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Risk prediction model for surgical site infection in patients with gastrointestinal cancer: a systematic review and meta-analysis

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Abstract

Background Currently, various risk prediction models for surgical site infection (SSI) in patients with gastrointestinal tumors have been developed, but comprehensive comparisons regarding the model construction process, performance, and data sample bias are lacking. This study conducts a systematic review of relevant research to evaluate the risk bias and clinical applicability of these models.

Materials and methods The Web of Science, PubMed, Cochrane Library, Embase, CINAHL, CBM, CNKI, Wanfang, and VIP databases were searched for studies related to SSI prediction models in gastrointestinal cancer patients published up to August 19, 2024. Two researchers independently screened the literature, extracted the data, and evaluated the quality. A meta-analysis was conducted on the common predictive factors included in the model, using odds ratio (*OR*) values and 95% confidence interval (*CI*) as effect statistics. The *Q* test and heterogeneity index I^2 were used to assess heterogeneity. All the statistical analyses were performed via Stata 16.0 software. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) checklist was submitted as a supplement.

Results A total of 28 articles were included, and 39 models were constructed. The area under the receiver operating characteristic curve (*AUC*) for the models ranged from 0.660 to 0.950, indicating good predictive performance. Eight studies conducted internal validation, eight studies conducted external validation, and two studies used a combination of internal and external validation for model evaluation. The overall risk of bias in the literature was high, but the applicability was good. The results of the meta-analysis revealed that factors such as underlying diseases, surgical factors, demographic factors, and laboratory-related indicators are the main predictors of surgical site infections in patients with gastrointestinal tumors.

Conclusions Currently, risk prediction models for surgical site infections in patients with gastrointestinal cancer remain in the developmental phase, and there is a high risk of bias in the areas of study subjects, outcomes, and analysis. Researchers need to enhance research methodologies, conduct large-scale prospective studies, and refer to the reporting standards of the bias risk assessment tool for predictive models to construct predictive models with low bias risk and high applicability.

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Keywords Neoplasms, Digestive system, Surgical site infection, Prediction model, Systematic review

Introduction

GLOBOCAN statistics [1] show that there were approximately 4.98 million new cases and 3.25 million deaths from digestive system tumors worldwide in 2022. The annual number of new cases and deaths from digestive system tumors ranks highest among all cancer types, and it is already a major public health concern on a global scale. Surgery, as one of the main treatments for digestive system tumors, can prevent the spread of tumor cells by removing diseased tissues, thereby controlling disease progression and prolonging patient survival. Surgical site infection (SSI) [2] is a serious complication after surgical treatment of digestive system tumors. The occurrence of SSI not only increases the postoperative hospital stay of patients but also aggravates the economic burden on patients and society [3, 4] and seriously affects the postoperative rehabilitation process and quality of life of patients. It can even significantly shorten the survival time of these patients [5, 6]. At present, many medical and health organizations worldwide have issued guidelines for the prevention and control of SSI [7, 8], which indicate that the key to controlling the occurrence of SSI lies in the early detection of high-risk groups, the determination of their related risk factors, and the adoption of multimode joint intervention strategies.

The risk prediction model can establish a statistical model based on multiple predictive variables and predict the occurrence probability of related outcome events [9, 10], which can help medical staff identify high-risk groups at an early stage, take targeted interventions to reduce their incidence, improve patient prognosis and save medical resources. In the context of promoting clinical decision-making on the basis of data, early monitoring and warning of high-risk groups of patients undergoing digestive system tumor surgery via risk prediction models has become a research hotspot in the field of SSI prevention and control in recent years. At present, SSI risk prediction models for patients with digestive system cancer have been developed. Nevertheless, comprehensive comparisons of the model construction process, performance, and data sample bias are lacking. Further research is still needed to determine the predictive ability and clinical value of these models. This study conducted a systematic review of the risk bias and clinical applicability of SSI risk prediction models via standardized retrieval of related studies on SSI risk prediction models for patients with digestive system tumors to provide a scientific basis for the development, application, optimization, and personalized prevention and treatment of such risk prediction models in the future. This study was approved by the PROSPERO platform (CRD42024579877).

Materials and methods

Study design

This study was conducted following the PRISMA guidelines, ensuring transparent and comprehensive reporting of methods and results. Additionally, the study has been registered with PROSPERO (ID: CRD42024579877). Ethical approval was deemed unnecessary, as this study included a meta-analysis and systematic review of previously published research.

Construct evidence-based questions

The PICOTS model [11] recommended by the Cochrane Library was adopted.

- Population: Patients with digestive system cancer.
- Index prediction model: SSI risk prediction model.
- Comparator: None.
- Outcome: Postoperative SSI in patients with digestive system cancer.
- Timing: Within 30 days after surgery.
- Setting: Hospital or other medical institution.

Search strategy

Computer searches were conducted in the Web of Science, PubMed, Cochrane Library, Embase, CINHAL, CBM, CNKI, Wanfang, and VIP databases for studies on SSI risk prediction models in patients with gastrointestinal tumors, including those published up to August 19, 2024. The search strategy combined subject headings and free-text terms, employed citation tracking and utilized synonyms and Boolean operators. The search terms included variations of "digestive system neoplasms" and "surgical site infections", combined with terms for "risk prediction models". Supplementary material 3 contains the detailed search strategies. To avoid discrepancies caused by database updates, all data retrieval and collection tasks were completed on August 20, 2024.

Inclusion and exclusion criteria

Inclusion criteria

- The study subjects were patients aged ≥ 18 years with digestive system tumors.
- This research included the construction and/or validation of SSI prediction models for patients with digestive system tumors.
- The model included more than 2 predictor variables.
- The study design included prospective studies, retrospective studies, and cross-sectional studies.

Exclusion criteria

- The full text could not be obtained.
- The risk factors for SSI in patients with digestive system tumors were analyzed without the need to establish a model.
- Prediction model based on a systematic review.
- When information is incomplete, important indicators cannot be extracted or published repeatedly.

