Asia Pacific Science Press

Asia Pacific Journal of Clinical Medical Research
ISSN(O):3079-8345
ISSN(P):3079-8337
Vol. 2 No.4 (2026)

Machine Learning-Based Prediction of Fear of Cancer Recurrence in Gastrointestinal Cancer Survivors: A Cross-Sectional Study

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Abstract: Aims: To explore the current status of fear of cancer recurrence (FCR) in gastrointestinal (GI) cancer survivors, and analyze its infl uencing factors based on random forest algorithms. Design: A cross-sectional study design. **Method:** A convenient sampling method was used to select GI cancer survivors who were hospitalized in a tertiary Grade A hospital in Guangdong Province from April 2024 to May 2025. Patients were surveyed using the General Information Questionnaire, Fear of Progression Questionnaire-Short Form (FoP-Q-SF), Brief Illness Perception Questionnaire (BIPQ), Herth Hope Index (HHI), Comprehensive Score for Financial Toxicity–Patient-Reported Outcome Measure (COST-PROM), and Social Support Rating Scale (SSRS). A two-stage analytical strategy was used for prediction: fi ve classifi ers (logistic regression, ridge regression, Bayesian logistic regression, support vector machine, and random forest) were compared; the optimal model was then further optimized and interpreted via variable importance ranking and partial dependence plots. **Results:** A total of 572 GI cancer survivors were recruited. The incidence of FCR (FoP-Q-SF score ≥ 34) was 75.0%. The random forest model showed better predictive performance (AUC = 0.904) than other algorithms. The top fi ve variables in order of importance were advanced cancer stage (39.79), illness perception (31.79), fi nancial toxicity (24.87), body mass index (21.19), and age (14.04). On the test set, the model achieved an AUC of 0.884, an accuracy of 0.824, a sensitivity of 0.643, and a specifi city of 0.883. **Conclusion:** The incidence of FCR is high among GI cancer survivors. Clinical nurses can identify high-risk patients early and implement eff ective nursing interventions based on the infl uencing factors of FCR in GI cancer survivors.

Keywords: Gastrointestinal Cancer; Fear of Cancer Recurrence; Random Forest Algorithm; Influencing Factors; Nursing

Published: Aug 26, 2026

DOI: https://doi.org/10.62177/apjcmr.v2i4.1631

1. Introduction

Gastrointestinal (GI) cancers, including gastric, colorectal, and esophageal malignancies, represent a signifi cant global health burden, ranking among the top fi ve for both incidence and mortality worldwide[1]. While advances in multimodal treatments, such as surgery, chemotherapy, and targeted therapies, have substantially improved survival rates[2], tumor recurrence and metastasis remain major unresolved challenges in modern medicine. Studies indicate that even among GI cancer survivors with no detectable tumor cells after first-line treatment, the recurrence rates remain as high as 35%[3]. GI treatments and their side eff ects have caused numerous adverse eff ects on patients' physical and mental health. Patients with GI undergoing

chemotherapy are experience a moderate to severe symptom burden[4], Previous traumatic experiences and uncertainty about cancer recurrence have made Fear of Cancer Recurrence (FCR) one of the most prominent psychological distresses in GI cancer survivors[5]. FCR defined as fear or worry about cancer potentially recurring at the original site or metastasizing to other body parts, can emerge immediately after diagnosis and persist for years[6]. Approximately 38-97% of cancer patients experience varying degrees of FCR, with even long-term survivors beyond five years post-treatment reporting low to moderate levels of FCR[7].

FCR is a normal psychological response to stress in patients. Appropriate fear of recurrence can heighten vigilance against cancer recurrence or metastasis, prompting patients to undergo timely examinations for early detection of recurrence, which facilitates early intervention[8]. However, high levels of fear of recurrence may intensify patients' uncertainty about their illness and future, increase perceived symptom burden, and negatively impact social functioning, future work and life planning, well-being, and quality of life[9]. Concurrently, patients with elevated FCR are more prone to negative behavioral changes (such as avoidance of monitoring, medication refusal, cancellation or postponement of follow-up examinations) or excessive healthcare utilization (including increased unscheduled medical visits, medication overuse, requests for clinically unnecessary tests, or refusing discharge)[10]. These behaviors thereby escalate national healthcare costs and household economic burdens[11].

