

Technical Note

A predictive model for poor wound healing at surgical site after gastrointestinal surgery

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Abstract: This single-centred retrospective study develops a nomogram for 30-day poor wound healing (PWH) after gastrointestinal surgery. Among 408 patients treated from December 2023 to December 2025, PWH occur in 110 (27.0%). The least absolute shrinkage and selection operator (LASSO) regression selects predictors and multivariate logistic regression identifies seven independent risk factors: blood urea nitrogen, postoperative day-3 C-reactive protein, platelet count, systemic immune-inflammatory index, fasting-only bowel preparation, emergency surgery and open surgery. The model shows good discrimination (area under the curve (AUC) of 0.849 in the training set and 0.822 in the validation set), satisfactory calibration, clinical net benefit at threshold probabilities of 15-65%, and a mean 5-fold cross-validation AUC of 0.831 ± 0.024 . This seven-variable LASSO-logistic model may support perioperative PWH risk assessment and management. In internal cross-validation, sensitivity, specificity and F1 score are 0.742, 0.815 and 0.718 respectively.

Keywords: gastrointestinal surgery, poor wound healing, prediction model, LASSO regression, logistic regression

INTRODUCTION

Poor wound healing (PWH) after gastrointestinal surgery is common and increases hospital stay, costs and mortality [1-5]. Gastrointestinal procedures have a high PWH risk because of complex anatomy and potential contamination [6, 7]. Surgical site infections (SSI) prevention has been extensively studied in colorectal surgery [8]. A recent study developed a nomogram for predicting PWH after the removal of thoracic and abdominal cavity drainage tubes; however, its predictors were primarily related to drainage management and drainage-site conditions rather than gastrointestinal surgical incisions [9]. Moreover, a nationwide prospective cohort study involving 17,353 patients from 57 participating units, which developed a 20-variable prediction model specifically for 30-day SSI after gastrointestinal surgery, further indicated that existing models primarily focus on infection-related outcomes and may require a relatively large number of predictors [10]. Therefore, this study uses the least absolute shrinkage and selection operator (LASSO) regression to reduce overfitting and multicollinearity [11] and develops a concise LASSO-logistic nomogram for PWH prediction.

METHODS

Research Design

This single-centred retrospective study included adults undergoing gastric, small-intestinal, colonic, rectal or appendiceal surgery between December 2023 and December 2025, with at least 30 days of follow-up. Patients with other thoracic or abdominal surgery histories, preoperative active infection or immunosuppression, severe mental illness or cognitive dysfunction, incomplete data or loss of follow-up were excluded. This study was approved by the Ethics Committee of Sir Run Run Shaw Hospital, Zhejiang University School of Medicine (Approval No. 20260339). Written informed consent was obtained from all patients prior to enrollment. The study was conducted in accordance with the principles of the Declaration of Helsinki.

Definition and Evaluation of PWH

PWH was defined, based on previous studies [2, 12], as any incision infection diagnosed by the Centers for Disease Control and Prevention criteria [13], wound dehiscence, hematoma or seroma requiring puncture or re-treatment, tissue necrosis, or unplanned re-surgery or re-hospitalisation due to wound problems. Outcomes were assessed by the attending physician and wound specialist nurse and confirmed through electronic records and telephone follow-up.

Predictors Collection

Electronic medical records were used to collect 47 candidate predictors covering demographics, laboratory tests, comorbidities, surgical variables, bowel preparation, antibiotic prophylaxis, corticosteroid use, stoma condition and postoperative follow-up. Two researchers independently extracted and verified all data. Systemic immune-inflammatory index (SII), system inflammation response index (SIRI) and the aggregate index of systemic inflammation (AISI) were calculated as $P \times N/L$ [14], $(N \times M)/L$ [15] and $(P \times N \times M)/L$ [16] respectively, where P, N, L and M denote platelet,

neutrophil, lymphocyte and monocyte counts.

Sample Size Determination

Sample size was estimated using the events-per-variable (EPV) rule for logistic regression (EPV ≥ 10) [17]. Among 408 patients, 110 developed 30-day PWH. The final seven-predictor model yielded an EPV of 15.7, supporting model construction and internal validation.