Study selection and data extraction

It was performed independently by two investigators who were both trained in evidence-based medicine. EndNote software was used for the literature review. Researchers screened the literature according to the inclusion and exclusion criteria, cross-checked the data after extraction, and negotiated with a third researcher in case of disputes. The data were extracted according to the CHARMS [12] data retrieval checklist. The extracted data included: first author, publication year, country, research design, research object, data source, SSI diagnostic standard source, modeling method, modeling sample size, prediction variable screening method, missing value processing method, prediction factor, model performance, model validation and presentation mode.

Quality assessment

The prediction model risk of bias assessment tool (PROBAST) [13], which was independently completed by two researchers who had received evidence-based training in oncology care, was used to evaluate the bias risk and applicability of the included studies. The evaluation results were cross-checked. The third researcher arbitrated if there were any doubts about the literature evaluation.

Statistical analysis

A meta-analysis of the model's common predictive factors was carried out via Stata 16.0 software, the odds ratio (*OR*) and 95% confidence interval (*CI*) were used as effect statistics, and the *Q* test and heterogeneity index (I^2) were used to evaluate heterogeneity. If $I^2 < 50\%$ and $P > 0.1$, the consistency was acceptable, and the fixed effect model was used for analysis. If $I^2 > 50\%$ and $P < 0.1$, further sensitivity analysis was performed. If heterogeneity could not be eliminated, random effects model analysis was used. $P < 0.05$ was considered statistically significant.

Results

Results of literature screening

A total of 5066 relevant articles were systematically retrieved. Using Endnote software for automatic deduplication, we initially screened the titles and abstracts, excluded irrelevant literature, then read the full texts, and finally included 28 articles. The search process is shown in supplementary material 1 (Fig. 1).

Basic characteristics of the included studies

The studies published from 2015 to 2024 included 22 studies [14–35] published in the past five years; 23 studies [15–23, 25–31, 33–39] conducted in China; 3 studies [14, 24, 40] conducted in Japan; 1 study [32] conducted in the United States; and 1 study [41] conducted in Turkey. Data were obtained from clinical data databases and patient reports. The basic information of the included studies is detailed in Table 1.

Model establishment

A total of 39 models were included, and the incidence of outcome events was 1.471%~49.153%. The modeling methods included logistic regression, random forests, gradient boosting, artificial neural networks, etc., of which 26 studies [14–23, 25–40] used logistic regression. In terms of missing data, one study [30] used multiple imputation, 16 studies [14–17, 19, 20, 22, 23, 25, 26, 31, 32, 34, 37, 40, 41] excluded subjects with incomplete data when the inclusion and exclusion criteria were met, and the remaining studies were not reported. Twelve studies' [14, 19, 21–23, 27, 28, 30, 31, 33, 35, 38] models were finally presented for the nomogram; 1 study [25] presented the decision tree; and 3 studies [24, 32, 40] failed to report. The remaining 12 studies [15–18, 20, 26, 29, 34, 36, 37, 39, 41] used risk scoring formulas or scoring systems. The basic model information is detailed in Table 2.

Model performance and predictors

In this study, the discriminative power of the model was evaluated by the area under the receiver operating characteristic curve (*AUC*) or concordance index (*C-index*). Two studies [19, 28] used the area under the curve *(AUC)* and *C-index* to evaluate the discrimination ability of the model simultaneously. Except for Saylam et al. [41], whose *AUC* was 0.660, and 1 study [33], whose *AUC* was not reported, the *AUC* of the remaining studies were all > 0.7, indicating high prediction performance. Fifteen studies [16, 18, 19, 21, 23, 27, 28, 30, 31, 35–37, 39–41] reported calibration methods, including the Hosmer–Lemeshow goodness-of-fit test, calibration curve, decision curve, Brier score, etc.; 8 studies [14, 21, 24, 28, 30, 31, 38, 40] carried out internal validation; 8 studies [16, 17, 19, 23, 35, 37, 39, 41] carried out external validation; and 2 studies [27, 32] used a combination of internal and external validation to evaluate the model. The model ultimately included 3–13 predictors, and the 5 most frequent predictors were operation time ($n = 14$), ALB level ($n = 12$), laparotomy ($n = 11$), BMI ($n = 11$) and diabetes