More and more literature has pointed out demographic and clinical factors related to FCR, such as younger age and advanced cancer. However, FCR is now generally recognized as a multi-factor construct affected by the interaction of complex clinical, psychological, and social factors[12], and recent studies have increasingly highlighted the role of modifiable psychosocial factors. According to Leventhal's self-regulation common sense model, individuals form cognitive representations of their illness, and these cognitive appraisals directly influence emotional responses such as FCR. Among cancer patient populations, negative illness perceptions have been consistently positively associated with higher FCR. In the groups of cancer patients, negative disease perception has always been positively correlated with a higher FCR[13-14]. The stress-buffering model proposes that social support can protect individuals from the adverse effects of stressful events[15], and lower perceived social support is linked to higher levels of FCR[16]. As a future-oriented positive psychological resource, hope can mitigate the negative impacts of cancer treatment by fostering adaptability and goal-directed thinking[17]. In recent years, the economic burden associated with cancer treatment, including objective and subjective financial pressure, has been regarded as an important source of stress. In addition to its material impact, this financial toxicity may also exacerbate negative emotions related to cancer treatment[18].

Currently, most existing research focuses on patient populations with breast, liver, or lung cancer, whereas relatively few studies have specifically explored the interactions among multiple complex factors underlying FCR among GI cancer survivors[19]. Meanwhile, given the multifactorial nature of FCR, which likely involves nonlinear relationships and interactions among predictive factors, traditional regression approaches may be insufficient for identifying high-risk individuals. machine learning algorithms such as random forests represent a powerful alternative by handling high-dimensional data, capturing complex patterns, and providing clinically interpretable rankings of predictor importance[20].

The objectives of the present study were as follows: (i) Investigating the status of FCR among GI cancer survivors; (ii) Employ a two-stage analytical approach to compare the performance of five machine learning algorithms in predicting FCR status, optimize the best-performing model, and identify and interpret the key predictors of FCR in this population, thereby providing actionable insights for personalized psycho-oncological care.

2. Materials and Methods

2.1 Study Design and Participants

A cross-sectional relational design was used in this study. The study was conducted between April 2024 and May 2025 in the gastrointestinal departments of one Grade III-A hospital in the Guangdong Province. We used convenience sampling and guaranteed patient confidentiality and the right to withdraw from the study at any time. The inclusion criteria were as follows: (1) diagnosed with gastrointestinal tumors in clinicopathological imaging and hospitalized for cancer treatment; (2) aged 18–80 years; (3) presence of clear consciousness and ability to complete the questionnaire and (4) ability to provide signed

informed consent. The exclusion criteria were as follows: (1) presence of tumor recurrence or distant metastasis; (2) Presence of severe hearing impairment and inability to communicate; (3) inability to complete the questionnaire owing to mental-health-related reasons (such as cognitive impairment or dementia) and (4) presence of concomitant severe systemic diseases, such as the heart, lungs or renal failure.

2.2 Sample Size Determination

G*power V.3.1 software was utilized to calculate the sample size[21]. With a significance level (α) of 0.05, a power (1-ß) of 95%, a medium effect size of 0.10, and 18 predictors, the sample size was determined to be 311. Considering a potential invalid questionnaire rate of 20%, we further adjusted the sample size to 374. The final sample size included was 572. Additionally, we conducted post-hoc power verification using G*Power, the results showed that the power of the final sample was 99.97%, which indicates a robust statistical power of the test.

2.3 Ethical Considerations

This study strictly followed the guidelines of the Declaration of Helsinki and was approved by the Ethics Committee of the first affiliated hospital of Sun Yat-sen University (Ethics Review Approval Number: 2024829). Written informed consent was obtained from all participants before the study was conducted.

2.4 Instrumentation

2.4.1 General Information Questionnaire

Researcher designed a general information form include demographic and clinical variables such as sex, age, educational level, marital status, geographic area, living condition (living alone or with family members), household income per capita (RMB/month), insurance type. Four items were used to investigate disease-related features, including tumor type, tumor stage, time of diagnosis (month) and medical history.

