

Preoperative coagulation-inflammation-nutrition profiling for postoperative ICU admission after gastrointestinal tumor surgery

FuYing Luo

Guangxi Medical University

Shibo Huang

Guangxi Medical University

Rong Zhou

Guangxi Medical University

Lanjing Liao

Guangxi Medical University

Zhiyi Tan

Guangxi Medical University

ChunMiao Wang

Guangxi Medical University

Tingan Wang

wang.tingan@gxmu.edu.cn

Guangxi Medical University

Research Article

Keywords: gastrointestinal tumor surgery, intensive care unit, fibrinogen, C-reactive protein, albumin, perioperative risk, composite biomarker, INSPIRE

Posted Date: October 6th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10704858/v1>

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Additional Declarations: No competing interests reported.

Abstract

Background: Postoperative intensive care unit (ICU) admission after gastrointestinal tumor surgery represents a clinically important escalation of perioperative care. Conventional risk assessment is dominated by demographic, comorbidity, and procedural information, whereas the host biological state before surgery is less directly captured. We aimed to develop and evaluate a parsimonious coagulation-inflammation-nutrition score (CINS) for postoperative ICU admission.

Methods: This retrospective cohort study used the INSPIRE perioperative database. Adults aged 18-90 years who underwent non-emergency gastrointestinal tumor surgery under general anesthesia were included. CINS was constructed from three routinely available preoperative biomarkers: albumin, fibrinogen, and C-reactive protein (CRP). One point was assigned for low albumin (≤ 3.7 g/dL), high fibrinogen (≥ 397 mg/dL), and high CRP (≥ 7.7 mg/L), generating a 0-3 score. Multivariable logistic regression adjusted for age, sex, body mass index, American Society of Anesthesiologists physical status, procedure group, and tumor site. Performance was benchmarked against the fibrinogen-to-albumin ratio (FAR), a continuous CIN-z index, and several immune-extended composite indices using discrimination, calibration, reclassification, decision curve analysis, bootstrap resampling, and repeated cross-validation.

Results: Among 4,776 eligible patients, 677 experienced postoperative ICU admission. ICU admission increased stepwise across CINS categories, from 8.7% in patients with score 0 to 26.7% in patients with score 3. Compared with score 0, adjusted odds ratios were 1.86 for score 1, 2.53 for score 2, and 3.30 for score 3; each 1-point increase in CINS was associated with 51% higher odds of ICU admission. The clinical model had an apparent AUC of 0.823. Adding FAR increased the AUC to 0.832, whereas adding CINS increased it to 0.837. Bootstrap analysis showed that CINS improved AUC compared with FAR by 0.0052, with a 95% bootstrap interval of 0.0018 to 0.0087. CIN-z achieved a similar AUC of 0.839. In a common complete-case comparison of multiple composite indices, more complex immune-extended scores did not outperform the three-component CINS/CIN-z construct. Repeated 5-fold cross-validation preserved the same ranking.

Conclusions: A simple preoperative score integrating fibrinogen, CRP, and albumin was independently associated with postoperative ICU admission after gastrointestinal tumor surgery and performed better than FAR and more complex immune-extended indices. CINS may provide a practical, biologically grounded adjunct to perioperative risk stratification.

1. Introduction

Patients undergoing major gastrointestinal tumor surgery often have heterogeneous physiological reserve, even within similar operative categories. Some recover through standard ward pathways, whereas others require postoperative ICU-level monitoring or support. Anticipating this transition before surgery is important for shared decision-making, postoperative bed planning, and perioperative optimization (1–3).

Postoperative ICU admission is a clinically useful endpoint because it occurs close to the surgical episode and reflects escalation of care intensity. Although it is not identical to postoperative morbidity, ICU admission integrates procedural risk, anesthetic planning, early organ dysfunction, and monitoring needs, making it relevant to hospitals with constrained critical care capacity (1, 2).

Perioperative risk stratification has been shaped by clinical variables such as age, comorbidity burden, functional status, American Society of Anesthesiologists physical status, and procedure type. These variables underpin widely used surgical risk frameworks, including the ACS NSQIP Surgical Risk Calculator, and remain essential for clinical judgment (1). Enhanced recovery and perioperative nutrition guidelines also emphasize preoperative optimization, including nutritional and inflammatory risk recognition (2, 3). Yet many routinely used risk frameworks represent host biology indirectly. In patients with gastrointestinal malignancy, the preoperative state often reflects a convergence of coagulation activation, systemic inflammation, and impaired nutritional reserve. Fibrinogen is both a coagulation substrate and an acute-phase reactant; CRP is a canonical marker of systemic inflammation; and albumin reflects nutritional reserve while also behaving as a negative acute-phase protein during inflammation and catabolic stress (4–7).

This biological triad has clinical plausibility, but the literature has largely examined its components or simplified ratios in different contexts. INSPIRE-based studies have recently linked the geriatric nutritional risk index and stress hyperglycemia ratio to postoperative ICU admission after gastrointestinal tumor surgery (8, 9). Separately, FAR and fibrinogen/albumin ratio indices have been studied in gastrointestinal malignancies, mainly as prognostic markers for recurrence, survival, or broader oncologic outcomes (10–12). These studies are important, but they leave a narrower perioperative question unresolved: whether a compact score that explicitly integrates coagulation, inflammation, and nutrition provides incremental risk information for postoperative ICU admission, and whether greater biomarker complexity adds meaningful value.

This distinction matters for study design. A two-component ratio such as FAR is attractive because it is simple and has a plausible biological basis, but it compresses two different processes into a single quotient and does not explicitly represent CRP-defined systemic inflammation. Conversely, large composite inflammatory scores may appear more comprehensive but can be less transparent, more sensitive to missing laboratory values, and harder to transport across perioperative settings. We reasoned that an intermediate strategy might be preferable: a score that is biologically richer than FAR but still simple enough for bedside interpretation. In this framework, the objective is not to maximize apparent model complexity, but to determine whether a small number of routinely measured biomarkers can capture a reproducible host-response phenotype.

We therefore developed CINS using preoperative fibrinogen, CRP, and albumin in the INSPIRE database (13). We benchmarked CINS against FAR and several alternative composite indices, including continuous and immune-extended formulations. Robustness was evaluated using adjusted regression, bootstrap performance metrics, calibration, decision curve analysis, reclassification measures, and repeated cross-

validation, in accordance with contemporary reporting and prediction-model evaluation principles(14, 15).

2. Methods

2.1 Study design and data source

This retrospective cohort study used INSPIRE version 1.4.2, a publicly available perioperative database containing surgical, anesthetic, laboratory, vital sign, diagnosis, medication, and outcome data from a large academic surgical population [1]. The study was designed and reported with reference to STROBE and TRIPOD principles for observational and prediction-oriented analyses (14, 16).

