and external validation cohorts, the LR model consistently achieved higher net benefit across a wide range of threshold probabilities compared with the RF, SVM, and KNN models, indicating greater potential clinical applicability. Considering the results of confusion matrix analysis, ROC curve analysis, and DCA, the LR model demonstrated the best overall predictive performance and was selected as the optimal model. Based on this model, a nomogram was subsequently developed to provide an individualized and visual assessment of UGIB recurrence risk in patients with liver cirrhosis(Fig. 4).

Table 2
Confusion matrices for the four models in theinternal and external validation sets.

Model	Internal Validation sets				External Validation sets			
	Accuracy	Precision	Recall	F1 Score	Accuracy	Precision	Recall	F1 Score
LR	0.795	0.905	0.819	0.860	0.791	0.880	0.841	0.859
RF	0.755	0.869	0.802	0.834	0.777	0.857	0.850	0.853
SVM	0.808	0.860	0.897	0.878	0.791	0.825	0.920	0.870
KNN	0.788	0.868	0.853	0.861	0.757	0.835	0.850	0.842

Note : LR,logistic regression; RF random forest; SVM, support vector machine; KNN,k-nearest neighbor.

4. Discussion

In this prospective study, we systematically integrated multidimensional variables to develop and validate a prediction model for recurrent upper gastrointestinal bleeding in patients with liver cirrhosis. The recurrence rates of UGIB within 6 months after discharge were 24.16% in the development cohort and 23.65% in the external validation cohort. Previous studies have reported that, despite standard secondary prophylaxis, the rebleeding rate in patients with cirrhosis remains as high as 22%–33%, with early rebleeding occurring in 9%–19% of patients[17–18], which is consistent with our findings. These results further confirm that recurrent UGIB remains a common clinical challenge in patients with cirrhosis[19]. This may be attributed to the persistent pathophysiological basis of portal hypertension, irreversible impairment of hepatic synthetic function, and permanent structural alterations of the portal venous system, all of which contribute to a sustained risk of recurrent bleeding and adversely affect long-term survival and quality of life. Therefore, identifying key risk factors for recurrent bleeding and developing reliable prediction tools are of considerable clinical importance for early risk stratification and individualized management.

Our study further identified age, history of chronic diseases, bleeding recurrence risk perception, WBC, PLT and ALB as independent predictors of recurrent UGIB in patients with liver cirrhosis. Advanced age was identified as an important risk factor for early rebleeding. Mostafa EF et al[20] reported that elderly patients have a significantly higher risk of recurrent bleeding. With increasing age, declines in immune function, increased vascular fragility, and impaired tissue repair may contribute to a greater susceptibility to recurrent hemorrhage. Although age is a non-modifiable demographic factor, early identification of elderly patients at high risk and implementation of targeted preventive interventions may help reduce the incidence of recurrent bleeding.

Liver cirrhosis is a chronic multisystem disease whose effects extend beyond the liver itself. Previous studies have demonstrated that patients with cirrhosis often have a high burden of comorbidities, including diabetes mellitus, cardiovascular disease, and chronic kidney disease, all of which adversely

affect long-term prognosis[21]. Consistent with these findings, our study identified a history of chronic diseases as an independent risk factor for recurrent UGIB. The underlying mechanism may involve persistent inflammation and metabolic dysregulation associated with chronic comorbidities, which increase the overall physiological burden, further impair hepatic reserve, and aggravate portal hypertension, thereby promoting rupture of gastroesophageal varices and increasing the risk of recurrent bleeding. These findings suggest that multidisciplinary management should be strengthened in cirrhotic patients with chronic comorbidities. In addition to controlling the progression of cirrhosis, optimizing the management of coexisting chronic diseases may improve long-term outcomes.

Notably, this is the first prospective study to incorporate patients' perceived risk of bleeding recurrence into a prediction model for recurrent UGIB in liver cirrhosis and to identify it as an independent predictor of rebleeding. Risk perception reflects an individual's subjective assessment of disease-related threats and may influence health behaviors, treatment adherence, and disease self-management. Previous studies have shown that patients' awareness of disease severity is closely associated with treatment adherence[22]. Patients with low risk perception tend to underestimate the severity of their disease and the likelihood of recurrent bleeding, resulting in poorer self-management, inadequate medication adherence, and insufficient maintenance of healthy behaviors, thereby increasing the risk of recurrence[23]. Similarly, the Health Belief Model emphasizes that individuals' perception of disease-related threats is a key determinant of health-related behavioral changes[24]. Our findings suggest that improving patients' awareness of bleeding recurrence risk through health education and self-management interventions may represent an effective strategy for reducing recurrent bleeding.