2.4.2 Fear of Progression Questionnaire-Short Form (FoP-Q-SF)

FoP was measured using the Chinese version of the FoP-Q-SF, Herschbach[22] developed the Fear of Progression Questionnaire (FoP-Q) and Mehnert et al[23] developed a short form of the questionnaire (FoP-Q-SF), This short-form questionnaire was translated into Chinese by Wu et al[24]. The questionnaire includes a total of 12 items in two dimensions, the physiological dimension (6 items) and social dimension (6 items), based on a 5-point Likert scale (1＝never, 5＝very often), for a total score ranging from 12 to 60. with a total score of >20 indicating mild fear, a total score of >32 indicating moderate fear, and a total score of >39 indicating severe fear. The total Cronbach's alpha for the Chinese version of the FoP-Q-SF was 0.922[25]. In this study, the Cronbach's alpha was 0.905.

2.4.3 Brief Illness Perception Questionnaire (BIPQ)

The BIPQ is a standardized instrument designed to quantify patients' cognitive and emotional representations of their illness[26]. The scale comprises 9 items, with 5 items assessing cognitive illness representations, 2 items evaluating emotional representations, 1 item measuring illness comprehensibility, and 1 open-ended question that prompts patients to list the three most salient perceived causes of their condition. Total scores range from 0 to 80, with higher scores reflecting a more threatening or negative illness perception. In 2015, it was sinicized and used by Ya[27]. In this present study, the Cronbach's alpha of total scale was 0.837.

2.4.4 Herth Hope Index (HHI)

Hope was measured using the Chinese version of the HHI[28]. This instrument includes 12 items in three dimensions: inner sense of temporality and future, inner positive readiness and expectancy, and inter-connectedness with self and others. Each item on the HHI is scored on a scale from 1 to 4(1=strong disagree, 2=disagree, 3=agree, 4=strong agree), a total score range from 12 to 48. A score of 12-23 indicates a low level of hope, 24-35 a moderate level of hope, and 36-48 indicates a high level of hope. The Chinese version of the HHI has been widely used in cancer patients with good reliability and validity[17]. In this present study, the Cronbach's alpha of total scale was 0.898.

2.4.5 Comprehensive Scores for Financial Toxicity Based on the Patient-Reported Outcome Measures (COST-PROM)

Financial toxicity was measured by COST-PROM, which was constructed by Souza[29] and translated into Chinese by Yu[30].

The purpose of this instrument was to assess the subjective and objective financial and job-related stress perceived by cancer patients. The scale consists of 11 items and 3 dimensions (financial expenditure, financial resources, and psycho-social responses). A 5-point Likert scale ranging from 0 (not at all) to 4 (very) was used, with a total possible score ranging from 0 to 44; The lower the total score, the more severe the financial toxicity. The scale has been verified by multiple studies to have high reliability and validity[30]. In this present study, the Cronbach's alpha of total scale was 0.908.

2.4.6 Social Support Rating Scale (SSRS)

Social support was measured by SSRS, The scale was developed by Chinese expert Xiao and consists of 3 dimensions with a total of 10 items: objective support, subjective support, and utilization of support. The total SSRS score rang from 12 to 66. ≤22 indicate a low level of social support, 23–44 a moderate level of social support, 45–66 indicate a high level of social support, A higher score indicates a greater level of social support. In this present study, the Cronbach's alpha of total scale was 0.892.

2.5 Data Collection

Study recruitment information was posted by the research staff at the time of admission. The investigators screened inpatients with gastrointestinal cancer patients who met the eligibility requirements in person on the hospital ward from April 2024 to May 2025. Before the formal survey, we fully explained the purpose and content of the study to patients again and then distributed questionnaires. The data collection method was a combination of electronic medical record review and a paper questionnaire survey. Approximately 15-20 min were required to complete the questionnaire. After completing the questionnaire, the investigators checked the quality of the questionnaire promptly, asked patients about missing or unclear items, and corrected and completed the information to ensure the quality of the questionnaire. We made sure to avoid any inductive language during questioning.

2.6 Data Analysis

2.6.1 Data Preprocessing and Separation Handling

Categorical variables were converted to factors; continuous variables retained as numeric. FCR was recoded as binary (1 = fear present, 0 = absent). Complete case analysis was used for missing data. Contingency tables revealed complete separation: all stage I patients were FCR-negative, and one level of time after diagnosis contained a single observation. To address data sparsity and complete separation, two variables were recoded based on clinical relevance and frequency distribution. Cancer staging was dichotomized into early (stage I-II) and advanced (stage III-IV) according to standard clinical criteria. Time after diagnosis was recoded by merging the sparse category '≥25 months' (n=1) with the adjacent category '13-24 months' to ensure stable model estimation.