The analysis was conceived as a biomarker-development and comparative-validation study rather than as a causal effect analysis. Accordingly, the primary objective was to determine whether preoperative laboratory information improved risk stratification for postoperative ICU admission beyond routinely available clinical variables. All biomarker definitions were based on preoperative values only, and prediction-oriented validation steps were designed to avoid using information from the validation fold when thresholds or standardization parameters were required. The cohort definitions and analytical populations are summarized in Fig. 1.

2.2 Study population

Eligible patients were aged 18–90 years and underwent non-emergency gastrointestinal tumor surgery under general anesthesia. Gastrointestinal malignancy was identified using ICD-10 diagnosis prefixes C16, C18, C19, C20, C22, C23, C24, and C25. Eligible procedures were identified using ICD-10-PCS prefixes 0DB, 0DT, 0FB, 0FT, and 0D1. For patients with multiple eligible operations, the first qualifying operation was retained (Fig. 1).

The cohort definition was intentionally restricted to non-emergency gastrointestinal tumor surgery to reduce heterogeneity from emergency physiology and non-oncologic surgical indications. Upper gastrointestinal, colorectal, hepatobiliary, pancreatic, and related gastrointestinal tumor procedures were retained because they represent a clinically coherent population in which nutritional depletion, inflammation, and coagulation activation are common perioperative concerns. Patients without the biomarker data required for a given index were excluded from the corresponding complete-case analysis; therefore, cohort size differed between the primary CINS analysis and the multi-index complete-case comparison.

2.3 Biomarker extraction

Preoperative laboratory measurements were identified as the nearest available value before operation start. Albumin was measured in g/dL. Fibrinogen was measured in mg/dL and converted to g/L when required for ratio-based indices. CRP was measured in mg/dL and converted to mg/L. Additional

immune markers included neutrophil percentage, lymphocyte percentage, platelet count, and systemic immune-inflammation index(11).

- Using the nearest preoperative measurement was intended to reflect the biological state most proximate to surgery while preserving sample size. Laboratory values recorded after operation start were not used for biomarker construction, because postoperative measurements may already reflect surgical trauma, resuscitation, bleeding, infection, or early complications. CRP was log-transformed for the continuous CIN-z formulation because inflammatory biomarkers are commonly right-skewed and extreme values can dominate linear indices.

2.4 Composite biomarker indices

CINS assigned one point each for low albumin, high fibrinogen, and high CRP. The final cutoffs were albumin ≤ 3.7 g/dL, fibrinogen ≥ 397 mg/dL, and CRP ≥ 7.7 mg/L. CIN-z was calculated as $z(\text{fibrinogen}) + z(\log(\text{CRP} + 1)) - z(\text{albumin})$. Additional exploratory indices included FAR, a fibrinogen-CRP-albumin ratio index, immune-CINS5, SII-CINS4, and CIN-z5.

The categorical CINS formulation was designed for interpretability. A patient could therefore be described according to the number of abnormal biological domains rather than by an opaque regression coefficient or ratio. The continuous CIN-z index was developed as a sensitivity formulation to test whether the signal depended on the specific cutoffs used for CINS. In the multi-index comparison, immune-extended scores were included to test whether adding hematologic inflammatory information improved prediction beyond the three core domains. This design allowed us to distinguish a genuinely useful biological expansion from complexity that increased the number of inputs without improving performance.

2.5 Outcome

The primary outcome was postoperative ICU admission, defined as ICU admission recorded after operation start and before hospital discharge.

2.6 Statistical analysis

Continuous variables were summarized using appropriate measures of central tendency and dispersion, and categorical variables were summarized as counts and percentages. Multivariable logistic regression adjusted for age, sex, body mass index, American Society of Anesthesiologists physical status, procedure group, and tumor site. CINS was examined both categorically and ordinally.

Model performance was evaluated using AUC and Brier score. Bootstrap resampling estimated AUC intervals, AUC differences, integrated discrimination improvement, and continuous net reclassification improvement (15, 17, 18). Calibration was assessed graphically using decile-based calibration curves. Decision curve analysis evaluated net benefit across threshold probabilities(19). Repeated 5-fold cross-validation with 10 repeats was performed for internal validation; biomarker thresholds and

standardization parameters were recalculated within training folds and applied to validation folds (20–24).

The base clinical model was selected to represent information that is usually available before surgery and that is commonly used in perioperative risk assessment. Incremental value was evaluated by adding each biomarker index to this clinical model rather than by comparing unadjusted biomarker-only models. Apparent performance was first assessed in the full analytic sample, followed by bootstrap and repeated cross-validation analyses to examine internal robustness.

3. Results

3.1 Baseline characteristics and CINS distribution

The CINS analysis included 4,776 adults undergoing non-emergency gastrointestinal tumor surgery under general anesthesia. The primary outcome occurred in 677 patients. The score distribution supported clinically interpretable strata: 2,598 patients had score 0, 1,078 had score 1, 661 had score 2, and 439 had score 3. ICU admission increased monotonically across these categories: 8.7%, 17.5%, 21.9%, and 26.7% for scores 0, 1, 2, and 3, respectively (Table 1; Fig. 3).

This distribution indicated that the score did not merely isolate a very small extreme-risk subgroup. More than 45% of patients had at least one abnormal CINS component, and approximately one quarter of the cohort had two or more abnormal domains. The observed risk gradient was therefore present across clinically meaningful strata rather than being driven solely by rare outliers. The near tripling of crude ICU admission rate from score 0 to score 3 supported the hypothesis that concurrent coagulation activation, inflammatory burden, and reduced albumin reserve identify a higher-risk perioperative phenotype.

The component biomarkers changed in the expected biological direction across CINS strata. Median albumin declined from 4.1 g/dL in score 0 to 3.3 g/dL in score 3, while median fibrinogen increased from 301 mg/dL to 452 mg/dL. Median CRP showed the steepest gradient, rising from 0.6 mg/L in score 0 to 29.3 mg/L in score 3. FAR x100 also increased across the score categories, from 7.34 in score 0 to 14.07 in score 3. These gradients confirm that the score captured progressive accumulation of nutritional depletion, coagulation activation, and systemic inflammation rather than arbitrary category assignment.

Baseline clinical characteristics also varied across CINS strata. Patients with higher CINS tended to be older, more often male, and had lower BMI. ASA physical status shifted toward higher risk with increasing CINS: ASA ≥ 3 was present in 7.4% of patients with score 0 and 19.4% of patients with score 3. Tumor site distribution also differed, with colorectal and hepatobiliary-pancreatic tumors accounting for a larger proportion of higher CINS categories, whereas gastric tumors were more frequent in the lowest CINS category. These differences support adjustment for clinical and procedural covariates in subsequent association and prediction models.