Regarding laboratory parameters, our study demonstrated that WBC count, PLT count, and serum ALB level were significantly associated with recurrent bleeding. Previous studies have shown that WBC count, as an important marker of systemic inflammation, plays a critical role in the development of UGIB and recurrent bleeding in cirrhosis[25–26], which is consistent with our findings. An elevated WBC count may indicate infection or systemic inflammation, leading to the release of inflammatory mediators, increased portal venous pressure, and a higher risk of recurrent rupture of gastroesophageal varices. Therefore, early detection and effective control of infection may be important for preventing recurrent bleeding.

In addition, decreased PLT count was identified as an important predictor of recurrent UGIB, consistent with previous studies. Reduced platelet counts have been associated with an increased risk of esophageal varices[27], and lower platelet levels are closely associated with recurrent variceal bleeding[28]. Thrombocytopenia reflects not only hypersplenism caused by portal hypertension and impaired hepatic synthetic function but also compromised hemostatic capacity, thereby increasing the risk of recurrent bleeding. Consequently, platelet count remains an important clinical indicator for evaluating the risk of recurrent bleeding in patients with cirrhosis.

Furthermore, serum ALB level was significantly associated with recurrent bleeding, consistent with the findings of Liu et al[29]. Serum albumin reflects both hepatic synthetic function and nutritional status. Hypoalbuminemia indicates impaired hepatic reserve and may further increase the risk of recurrent

bleeding by reducing plasma colloid osmotic pressure, promoting ascites formation, and aggravating portal hypertension. Therefore, improving nutritional status and preserving hepatic functional reserve may contribute to reducing the risk of recurrent bleeding.

Regarding model performance, we compared four prediction models based on LR, RF, SVM and KNN algorithms. Among them, the LR model demonstrated the best overall predictive performance, with an AUC of 0.862 in the internal validation cohort and 0.827 in the external validation cohort, outperforming the other three models. Moreover, decision curve analysis demonstrated that the model achieved a higher net benefit across a wide range of threshold probabilities, further supporting its favorable clinical applicability.These findings indicate that the LR model possesses favorable discrimination, calibration, and clinical utility.

Based on the optimal LR model, a nomogram was subsequently developed using the regression coefficients and odds ratios of the identified predictors, enabling individualized and visual assessment of recurrent bleeding risk. Owing to its simplicity and interpretability, the nomogram may assist clinicians in rapidly identifying high-risk patients and provide practical support for individualized prevention and intervention strategies, thereby enhancing the clinical applicability of the prediction model.

Several limitations of this study should be acknowledged. First, the follow-up period was limited to six months, and therefore only short-term recurrence was evaluated. The predictive performance of the model for long-term recurrence requires further investigation. Second, several potentially important predictors, such as endoscopic treatment modalities and hepatic venous pressure gradient, were not included. Future studies incorporating imaging findings, multi-omics data, and additional disease-specific characteristics may further optimize the model and improve its predictive accuracy. Finally, large-scale, multicenter studies with longer follow-up are warranted to further externally validate and dynamically update the model, thereby enhancing its robustness, generalizability, and clinical applicability.

5. Conclusion

In conclusion, this prospective study developed and externally validated a risk prediction model for recurrent UGIB in patients with liver cirrhosis by integrating multidimensional clinical, laboratory, and psychosocial factors. The LR model demonstrated superior predictive performance, good discrimination, and clinical utility compared with other machine learning algorithms. The developed nomogram provides an individualized and visual tool for early identification of patients at high risk of recurrent bleeding, which may facilitate risk stratification and personalized prevention strategies in clinical practice.

Declarations

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Author contributions

R.L., A-Q.L.and Y-L.Q. were responsible for the study design and the initial draft of the manuscript. Y-P.F. and J.D. undertook data collection and statistical analyses. Z-Y.L. and T-X.Z. contributed to revising the manuscript critically for important intellectual content and approved the final version for publication. H.X. and Y-M.Z. contributed to the revision of the manuscript. All authors reviewed the manuscript critically for important intellectual content and have read and approved the final manuscript.

