Neuropsychiatric Disease and Treatment

Dovepress
Taylor & Francis Group

Open Access Full Text Article

ORIGINAL RESEARCH

Nomogram Model for Predicting Risk of Postoperative Delirium in Adult Liver Transplant Patients: A Retrospective Study

Ling-Ling Yu[1,*], Yu Gong[1,*], Fang Fang[2,*], Ting Wang[1], Jing Cang[2]

[1]Department of Critical Care Medicine, Zhongshan Hospital, Fudan University, Shanghai, 200032, People's Republic of China; [2]Department of Anesthesiology, Zhongshan Hospital, Fudan University, Shanghai, 200032, People's Republic of China

*These authors contributed equally to this work

Correspondence: Jing Cang, Department of Anesthesiology, Zhongshan Hospital, Fudan University, 180 Fenglin Road, Shanghai, 200032, People's Republic of China, Tel +86-13636578221, Email Cang.Jing@zs-hospital.sh.cn; Ting Wang, Department of Critical Care Medicine, Zhongshan Hospital, Fudan University, Shanghai, 200032, People's Republic of China, Tel +86-13621949433, Email Wang.Ting@zs-hospital.sh.cn

Background: Postoperative delirium is a common and serious complication following liver transplantation, early identification of high-risk patients is crucial for implementing preventive strategies and improving clinical outcomes.

Objective: To develop and validate a prediction model for postoperative delirium (POD) in adult liver transplant patients using preoperative baseline characteristics, intraoperative factors and postoperative parameters available within 24 hours after surgery. The model aims to assess the risk of POD and provide early identification of high-risk patients.

Methods: A retrospective analysis was conducted on liver transplant patients, classified based on the presence or absence of POD. Key risk factors were identified using univariate and multivariate logistic regression. The prediction model was established and validated, with performance evaluated using the area under the receiver operating characteristic curve (AUROC). The prediction model was visualized as a nomogram for practical application.

Results: A total of 480 patients were included, with a POD incidence of 30.8%. Six key predictors were identified: age, APACHE score, albumin, AST, BUN, and blood ammonia. The final model achieved an AUROC of 0.757 (95% CI: 0.709–0.806), sensitivity of 66.2%, and specificity of 77.7%. The optimal classification threshold of the model is 0.341, that is, patients with a predicted probability exceeding 0.341 were classified as high-risk for delirium.

Conclusion: The developed nomogram effectively predicts postoperative delirium risk in liver transplant patients, offering clinical utility for risk stratification and management.

Keywords: postoperative delirium, nomogram model, liver transplant

Introduction

Postoperative delirium (POD) is an acute brain dysfunction characterized by sudden onset, altered consciousness, and cognitive impairment. It frequently occurs within 24~72 hours post-surgery, particularly in intensive care unit (ICU) settings, with an incidence rate ranging from 11% to 42%,[1] depending on patient populations. In liver transplant patients, the risk of POD is even higher due to preexisting hepatic encephalopathy, hepatorenal syndrome, and the complexity of liver transplantation procedures, which include prolonged surgery, significant blood loss, and immunosuppressive therapy. Studies have shown that delirium prevalence in this population ranges from 17% to 47.4%.[2,3] POD has been associated with adverse outcomes, such as prolonged ICU stays, increased mortality rates, long-term cognitive decline, and elevated healthcare costs.[4,5] As such, POD has become a critical area of focus in clinical practice.

Although various models like PRE-DELIRIC and E-PRE-DELIRIC have been developed to predict ICU delirium, they are rarely tailored to liver transplant recipients.[6,7] Therefore, a prediction model tailored to liver transplant patients is needed to better assess the risk of delirium, facilitate early detection, and guide appropriate preventive and therapeutic interventions.

Received: 10 February 2025
Accepted: 23 June 2025
Published: 8 July 2025

This study aimed to develop a nomogram-based prediction model that integrates liver-specific parameters to provide early identification of high-risk liver transplant patients.

Methods

Study Design and Population

This was a retrospective, single-center study aimed at developing a prediction model for POD in liver transplant patients in the ICU. Patients who received liver transplantation between June 2018 and June 2020 and were aged ≥18 years were included. Exclusion criteria were preoperative delirium, ICU stays <3 days, combined organ transplantation, or conditions impeding delirium assessment (eg, coma, severe mental disabilities).

All operations were performed by the same surgical team. Intraoperative anaesthesia was performed according to a uniform anaesthesia protocol: sevoflurane, alfentanil, sufentanil, rocuronium, cyclopofol. All patients received standard immunosuppressive therapy with basiliximab, methylprednisolone, mycophenolate mofetil, and tacrolimus.

This study was approved by the Medical Ethics Committee of Zhongshan Hospital (Approval No. B2022-447) and was conducted in accordance with the applicable regulations for research ethics committee review and informed consent. Our study complies with the Declaration of Helsinki. All organs were donated voluntarily with written informed consent, and that these were conducted in accordance with the Declaration of Istanbul.

Data Collection

We collected a range of preoperative, intraoperative and postoperative data from the enrolled patients. Preoperative data included: age, gender, primary disease, BMI, Child-Pugh grade, Model for End-stage Liver Disease (MELD) score, number of complications, use of artificial liver treatment. Intraoperative data included operation duration, blood loss volume, blood transfusion volume, liver cold ischemia duration, hepatic-free phase. Postoperative data included the Acute Physiology and Chronic Health Evaluation (APACHE) II score, use of vasoactive agent and lab results within 24 hours of ICU admission.