Statistical Analysis

Analyses were performed in R 4.5.0. Missing data were handled by multiple imputation. Continuous variables are shown as mean $\pm$ SD and categorical variables as n (%). LASSO regression with 10-fold cross-validation selected predictors from 47 candidates. The cohort was randomly divided into training (70%) and validation (30%) sets. Multivariate logistic regression estimated odds ratios (ORs) and 95% confidence intervals (CIs). Discrimination, calibration, clinical utility and stability were assessed by area under the curve (AUC), Hosmer-Lemeshow test, decision curve analysis and 5-fold cross-validation. For terminology consistency, ‘candidate predictors’ refers to the 47 pre-specified variables considered during model development, whereas ‘independent risk factors’ refers to variables retained after LASSO selection and confirmed in the multivariate logistic regression model. Model performance was reported using discrimination (AUC with 95% CI), calibration (Hosmer-Lemeshow test and calibration curves), classification performance (sensitivity, specificity and F1 score), internal validation by 5-fold cross-validation, and clinical utility by decision curve analysis. Before finalisation, numerical values in the results, tables and plotted figures were cross-checked for concordance.

RESULTS

Sample Characteristics

Among 408 patients, 336 (82.4%) underwent single-site surgery and 72 (17.6%) underwent multi-site surgery. PWH occurred in 110 patients (27.0%) (Table 1). Univariate analysis identifies 18 potential predictors ($P < 0.05$) including inflammatory markers, bowel preparation, surgical urgency, surgical approach, stoma status at surgery end and surgical duration.

Table 1. Univariate analysis of patient characteristics and PWH incidence

	Total (N=408)	Without PWH (N=298)	With PWH (N=110)	P-value
Sex (%)				0.792
Male	261 (64.0)	189 (63.4)	72 (65.5)	
Female	147 (36.0)	109 (36.6)	38 (34.5)	
Age, Mean (SD), years	62.18 (16.05)	61.51 (16.36)	64.00 (15.11)	0.150

Table 1. (Continued)

	Total (N=408)	Without PWH (N=298)	With PWH (N=110)	P-value
Drinking history (%)				0.935
No	387 (94.9)	282 (94.6)	105 (95.5)	
Yes	21 (5.1)	16 (5.4)	5 (4.5)	
Smoking history (%)				0.709
No	373 (91.4)	271 (90.9)	102 (92.7)	
Yes	35 (8.6)	27 (9.1)	8 (7.3)	
BMI, Mean (SD), kg/m²	21.67 (3.90)	21.65 (3.77)	21.72 (4.24)	0.871
ASA, n (%)				0.330
1	1 (0.2)	1 (0.3)	0 (0.0)	
2	275 (67.4)	208 (69.8)	67 (60.9)	
3	126 (30.9)	85 (28.5)	41 (37.3)	
4	6 (1.5)	4 (1.3)	2 (1.8)	
Surgical site (%)				0.750
Single-site surgery	336 (82.4)	247 (82.9)	89 (80.9)	
Multi-site surgery (two or more)	72 (17.6)	51 (17.1)	21 (19.1)	
Total bilirubin, Mean (SD), µmol/L	16.01 (21.80)	14.94 (21.78)	18.91 (21.69)	0.103
Blood glucose, Mean (SD), mmol/L	6.68 (2.84)	6.55 (2.85)	7.04 (2.77)	0.117
Albumin, Mean (SD), g/L	36.89 (6.41)	36.82 (6.11)	37.08 (7.21)	0.731
AST, Mean (SD), U/L	29.34 (30.12)	29.59 (29.11)	28.64 (32.81)	0.788
ALT, Mean (SD), U/L	27.09 (43.87)	27.31 (44.47)	26.49 (42.40)	0.865
Creatinine, Mean (SD), µmol/L	81.02 (66.65)	81.35 (72.33)	80.14 (48.27)	0.845
BUN, Mean (SD), mmol/L	6.54 (5.06)	6.08 (3.68)	7.79 (7.51)	0.024
CRP, Mean (SD), mg/L	38.12 (72.91)	33.13 (66.61)	51.64 (86.64)	0.044
Postoperative day-3 CRP, Mean (SD), mg/L	95.54 (74.01)	89.18 (67.60)	112.70 (87.11)	0.011
White blood cell count, Mean (SD), ×10⁹/L	7.02 (3.39)	6.74 (3.44)	7.77 (3.13)	0.005