2.6.2 Multi-model Comparison and Algorithm Selection

Five classifiers were systematically compared: standard logistic regression, ridge regression, Bayesian logistic regression, random forest, and SVM. All models were trained and tested on the same dataset, with performance assessed by accuracy, sensitivity, specificity, AUC, and F1 score. Based on 10-fold cross-validation and independent test set validation, random forest and support vector machine achieved identical performance in accuracy, sensitivity, specificity, PPV, NPV, and F1 score, with random forest showing a slightly higher AUC (0.904 vs. 0.859). Given its superior discriminative ability and built-in variable importance ranking, random forest was selected for subsequent in-depth analysis.

2.6.3 Random Forest Optimization and Interpretation

Building on these results, we focused on in-depth random forest modeling. Feature selection: An initial random forest (ntree = 300) was fitted to assess variable importance via mean decrease in Gini. Variables with importance exceeding the overall mean were retained. Hyperparameter tuning: An adaptive cross-validation strategy was applied to tune mtry based on class distribution. The final model was trained with ntree = 500 and optimal mtry. Interpretation: Partial dependence plots were generated for core predictors to visualize marginal effects on FCR probability.

2.6.4 Two-stage Analytical Strategy

A two-stage strategy was employed: Phase 1 horizontally compared multiple models to select the optimal algorithm; Phase 2 vertically optimized and interpreted the selected model. This framework ensured both objective model selection and robust

interpretability.

2.6.5 Software Implementation

Statistical analysis were conducted using SPSS 29.0 and R 4.2.2 software. The normal distribution of numeric variables was tested by the Shapiro–Wilk test. Continuous variables with a normal distribution were described using the mean±standard deviation (SD) and compared using the independent-sample t-test. Continuous variables with non-normal distribution were described using the median (IQR) and compared using Mann–Whitney U test. Categorical data were expressed as number (%) and analyzed using the chi-square test or Fisher's exact probability test. All analyses were performed in R 4.2.1 using key packages: randomForest, glmnet, arm, e1071, caret, pROC, pdp, ggplot2, and reshape2. The full code is available for reproducibility.

3. Results

3.1 General Demographic Characteristics of Patients

In this survey, 581 questionnaires were distributed, and 581 were recovered. After eliminating invalid questionnaires, A total of 572 patients were enrolled in this study, for a 98.45% effective recovery rate. Based on the FoP-Q-SF score, patients with a score of ≥ 34 were classified into the FCR group, while those with a score of < 34 were classified into the normal group. A total of 429 cases (75.0%) of gastrointestinal tumor patients developed FCR, and 143 cases (25.0%) did not. After univariate analysis, seventeen characteristics were retained for subsequent Lasso analysis. The demographic characteristics of all enrolled patients are shown in Table 1.

Table 1 Characteristics of the participants (N = 572)

Variables	FCR(N=429) FoP-Q-SF ≥ 34	normal(N=143)	X2/Z	P
Gender				
Male	241	95	4.655	0.031
Female	188	48		
Age [Years old, M (P25, P75)]	64 (57, 71)	60 (53, 69)	-2.789	0.005
BMI	23.10 (21.60, 24.50)	22.26 (20.30, 22.33)	-2.522	0.012
Educational level				
Primary school or below	124	41	31.428	<0.001
High school	126	12		
Senior high/Technical secondary school	101	47		
Junior college/Bachelor's	66	39		
Postgraduate degree or above	12	4		
Marital status				
Married/Cohabiting partner	9	5	3.748	0.290
Unmarried	376	130		
Divorced/Separated	21	3		
Windowed	23	5		
Residence				
Town	297	121	12.902	<0.001
Rural	132	22		
Living arrangements				
Living alone	25	4	12.144	0.016
Living with spouse	192	45		