Definitions

Delirium was assessed using the Confusion Assessment Method for the ICU (CAM-ICU), performed three times daily by trained nurses. A CAM-ICU positive result confirmed a POD diagnosis.

Statistical Analysis

Descriptive Statistics

For the small number of missing values in the predictors (one case each of glucose, sodium and hepatic-free stage, accounting for 0.2%), we employed Multiple Imputation by Chained Equations (MICE).

Frequencies and percentages were used for categorical variables, and chi-squared tests for comparisons between groups. For continuous variables, mean ± standard deviation (mean ± SD) was used for description, and median and interquartile range (median [Q1; Q3]) were used when data did not conform to a normal distribution. For continuous variables that followed a normal distribution, independent samples *t*-tests were used to compare differences between groups. For continuous variables that did not follow a normal distribution, the Mann–Whitney *U*-test was used to compare differences between groups.

Development and Assessment of the Nomogram

All analyses were performed using R (version 4.1.3) and associated packages. Univariate logistic regression was used to identify potential predictors of postoperative delirium (POD). Variables with a p-value <0.15 in univariate analysis were included in the multivariate logistic regression model to refine the prediction model. The final model's performance was evaluated using the area under the receiver operating characteristic curve (AUROC). The optimal classification threshold was determined based on the maximum Youden index of the ROC curve. Internal validation was performed using bootstrapping with 200 iterations to assess the model's stability and generalisability. In addition, the Hosmer-Lemeshow goodness of fit test ($p > 0.05$) was used to further validate the fit of the model. A nomogram was created to visualize the prediction model for practical application.

Results

General Characteristics

Of the 493 screened patients, 480 were included in the study, with 148 (30.8%) developing POD (Figure 1). The presence of delirium was used as a grouping variable to compare differences in each patient characteristic. Differences in patient characteristics between POD group and non-POD group are detailed in Table 1.

Development of Prediction Model

Using delirium as the dependent variable, we considered 31 potential factors as independent variables, including age, gender, primary disease, BMI, APACHE score, Child-Pugh classification, MELD score, artificial liver treatment, number of complications, operation duration, volume of hemorrhage, blood transfusion volume, liver cold ischemia duration, hepatic-free phase, vasoactive drugs, and various blood markers. Blood markers included total bilirubin (TB), albumin (Alb), glutamic oxalacetic transaminase (AST), blood glucose (Glu), sodium (Na), blood Urea nitrogen (BUN), creatinine (Cr), C-reactive protein (CRP), blood ammonia(AMON), lactate(LAC), prothrombin time (PT), International normalized ratio(INR), hemoglobin (Hb), platelet (PLT), white blood cell (WBC) and procalcitonin (PCT). Univariate logistic regression analysis identified six variables with $P < 0.15$: age, APACHE score, albumin, AST, BUN, and AMON. These variables were considered for multivariate analysis (Table 2).

Multivariate logistic regression revealed that all six variables were independent predictors of postoperative delirium. The regression coefficients, odds ratios (OR), and 95% confidence intervals (CI) are shown in Table 3. The area under receiver operating characteristic curve (AUROC) of this model was 0.757 (95% CI: 0.709 ~ 0.806), with good differentiation ability. The optimal threshold for classifying patients at risk of delirium was 0.341, with a sensitivity of 66.2% and specificity of 77.7% (Figure 2). These data demonstrated that our nomogram had a significant potential for clinical decision-making.

Validation of Prediction Model

To assess the model's stability, we used bootstrapping (B=200) for internal validation, generating a calibration curve (Figure 3). The calibration curve closely aligned with the reference line, indicating good consistency and stability. The Hosmer-Lemeshow test also confirmed the model's goodness of fit (χ^2 =2.1505, P=0.3412). The AUROC was 0.757 before the calibration using the bootstrapping technique, and 0.743 after the calibration.