Table1. (Continued)

	Total (N=408)	Without PWH (N=298)	With PWH (N=110)	P-value
Absolute neutrophil count, Mean (SD), ×10⁹/L	5.34 (4.23)	5.09 (4.59)	6.02 (2.93)	0.017
Absolute lymphocyte count, Mean (SD), ×10⁹/L	1.23 (1.21)	1.28 (1.36)	1.09 (0.61)	0.047
Haemoglobin, Mean (SD), g/L	117.17 (25.71)	116.05 (24.85)	120.21 (27.78)	0.169
Platelet distribution width, Mean (SD), fL	16.10 (1.60)	16.13 (1.86)	16.02 (0.39)	0.353
Mean platelet volume, Mean (SD), fL	9.34 (1.42)	9.34 (1.54)	9.33 (1.07)	0.919
Absolute monocyte count, Mean (SD), ×10⁹/L	0.44 (0.24)	0.43 (0.22)	0.48 (0.28)	0.061
Platelet count, Mean (SD), ×10⁹/L	231.46 (103.86)	225.26 (104.10)	248.25 (101.79)	0.046
SII, Mean (SD)	1355.72 (1585.31)	1137.67 (1055.65)	1946.45 (2421.88)	0.001
SIRI, Mean (SD)	2.72 (3.42)	2.31 (2.99)	3.80 (4.21)	0.001
NLR, Mean (SD)	6.21 (7.44)	5.28 (5.03)	8.73 (11.35)	0.003
PLR, Mean (SD)	248.54 (181.96)	228.39 (158.82)	303.12 (225.35)	0.002
AISI, Mean (SD)	632.10 (858.12)	523.48 (718.48)	926.36 (1106.05)	0.001
Diabetes mellitus (%)				0.872
No	356 (87.3)	261 (87.6)	95 (86.4)	
Yes	52 (12.7)	37 (12.4)	15 (13.6)	
Hypertension (%)				0.847
No	283 (69.4)	208 (69.8)	75 (68.2)	
Yes	125 (30.6)	90 (30.2)	35 (31.8)	
Chronic liver disease (%)				0.633
No	404 (99.0)	296 (99.3)	108 (98.2)	
Yes	4 (1.0)	2 (0.7)	2 (1.8)	

Table1. (Continued)

	Total (N=408)	Without PWH (N=298)	With PWH (N=110)	P-value
Chronic kidney disease (%)				0.687
No	405 (99.3)	295 (99.0)	110 (100.0)	
Yes	3 (0.7)	3 (1.0)	0 (0.0)	
Chronic heart disease (%)				0.742
No	389 (95.3)	283 (95.0)	106 (96.4)	
Yes	19 (4.7)	15 (5.0)	4 (3.6)	
Tuberculosis (%)				0.950
No	406 (99.5)	296 (99.3)	110 (100.0)	
Yes	2 (0.5)	2 (0.7)	0 (0.0)	
Bowel preparation (%)				<0.001
MBP only	54 (13.6)	44 (15.3)	10 (9.1)	
OABP only	110 (27.6)	89 (30.9)	21 (19.1)	
MBP + OABP	79(19.4)	65 (21.8)	14 (12.7)	
Fasting only	165 (41.5)	100 (34.7)	65 (59.1)	
Surgical antibiotic prophylaxis (%)				0.866
No	14 (3.4)	11 (3.7)	3 (2.7)	
Yes	394 (96.6)	287 (96.3)	107 (97.3)	
Surgical type (%)				0.086
Clean	3 (0.7)	3 (1.0)	0 (0.0)	
Clean-contaminated	367 (90.0)	268 (89.9)	99 (90.0)	
Contaminated	36 (8.8)	27 (9.1)	9 (8.2)	
Infected	2 (0.5)	0 (0.0)	2 (1.8)	
Surgical urgency (%)				0.001
Emergency surgery	75 (18.4)	43 (14.4)	32 (29.1)	
Elective surgery	333 (81.6)	255 (85.6)	78 (70.9)	
Approach (%)				<0.001
Laparoscopic or robotic surgery	237 (58.1)	194 (65.1)	43 (39.1)	
Open surgery	171 (41.9)	104 (34.9)	67 (60.9)	
Incision type (%)				0.086
Class I incision	3 (0.7)	3 (1.0)	0 (0.0)	