Variables	FCR(N=429) FoP-Q-SF ≥ 34	normal(N=143)	X2/Z	P
Living with children	20	9		
Living with spouse and children	180	81		
Other	12	4		
Monthly income(yuan)				
<1000	62	1	34.275	<0.001
1000 ≤ Income<3000	36	1		
3000≤ Income<5000	250	108		
≥ 5000	81	33		
Medical insurance				
New rural cooperative	54	5	37.890	<0.001
Resident Medical Insurance	239	107		
Employee Medical Insurance	127	19		
Provincial/municipal	1	1		
Self-paying	8	11		
Free of charge	0	0		
Other	0	0		
Disease diagnosis				
Gastric cancer	164	45	9.076	0.011
Colon cancer	147	69		
Rectal cancer	118	29		
Time after diagnosis				
≤6 months	199	47	572.000	<0.001
7–12 months	106	46		
13–24 months	124	49		
≥ 25 months	0	1		
cancer staging				
I	1	30	248.400	<0.001
II	14	53		
III	214	55		
IV	200	5		
chemotherapy plan				
Yes	293	68	19.827	<0.001
No	136	75		
Lymph node metastasis				
Yes	373	57	127.415	<0.001
No	56	86		
BIPQ [Score, M (P25, P75)]	60 (59, 62)	44 (28, 62)	-6.563	<0.001
SSRS [Score, M (P25, P75)]	37 (34, 40)	40 (37, 42)	-4.103	<0.001
HHI [Score, M (P25, P75)]	37 (35, 40)	41 (36, 44)	-4.457	<0.001
COST-PROM [Score, M (P25, P75)]	28 (23, 32)	26 (23, 28)	-4.252	<0.001

3.2 Multi-model Performance Comparison

To identify the optimal prediction algorithm, we compared the predictive performance of five classification models on the test set. As shown in Table 2 and Figure 1, all five prediction models demonstrated good discriminatory performance on the test set (all AUCs > 0.80). Random forest and support vector machine achieved identical performance in accuracy, sensitivity, specificity, positive predictive value, negative predictive value, and F1 score, with random forest showing a slightly higher AUC (0.904 vs. 0.859) (Table 3). Given that random forest provides variable importance ranking, which facilitates the identification of key predictors of FCR and enhances clinical interpretability, it was selected as the core algorithm for subsequent in-depth modeling and interpretation (Table 4).

Table 2 A comparison of the performance of five prediction models on the test set

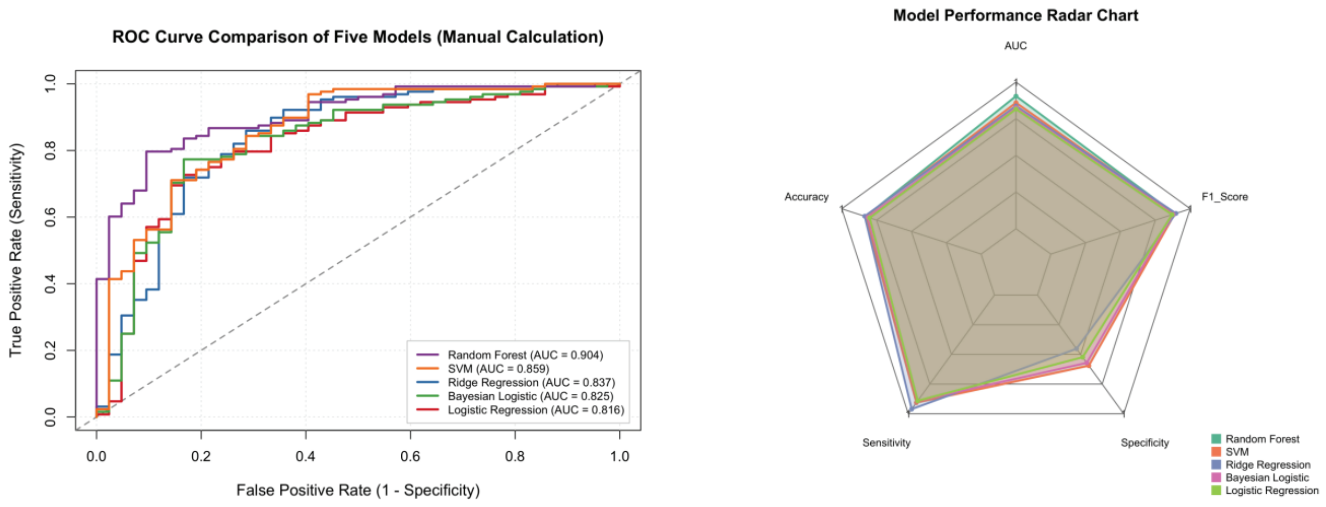
Model	AUC	Accuracy	Sensitivity	Specificity	PPV	NPV	F1 score
Random Forest	0.904	0.829	0.906	0.595	0.872	0.676	0.889
SVM	0.859	0.829	0.906	0.595	0.872	0.676	0.889
Ridge Regression	0.837	0.835	0.961	0.452	0.843	0.792	0.898
Bayesian Logistic	0.825	0.812	0.891	0.571	0.864	0.632	0.877
Logistic Regression	0.816	0.8	0.891	0.524	0.851	0.611	0.87