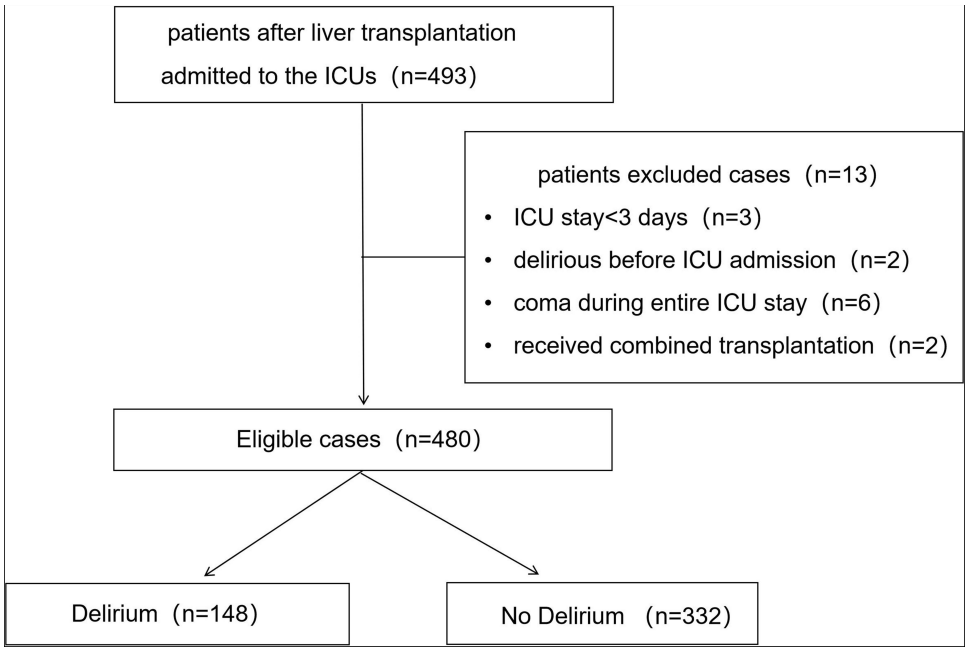

Figure 1 Flow chart for patient selection.

https://doi.org/10.2147/NDT.S521718

Table 1 General Characteristics of the Patients

Variables	No Delirium (N=332)	Delirium (N=148)	p
Gender			
Female	59 (17.8%)	23 (15.5%)	0.640
Male	273 (82.2%)	125 (84.5%)	
Age(years)	53.0 [46.0;60.0]	57.0 [50.5;64.0]	
BMI (kg/m2)	22.0 [20.0;25.0]	21.0 [19.0;25.0]	< 0.001*
Primary diagnosis, n (%)			0.128
HCC	231 (69.6%)	97 (65.5%)	0.665
Alcoholic liver disease	11 (3.3%)	5 (3.4%)	
Cirrhosis of other causes	90 (27.1%)	46 (31.1%)	
APACHE II			
APACHE<15	285 (85.8%)	94 (63.5%)	< 0.001*
APACHE≥15	47 (14.2%)	54 (36.5%)	
Child-Pugh score			
A	199 (59.9%)	56 (37.8%)	< 0.001*
B	85 (25.6%)	41 (27.7%)	
C	48 (14.5%)	51 (34.5%)	
MELD score	10.0 [8.0;13.5]	13.0 [9.0;22.0]	< 0.001*
Artificial liver therapy			
No	327 (98.5%)	135 (91.2%)	< 0.001*
Yes	5 (1.5%)	13 (8.8%)	
Complication, n (%)			
None	189 (56.9%)	53 (35.8%)	< 0.001*
One kind	105 (31.6%)	63 (42.6%)	
Two kinds	37 (11.1%)	30 (20.3%)	
Three kinds	1 (0.3%)	2 (1.4%)	
Operation duration(mins)	285.0 [244.5;330.5]	296.0 [255.0;333.0]	0.192
Volume of hemorrhage(mL)	800.0 [500.0;1500.0]	1000.0 [500.0;1850.0]	0.041*
Blood transfusion volume(mL)	800.0 [0.0;1600.0]	1200.0 [350.0;2300.0]	< 0.001*
Cold Ischemia Duration(min)	567.0 [497.0;628.0]	573.5 [499.5;643.0]	0.371
Hepatic-free stage(min)	46.0 [40.0;51.0]	45.0 [40.0;50.0]	0.256
Use of vasoactive agent in ICU			
No	262 (78.9%)	93 (62.8%)	< 0.001*
Yes	70 (21.1%)	55 (37.2%)	
TB (μmol/L)	49.7 [37.3;72.5]	65.9 [40.9;128.1]	< 0.001*
ALB (g/L)	30.0 [27.0;33.0]	28.0 [25.0;31.0]	< 0.001*
AST (U/L)	1729.0 [915.5;2800.0]	1550.0 [753.0;2240.5]	0.094
Glu (mmol/L)	10.5 [9.0;12.1]	10.8 [9.1;12.5]	0.236
Na (mmol/L)	141.0 [139.0;143.0]	139.0 [137.0;142.0]	< 0.001*
BUN (mmol/L)	5.7 [4.8; 6.9]	7.1 [5.7; 9.6]	< 0.001*
Cr (μmol/L)	69.0 [58.0;83.5]	73.0 [63.0;93.5]	0.004*
CRP (mg/L)			
Normal	83 (25.0%)	37 (25.0%)	1.000
Abnormal	249 (75.0%)	111 (75.0%)	
AMON (μmol/L)	19.0 [12.0;29.0]	24.5 [15.0;40.5]	< 0.001*
LAC (mmol/L)	3.1 [2.1; 4.9]	3.5 [2.2; 5.9]	0.151
PT (s)	19.3 [16.7;22.0]	19.9 [17.7;24.6]	0.007*
INR	1.7 [1.5; 2.0]	1.8 [1.6; 2.2]	0.007*
Hb (g/L)	104.0 [93.0;115.5]	96.0 [88.0;106.0]	< 0.001

(*Continued*)

Table 1 (Continued).