Table 1. (Continued)

	Total (N=408)	Without PWH (N=298)	With PWH (N=110)	P-value
Class II incision	367 (90.0)	268 (89.9)	99 (90.0)	
Class III incision	36 (8.8)	27 (9.1)	9 (8.2)	
Class IV incision	2 (0.5)	0 (0.0)	2 (1.8)	
Incision length, Mean (SD), cm	10.24 (7.66)	9.70 (7.30)	14.28 (9.24)	0.057
Colostomy/ileostomy at surgery start (%)				0.958
No	335 (82.1)	244 (81.9)	91 (82.7)	
Yes	73 (17.9)	54 (18.1)	19 (17.3)	
Colostomy/ileostomy at surgery end (%)				<0.001
No	146 (35.8)	81 (27.2)	65 (59.1)	
Yes	262 (64.2)	217 (72.8)	45 (40.9)	
Surgical duration, Mean (SD), min.	191.67 (95.21)	199.41 (97.45)	170.77 (85.87)	0.004
Intraoperative blood loss, Mean (SD), mL	66.79 (253.92)	68.55 (292.44)	62.05 (88.82)	0.732

Note: AST=aspartate aminotransferase; ALT=alanine aminotransferase; BUN=blood urea nitrogen; CRP=C-reactive protein; SII= systemic immune-inflammatory index; SIRI=systemic inflammatory response index; NLR=neutrophil-to-lymphocyte ratio; PLR= platelet-to-lymphocyte ratio; AISI=aggregate index of systemic inflammation; ASA= American Society of Anesthesiologists physical status classification system; MBP=mechanical bowel preparation; OABP=oral antibiotic bowel preparation

Logistic Regression Results

Multivariate logistic regression using the seven LASSO-selected variables identifies BUN, postoperative day-3 CRP, platelet count, SII, fasting-only bowel preparation, emergency surgery and open surgery as independent risk factors for PWH (Table 2). ORs are 1.36, 1.35, 1.23, 1.71, 2.93, 2.43 and 2.91 respectively, with all P values ≤ 0.050 .

Table 2. Multivariate logistic regression analysis of independent risk factors for PWH

Variable	OR	SE	Statistic	95% CI Lower	95% CI Upper	P-value
BUN	1.36	0.113	2.74	1.10	1.72	0.006
Postoperative day-3 CRP	1.35	0.108	2.81	1.10	1.67	0.005

Table 2. (Continued)

Variable	OR	SE	Statistic	95% CI Lower	95% CI Upper	P-value
Platelet count	1.23	0.108	1.96	1.00	1.53	0.050
SII	1.71	0.138	3.90	1.33	2.27	<0.001
Bowel preparation						
MBP	Reference					
OABP	1.04	0.424	0.09	0.46	2.47	0.930
MBP + OABP	0.94	0.506	0.12	0.34	2.55	0.900
Fasting only	2.93	0.383	2.81	1.43	6.52	0.005
Urgency of surgery	Reference					
Elective surgery						
Emergency surgery	2.43	0.267	3.33	1.44	4.10	0.001
Surgical approach						
Laparoscopic or robotic surgery	Reference					
Open surgery	2.91	0.230	4.64	1.86	4.59	<0.001

Note: SE=standard error; BUN=blood urea nitrogen; CRP=C-reactive protein; SII=systemic immune-inflammatory index; MBP=mechanical bowel preparation; OABP=oral antibiotic bowel preparation

Model Construction and Evaluation

The model achieves AUCs of 0.849 (95% CI 0.808-0.890) in the training set and 0.822 (95% CI 0.771-0.873) in the validation set (Figures 1-3). Calibration is good (Hosmer-Lemeshow $P=0.327$ and $P=0.415$). Fivefold cross-validation yields a mean AUC of 0.831 ± 0.024 , sensitivity of 0.742, specificity of 0.815 and F1 score of 0.718. Decision curve analysis shows net benefit at thresholds of 15-65%. The nomogram is shown in Figure 4. These estimates represent internal validation performance and should not be interpreted as externally confirmed predictive accuracy.