Table 3 The performance of the random forest model in the training set and the test set

Data set	AUC	Accuracy	Sensitivity	Specificity	Kappa
training set	0.921	0.856	0.712	0.908	0.624
test set	0.884	0.824	0.643	0.883	0.529

Table 4 The important variables selected by the random forest model (the top 5)

Data set	Variables	Importance (Decrease in Gini Coefficient)	Variable type
1	cancer staging	39.791	Classification
2	BIPQ	31.787	Consecutive
3	COST PROM	24.866	Consecutive
4	BMI	21.187	Consecutive
5	Age	14.039	Consecutive



(A) *(B)*

Figure 1: Comparison between different methods based on ROC curves and Radar chart

(A) Receiver Operating Characteristic (ROC) Curves for Five Predictive Models

(B) The Radar chart of the AUC, Accuracy, Sensitivity, Specificity and F1 score of Five Predictive Models

3.3 Random Forest Algorithm-Based Prediction Model

Variable importance was assessed using the mean decrease in Gini impurity from a random forest model. Five variables with importance exceeding the overall mean were retained for subsequent modeling, including dichotomized cancer staging, BIPQ, COST-PROM, BMI, and age. A random forest model was developed using the six selected features and evaluated on an independent test set. The model achieved an AUC of 0.884, with an accuracy of 0.824, sensitivity of 0.643, and specificity of 0.883. A comparison of training and test set performance metrics is presented in Figure 2, and the ROC curve is shown in Figure 3. Variable importance derived from the random forest model (based on mean decrease in Gini impurity) revealed that dichotomized cancer staging was the most important predictor(importance = 39.791), followed by BIPQ (31.787), COST-PROM (24.866), BMI (21.187), and age (14.039). The ranking of the top five important variables is illustrated in Figure 4, and the marginal effects of the top three core predictor variables (cancer stage, BIPQ, COST-PROM) on the probability of FCR occurrence were visualized through partial dependence plots (Figure 5), Results showed that patients with advanced cancer had a substantially higher predicted probability of FCR (0.83) than those with early-stage cancer (0.29). BIPQ score was positively associated with FCR probability, with a sharp increase observed when BIPQ exceeded 52. COST-PROM score showed a strong negative association with FCR probability in the range of 20-30, indicating that greater financial toxicity (lower COST-PROM score) was associated with increased FCR risk.