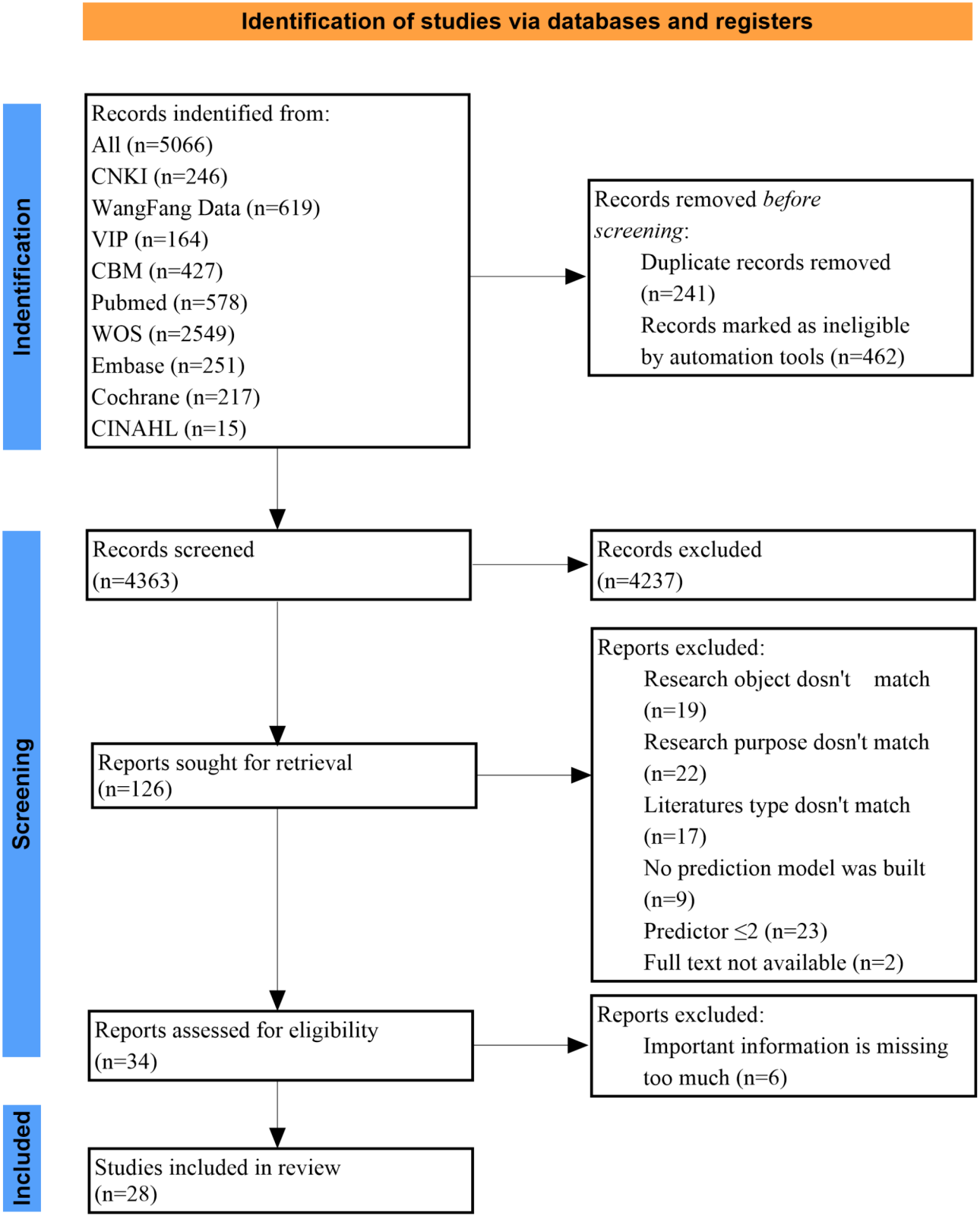

Fig. 1 Flow diagram for study selection

Table 1 Basic characteristics of the included studies

Author	Year	Country	Study type	Research object	Data sources	Incidence of IAI (%)	Diagnostic method of prediction results	Overall merit	
								Risk of bias	Applicability
Ushiku H[40]	2015	Japan	Retrospective	Patients who underwent gastric cancer resection	Kitasato University	13.797	Guideline for prevention of surgical site infection	H	L
Ma C[36]	2016	China	Retrospective	Patients who underwent radical colon cancer resection	Qilu Hospital of Shandong University	21.023	Hospital infection diagnostic criteria (Trial)	H	L
Tu RH[37]	2016	China	Retrospective	Patients who underwent laparoscopic resection for gastric cancer	Fujian Medical University Union Hospital	11.083	Guideline for prevention of surgical site infection	H	L
Li L[38]	2017	China	Retrospective	Patients who underwent radical resection for perihilar cholangiocarcinoma	The West China Hospital	10.149	Guideline for prevention of surgical site infection	H	L
Saylam B[41]	2017	Turkey	Retrospective	Patients who underwent rectal cancer surgery	Ankara Numune Education and Research Hospital	30.435	Guideline for prevention of surgical site infection	H	L
Yin LX[39]	2018	China	Retrospective	Patients who underwent esophagectomy with cervical anastomosis	The Chinese Academy of Medical Sciences Cancer Hospital	20.534	Centers for Disease Control and Prevention (CDC) criteria	H	L
Okui J[14]	2020	Japan	Retrospective	Patients who underwent gastrointestinal or hepatopancreatobiliary cancer resection	Kameda Medical Center	6.781	Centers for Disease Control and Prevention (CDC) criteria	H	L
Shen J[15]	2020	China	Retrospective	Patients who underwent hepatectomy for hepatocellular carcinoma	First Affiliated Hospital, Zhejiang University School of Medicine	3.818	Centers for Disease Control and Prevention (CDC) criteria	H	L
Wang Y[16]	2021	China	Retrospective	Patients with colorectal cancer who underwent surgeries	Hainan Western Central Hospital	21.176	Hospital infection diagnostic criteria (Trial)	H	L
Hu B[17]	2021	China	Retrospective	Patients who underwent pancreaticoduodenectomy	The Second Affiliated Hospital of Chongqing Medical University	49.153	Centers for Disease Control and Prevention (CDC) criteria	H	L
Sun C[18]	2021	China	Prospective	Patients who undergoing radical resection of advanced digestive system cancer	Peking Union Medical College Hospital	6.079	Centers for Disease Control and Prevention (CDC) criteria	H	H
Bu N[19]	2022	China	Retrospective	Patients who underwent colorectal cancer surgery	First Affiliated Hospital of Xi'an Jiaotong University	9.685	Risk stratification for surgical site infections in colon cancer	H	L
Cheng YP[20]	2022	China	Retrospective	Colorectal cancer surgery patients	Beijing Jishuitan Hospital	22.000	Clinical features combined with imaging or endoscopic findings	H	N
Huang DX[21]	2022	China	Retrospective	Patients who underwent radical resection of gastric cancer	First Affiliated Hospital of Xinjiang Medical University	18.592	APSIC guidelines for the prevention of surgical site infections	H	L
Luo J[22]	2022	China	Retrospective	Patients who underwent radical resection of gastric cancer	Qinghai University Affiliated Hospital	14.901	Chinese Guideline for the Prevention of Surgical Site Infection	H	L
Xu J[23]	2022	China	Retrospective	Postoperative patients with cancer of gastrointestinal, liver, pancreatic, bile duct	The First Affiliated Hospital of Soochow University	9.572	Clinical features combined with imaging or endoscopic findings	H	N
Ohno Y[24]	2022	Japan	Retrospective	Patients who underwent radical surgery for stage II-III colon cancer	Tokyo Medical University Hospital	12.603	Centers for Disease Control and Prevention (CDC) criteria	H	L
Fu GH[25]	2023	China	Retrospective	Patients who underwent theradical resection of colorectal cancer	Hainan Third People's Hospital	18.595	Guideline for the prevention of surgical site infection (2017)	H	L

Table 1 (continued)