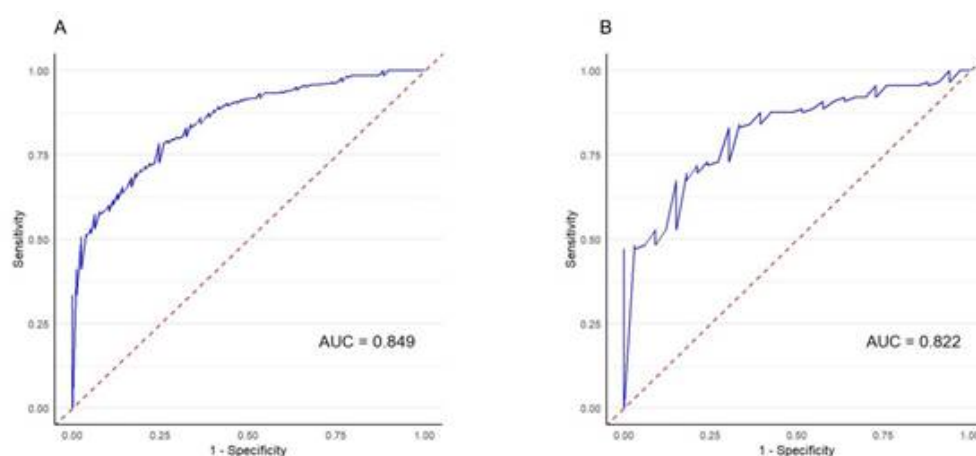


Figure 1. ROC curves: AUCs are 0.849 in training set (A) and 0.822 in validation set (B)

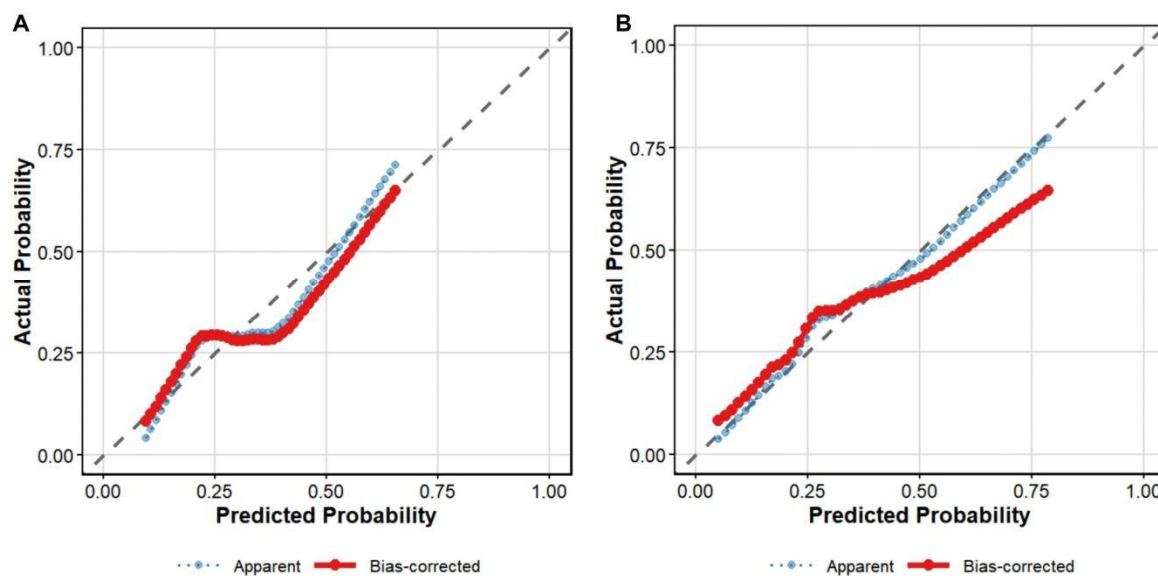


Figure 2. Calibration curves: (A) Training set; (B) validation set. Hosmer-Lemeshow $P=0.327$ and $P=0.415$ respectively