Variables	No Delirium (N=332)	Delirium (N=148)	p
PLT (×10 9/L)	82.0 [56.5;119.0]	71.5 [51.5;95.5]	0.002*
WBC (×10 9/L)	8.1 [5.1;12.0]	7.0 [4.4;11.7]	0.134
PCT (ng/mL)	1.2 [0.5; 3.0]	1.6 [0.7; 3.5]	0.076

Notes: Complication include hepatic encephalopathy, ascites, variceal bleeding. *P<0.15, **P<0.2.
Abbreviations: TB, total bilirubin; Alb, albumin; AST, glutamic oxalacetic transaminase; Glu, blood glucose; Na, sodium; BUN, blood Urea nitrogen; Cr, creatinine; CRP, C-reactive protein; AMON, blood ammonia; LAC, lactate; PT, prothrombin time; INR, International normalized ratio; Hb, hemoglobin; PLT, platelet; WBC, white blood cell; PCT, procalcitonin.

Table 2 Single Factor Logistic Regression Analyses for Screening Predictors

Variables	β	P	OR	OR 95% CI
Gender (female)	0.161	0.549	1.175	0.702–2.020
Age	0.034	0.000*	1.035	1.016–1.056
BMI	−0.035	0.199**	0.966	0.915–1.018
Primary diagnosis				
Cirrhosis of other causes	Reference			
Alcoholic liver disease	−0.117	0.837	0.889	0.267–2.603
HCC	−0.197	0.367	0.822	0.538–1.265
APACHE≥15	1.248	0.000*	3.483	2.213–5.510
Child-Pugh score				
A	Reference			
B	0.539	0.027*	1.714	1.062–2.757
C	1.329	0.000*	3.776	2.312–6.210
MELD score	0.076	0.000*	1.079	1.050–1.111
Artificial liver therapy	1.840	0.001*	6.298	2.326–19.944
Complication				
None	Reference			
One kind	0.761	0.001*	2.140	1.385–3.319
Two kinds	1.062	0.000*	2.891	1.632–5.118
Three kinds	1.965	0.112*	7.132	0.671–155.225
Operation duration	0.002	0.140*	1.002	0.999–1.005
Volume of hemorrhage	0.000	0.017*	1.000	1.000–1.000
Blood transfusion volume	0.000	0.000*	1.000	1.000–1.000
Cold Ischemia Duration	0.000	0.913	1.000	0.999–1.001
The anhepatic Phase	−0.009	0.426	0.991	0.970–1.012
Use of vasoactive agent in ICU	0.795	0.000*	2.214	1.446–3.387
TB	0.007	0.000*	1.007	1.004–1.010
ALB	−0.089	0.000*	0.915	0.877
AST	0.000	0.020*	1.000	1.000–1.000
Glu	0.046	0.258	1.047	0.967–1.135
Na	−0.112	0.000*	0.894	0.846–0.943
BUN	0.154	0.000*	1.167	1.100–1.247
Cr	0.010	0.003*	1.010	1.004–1.018
Abnormal CRP	0.000	1.000	1.000	0.643–1.576
AMON	0.020	0.000*	1.021	1.010–1.032
LAC	0.064	0.113	1.066	0.984–1.154
PT	0.036	0.029*	1.036	1.003–1.070
INR	0.378	0.032*	1.459	1.031–2.068

(*Continued*)

Table 2 (Continued).

Variables	β	P	OR	OR 95% CI
Hb	−0.022	0.000*	0.978	0.966–0.990
PLT	−0.007	0.002*	0.993	0.988–0.997
WBC	−0.010	0.557	0.990	0.957–1.023
PCT	0.005	0.607	1.005	0.986–1.022

Notes: *P<0.15, **P<0.2.

Table 3 Results of Multivariate Unconditioned Logsitic Regression Analysis

Variables	β	P	OR (95% CI)
Intercept	−1.785	0.075	0.168 (0.023–1.170
Age(years)	0.035	0.002	1.036 (1.014–1.059)
APACHE score≥15	0.821	0.002	2.273 (1.365–3.782)
ALB	−0.073	0.002	0.930 (0.888–0.972)
AST	−0.0002	0.006	0.999 (0.999–0.999)
BUN	0.113	0.0004	1.119 (1.055–1.195)
AMON	0.024	0.0002	1.025 (1.012–1.038)

Note: *P<0.05.

The regression coefficients before and after the calibration are detailed in Table 4. The equations for predicting the risk of delirium are as follows:

(1) The risk of delirium before the calibration: 1/[1+exp-(−1.785+0.035×Age+0.821×APACHE≧15-0.073×ALB-0.0002×AST+0.113×BUN+0.024×AMON]

(2) The risk of delirium After the calibration:
1/[1+exp-(−1.940+0.037×Age+0.793×APACHE≧15-0.078×ALB-0.0002×AST+0.124×BUN+0.024×AMON)]

Visualization of Risk Prediction Model for Delirium

A nomogram was created based on the multivariate logistic regression model to visually predict the risk of delirium (Figure 4). Each predictor variable was assigned a score, and the total score was used to determine the likelihood of a patient developing delirium. The model's performance was confirmed by an AUROC of 0.757 (95% CI: 0.709–0.806), demonstrating good consistency and clinical applicability for decision-making.

Discussion

This study presents a novel nomogram-based prediction model for assessing the risk of postoperative delirium (POD) in liver transplant patients. The model incorporates six significant perioperative factors - age, APACHE score, albumin (ALB), glutamic oxalacetic transaminase (AST), blood urea nitrogen (BUN) and ammonia (AMON) - and demonstrates good discriminatory ability with an AUROC of 0.757. By enabling early identification of high-risk patients, the model facilitates timely clinical intervention, potentially reducing the incidence and severity of POD.