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Data availability statement

The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

Ethics approval and consent to participate

This study was approved by the ethics committee of Shandong Second Medical University (approval number: SDSMU 2026YX169). All participants signed written informed consent before inclusion.

Consent for publication

Not applicable.

Conflicts of Interest
The authors declare that there are no conflicts of interest regarding the publication of this article. All authors have no financial, commercial, or personal affiliations that could be perceived as potential conflicts of interest and that may have influenced the research process, including study design, data analysis, interpretation of findings, or manuscript preparation.

TRIPOD guidelines

This study adheres to the TRIPOD reporting guidelines to ensure transparency and rigor in the development of the prediction model.

References

1. Devarbhavi H, Asrani SK, Arab JP, Nartey YA, Pose E, Kamath PS. Global burden of liver disease: 2023 update. J Hepatol. 2023;79(2):516–37. 10.1016/j.jhep.2023.03.017.
2. del Olmo JA, Peña A, Serra MA, Wassel AH, Benages A, Rodrigo JM. Predictors of morbidity and mortality after the first episode of upper gastrointestinal bleeding in liver cirrhosis. J Hepatol. 2000;32(1):19–24. 10.1016/s0168-8278(01)68827-5.
3. Ginès P, Krag A, Abraldes JG, Solà E, Fabrellas N, Kamath PS. Liver cirrhosis. Lancet. 2021;398(10308):1359–76. 10.1016/S0140-6736(21)01374-X.
4. Carbonell N, Pauwels A, Serfaty L, Fourdan O, Lévy VG, Poupon R. Improved survival after variceal bleeding in patients with cirrhosis over the past two decades. Hepatology. 2004;40(3):652–9. 10.1002/hep.20339.
5. Aluizio CLS, Montes CG, Reis GFSR, Nagasako CK. Risk stratification in acute variceal bleeding: Far from an ideal score. Clin (Sao Paulo). 2021;76:e2921. 10.6061/clinics/2021/e2921. Published 2021 Jun 28.
6. Balcar L, Mandorfer M, Hernández-Gea V, et al. Predicting survival in patients with 'non-high-risk' acute variceal bleeding receiving β-blockers+ligation to prevent re-bleeding. J Hepatol. 2024;80(1):73–81. 10.1016/j.jhep.2023.10.007.
7. Wang J, Wang AJ, Li BM, et al. MELD-Na: effective in predicting rebleeding in cirrhosis after cessation of esophageal variceal hemorrhage by endoscopic therapy. J Clin Gastroenterol. 2014;48(10):870–7. 10.1097/MCG.0000000000000043.
8. Deng F, Cao Y, Wang H, Zhao S. Prognosis of major bleeding based on residual variables and machine learning for critical patients with upper gastrointestinal bleeding: A multicenter study. J Crit Care. 2025;85:154923. 10.1016/j.jcrc.2024.154923.
9. Zhan JY, Chen J, Yu JZ, et al. Prognostic model for esophagogastric variceal rebleeding after endoscopic treatment in liver cirrhosis: A Chinese multicenter study. World J Gastroenterol. 2025;31(2):100234. 10.3748/wjg.v31.i2.100234.
10. Liu L, Nie Y, Liu Q, Zhu X. A Practical Model for Predicting Esophageal Variceal Rebleeding in Patients with Hepatitis B-Associated Cirrhosis. Int J Clin Pract. 2023;2023:9701841. Published 2023 Aug 3. 10.1155/2023/9701841
11. Guidelines for the diagnosis and treatment of liver cirrhosis. Modern Medicine and Health(02),320 + 1–18. doi:CNKI:SUN:XYWS.0.2020-02-063.
12. Peduzzi P, Concato J, Kemper E, Holford TR, Feinstein AR. A simulation study of the number of events per variable in logistic regression analysis. J Clin Epidemiol. 1996;49(12):1373–9. 10.1016/s0895-4356(96)00236-3.
13. Moons KGM, Wolff RF, Riley RD, et al. PROBAST: A Tool to Assess Risk of Bias and Applicability of Prediction Model Studies: Explanation and Elaboration. Ann Intern Med. 2019;170(1):W1–33. 10.7326/M18-1377.
14. de Franchis R. Evolving consensus in portal hypertension. Report of the Baveno IV consensus workshop on methodology of diagnosis and therapy in portal hypertension. J Hepatol.