Author	Year	Country	Study type	Research object	Data sources	Incidence of IAI (%)	Diagnostic method of prediction results	Overall merit	
								Risk of bias	Applicability
Li WX[26]	2023	China	Retrospective	Patients with colorectal cancer who underwent surgeries	Affiliated Hospital of Chengde Medical College	8.543	Hospital infection diagnostic criteria (Trial)	H	L
Miao FF[27]	2023	China	Retrospective	Patients with colon cancer and intestinal obstruction who underwent surgical treatment	Hengshui People's Hospital	16.312	Hospital infection diagnostic criteria (Trial)	H	H
Qin T[28]	2023	China	Retrospective	Patients with colorectal cancer who underwent surgical treatment	Affiliated Cancer Hospital of Guizhou	21.667	Hospital infection diagnostic criteria (Trial)	H	L
Wang HN[29]	2023	China	Retrospective	Patients who underwent radical gastrectomy for gastric cancer	First Affiliated Hospital of Zhengzhou University	1.471	Hospital infection diagnostic criteria (Trial)	H	L
Wang XQ[30]	2023	China	Retrospective	Elderly patients who underwent radical resection of colon cancer	Xijing Hospital, Air Force Medical University	3.178	Hospital infection diagnostic criteria (Trial)	H	H
Xu YL[31]	2023	China	Retrospective	Patients with gastric cancer and patients with colorectal cancer who underwent radical surgery	First Affiliated Hospital of Soochow University	gastric cancer: 8.427 colorectal cancer: 9.508	Centers for Disease Control and Prevention (CDC) and National Nosocomial Infection Surveillance (NNIS) criteria	H	L
Chen KA[32]	2023	United States	Retrospective	Patients who underwent colorectal surgery	The American College of Surgeons National Quality Improvement Program (NSQIP) database	10.700	Centers for Disease Control and Prevention (CDC) criteria	H	L
Han C[33]	2023	China	Retrospective	Colorectal cancer patients who underwent surgery	Huangshan Shoukang Hospital	7.657	Centers for Disease Control and Prevention (CDC) criteria	H	L
Chen T[34]	2024	China	Retrospective	Patients who underwent laparoscopic radical gastrectomy	Zhongshan Hospital Xiamen University	22.857	American College of Surgeons and Surgical Infection Society: Surgical Site Infection Guidelines (2016 Update)	H	L
Cui DD[35]	2024	China	Retrospective	Patients with colorectal cancer who underwent surgeries	A top three hospital in Inner Mongolia	9.371	Hospital infection diagnostic criteria (Trial)	H	L

Table 2 Establishment and prediction performance of the risk prediction model

Included studies	Modeling method	Variable selection	Sample size		Method of missing value processing	Variable processing method	Included factors	Model performance		Model validation	Model presentation mode
			Negative events	Positive events				Discrimination	Calibration method		
Ushiku H[40]	LR	Single + Multiple	681	109	Exclude	Categorical variables	Laparotomy, combined organ resection, BMI, operation time, gender	*C* = 0.840	*H-L* test, calibration curve	Internal validation	Not mentioned
Ma C[36]	LR	Single + Multiple	139	37	Not mentioned	Continuous variable	ALB, gender, weight, irrigation medication, subcutaneous catheterization, tumor location	*AUC* = 0.911	*H-L* test	Not mentioned	①
Tu RH[37]	LR	Single + Multiple	2102	262	Exclude	Categorical variables	BMI, blood loss, operation time, blood transfusion	Training sets *AUC* = 0.739 Validation sets *AUC* = 0.734	*H-L* test	External validation	②
Li L[38]	LR	Single + Multiple	301	34	Not mentioned	Categorical variables	Bile duct stones, blood loss, history of abdominal surgery, bile leakage	*AUC* = 0.851	Not mentioned	Internal validation	①+③
Saylam B[41]	Not mentioned	Not mentioned	64	28	Exclude	Categorical variables	Contamination, obesity, laparotomy, ASA classification	*AUC* = 0.660	*H-L* test, calibration curve	External validation	②
Yin LX[39]	LR	Single + Multiple	565	146	Not mentioned	Categorical variables	Peripheral vascular disease, previous chest surgery, no prophylactic use of preoperative antibiotics, ALB	Training sets *AUC* = 0.706 Validation sets *AUC* = 0.824	*H-L* test	External validation	②
Okui J[14]	LR	Single + Multiple	1471	107	Exclude	Continuous variable	WBC, platelet, ALB, CRP, eGFR	*AUC* = 0.883	Not mentioned	Internal validation	③
Shen J[15]	LR	Single + Multiple	781	31	Exclude	Categorical variables	Combined organ resection, blood transfusion, ICU admission, ALB	*C* = 0.700	Not mentioned	Not mentioned	①+②
Wang Y[16]	LR	Single + Multiple	67	18	Exclude	Categorical variables	Age, BMI, diabetes mellitus, Dukes stage, operation time, laparotomy, type of surgical incision, ALB, probiotics	Training sets *AUC* = 0.869 Validation sets *AUC* = 0.836	*H-L* test	External validation	①
Hu B[17]	LR	Single + Multiple	90	87	Exclude	Continuous variable	ALB, tumor nature, pancreatic fistula, cough, blood transfusion history	Training sets *AUC* = 0.946 Validation sets *AUC* = 0.768	Not mentioned	External validation	②
Sun C[18]	LR	Single + Multiple	788	51	No missing information	Categorical variables	Gastrectomy, colorectal resection, pancreaticoduodenectomy, duration of anesthesia, length of ICU stay	*AUC* = 0.780	*H-L* test	Not mentioned	②
Bu N[19]	LR	Single + Multiple	373	40	Exclude	Categorical variables	Gender, BMI, diabetes mellitus, preoperative chemotherapy, laparotomy, hemoglobin	Training sets *AUC* = 0.862 Validation sets *AUC* = 0.873	Calibration curve, decision curve	External validation	③
Cheng YP[20]	LR	Single + Multiple	1170	330	Exclude	Continuous variable	Age, BMI, diabetes mellitus, intestinal obstruction, laparotomy, incision length, operation time, drainage time, ALB, nursing quality score	*AUC* = 0.950	Not mentioned	Not mentioned	①

Table 2 (continued)