In view of the high prevalence of delirium in ICU patients[8,9] and its serious consequences,[10,11] predicting ICU delirium is clinically important. Early identification of patients at risk can inform caregivers and families, helping them make decisions regarding preventive measures. Researchers have attempted to develop delirium prediction models for different patient groups. The PRE-DELIRIC (PREdiction of DELIRium in ICu patients)[6] model was constructed using 3056 patients from five intensive care units across the Netherlands, the model contains 10 risk factors—age, APACHE-II

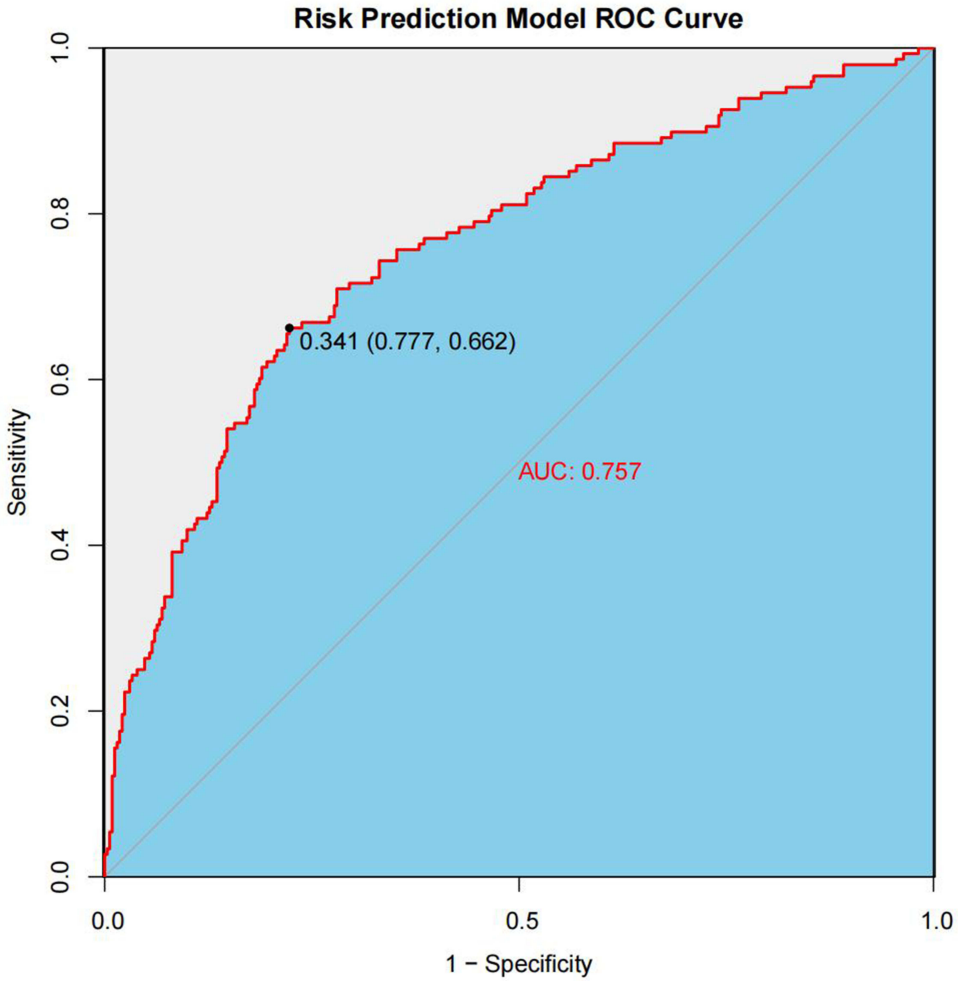

Figure 2 ROC curves.
Abbreviations: ROC, receiver operating characteristic; AUC, area under the ROC curve.

score, admission group, coma, infection, metabolic acidosis, use of sedatives and morphine, urea concentration, and urgent admission. The model had an AUC of 0.87 and outperformed the clinical prediction by nurses and physicians. Varga-Martínez et al incorporated factors such as low cognitive function, advanced age, low physical activity, and insomnia into the postoperative delirium prediction model for patients undergoing cardiac surgery,[12] with an AUC of 0.833. Although existing studies have developed high-quality delirium prediction models for general ICU populations,[13] their applicability to liver transplant recipients remains limited. This population faces unique delirium risks rooted in both preoperative comorbidities (eg, decompensated cirrhosis, hepatic encephalopathy, hepatorenal syndrome) and perioperative stressors (eg, prolonged anhepatic phase, major bleeding). Importantly, liver-specific pathways—such as ammonia metabolism dysregulation[3] during graft dysfunction or neurotoxicity from calcineurin inhibitors[14] —are rarely incorporated into general ICU models. Previous studies have identified specific risk factors for delirium in liver transplant patients. Si-Yuan Wu et al[15] reported that Liver recipients'age, body mass index, Child-Pugh class C, history of preoperative hepatic encephalopathy or mental disorders, day 7 tacrolimus level > 8.9 ng/mL, and postoperative intra-abdominal infection were more likely associated with early neurologic complications after liver transplantation. Our model addresses this gap by incorporating liver-specific parameters, providing a tailored risk assessment tool for this high-risk population.