2005;43(1):167–76. 10.1016/j.jhep.2005.05.009.

15. Zhu Xinying Y, Wenxuan et al. Development of a scale to measure the perceived risk of recurrence of upper gastrointestinal bleeding in patients with liver cirrhosis[J]. J Nurs(04),41–5. doi:CNKI:SUN:HLXZ.0.2025-04-009.
16. Xiao Shuiyuan. (1994). Theoretical basis and research applications of the Social Support Rating Scale. J Clin Psychiatry (02). doi:CNKI:SUN:LCJS.0.1994-02-019.
17. Yang J, Ge K, Chen L, Yang JL. The efficacy comparison of carvedilol plus endoscopic variceal ligation and traditional, nonselective β-blockers plus endoscopic variceal ligation in cirrhosis patients for the prevention of variceal rebleeding: a meta-analysis. Eur J Gastroenterol Hepatol. 2019;31(12):1518–26. 10.1097/MEG.0000000000001442.
18. Harewood GC, Baron TH, Song LM. Factors predicting success of endoscopic variceal ligation for secondary prophylaxis of esophageal variceal bleeding. J Gastroenterol Hepatol. 2006;21(1 Pt 2):237–41. 10.1111/j.1440-1746.2006.04169.x.
19. Lecleire S, Di Fiore F, Merle V, et al. Acute upper gastrointestinal bleeding in patients with liver cirrhosis and in noncirrhotic patients: epidemiology and predictive factors of mortality in a prospective multicenter population-based study. J Clin Gastroenterol. 2005;39(4):321–7. 10.1097/01.mcg.0000155133.50562.c9.
20. Mostafa EF, Mohammad AN. Incidence and predictors of rebleeding after band ligation of oesophageal varices. Arab J Gastroenterol. 2014;15(3–4):135–41. 10.1016/j.ajg.2014.10.002.
21. Bettinger D, Thimme R, Schultheiß M. Die Leberzirrhose als Multisystemerkrankung [Liver cirrhosis as a multisystem disease]. Dtsch Med Wochenschr. 2024;149(12):690–5. 10.1055/a-2146-7514.
22. Hayward KL, Valery PC, Martin JH, et al. Medication beliefs predict medication adherence in ambulatory patients with decompensated cirrhosis. World J Gastroenterol. 2017;23(40):7321–31. 10.3748/wjg.v23.i40.7321.
23. Desai AP, Duzdar S, Stump T, et al. Measuring Medication Use, Obstacles, and Knowledge in Individuals With Cirrhosis. Clin Gastroenterol Hepatol. 2023;21(7):1819–e18305. 10.1016/j.cgh.2022.08.025.
24. Rosenstock IM, Strecher VJ, Becker MH. Social learning theory and the Health Belief Model[J]. Health Educ Q. 1988;15(2):175–83.
25. Liu L, Liu Q, Xiao N, Zhang Y, Nie Y, Zhu X. A Liver Stiffness Measurement-Based Nomogram Predicts Variceal Rebleeding in Hepatitis B-Related Cirrhosis. Dis Markers. 2022;2022:4107877. 10.1155/2022/4107877. Published 2022 Jun 2.
26. Tatlıparmak AC, Dikme Ö, Dikme Ö, Topaçoğlu H. Cancer, platelet distribution width, and total protein levels as predictors of rebleeding in upper gastrointestinal bleeding. PeerJ. 2022;10:e14061. Published 2022 Sep 15. 10.7717/peerj.14061
27. Afsar A, Nadeem M, Shah SAA, Hussain H, Rani A, Ghaffar S. Platelet count can predict the grade of esophageal varices in cirrhotic patients: a cross-sectional study. F1000Res. 2021;10:101. 10.12688/f1000research.28005.2. Published 2021 Feb 11.

28. Heuman DM, Abou-Assi SG, Habib A, et al. Persistent ascites and low serum sodium identify patients with cirrhosis and low MELD scores who are at high risk for early death. Hepatology. 2004;40(4):802–10. 10.1002/hep.20405.
29. Liu Y, Wu S, Cai S, Xie B. The prognostic evaluation of ALBI score in endoscopic treatment of esophagogastric varices hemorrhage in liver cirrhosis. Sci Rep. 2024;14(1):780. 10.1038/s41598-023-50629-9. Published 2024 Jan 8.