Included studies	Modeling method	Variable selection	Sample size		Method of missing value processing	Variable processing method	Included factors	Model performance		Model validation	Model presentation mode
			Negative events	Positive events				Discrimination	Calibration method		
Huang DX[21]	LR	Single + Multiple	289	66	Not mentioned	Continuous variable	Age, diabetes mellitus, BMI, body temperature at admission, duration of heat preservation, minimum body temperature during operation, laparotomy, and duration of operation	*AUC* = 0.826	Calibration curve, decision curve, Brier score	Internal validation	①+③
Luo J[22]	LR	Single + Multiple	771	135	Exclude	Categorical variables	Age, operation time, total gastrectomy, number of drainage tubes	*C* = 0.726	Not mentioned	Not mentioned	③
Xu J[23]	LR	Single + Multiple	888	94	Exclude	Continuous variable	WBC, NLR, total bilirubin, CRP, mean body temperature	Training sets *AUC* = 0.754 Validation sets *AUC* = 0.708	*H-L* test	External validation	③
Ohno Y[24]	AI	Not mentioned	638	92	Not mentioned	Continuous variable	Length of stay, blood loss, LMR, insulin use, differentiation, laparoscopy, emergency surgery, tumor size, lymphatic invasion, CAR, operation time, CA19-9, smoking status	*AUC* = 0.731	Not mentioned	Internal validation	Not mentioned
Fu GH[25]	LR	Single + Multiple	197	45	Exclude	Categorical variables	Diabetes mellitus, tumor TNM classification, blood loss, operation time, ALB	*AUC* = 0.806	Not mentioned	Not mentioned	④
Li WX[26]	LR	Single + Multiple	364	34	Exclude	Categorical variables	BMI, operation time, ALB	*AUC* = 0.905	Not mentioned	Not mentioned	①
Miao FF[27]	LR	Single + Multiple	354	69	Not mentioned	Categorical variables	Age, diabetes mellitus, operation time, duration of indwelling catheter, preoperative chemotherapy, laparotomy	Training sets *AUC* = 0.892 Validation sets *AUC* = 0.786	*H-L* test、calibration curve, decision curve	Internal validation + External validation	③
Qin T[28]	LR	Single + Multiple	188	52	Not mentioned	Categorical variables	Age, clinical stage, laparotomy, blood transfusion, diabetes mellitus, BMI, malnutrition, history of abdominal surgery	*AUC* = 0.832	Calibration curve	Internal validation	③
Wang HN[29]	LR	Single + Multiple	2143	32	Not mentioned	Continuous variable	Age, operation time, nonprophylactic use of antibiotics, postoperative bed rest time, CD36/mTORC1	*AUC* = 0.900	Not mentioned	Not mentioned	①
Wang XQ[30]	LR, machine learning	Single + Multiple	1493	49	Multiple imputations	Continuous variable	Tumor size, ALB, WBC	*AUC* = 0.767	*H-L* test	Internal validation	③
Xu YL[31]	LR	Single + Multiple	326	30	Exclude	Categorical variables	Gastric cancer: gender, ASA classification, combined organ resection, blood loss	*C* = 0.808	Calibration curve, decision curve	Internal validation	③
			276	29			Colorectal cancer: ASA classification, combined organ resection, operation time	*C* = 0.763			

Table 2 (continued)

Included studies	Modeling method	Variable selection	Sample size		Method of missing value processing	Variable processing method	Included factors	Model performance		Model validation	Model presentation mode
			Negative events	Positive events				Discrimination	Calibration method		
Chen KA[32]	LR, machine learning	Not mentioned	245,710	29,442	Exclude	Categorical variables	Infections already present at the time of surgery, operation time, oral antibiotic bowel preparation, and laparotomy	Artificial neural network model *AUC* = 0.769	Not mentioned	Internal validation + External validation	Not mentioned
Han C[33]	LR	Single + Multiple	398	33	Not mentioned	Categorical variables	Diabetes mellitus, laparotomy, colostomy/ileostomy	Not mentioned	Not mentioned	Not mentioned	③
Chen T[34]	LR	Single + Multiple	135	40	Exclude	Continuous variable	Age, diabetes mellitus, ALB, operation time, MCP1, sCD14	*AUC* = 0.912	Not mentioned	Not mentioned	①
Cui DD[35]	LR	Single + Multiple	648	67	Not mentioned	Categorical variables	BMI, diabetes mellitus, ALB, preoperative chemoradiotherapy, emergency surgery, stoma	Training sets *AUC* = 0.850 Validation sets *AUC* = 0.846	*H-L* test	External validation	①+③

Note: LR: logistic regression; AI: artificial intelligence; Single: single factor analysis; Multiple: multifactor analysis; ALB: serum albumin; WBC: white blood cell count; NLR: neutrophil-to-lymphocyte ratio; CRP: C-reactive protein; BMI: body mass index; mTORC1: the mechanistic target of rapamycin complex 1; ASA classification: American Society of Anesthesiologists physical status classification system; MCP-1: monocyte chemotactic protein-1; sCD14: soluble leukocyte differentiation antigen-14; eGFR: estimated glomerular filtration rate; LMR: lymphocyte-to-monocyte ratio; CAR: C-reactive protein-to-albumin ratio; cA19-9: carbohydrate antigen 19–9; *AUC*: area under the participant curve; *C*: consistency index; *H-L* test: Hosmer–Lemeshow goodness-of-fit test; ①: risk score formula; ②: risk scoring system; ③: nomogram; ④: decision tree

mellitus ($n = 10$). The model performance and presentation form are detailed in Table 2.

Risk of bias and applicability evaluation

(1) All 28 studies were at high risk of bias. ① Subject areas: Except for the research by Scholar Sun [18], the remaining 27 studies were at high risk of bias due to the bias of sample size in their retrospective studies. ② In the field of predictors, one study [32] involved multicenter samples, and the data collected by each center may be different, so it was rated as "high risk". ③ Outcome domain: Five studies were rated as having a high risk of bias: 4 studies [14, 23, 30, 32] had partial duplications of predictors and outcome indicators, and 1 study [36] had short time intervals between predictor measurement and outcome determination, which may have led to bias in model performance. Two studies [20, 23] did not state the source of the outcome definitions, and the risk of bias was unclear. ④ Analysis field: All studies were rated as having a high risk of bias; 21 studies [15–19, 21, 23–31, 33–36, 38, 41] had insufficient outcome events, and the number of events per variable (EPV) was less than 20; 18 studies [15, 16, 18, 19, 22, 25–28, 31–33, 35, 37–41] discretized the continuous variables partially or completely; and 10 studies [21, 24, 27–29, 33, 35, 36, 38, 39] did not report methods for handling missing data. Thirteen articles [14, 15, 17, 20, 22, 24–26, 29, 32–34, 38] did not report a calibration test of the model. Ten studies [15, 18, 20, 22, 25, 26, 29, 33, 34, 36] did not indicate whether validation was carried out. (2) In the applicability evaluation, 3 studies [18, 27, 30] in the subject field were rated as having high applicability risk because they limited their study subjects to a specific population. Two studies [20, 23] were judged to be unclear in the outcome domain because it was not clear where the definitions of the reported outcome measures came from. The other items had good applicability. The overall risk of bias and applicability are shown in Table 1.