We collected 31 items of data included the patient demographics, health conditions, and postoperative laboratory results within 24 hours of admission to intensive care. This study revealed that age, APACHE score, ALB, AST, BUN

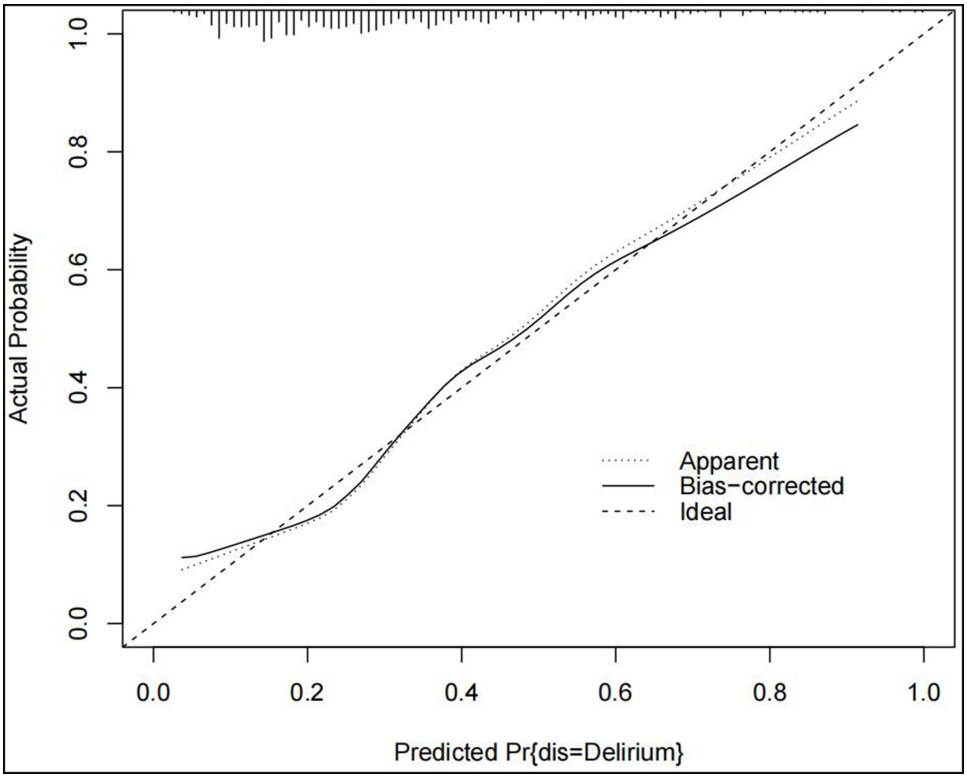

Figure 3 Calibration curve for predicting probability of LTP-delirium.
Abbreviations: LTP-delirium, delirium for liver transplantation patients.

and AMON were predictors of delirium in patients who experienced liver transplantation. Age and APACHE scores are widely recognized as predictors of delirium across different patient populations.[16] The liver-specific markers, including ALB, AST, BUN, and AMON, are closely related to the liver's functioning and reflect complications commonly seen in liver transplant patients. For example, low albumin levels, high urea nitrogen, and elevated ammonia levels are frequently observed in patients with significant ascites, hepatorenal syndrome, and hepatic encephalopathy, conditions common among liver transplant recipients. These findings align with previous research, which has also identified these markers as significant predictors of postoperative delirium in liver transplant patients. Albumin (ALB) is synthesized exclusively by hepatocytes, reflects hepatic synthetic function. Sung Ae Park et al found that a low plasma albumin level was an independent predictor of postoperative delirium in patients undergoing hepatectomy.[17] The study by Rudolph et al found that abnormal albumin is useful for predicting postoperative delirium in patient with cardiac surgery.[18] By interfering with glutamate metabolism and pyruvate metabolism, high blood ammonia alters the concentration and

Table 4 Model Variables and Corresponding Regression Coefficients

Variables	β	β (95% CI)		Compression Regression Coefficient*
Intercept	−1.785	−3.761	0.356	−1.940
Age(years)	0.035	0.011	0.061	0.037
APACHE score≥15	0.821	0.272	1.297	0.793
ALB	−0.073	−0.136	−0.032	−0.078
AST	−0.0002	−0.0004	−0.0001	−0.0002
BUN	0.113	0.053	0.208	0.124
AMON	0.024	0.012	0.045	0.024

Notes: *The regression coefficient after overfitting was calibrated using bootstrapping.