Figures

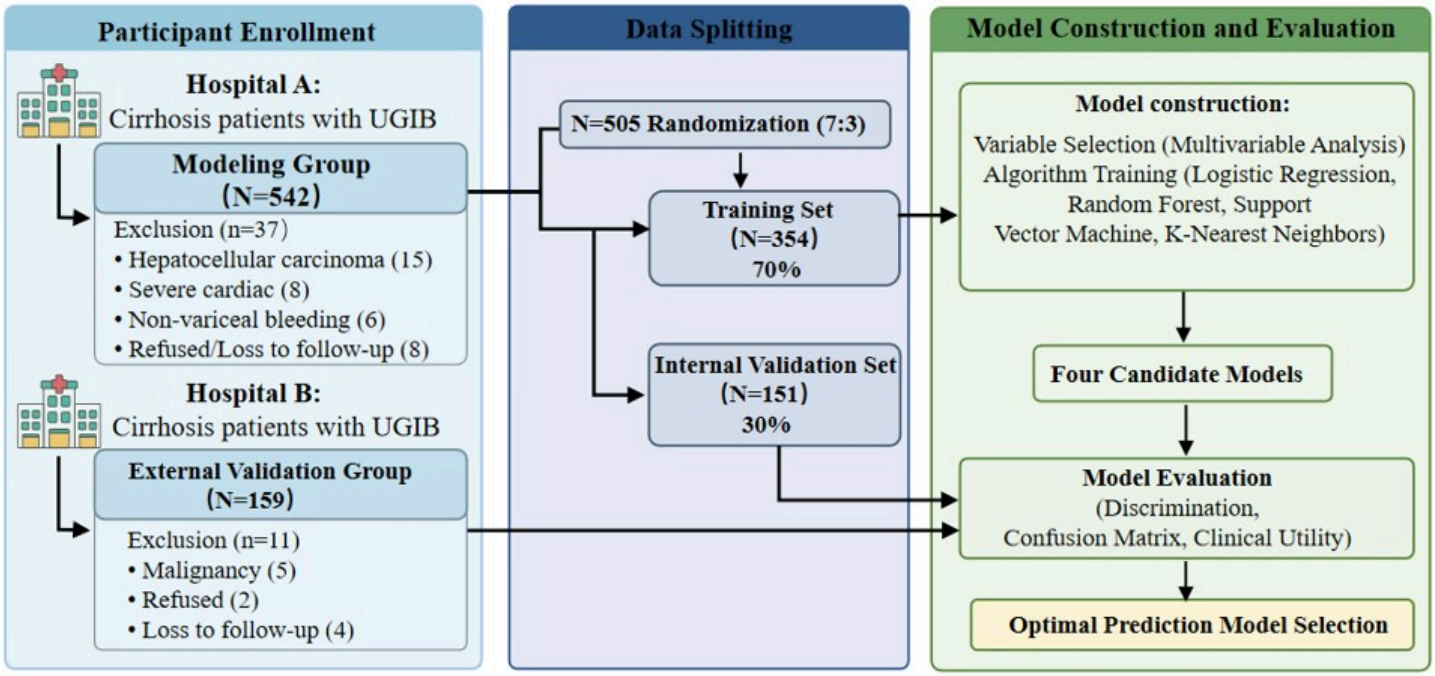