3.2 Association between CINS and postoperative ICU admission

In multivariable logistic regression adjusted for age, sex, body mass index, American Society of Anesthesiologists physical status, procedure group, and tumor site, CINS demonstrated a graded association with postoperative ICU admission. Compared with score 0, adjusted odds ratios were 1.86 for score 1, 2.53 for score 2, and 3.30 for score 3 (Table 2; Fig. 3). When modeled ordinally, each 1-point increase in CINS was associated with 51% higher odds of ICU admission.

The persistence of the association after adjustment suggests that CINS was not simply a surrogate for broad anesthetic risk or procedure category. The categorical model showed a dose-response pattern, while the ordinal model summarized the same relationship in a single clinically intuitive estimate. These complementary analyses support use of CINS either as a categorical staging tool or as an ordinal risk marker in future perioperative workflows.

The adjusted model was estimated in 4,760 patients with complete covariate information, among whom 673 ICU admission events were available. All CINS contrasts were statistically robust, with P values less than 0.001. The stepwise pattern was maintained despite adjustment for ASA physical status and surgical grouping, two covariate domains that would be expected to absorb a substantial proportion of perioperative risk. This strengthens the interpretation that preoperative coagulation-inflammation-nutrition status adds risk information beyond conventional clinical descriptors.

3.3 Incremental performance beyond clinical variables and FAR

The clinical model had an AUC of 0.823. Adding FAR increased the AUC to 0.832, whereas adding CINS increased it to 0.837, and CIN-z achieved a similar AUC of 0.839. Bootstrap intervals supported the stability of these estimates: the AUC intervals were 0.806–0.838 for the clinical model, 0.815–0.846 for clinical plus FAR, 0.822–0.852 for clinical plus CINS, and 0.823–0.854 for clinical plus CIN-z (Table 3; Figs. 2 and 4).

Bootstrap analysis showed that CINS improved AUC compared with FAR by 0.0052, with a 95% bootstrap interval of 0.0018 to 0.0087. CINS also improved integrated discrimination improvement by 0.0094 compared with FAR, and the continuous net reclassification improvement was 0.247. Compared with the clinical model alone, CINS improved AUC by 0.0147, integrated discrimination improvement by 0.0193, and continuous net reclassification improvement by 0.376. Calibration curves showed acceptable agreement between predicted and observed ICU admission, and decision curve analysis suggested modest net-benefit advantages for CINS and CIN-z across clinically plausible threshold probabilities (Fig. 4; Supplementary Figures S1 and S2).

To evaluate whether categorization drove the observed signal, CIN-z was constructed as a continuous sensitivity index. CIN-z achieved an AUC of 0.839, similar to CINS and higher than FAR, supporting the

underlying biological construct rather than a single thresholding scheme.

The improvement in discrimination was numerically modest, as expected when biomarkers are added to an already informative clinical model. However, the direction of improvement was consistent across AUC, reclassification, calibration, and decision-analytic evaluation. This pattern is more persuasive than reliance on a single performance metric, because AUC alone can understate clinically relevant changes in predicted risk distribution, whereas reclassification and net-benefit analyses provide complementary information about risk separation and threshold-based decision-making.

3.4 Comparison with more complex composite indices

We compared multiple composite indicators in a common complete-case cohort of 4,578 patients with 660 ICU events. In addition to FAR, CINS3, and CIN-z3, we evaluated a fibrinogen-CRP-albumin ratio index, an immune-extended CINS5 incorporating neutrophil-to-lymphocyte ratio and platelet count, an SII-extended CINS4, and a five-component CIN-z5.

The three-component CIN-z3 had the highest apparent AUC (0.840; 95% bootstrap interval, 0.825–0.856), followed closely by CINS3 (0.839; 95% bootstrap interval, 0.824–0.855). More complex extensions did not improve discrimination: SII-CINS4 had an AUC of 0.838, the fibrinogen-CRP-albumin ratio index had an AUC of 0.837, CIN-z5 had an AUC of 0.837, and immune-CINS5 had an AUC of 0.836. FAR had a lower AUC of 0.834 (Table 4; Fig. 3). Thus, the most information-efficient signal was contained in the three-domain coagulation-inflammation-nutrition construct.

The same pattern was observed when Brier scores were considered. The lowest Brier score in the multi-index comparison was observed for CINS3 (0.0971), while CIN-z3 had a similar value (0.0971). Immune-extended indices had slightly higher Brier scores, ranging from 0.0975 to 0.0979, and FAR had a Brier score of 0.0982. These small differences are not large enough to justify overinterpretation, but they reinforce the broader conclusion that additional immune-cell components did not produce a meaningful performance gain.

The comparative ranking is central to the study's novelty. The analysis did not stop after showing that a new score was associated with ICU admission. Instead, it asked whether the score remained preferable when directly challenged by simpler, continuous, ratio-based, and immune-extended alternatives in the same patients. The finding that the three-component formulation remained at the top of the ranking argues against unnecessary biomarker expansion and supports a practical score architecture.

3.5 Internal validation

Repeated 5-fold cross-validation with 10 repeats preserved the same ranking. The mean cross-validated AUC was 0.821 for the clinical model, 0.830 for FAR, 0.835 for CINS3, and 0.836 for CIN-z3 (Table 5; Fig. 4). Immune-extended scores again failed to outperform the three-component indices.

Importantly, thresholds and standardization parameters were recalculated within each training fold before being applied to the corresponding validation fold. This approach reduces the risk that the

validation results are inflated by information leakage from the full dataset. The preservation of the same ordering in cross-validation supports the robustness of the CINS/CIN-z signal and suggests that the apparent advantage over FAR was not solely a product of overfitting in the derivation sample.

Cross-validated Brier scores were closely aligned with the AUC results. CINS3 had the lowest mean Brier score among the biomarker-augmented models (0.0981), followed by CIN-z3 (0.0981), whereas FAR had a higher mean Brier score (0.0992) and the clinical model had the highest value (0.0999). Although the absolute differences were modest, the consistent direction across discrimination and overall prediction error further supports CINS as the preferred categorical index.

3.6 CINS-augmented prediction model and risk strata

As a secondary prediction-model analysis, we fitted a CINS-augmented perioperative model incorporating age, sex, BMI, ASA physical status, procedure group, tumor site, and CINS. In this final model, each 1-point increase in CINS remained independently associated with postoperative ICU admission (odds ratio, 1.51; 95% CI, 1.38–1.66). The coefficient profile showed that CINS contributed risk information alongside established clinical predictors such as ASA physical status and age (Fig. 5; Supplementary Figure S3).