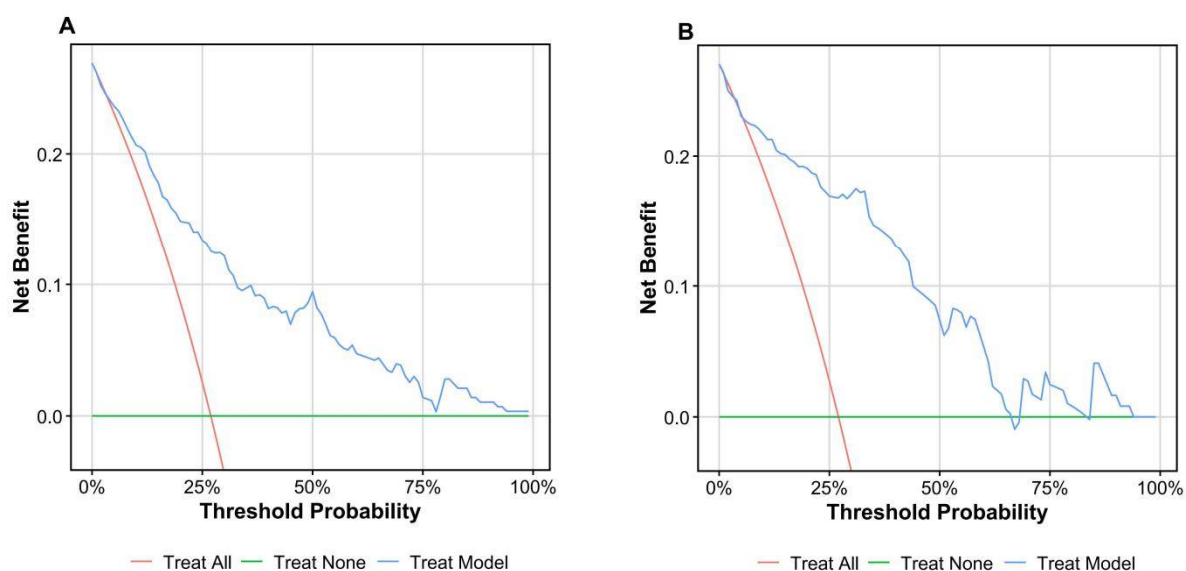


Figure 3. Decision curve analysis: (A) Training set; (B) Validation set. Net benefit is observed at threshold probabilities of 15-65%.