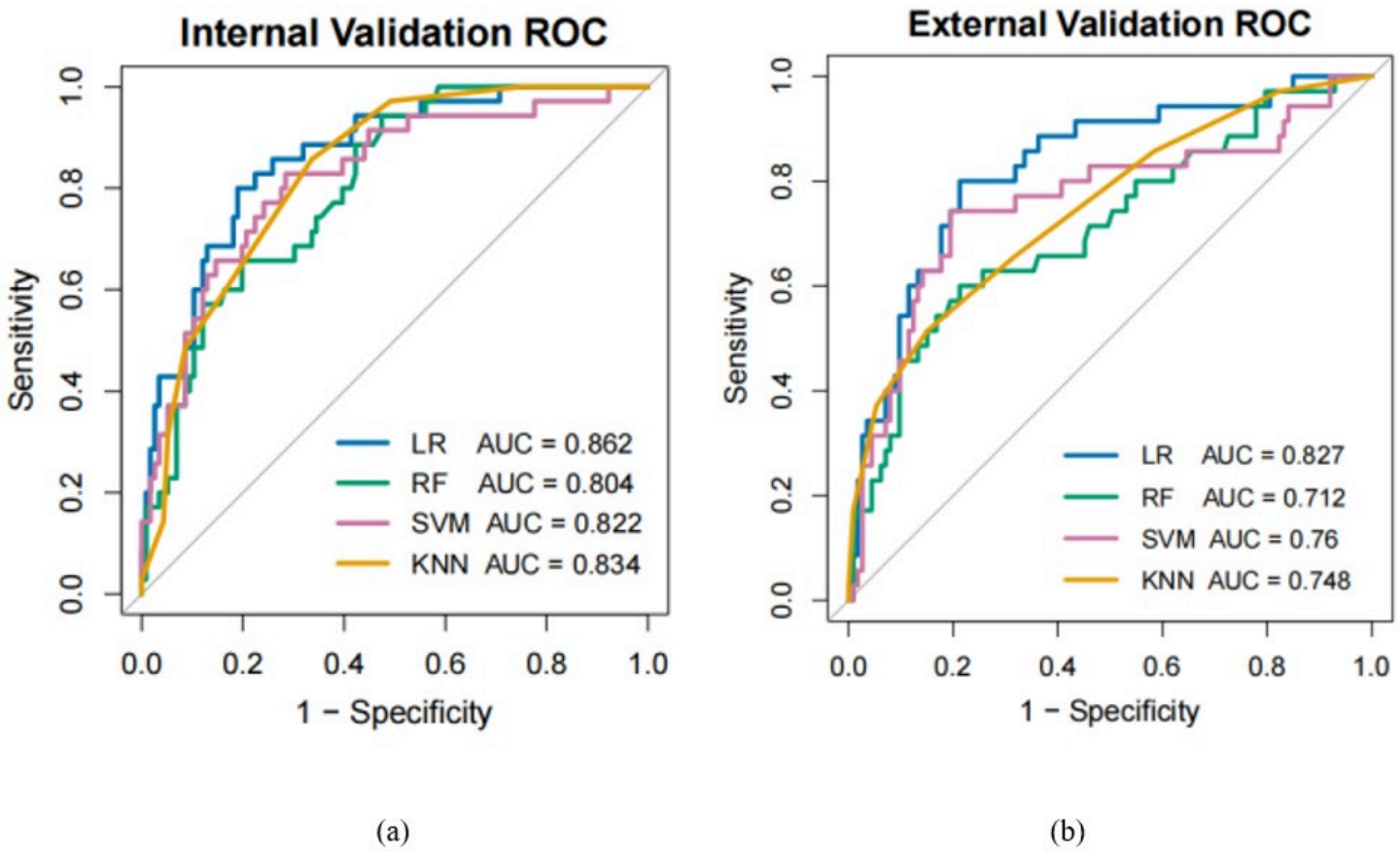