Predicted probabilities from the final model separated patients into clinically interpretable risk strata. Among patients classified as low risk (< 10% predicted risk), the observed ICU admission rate was 3.2% (89/2,759). Among intermediate-risk patients (10% to < 20%), the observed rate was 14.5% (125/865). Among high-risk patients ($\geq$ 20%), the observed rate was 40.4% (459/1,136). The distribution of predicted probabilities also showed clear separation between patients with and without postoperative ICU admission, although overlap remained, as expected for a clinical risk model. These findings support use of the CINS-augmented model for risk stratification rather than deterministic prediction.

Bootstrap optimism correction indicated limited overfitting. The optimism-corrected Somers' Dxy was 0.665, corresponding to an optimism-corrected AUC of approximately 0.833, compared with an apparent AUC of 0.837. The calibration slope was 0.975, and the maximum absolute calibration error was approximately 0.022. These findings indicate that the final model retained most of its apparent performance after internal correction.

The ordinal linearity assumption for CINS was also examined. A likelihood-ratio comparison between the ordinal-linear CINS formulation and a categorical formulation did not demonstrate a statistically meaningful improvement with categorization (likelihood-ratio $P = 0.122$). This supports retaining CINS as a simple per-point term in the final model rather than introducing additional degrees of freedom.

3.7 Subgroup audit

The association between CINS and postoperative ICU admission was directionally consistent across prespecified clinical subgroups (Fig. 6). The adjusted odds ratio per 1-point increase in CINS was 1.67 in patients undergoing gastric surgery, 1.57 in colorectal surgery, and 1.39 in hepatobiliary-pancreatic

surgery. The association was also present in patients with ASA physical status 1–2 (OR, 1.53) and in those with ASA physical status ≥ 3 (OR, 1.42). Subgroup AUCs ranged from 0.746 in the hepatobiliary-pancreatic subgroup to 0.839 in the gastric subgroup, reflecting differences in baseline heterogeneity and clinical complexity rather than reversal of the CINS effect.

3.8 Decision-impact analysis

To translate discrimination into clinically interpretable threshold-based performance, we summarized decision-impact metrics using repeated cross-validated predictions at 10%, 15%, and 20% predicted ICU-admission risk thresholds (Table 6). At the 10% threshold, the clinical model classified 1,959 patients as high risk and captured 557 ICU events. Clinical plus CINS3 classified a similar number of patients as high risk but captured 572 events, reducing missed ICU events from 103 to 88. Clinical plus CIN-z3 showed the same number of captured events while slightly improving the positive predictive value among high-risk patients.

At the 15% threshold, clinical plus CIN-z3 captured 517 ICU events compared with 504 for the clinical model, with sensitivity increasing from 76.4% to 78.3%. The number of missed ICU events decreased from 156 to 143, and positive predictive value increased from 33.1% to 34.5%. At the 20% threshold, clinical plus CINS3 classified fewer patients as high risk than the clinical model (1,146 vs 1,187) while capturing more ICU events (452 vs 436), improving positive predictive value from 36.7% to 39.4% and reducing missed ICU events from 224 to 208. These threshold-based findings support the practical value of CINS/CIN-z as risk-stratification adjuncts rather than merely statistically significant predictors.

4. Discussion

4.1 Principal findings

This study identifies a compact preoperative biomarker construct associated with postoperative ICU admission after gastrointestinal tumor surgery. CINS integrates fibrinogen, CRP, and albumin, representing coagulation activation, systemic inflammation, and nutritional reserve. The association was graded, clinically interpretable, and independent of core perioperative covariates. Patients with abnormalities in all three domains had more than threefold higher adjusted odds of postoperative ICU admission compared with patients without any abnormal domain.

Several aspects of the findings are clinically relevant. First, CINS separated postoperative ICU admission risk in a simple 0–3 format that can be understood without specialized software. Second, the association persisted after adjustment for major preoperative clinical variables, suggesting that the score captured information not fully contained in demographic or procedural risk factors. Third, CINS outperformed FAR, indicating that adding explicit CRP-defined inflammatory information to the coagulation-nutrition axis improved risk characterization. Fourth, more complex immune-extended indices did not provide additional benefit, reinforcing the value of a parsimonious biomarker set.

4.2 Relationship to previous studies

The contribution of this work is not that fibrinogen, CRP, albumin, or FAR are newly discovered markers. They are not. FAR has already been evaluated in gastrointestinal cancers, including gastric cancer and gastrointestinal stromal tumors, mainly in relation to recurrence or survival (10, 12). The more specific contribution is the development and comparative validation of a perioperative host-response score for the endpoint of postoperative ICU admission in gastrointestinal tumor surgery. This endpoint is operationally meaningful: ICU admission reflects a transition in postoperative care intensity, affects resource planning, and may identify patients whose preoperative biological vulnerability is not fully captured by standard clinical covariates.

The study also extends recent INSPIRE-based work. Prior analyses have shown that nutritional risk, represented by the geriatric nutritional risk index, and metabolic stress, represented by the stress hyperglycemia ratio, are associated with postoperative ICU admission after gastrointestinal tumor surgery (8, 9). Those studies support the broader concept that preoperative host physiology is relevant to perioperative care escalation. The present analysis builds on that concept by focusing on a different biological axis and by formally comparing multiple composite biomarker architectures(25, 26). Rather than evaluating one isolated marker, we tested whether coagulation, inflammation, and nutrition could be combined into a compact and transportable risk construct.

FAR remains an important comparator because it is simple, biologically plausible, and already familiar in gastrointestinal oncology literature(27, 28). However, FAR cannot distinguish whether risk is driven primarily by high fibrinogen, low albumin, or their combination, and it does not directly incorporate CRP. In cancer surgery, inflammatory activation may influence perioperative risk through endothelial activation, hypercoagulability, pulmonary vulnerability, infection susceptibility, catabolic stress, and impaired tissue repair. By adding CRP as a distinct component, CINS may better represent the inflammatory dimension of surgical vulnerability while preserving clinical interpretability.

4.4 Biological interpretation

Expanding the score with immune-cell indices, platelet-based inflammation measures, or additional continuous components did not improve performance. This is clinically and methodologically important(24). Composite biomarkers are often made more elaborate in the hope of appearing more comprehensive, but additional variables can increase missingness, reduce transportability, and obscure interpretation. In this analysis, the simpler three-domain construct performed as well as or better than larger alternatives, suggesting that fibrinogen, CRP, and albumin capture a coherent perioperative phenotype without requiring a heavier biomarker architecture.

The three CINS components plausibly converge on perioperative resilience. Fibrinogen rises during acute-phase activation and contributes to clot formation, blood viscosity, platelet interactions, and inflammatory signaling(6). CRP is a downstream marker of interleukin-driven systemic inflammation and may signal infection, tumor-related inflammation, tissue injury, or metabolic stress before surgery. Albumin is influenced by nutritional intake, hepatic synthesis, inflammation-mediated redistribution, vascular permeability, and catabolism(29). A patient with high fibrinogen, high CRP, and low albumin may

therefore have a combined phenotype of inflammatory activation, prothrombotic tendency, and reduced nutritional reserve. Such a phenotype could reasonably increase the likelihood of planned ICU monitoring, delayed extubation, hemodynamic instability, infectious complications, or early postoperative organ support.