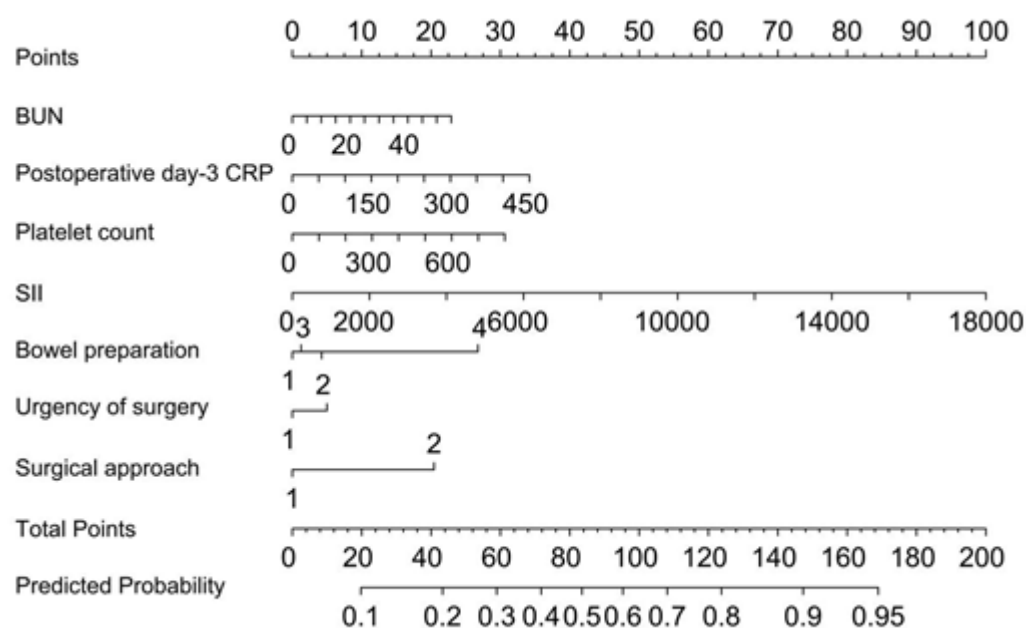


Figure 4. Nomogram for predicting PWH. Coding: bowel preparation 1=MBP, 2=OABP, 3=MBP+OABP, 4=fasting; urgency 1=elective, 2=emergency; approach 1=laparoscopic/robotic, 2=open

DISCUSSION

This study develops and internally validates a seven-variable LASSO-logistic model for 30-day PWH after gastrointestinal surgery. Unlike previous models which focused mainly on SSI [10, 18], this model uses a broader PWH endpoint and incorporates routine markers of renal/metabolic status, systemic and early postoperative inflammation, platelet-related inflammatory response, and surgical stress. BUN, postoperative day-3 CRP, platelet count, SII, fasting-only bowel preparation, emergency surgery and open surgery are independently associated with PWH, consistent with mechanisms involving impaired perfusion and nutrition, excessive inflammation, matrix degradation, reduced fibroblast activity and collagen synthesis, larger tissue injury, wound exposure, and limited preoperative optimisation [6, 19-25]. Earlier evidence from a cohort of 525 patients undergoing gastrointestinal surgery showed a substantially higher incidence of tissue and wound complications after emergency surgery than those after elective surgery. Smoking, comorbidity, perioperative blood loss and operation type were independent predictors in elective surgery, whereas male sex, peritonitis, operation type and multiple operations were independent predictors in emergency surgery [26].

Similarly, a retrospective study of patients undergoing gastrointestinal surgery identified leukocytosis, hypoalbuminemia, contaminated or dirty wounds, prolonged operative duration and emergency surgery as independent predictors of 30-day SSI [27]. Although its outcome was SSI rather than the broader PWH composite, a prospective study conducted at a resource-limited tertiary hospital identified laparotomy, malnutrition, contaminated or dirty wounds, and an operative duration

exceeding 1 hr as independent predictors of postoperative SSI; the resulting predictive model achieved an AUC of 0.917 [28]. In a larger retrospective cohort of patients undergoing elective abdominal surgery, Zhang et al [29]. developed a nomogram incorporating demographic characteristics, nutritional and inflammatory indicators, anaesthetic factors and intraoperative variables. The model achieved an AUC of 0.926, supporting the value of integrating routinely available clinical and laboratory information for SSI risk stratification.

The LASSO-logistic strategy provides an interpretable framework for clinical risk prediction [30, 31]. This balance between predictive performance and interpretability is also supported by the Global Surgical-Site Infection (GloSSI) study [32]. Using two independent international prospective cohorts, the investigators selected a six-variable LASSO model because it achieved performance similar to that of XGBoost while offering greater explainability. The GloSSI score achieved an AUC of 0.730 on external validation and included country income level, ASA grade, diabetes, operative contamination, surgical approach, and operative duration [32].

More recently, machine learning algorithms have been applied to predict surgical site infections after major abdominal surgery, further demonstrating the potential of data-driven approaches for perioperative risk stratification [33]. Compared with such complex algorithms, the present seven-variable model emphasises parsimony, interpretability and the availability of routinely collected clinical variables. Because all seven variables are available from routine tests and records, the nomogram can identify higher-risk patients for nutritional optimisation, anemia correction, careful tissue handling, selective delayed closure, intensified wound monitoring, preventive negative-pressure therapy, or delayed suture removal.