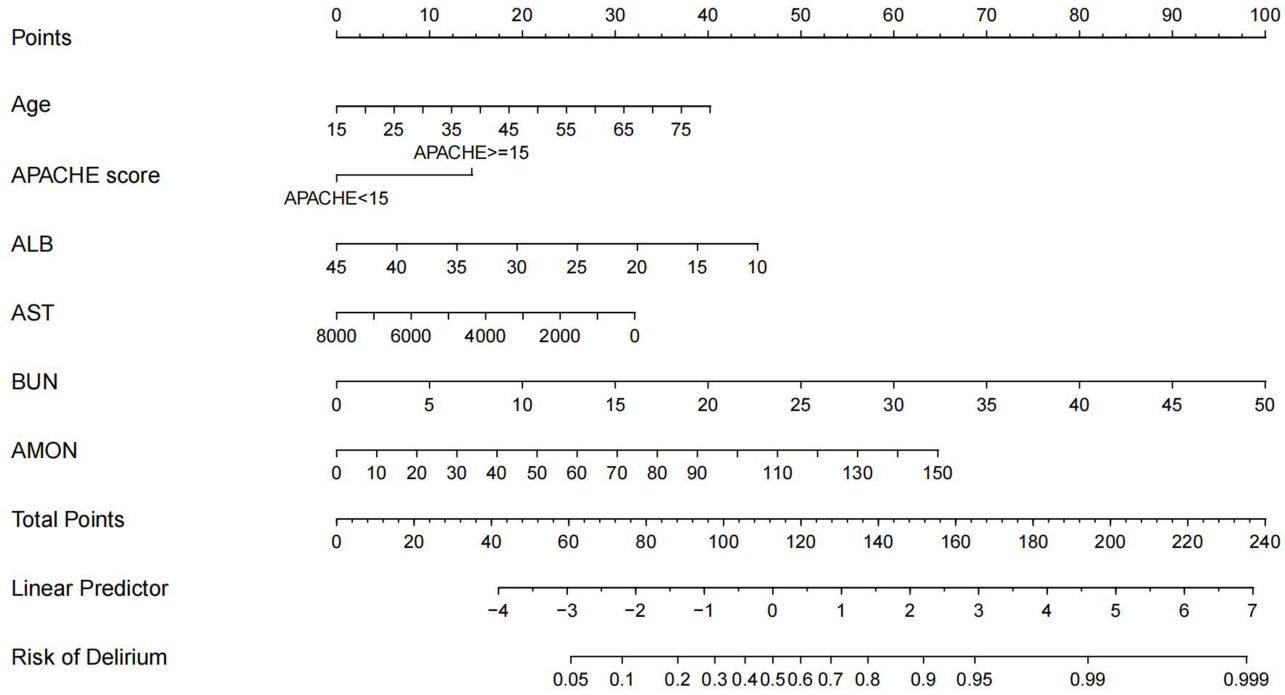

Figure 4 Nomogram for the prediction of LTP-delirium.

mutual balance of certain neurotransmitters in the brain, causes astrocyte swelling and neuroinflammation, thereby disrupting the normal function of the central nervous system. Studies such as those by Zhou have further emphasized the role of ammonia in the development of delirium post-liver transplant.[2] Low BUN in advanced cirrhosis reflects impaired urea cycle (hepatocyte dysfunction). Excessive peak AST after transplantation suggests ischaemia-reperfusion injury and predicts graft dysfunction. Our model incorporates these variables specific to liver transplant patients. The inclusion of these liver-specific markers enhances the model's applicability and predictive power for this unique patient group.

The developed nomogram provides a practical tool for early identification of high-risk patients, enabling clinicians to implement targeted preventive measures, such as optimizing perioperative care and closely monitoring identified risk factors. The visual representation of the nomogram enhances its usability in clinical settings, supporting real-time decision-making and improving patient outcomes.

Our study has several limitations. First, due to time constraints and other reasons, the final number of cases included was small at 480. Nevertheless, we believe that this sample size is representative within the scope of this study and that the results of the statistical analyses have a certain degree of reliability. When analysing the data, we fully considered the potential impact of insufficient sample size and used appropriate statistical methods to make adjustments: 1. Use of one-way regression to screen for variables with strong predictive ability, avoiding the introduction of too many irrelevant variables with a small sample size; 2. Variable selection in the multifactorial regression model to improve the accuracy of the model; 3. Use of the bootstrap method to generate multiple data sets through self-sampling to improve the robustness of the model and the reported confidence intervals. These methods helped us to maximise the use of the available samples and ensure the reliability of the model assessment. Second, it is a single-center, retrospective study, which may limit the generalizability of the findings. While the model demonstrated good performance in internal validation, external validation using data from multiple centers is needed to confirm its robustness and applicability across diverse patient populations. Third, the reliance on traditional statistical methods limits the model's potential compared to machine learning approaches,[19–21] which could capture more complex interactions among variables. Future studies incorporating machine learning could potentially improve prediction accuracy. A multicenter cohort study with a larger sample size would also be valuable for further validating our model.

Conclusion

This study presents a novel prediction model tailored to liver transplant patients, offering a significant advancement in postoperative delirium risk stratification. Future studies should focus on multicentre validation to improve the generalisability of the model. Incorporation of advanced machine learning techniques could further improve predictive performance.

Data Sharing Statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation. Requests to access the datasets should be directed to the corresponding Author.

Informed Consent Statement

Written informed consent for participation was not required for this study in accordance with the national legislation and the institutional requirements.

Institutional Review Board Statement

The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the Ethics Committee of Zhongshan Hospital, Fudan University, (approval No. B2022-447). Donor livers are derived from organ donation after cardiac death and allocated by the National Donor Allocation System.

Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

Funding

This research was funded by [Shanghai Municipal Key Clinical Specialty] grant number [shslczdzk03603], and [the Key Discipline Construction Fund of Health System in Shanghai Xuhui District] grant number [SHXHZDXK202324].

Disclosure

The authors report no conflicts of interest in this work.