Figure 2: A comparison of training and test set performance metrics

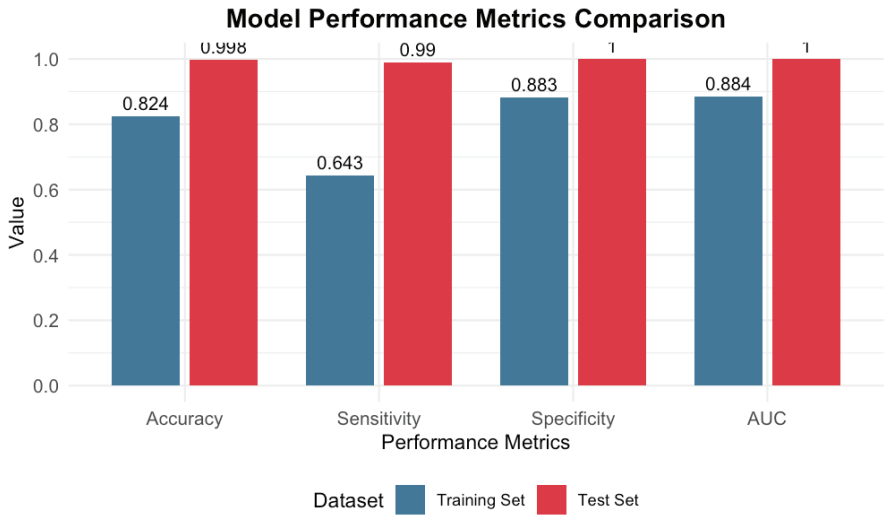


Figure 3: ROC curve of training set and test set

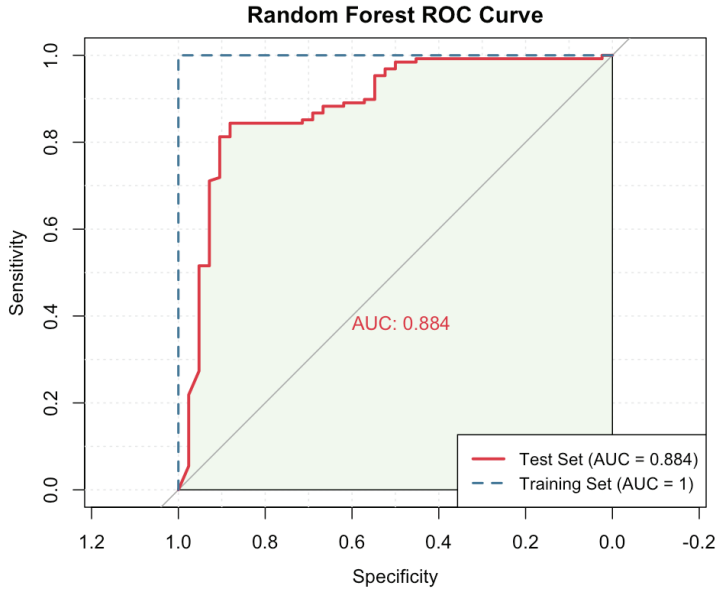


Figure 4: The ranking of the top five important variables

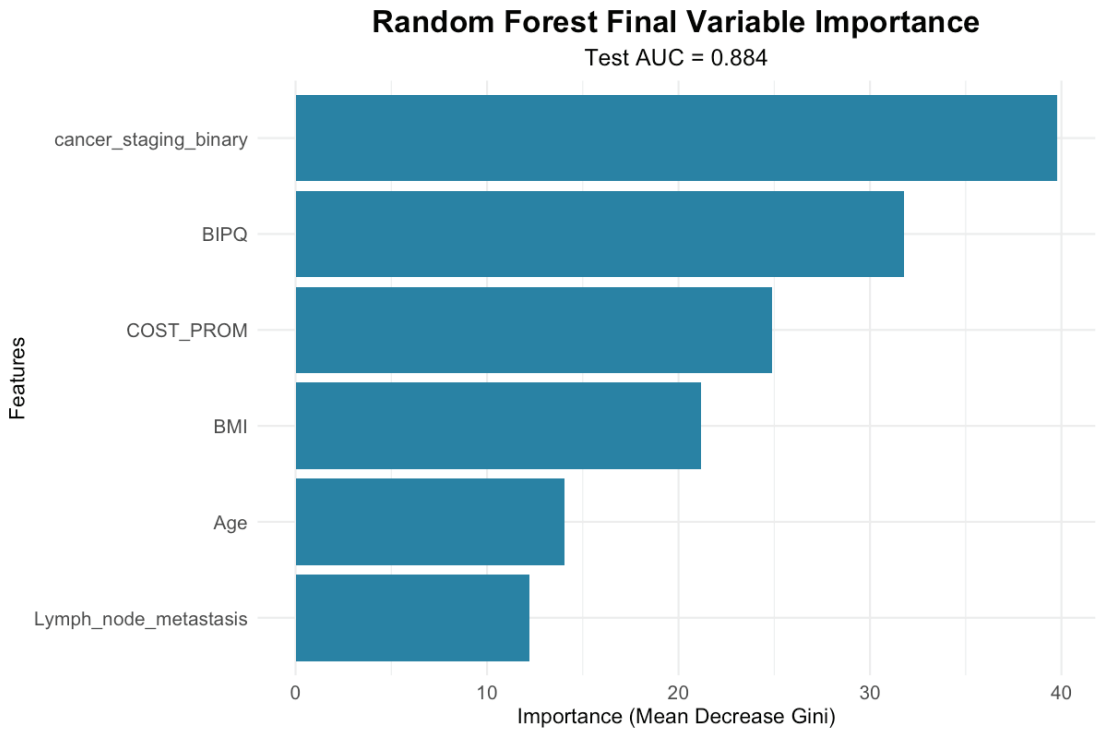
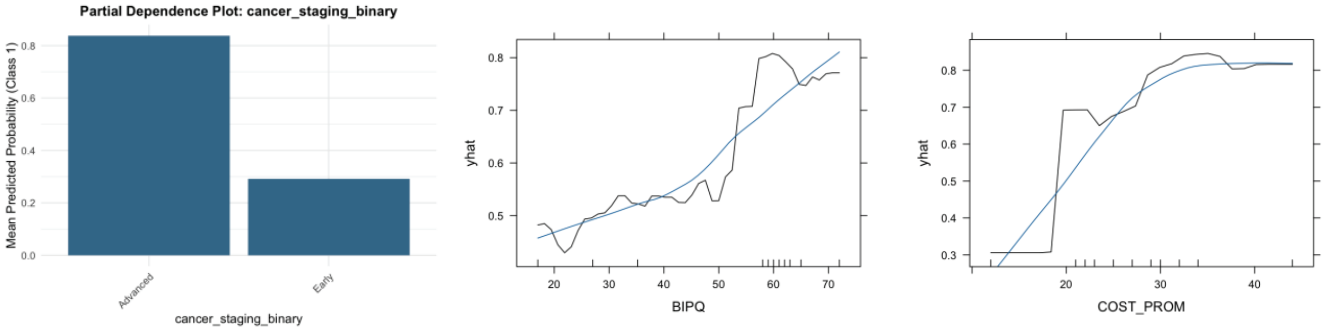