The finding that immune-extended indices did not improve performance does not imply that neutrophils, lymphocytes, platelets, or SII are biologically irrelevant. Rather, it suggests that, for the endpoint and dataset studied here, their incremental information was limited once fibrinogen, CRP, albumin, and clinical variables were considered(11). This is a useful negative result. It discourages uncritical expansion of composite scores and supports the principle that biomarker models should be evaluated not only by apparent sophistication but also by incremental value, interpretability, missingness burden, and ease of implementation.

4.5 Clinical implications

The incremental gain in discrimination was consistent but modest. CINS should therefore be viewed as a risk-stratification adjunct rather than a standalone prediction model. Its pragmatic value is that it uses routine laboratory measures, produces an interpretable 0–3 score, and may help identify patients who warrant closer postoperative monitoring, deliberate ICU-bed planning, or intensified preoperative optimization.

A possible clinical use case is preoperative multidisciplinary planning. Patients with high CINS may merit anesthesiology review, explicit postoperative disposition planning, nutritional assessment, inflammatory or infectious source evaluation, and individualized discussion about postoperative monitoring intensity. Conversely, low CINS should not be interpreted as a guarantee of uncomplicated recovery; it should be integrated with procedure type, ASA physical status, frailty, and clinician judgment.

The decision curve results are relevant because a model with a modest AUC improvement may still be useful if it changes risk classification around clinically meaningful thresholds. For postoperative ICU admission, those thresholds may vary according to ICU capacity, step-down unit availability, surgical pathway, and local triage policy.

The decision-impact analysis illustrates this point. At a 20% risk threshold, adding CINS3 classified fewer patients as high risk while capturing more ICU events than the clinical model alone. This pattern is operationally interpretable: fewer high-risk flags per captured ICU event and fewer missed ICU admissions at the same threshold.

The secondary prediction-model analysis further supports this translational framing. The final model created three risk strata with observed ICU admission rates of approximately 3%, 15%, and 40%, respectively. Nevertheless, the model should remain an internally validated risk-stratification tool until external validation and local calibration confirm clinical utility in other perioperative settings.

4.6 Strengths

This study has several strengths. It used a large, publicly available perioperative database, which improves transparency and reproducibility. It focused on a clinically operational endpoint that matters to both patients and hospitals. It evaluated CINS against FAR and multiple alternative composite indices rather than presenting a single unchallenged biomarker. It examined both categorical and continuous formulations, reducing concern that results depended entirely on one thresholding strategy. Finally, it incorporated calibration, reclassification, decision curve analysis, bootstrap evaluation, and repeated cross-validation with threshold recalculation inside training folds. These analyses provide a broader assessment of model behavior than discrimination alone.

4.7 Limitations

Several limitations deserve emphasis. First, this was a retrospective database study, and causal inference is not possible. CINS should not be interpreted as proving that modifying fibrinogen, CRP, or albumin will directly reduce ICU admission risk. Second, ICU admission may reflect institutional policy, planned postoperative monitoring, surgical complexity, or true clinical deterioration; these mechanisms cannot be fully disentangled in the current dataset. Third, tumor stage, detailed frailty measures, operative complexity, neoadjuvant therapy, intraoperative events, and granular postoperative complication trajectories were not fully available. These unmeasured factors may confound the association between CINS and postoperative ICU admission. Finally, the study was conducted within a single public perioperative database, and transportability to other countries, institutions, surgical pathways, and laboratory measurement systems remains to be established.

4.8 Conclusions

A parsimonious coagulation-inflammation-nutrition score based on fibrinogen, CRP, and albumin was associated with postoperative ICU admission after gastrointestinal tumor surgery and outperformed FAR and more complex immune-extended indices. The findings support further external validation of CINS as a practical, biologically grounded adjunct to perioperative risk stratification.

Declarations

Ethics approval and consent to participate

INSPIRE is a de-identified public research dataset. The present secondary analysis used de-identified data only and did not involve direct patient contact.

Clinical trial number: not applicable.

Data availability

The analysis used the publicly available INSPIRE database [1]. Derived analytic tables and figure-ready outputs generated for this manuscript are stored in the local project directory.

Competing interests

The authors declare no competing interests.

Funding

The study was supported by National Natural Science Foundation of China (No. 82360593), Joint Project on Regional High-Incidence Diseases Research of Guangxi Natural Science Foundation (No. 2023GXNSFAA026133) and First-class discipline innovation-driven talentprogram of Guangxi Medical University.

Author contributions

FuYing Luo:: data analysis, figure preparation, manuscript drafting.

Shibo Huang: data analysis, table preparation, manuscript revision.

Lanjing Liao: clinical interpretation, manuscript revision.

Rong Zhou: clinical interpretation, manuscript revision.

Zhiyi Tan: data interpretation, manuscript revision.

ChunMiao Wang: study supervision, clinical interpretation, manuscript revision.

Tingan Wang: study conception, study supervision, manuscript revision.