References

1. Siddiqi N, House AO, Holmes JD. Occurrence and outcome of delirium in medical in-patients: a systematic literature review. *Age Ageing*. 2006;35(4):350–364. doi:10.1093/ageing/afl005
2. Zhou J, Xu X, Liang Y, Zhang X, Tu H, Chu H. Risk factors of postoperative delirium after liver transplantation: a systematic review and meta-analysis. *Minerva Anestesiol*. 2021;87(6):684–694. doi:10.23736/s0375-9393.21.15163-6
3. Chen J, Wang H, He Z, Li T. Analysis of risk factors for postoperative delirium after liver transplantation. *Neuropsychiatr Dis Treat*. 2020;16:1645–1652. doi:10.2147/ndt.S254920
4. Goldberg TE, Chen C, Wang Y, et al. Association of delirium with long-term cognitive decline. *JAMA Neurol*. 2020;77(11). doi:10.1001/jamaneurol.2020.2273
5. Hughes CG, Boncyk CS, Culley DJ, et al. American society for enhanced recovery and perioperative quality initiative joint consensus statement on postoperative delirium prevention. *Anesthesia Analg*. 2020;130(6):1572–1590. doi:10.1213/ane.0000000000004641
6. Boogaard MVD, Pickkers P, Slooter AJC, et al. Development and validation of PRE-DELIRIC (PREdiction of DELIRium in ICu patients) delirium prediction model for intensive care patients: observational multicentre study. *BMJ*. 2012;344(feb09 3):e420–e420. doi:10.1136/bmj.e420
7. Wassenaar A, van den Boogaard M, van Achterberg T, et al. Multinational development and validation of an early prediction model for delirium in ICU patients. *Intensive Care Med*. 2015;41(6):1048–1056. doi:10.1007/s00134-015-3777-2
8. Stollings JL, Kotfis K, Chanques G, Pun BT, Pandharipande PP, Ely EW. Delirium in critical illness: clinical manifestations, outcomes, and management. *Intensive Care Med*. 2021;47(10):1089–1103. doi:10.1007/s00134-021-06503-1
9. Marcantonio ER, Solomon CG. Delirium in hospitalized older adults. *N Engl J Med*. 2017;377(15):1456–1466. doi:10.1056/NEJMcp1605501
10. Bhattacharya B, Maung A, Barre K, et al. Postoperative delirium is associated with increased intensive care unit and hospital length of stays after liver transplantation. *J Surg Res*. 2017;207:223–228. doi:10.1016/j.jss.2016.08.084

11. Mattison MLP. Delirium. *Ann Internal Med*. 2020;173(7):ITC49–ITC64. doi:10.7326/aitc202010060
12. de la Varga-Martínez O, Gómez-Pesquera E, Muñoz-Moreno MF, et al. Development and validation of a delirium risk prediction preoperative model for cardiac surgery patients (DELIPRECAS): an observational multicentre study. *J Clin Anesth*. 2021;69:110158. doi:10.1016/j.jclinane.2020.110158
13. Wang ML, Kuo YT, Kuo LC, et al. Early prediction of delirium upon intensive care unit admission: model development, validation, and deployment. *J Clin Anesth*. 2023;88:111121. doi:10.1016/j.jclinane.2023.111121
14. Bican Demir A, Erer Özbek S, Bora I, Hakyemez B, Tırnova I, Kaya E. Two cases with developing neurologic complications after liver transplant. *Exp Clin Transplant*. 2016;14(6):685–687. doi:10.6002/ect.2014.0204
15. Wu S-Y, Chen T-W, Feng A-C, Fan H-L, Hsieh C-B, Chung K-P. Comprehensive risk assessment for early neurologic complications after liver transplantation. *World J Gastroenterol*. 2016;22(24). doi:10.3748/wjg.v22.i24.5548
16. Cai S, Cui H, Pan W, Li J, Lin X, Zhang Y. Two-stage prediction model for postoperative delirium in patients in the intensive care unit after cardiac surgery. *Eur J Cardiothorac Surg*. 2022;63:1. doi:10.1093/ejcts/ezac573
17. Park SA, Tomimaru Y, Shibata A, Miyagawa S, Noguchi K, Dono K. Incidence and risk factors for postoperative delirium in patients after hepatectomy. *World J Surg*. 2017;41(11):2847–2853. doi:10.1007/s00268-017-4079-3
18. Rudolph JL, Jones RN, Levkoff SE, et al. Derivation and validation of a preoperative prediction rule for delirium after cardiac surgery. *Circulation*. 2009;119(2):229–236. doi:10.1161/circulationaha.108.795260
19. Girard TD, Thompson JL, Pandharipande PP, et al. Clinical phenotypes of delirium during critical illness and severity of subsequent long-term cognitive impairment: a prospective cohort study. *Lancet Respir Med*. 2018;6(3):213–222. doi:10.1016/s2213-2600(18)30062-6
20. Potter KM, Kennedy JN, Onyemekwu C, et al. Data-derived subtypes of delirium during critical illness. *eBioMedicine*. 2024;100. doi:10.1016/j.ebiom.2023.104942
21. Potter KM, Prendergast NT, Boyd JG. From traditional typing to intelligent insights: a narrative review of directions toward targeted therapies in delirium. *Crit Care Med*. 2024;52(8):1285–1294. doi:10.1097/ccm.0000000000006362