Results of the meta-analysis

One study [33] did not report the construction of a model of *AUC*, whereas 8 studies [16, 17, 22, 24, 26, 36, 39, 40] did not report the *AUC* value. Therefore, 19 studies [14, 15, 18–21, 23, 25, 27–32, 34, 35, 37, 38, 41] were included in the meta-analysis. There was high heterogeneity in the SSI prediction models for patients with digestive system cancer [$I^2 = 99.1\%$, $P < 0.001$]. After gradual elimination, a random effects model was used for analysis: $AUC = 0.844$ (0.828, 0.861) [$I^2 = 74.9\%$, $P < 0.001$]. The meta-analysis of predictors with a frequency ≥ 3 times revealed that operation time, diabetes mellitus, BMI, ALB, surgical approach, age, blood loss, gender, blood transfusion, combined organ resection, and preoperative chemotherapy were independent risk factors for SSI in patients

Table 3 Meta-analysis results of predictors

Predictor	Included studies	Heterogeneity test		Effects models	Meta-analysis		
		I^2 Value (%)	*P*Value		OR (95%CI)	Z Value	*P*Value
Operation time	12	73.200	< 0.001	Random effect model	2.125(1.860,2.429)	11.076	< 0.001
Diabetes mellitus	10	62.200	0.005	Random effect model	2.065(1.746,2.441)	8.484	< 0.001
BMI	9	56.300	0.019	Random effect model	2.137(1.773,2.575)	7.981	< 0.001
ALB	9	71.400	< 0.001	Random effect model	1.764(1.619,1.922)	12.989	< 0.001
Surgical approach	8	77.500	< 0.001	Random effect model	1.734(1.495,2.012)	7.262	< 0.001
Age	8	72.100	< 0.001	Random effect model	1.662(1.453,1.902)	7.412	< 0.001
Blood loss	4	0	0.434	Fixed effect model	2.445(1.732,3.451)	5.084	< 0.001
Gender	3	0	0.571	Fixed effect model	3.114(1.702,5.696)	3.685	< 0.001
Blood transfusion	3	0	0.603	Fixed effect model	3.424(2.262,5.183)	5.817	< 0.001
Combined organ resection	3	0	0.866	Fixed effect model	3.986(2.473,6.423)	5.679	< 0.001
Preoperative chemotherapy	3	31.100	0.234	Fixed effect model	7.239(3.875,13.521)	6.209	< 0.001

with digestive system tumors ($P < 0.05$). The results of the meta-analysis are detailed in Table 3.

Discussion

The existing prediction models have guiding significance for clinical practice. The incidence of SSI in patients with digestive system tumors is high, and it is closely related to prolonged hospital stay, decreased quality of life, and increased mortality [8]. The risk prediction model of SSI can identify high-risk groups early and provide timely prevention and control interventions to reduce their incidence and adverse outcomes. The 39 prediction models included in this study had good predictive performance and could accurately identify high-risk populations for SSI in patients with digestive system tumors. The predictors with high frequency in their models were statistically significant ($P < 0.05$) after combined effect size meta-analysis. However, there is still a lack of research in areas such as model construction, validation, and reporting.

The overall prediction performance of the SSI risk prediction model for patients with digestive system cancer is good, but the bias is high

All the prediction models included in this study had a high risk of bias, and most of them focused on research subjects, outcomes, and analysis fields. The main reasons are as follows: ① Retrospective studies using existing data cannot ensure the accuracy of data collection, which may affect the overall quality of the constructed model, and interference from existing results easily occurs, resulting in increased model heterogeneity. A cohort study or nested case–control study can be used in future research [13] to reduce the risk of data bias. ② Some studies included predictors in the outcome definition. PROBAST [13] noted that the predictors of the constructed model included outcome evaluation indicators, and the correlation between them was overestimated, which affected the objectivity and accuracy of the model and led to an increased risk of bias. ③ If the outcome events corresponding to the predictors were insufficient, an EPV < 20 would lead to an increased risk of bias and decreased reliability of the model. PROBAST [13] reported that an EPV of ≥ 20 cases in model development studies can reduce overfitting of the model. Researchers in various countries can actively carry out large sample size studies in the next step to capture more variability and potential confounding factors, estimate the predictor effect more accurately, and help ensure the generalization of the model. ④ Most studies use multivariate analysis to screen predictor variables on the basis of a single factor, which cannot fully evaluate the interactions and internal relationships between candidate variables, and it is easy to ignore important variables. New methods, such as LASSO regression, ridge regression, and ElasticNet regression [42], should be adopted in combination with clinical practice for variable screening in the future to improve the accuracy of screening. In addition, clinical significance, measurement accessibility, and measurement cost should be fully considered to comprehensively incorporate predictors. ⑤ The continuous variables were poorly processed, and the continuous data were transformed into categorical variables for modeling, which resulted in partial information loss and reduced the predictive ability of the model. When the model is in the stage of clinical promotion and it is necessary to convert continuous variables into categorical variables to improve the convenience of researchers' application, the nonlinear fitting of continuous variables or the classification of variables can be verified via universally accepted standard definitions, clinical significance, etc [13]. ⑥ Improper processing of missing data biases the relationships between predictors and outcomes, which may affect the accuracy and increase the bias of the model. In the future, attention should be given to improving missing data and using the weighting method, imputation method, and other methods to correctly address missing values to improve the reliability of the prediction model. ⑦ To fully measure the performance of the model, both

discrimination and calibration should be evaluated. Calibration reflects the degree of agreement between the predicted risk and the actual risk, usually using calibration curves, decision curves, Brier score measures, etc. Using only the Hosmer–Lemeshow goodness-of-fit test calibration or not reporting the calibration information of the prediction model will lead to a high risk of bias. Future studies should be evaluated and reported in time after modeling to facilitate the comparison of developed risk prediction models and facilitate clinical transformation. ⑧ Due to the differences in research sites and subjects, internal and external validation should be performed before the prediction model is applied to clinical practice to reduce overfitting and ensure its applicability and validity. In addition, external validation can improve the extendibility of the model, which is more time-saving and cost-saving than reconstructing the model. High-quality models can be selected for optimization and calibration on the basis of this study in the future, and spatial and temporal validation methods can be used to improve the performance of the model.