Figure 1

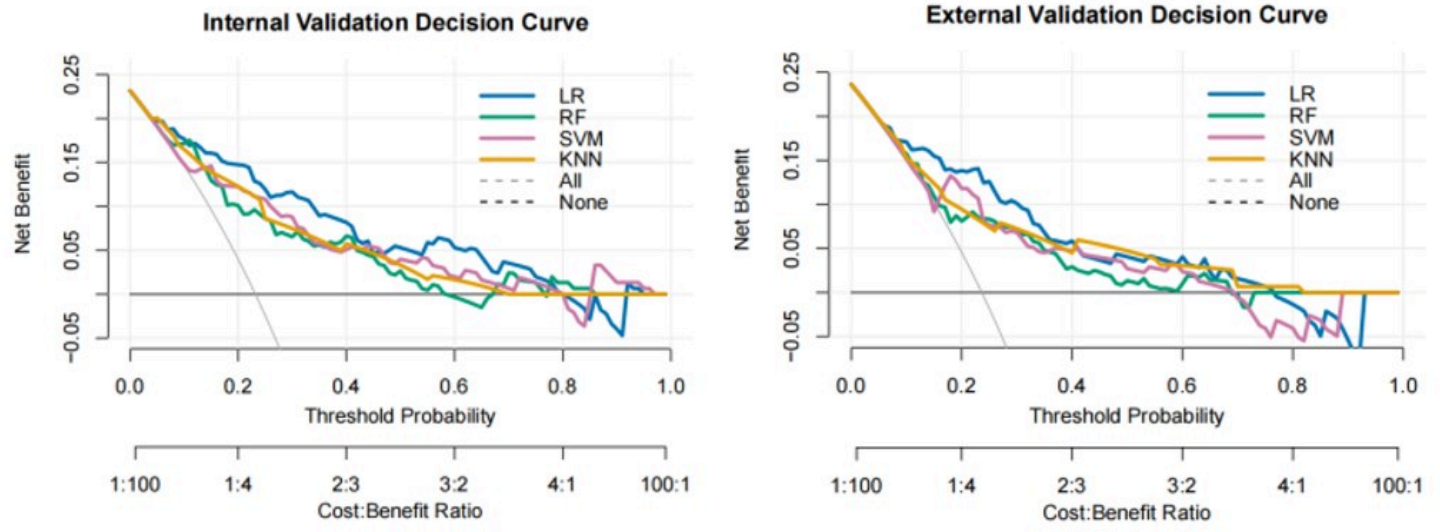
Research Framework Diagram



(a) (b)

Figure 2

ROC Curve for the Internal and External Validation Set (a)Internal Validation set; (b) External Validation Set. Note :LR,logistic regression; RF random forest; SVM, support vector machine; KNN,k-nearest neighbor.



(a) (b)

Figure 3

DCA Curve for the Internal and External Validation Set (a)Internal Validation set; (b) External Validation Set.

Note :DCA,decision curve analysis; LR, logistic regression; RF, random forest; SVM, support vector machine; KNN, k-nearest neighbor.

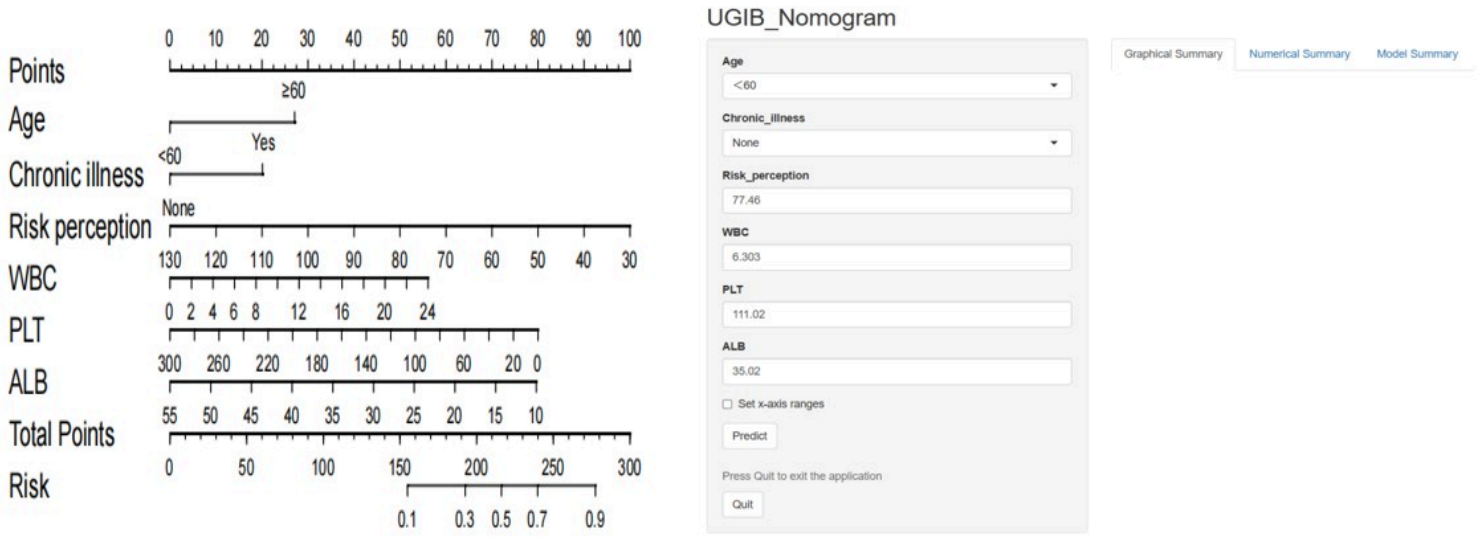


Figure 4

Nomogram (a) and interactive web-based nomogram (b) for UGIB Recurrent Risk Prediction Model.

Supplementary Files

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