As no independent external cohort was available, the observed discrimination, calibration and decision-curve findings should be interpreted as preliminary evidence of model performance rather than definitive proof of generalisability. Unlike the GloSSI score [32], which was evaluated in an independent international cohort, the present nomogram has undergone internal validation only. This concern is supported by a recent systematic review of 28 studies comprising 39 SSI prediction models in patients with gastrointestinal cancer, which reported AUCs ranging from 0.660 to 0.950 but identified a high overall risk of bias and incomplete calibration and validation across existing models [34].

Similarly, a broader systematic review of abdominal surgery identified 28 SSI prediction models across 25 studies. Although the 25 models achieved an AUC greater than 0.70, all included studies were judged to have a high risk of bias, indicating that satisfactory discrimination alone does not establish clinical generalisability [35]. Consistent with these findings, a systematic review focusing specifically on gastrointestinal surgery identified 23 SSI prognostic models: 57% lacked internal validation and only 17% had undergone external validation. Calibration was assessed in only 22% and all models were judged to have a high risk of bias [36]. Clinical use should therefore be considered exploratory until the nomogram is externally validated in different hospitals, surgical populations, and perioperative care settings.

Limitations

Several limitations warrant consideration. First, the single-centred retrospective design may introduce selection and information bias. Variables derived from electronic medical records are subject to documentation quality. External validation in prospective, multi-centred cohorts is essential. Second, although the sample size (408 patients, 110 events) satisfies the EPV requirement ($EPV=15.7$), it is insufficient for subgroup analyses (e.g. gastric vs colorectal surgery) or more complex machine learning approaches. Third, due to the retrospective design, we could not include several potentially relevant variables, i.e. intraoperative details (suture materials, drain management, blood glucose control), postoperative care (dressing change frequency, nutritional support), socioeconomic factors and tumour-specific characteristics (stage, neoadjuvant therapy). Fourth, the 30-day follow-up may not capture long-term wound complications such as incisional hernia. Moreover, PWH was defined as a composite endpoint; risk factors may differ between infectious and non-infectious subtypes, but we did not perform subtype-specific analyses. Fifth, the objective prediction model was constructed solely using retrospective clinical data and did not incorporate patient-reported outcomes related to incisional pain, scar cosmesis or surgical decision-making. A qualitative study by Xu et al [37] indicated that patients' incision-related experiences included pain-management concerns, preferences regarding incision location and size, and cosmetic considerations, which represent important aspects of perioperative incision management.

Future directions include multi-centred external validation, integration of real-time postoperative data for dynamic prediction, prospective mixed-methods studies based on the present prediction model, and randomised controlled trials to assess the clinical impact of model-guided preventive strategies. In addition to these limitations, the absence of external validation is a major methodological constraint. The random split and 5-fold cross-validation evaluate internal reproducibility but cannot assess transportability to other institutions, case-mix profiles, surgical teams, or perioperative protocols. Consequently, the reported AUC, calibration, sensitivity and specificity may be optimistic relative to real-world performance in independent cohorts. The retrospective design also creates a risk of selection bias, residual confounding and information bias because treatment allocation, wound-care practices and timing of laboratory testing were not controlled prospectively. The variable-selection strategy should also be interpreted cautiously. Although LASSO reduces dimensionality and helps limit overfitting, the selected variables may be unstable when predictors are correlated, particularly among inflammation-related indices. Future studies should examine selection stability using bootstrap selection frequencies, penalised shrinkage or pre-specified clinically driven predictor sets before implementation.

CONCLUSIONS

This study, based on the LASSO-Logistic regression strategy, constructs and preliminarily validates a prediction model for PWH within 30 days after gastrointestinal surgery. The model includes seven easily obtainable clinical variables (BUN, postoperative day-3 CRP, platelet count, SII, only fasting intestinal preparation, emergency surgery and open surgery) and demonstrates good

discrimination, calibration and clinical net benefit in both the training set and the validation set. This model can provide a simple and effective risk assessment tool for clinicians, guiding the formulation of perioperative management strategies. However, its clinical implementation requires external validation and prospective impact assessment to confirm transportability, calibration stability and usefulness across different clinical settings.

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