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Figures

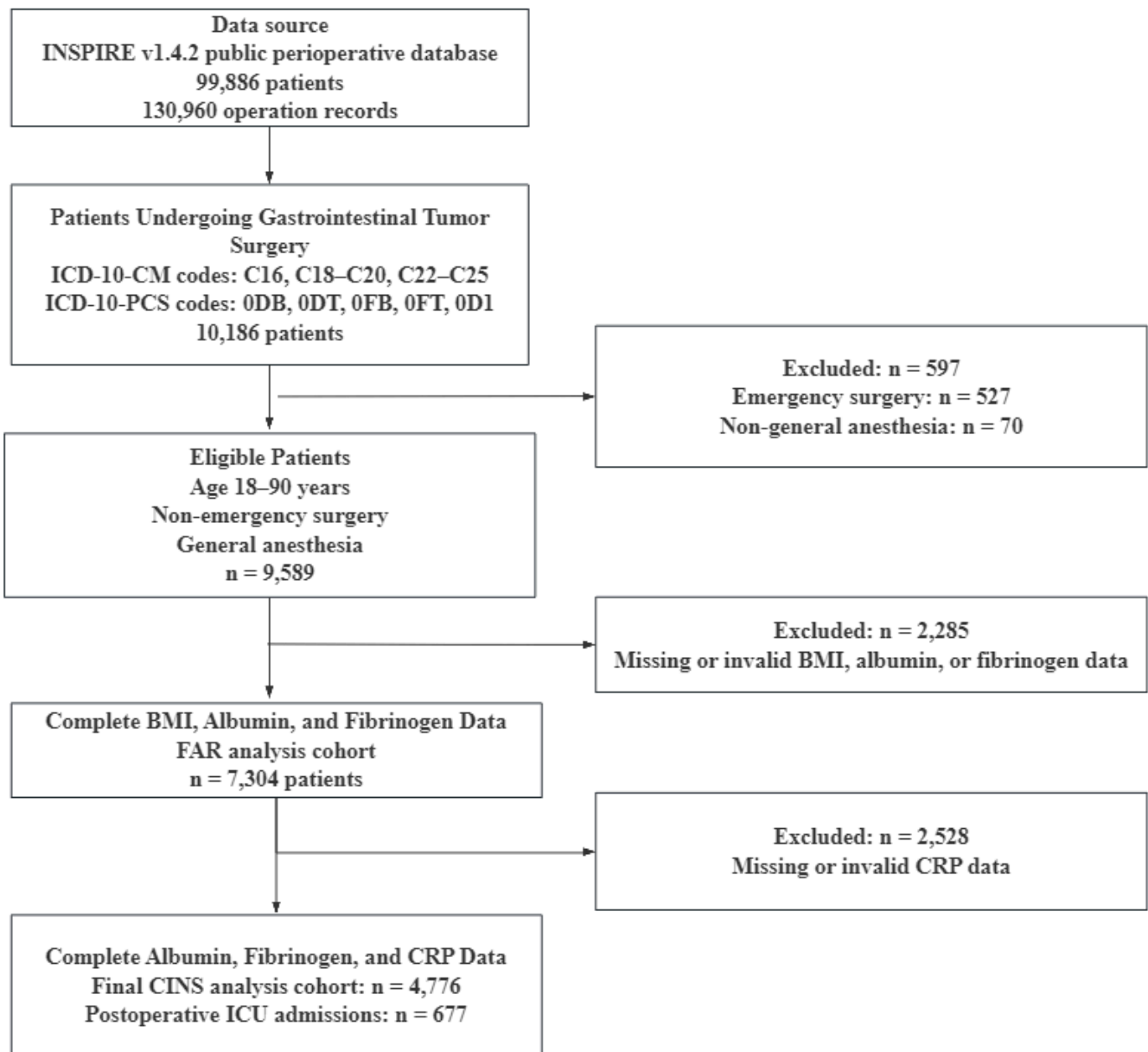


Figure 1

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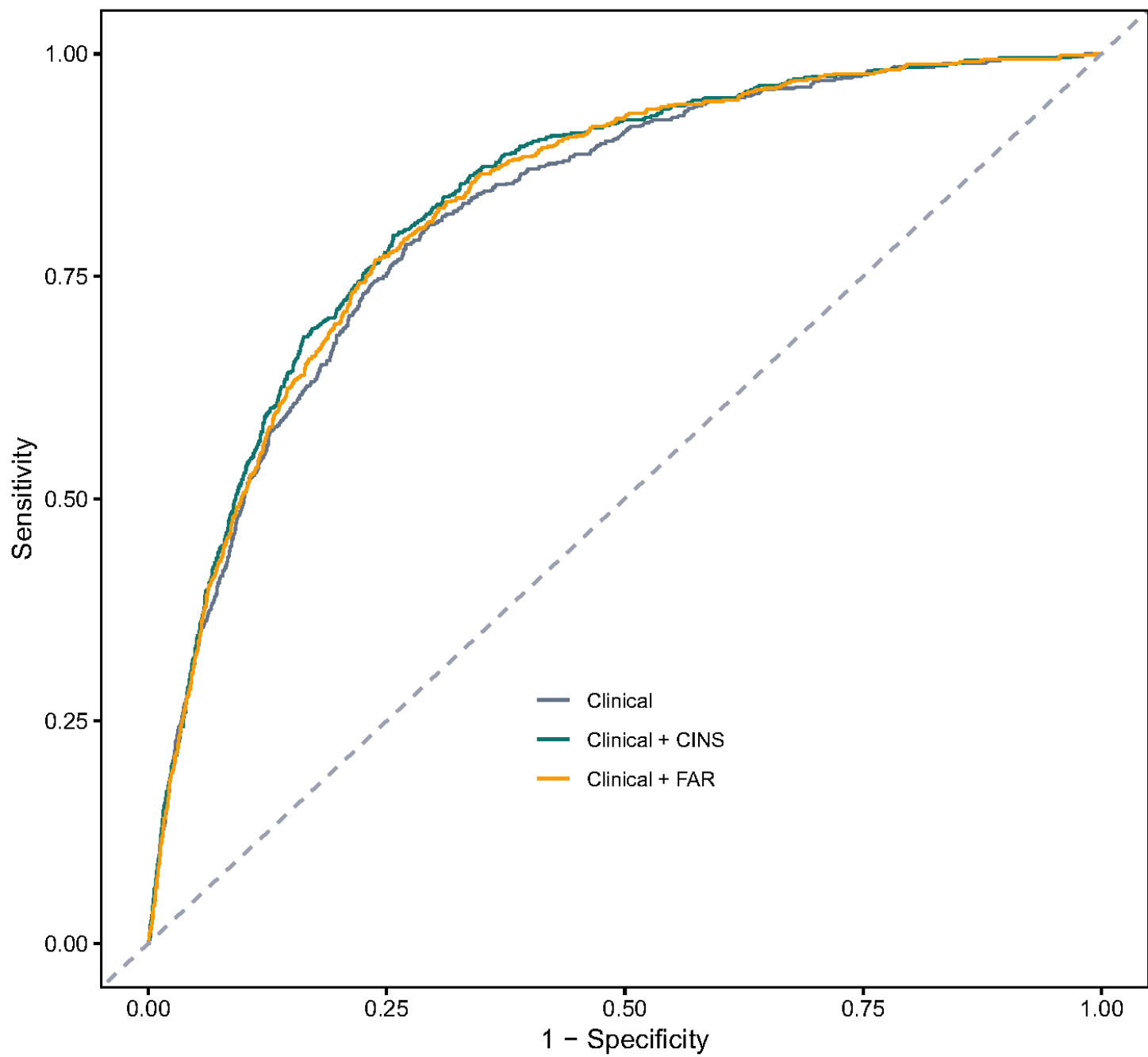