Risk factors for SSI in patients with digestive system tumors

Operation time, diabetes mellitus, BMI, ALB, surgical approach, age, blood loss, gender, blood transfusion, combined organ resection, and preoperative chemotherapy are common predictors of SSI in patients with digestive system tumors. Most of these factors are objective and easy to collect, and the model is more convenient. The results of the meta-analysis of this study all suggested medical statistical significance. The above 11 factors, which are divided into 4 categories, can be considered in future modeling. (1) Underlying disease factors include diabetes mellitus, preoperative chemotherapy, etc. Patients with diabetes mellitus are in a state of continuous high glucose, which can cause damage to vascular endothelial cells, inhibit capillary regeneration and granulation tissue growth, and increase blood glucose, which is conducive to the colonization and attachment of pathogenic bacteria and is more likely to cause SSI [28, 34]. Moreover, diabetes leads to a higher catabolic rate than anabolism and affects neutrophil chemotaxis and phagocytosis, which reduces the clearance of pathogens by the body's immune system and further increases the risk of SSI [43]. For such patients, basic diseases should be diagnosed and treated in a timely manner before the operation, and a blood glucose management process and intervention plan should be formulated to control blood glucose effectively. On the other hand, 3 studies [19, 27, 35] listed preoperative chemotherapy as a predictor because chemotherapy regimens are usually accompanied by toxic reactions, which affect the synthesis of related immune factors and cause immune dysfunction, leading to an increased risk of SSI [27]. In the future, more attention should be given to this population, targeted immunity enhancement should be carried out as soon as possible, and related clinical indicators should be continuously detected to reduce the incidence of SSI. (2) Surgical factors include operation time, surgical approach, blood transfusion, blood loss, combined organ resection, etc. ① The classic surgical method for digestive system tumors is laparotomy, but it is destructive to body tissue, and the internal organs are directly exposed to the surrounding environment, which increases the risk of infection with pathogenic bacteria [43]. ② Studies [44] have shown that a long operation time significantly increases the risk of SSI in patients with digestive system tumors. The long-term exposure of the surgical area led to bacterial colonization, and the prolonged traction and compression of the tissue by the tractor led to poor blood circulation and a reduced ability to resist bacteria [45]. ③ Perioperative blood transfusion can lead to an imbalance in the white blood cell proportion and increases in thromboxane and prostaglandin levels in the body, whereas prostaglandin can inhibit the activity of helper T cells, resulting in a decrease in the body's immunity and resistance to pathogenic bacteria [28, 46]. ④ A large amount of blood loss can cause local immune deficiency, which provides a good opportunity for pathogen invasion and proliferation. The above factors can lead to the occurrence of SSI in patients who have undergone digestive system tumor surgery. Clinicians should shorten the operation time, pay attention to surgical skills, reduce intraoperative blood loss and perioperative blood transfusion, and reduce the risk of SSI after surgery in patients with digestive system tumors on the premise of ensuring the safety of surgery as much as possible. In addition, three studies [15, 31, 40] included combined organ resection as a predictor, and combined resection may expose more internal organs to airborne microorganisms and increase the chance of postoperative SSI [44]. Surgeons should strictly grasp the indications for combined organ resection and avoid blindly expanding the scope of surgical resection. (3) Demographic factors: age, male sex, etc. Age is closely related to the organ function, tolerance, and immune function of patients. In addition, the body stress caused by surgery is more significant in elderly patients, which further inhibits the body's immune function and increases the likelihood of SSI [44, 47]. Some studies [19, 31, 36, 40] have included male sex as a risk factor, which may be related to the effects of the male visceral fat area and sex hormones on the immune system [31, 44], increasing the risk of infection. At present, the influence of gender factors on SSI in patients with digestive system tumors remains to be further explored. In the future, patients in different gender groups can be classified on the basis of disease characteristics, and cluster

analysis can be used to analyze the influence mechanism of gender on SSI after surgery. (4) Laboratory indicators: ALB, BMI, etc. A low level of ALB can reduce plasma osmotic pressure and immunoglobulin synthesis, leading to a decrease in the compensatory ability and defense ability of the patient, degenerative changes in the function of important organs, and increased possibility of SSI after surgery [34, 48]. Therefore, for patients with poor nutritional status, medical staff can guide patients to eat more high-calorie and high-protein foods according to their daily eating habits to ensure patients' comprehensive nutritional needs. On the other hand, patients with higher BMIs have thicker abdominal fat, and the surgical site is prone to fat liquefaction, fluid accumulation, and necrosis, which provides a good breeding and survival environment for pathogenic bacteria [28, 48]. In future clinical work, attention should be given to the relevant laboratory indicators of patients, with regular analysis and summary of their data. Targeted treatment should be initiated for high-risk groups as early as possible to reduce the incidence of postoperative SSI.

Inspiration for future research

In the literature included in this study, Fu GH et al. [25] established a decision tree model to analyze and predict the risk factors for SSI infection in patients with digestive system tumors, focused on the interaction between multiple independent variables, and screened 3 high-risk groups. The model was concise and easy to understand, and the prediction effect was closer to that of clinical practice. Wang XQ et al. [30] used the multiple imputation method to address missing data, which effectively reduced the negative impact of missing data on statistical analysis and model reliability, and used machine learning to build a prediction model, which was helpful for better capturing the complex nonlinear relationships and interactions in the data. The other two studies [32, 37] established risk prediction models on the basis of large sample data and made the models freely available to clinical workers as mobile applications to promote clinical application. The above studies provide new ideas for future model research from a new perspective of prevention and control and new modeling methods. Currently, research on SSI risk prediction models for patients with gastrointestinal tumors is developing rapidly, and most studies further stratify the population of gastrointestinal tumor patients. Nearly half of the studies ($n = 15$) limited the study population to colorectal cancer patients, possibly because colorectal cancer is the most common malignant tumor among gastrointestinal tumors. This may be related to the following two factors: on the one hand, colorectal cancer is the most prevalent malignant tumor among digestive system tumors; on the other hand, compared with other digestive system tumors, surgical procedures in the colorectal area are more prone to contamination of the intestinal flora due to its anatomical location and the complexity of the gut microbiome, thereby increasing the risk of SSI [33, 48]. In this study, *AUC* value extraction and meta-analysis were conducted on models targeting colorectal cancer patients, with $AUC = 0.755$ (0.751, 0.759), indicating that such models have good discrimination ability for high-risk groups of SSI occurrence in colorectal cancer patients. Moreover, conducting related research by refining the study subjects can avoid confounding factors of different tumor types affecting the model's accuracy, increasing the accuracy of the model in reflecting the risk situation of specific tumor patients and providing a basis for precision treatment. With the continuous development of modern medical technology, surgical treatments can now be categorized into open surgery, laparoscopic surgery, robotic surgical systems, and other methods, each with its own advantages and limitations. It is recommended that scholars from various countries use patients with gastrointestinal tumors undergoing different surgical methods as research subjects to construct SSI risk prediction models. This approach can be used to further investigate the differences in risk among various methods and adapt to specific surgical risk factors, thereby continuously improving risk prediction models and providing precise guidance for clinical practice. Moreover, relatively few studies have used multicenter data and external validation of existing risk prediction models for SSI infection in patients with gastrointestinal tumors, which may limit the predictive ability and scope of application of these models. In the future, multicenter and large-sample application validation studies should be carried out on a global scale, and external validation should be performed to promote the implementation of models to develop an SSI risk prediction model for patients with digestive system tumors that can meet both standardization and individualization, practicality and applicability requirements. On the other hand, when applying the prediction model to clinical work, medical staff should pay attention to combining the individual characteristics of high-risk groups, optimize and continuously calibrate the prediction model in a timely manner, which helps medical staff provide corresponding intervention measures for high-risk groups to ensure patient outcomes and reduce the economic burden on patients and medical costs. Finally, scholars from all over the world should construct more high-quality prediction models in strict accordance with the methodological guidelines in follow-up studies and conduct external validation to improve their applicability and generalizability. In addition, the model can also be transformed into technological forms such as online calculators and apps, giving full play to the positive role of

artificial intelligence and data mining technology in promoting the medical and health industry.

This study has certain limitations: ① To maintain research quality, this study is based solely on currently available models for analysis, excluding unpublished model studies, which may result in the omission of relevant research and potentially affect the completeness of the research results; ② Most of the predictive models included in this study are based on research conducted in the Chinese population, and this regional difference may impact the applicability to other populations; ③ Although literature searches were conducted across nine databases, it is still possible that some high-quality models were overlooked, potentially underestimating the number of developed and validated models. To address this issue, researchers should continue comprehensive searches across multiple databases and sources to minimize the likelihood of missing relevant studies. Additionally, to enhance the international comparability and overall quality of the research, future studies could be limited to the English literature. ④ The SSI risk prediction models for certain gastrointestinal tumor patients lack validation, so their generalizability remains to be confirmed. In the future, it is necessary to limit the search and analysis to validated studies to explore the generalizability, stability, and reproducibility of each model in detail. Despite these limitations, this study still provides a valuable analytical perspective on the current state of research regarding SSI risk prediction models for patients with gastrointestinal tumors. On this basis, future research can be optimized in multiple aspects: ① expanding the scope of literature screening to avoid missing key information; ② updating the timeframe to include the latest research findings; and ③ standardizing and coordinating statistical methods and research designs to increase the comparability between models. More comprehensive and accurate research results are expected to be obtained through these optimization measures, thereby promoting the further development of SSI risk prediction models for patients with gastrointestinal tumors.

Conclusion

A total of 28 articles were included in this study, and 39 prediction models were constructed. The results showed that the SSI risk prediction models for patients with digestive system tumors had good performance and applicability. However, some models have not been calibrated or validated, and there is a high risk of bias and heterogeneity. Scholars from various countries are recommended to conduct large-sample and multicenter prospective cohort studies, prioritize external validation, use advanced modeling algorithms to construct risk prediction models and follow the TRIPOD statement to standardize research design and reporting processes, further evaluating the effectiveness and feasibility of the models in clinical practice.

Abbreviations

AUC	Area under the receiver operating characteristic curve
SSI	Surgical site infection
OR	Odds ratio
CI	Confidence interval
PRISMA	Preferred reporting items for systematic reviews and meta-analyses
NLR	Neutrophil-to-lymphocyte ratio
C-index	Concordance index
EPV	Events per variable
LR	Logistic regression
AI	Artificial intelligence
ALB	Serum albumin
WBC	White blood cell count
CRP	C-reactive protein
BMI	Body mass index
mTORC1	The mechanistic target of rapamycin complex 1
ASA classification	American society of anesthesiologists physical status classification system
MCP-1	Monocyte chemotactic protein-1
sCDl4	Soluble leukocyte differentiation antigen-14
eGFR	Estimated glomerular filtration rate
LMR	Lymphocyte-to-monocyte ratio
CAR	C-reactive protein-to-albumin ratio
cA19-9	Carbohydrate antigen 19 – 9
H–L test	Hosmer–Lemeshow goodness-of-fit test

Supplementary Information

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Supplementary Material 1

Supplementary Material 2

Supplementary Material 3

Supplementary Material 4

Supplementary Material 5

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Author contributions
Yu WANG and Yao SHI# contributed equally to this work. All authors contributed to the study conception and design. Writing - original draft preparation: [Yu Wang]; Writing - review and editing: [Yu Wang & Yao Shi]; Conceptualization: [Yao Shi, Li Wang, Yunhong Du]; Methodology: [Yu Wang, Yuliang Duan]; Formal analysis and investigation: [Li Wang, Lili Peng]; Supervision: [Lili Peng]. All authors read and approved the final manuscript.

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Declarations

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Not applicable.

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