Figure 2

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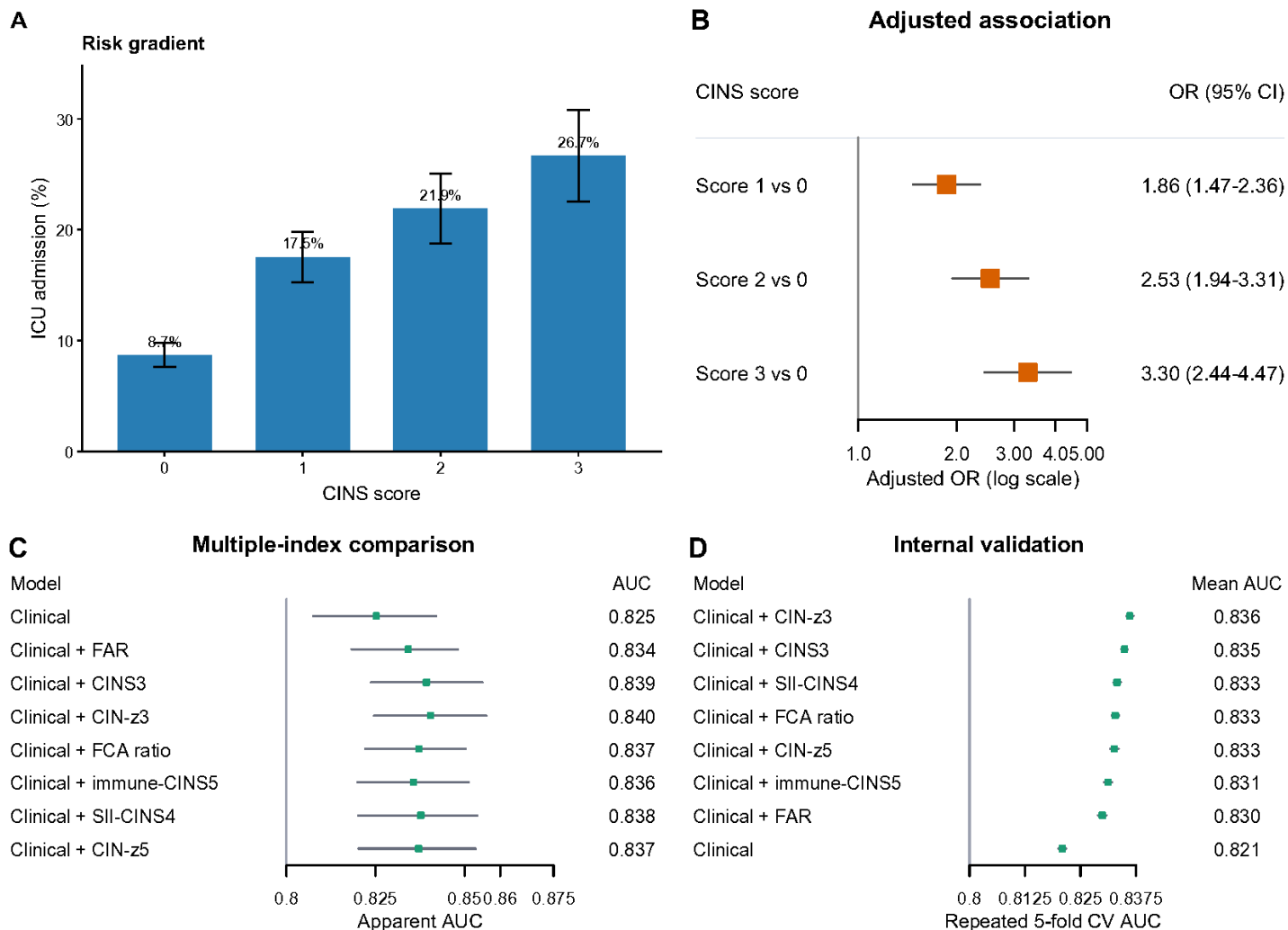


Figure 3

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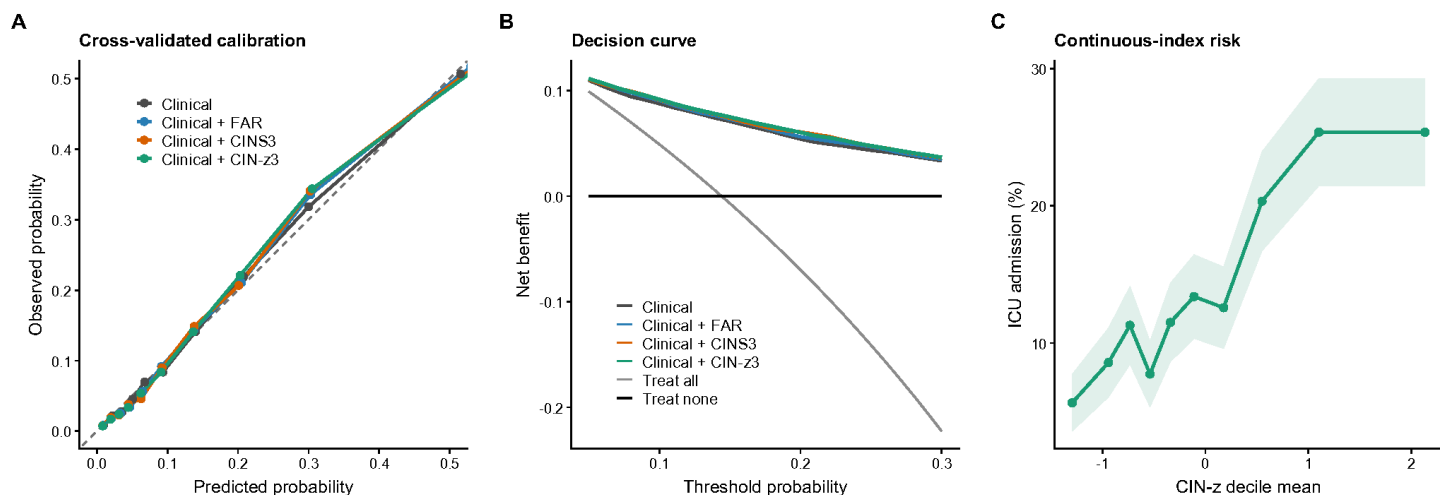


Figure 4

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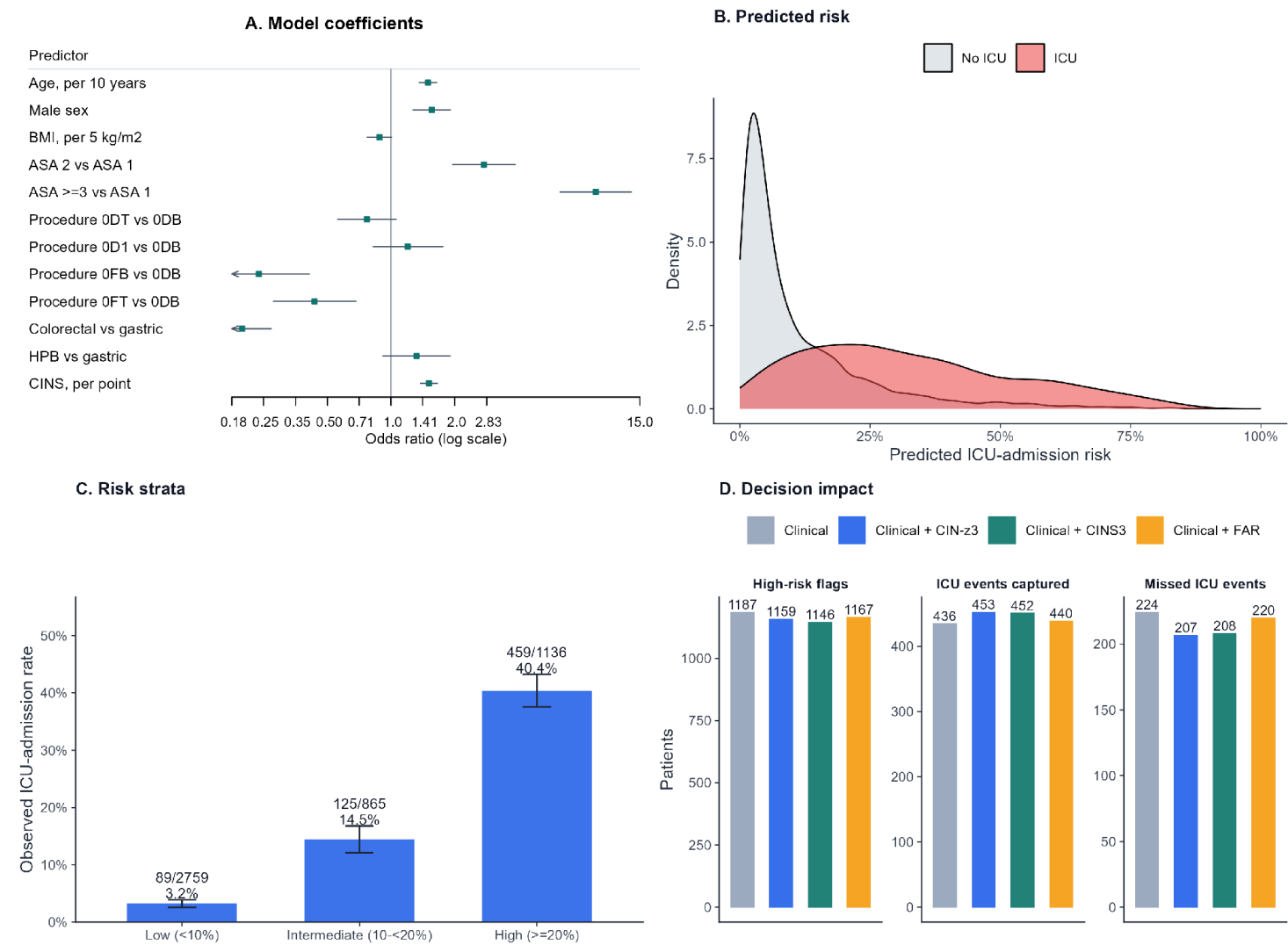


Figure 5

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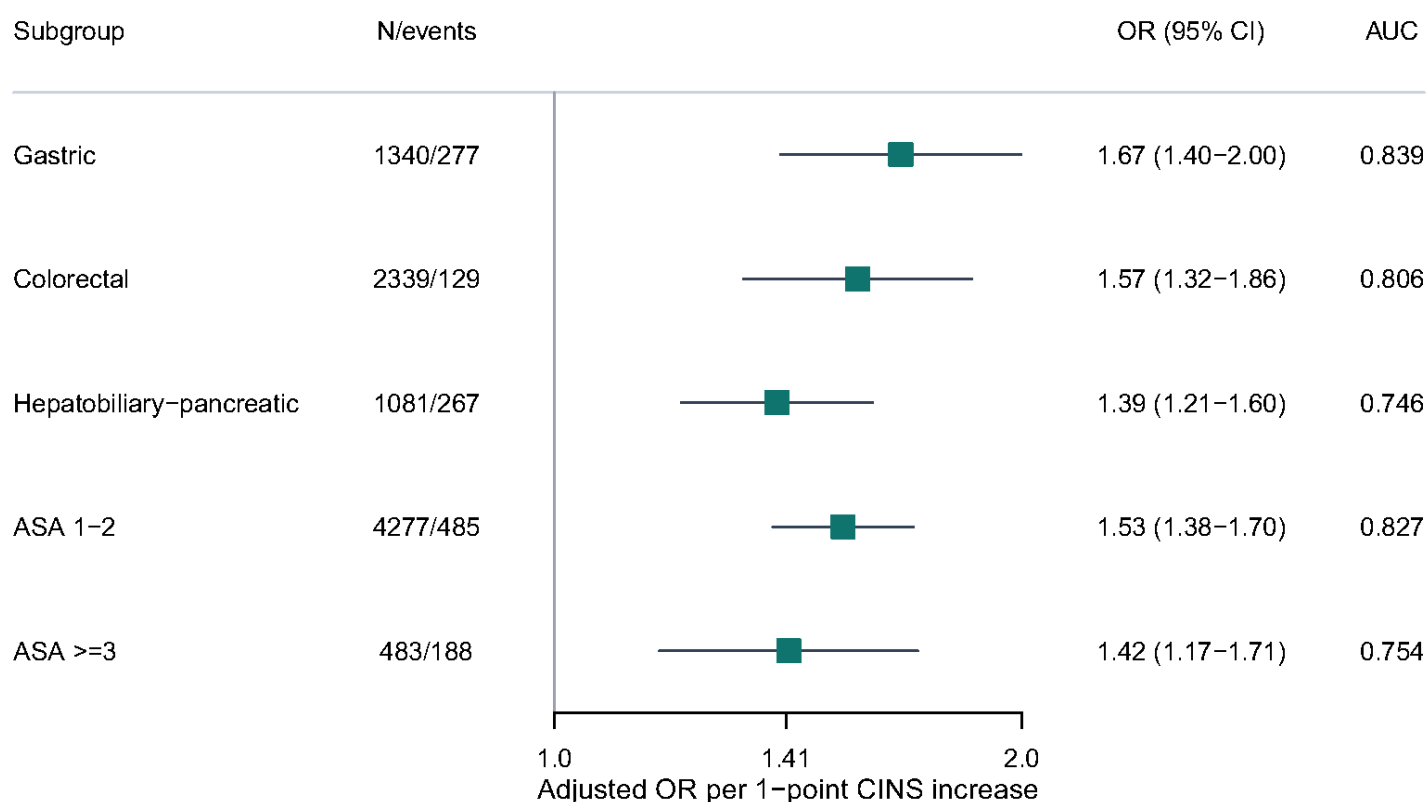


Figure 6

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