Figure 5. Partial dependence plots for the top three predictors.

(A) *(B)* *(C)*



(A) Cancer staging (binary): predicted probability of FCR by disease stage

(B) BIPQ: predicted probability of FCR across the range of BIPQ scores (solid line: mean prediction; dashed lines: ±1 standard deviation)

(C) COST-PROM: predicted probability of FCR across the range of COST-PROM scores (solid line: mean prediction; dashed lines: ±1 standard deviation)

4. Discussion

4.1 Principal Findings

The results indicate that 75.0% of GI cancer survivors experience FCR, a prevalence higher than the 58.9% reported by Luo et al.[31]. This difference may be attributed to different measuring instruments, different types of GI cancer covered, or the unique socio-cultural background of the study sample. In addition, we compared the predictive performance of five classification models on the test set. The results demonstrate that in the group of GI cancer survivors, the random forest algorithm showed better predictive performance in predicting the FCR. This indicates that the combination of clinical factors (cancer staging, BMI), psychosocial factors (illness perception, financial toxicity) and age can more effectively predict high-risk patients. Although the optimized model shows excellent distinguishing ability (AUC = 0.884) and high specificity (0.883), the same degree of sensitivity (0.643) still needs to be interpreted carefully. This finding shows that although the model

performs well in accurately excluding high-risk individuals, it may have missed a significant number of patients who actually present with FCR symptoms. Therefore, in terms of the current form, the model is more suitable as an auxiliary tool for comprehensive clinical evaluation than an independent screening tool.

4.2 Clinical and Psychosocial Predictors of FCR

The results show that advanced cancer staging is the most powerful predictor of FCR, which is consistent with the previous research results[32-33]. Several mechanisms may account for that: Firstly, advanced-stage disease is frequently accompanied by more severe physical symptoms, including pain, cachexia and fatigue, persistent physical symptoms may constantly remind the patient of his own condition, thus triggering disturbing thoughts about the cancer progression or recurrence[34-35]. Secondly, patients with advanced cancer face a poorer and more uncertain prognosis. Their subjective estimate of the risk of recurrence is often inflated, which may foster catastrophic thinking patterns and intense future-oriented anxiety[36]. Finally, advanced stage cancer usually requires more aggressive and continuous treatment, which may exacerbate patients' suffering and further highlight the severity of the disease. The interaction of these factors may be affected through a cognitive-emotional chain reaction mechanism, that is, physical sensations will be mistakenly interpreted as signs of disease recurrence, leading to a continuous cycle of hypervigilance and fear[37].

The results show that BIPQ is the second most influencing factor of FCR. Even patients in the early stage may have FCR symptoms if they have negative disease cognition, which shows that subjective evaluation can prevail over the objective clinical reality. This model is strongly supported by a large amount of evidence recently. Xu[13] found that there is a significant correlation between illness perception and FCR in patients with colorectal cancer. Liu[38] demonstrated that in bladder cancer patients, illness perception not only has a direct impact on FCR but also has an indirect impact through dyadic coping, of which the intermediary pathway accounts for 59.6% of the total effect. These findings are consistent with the cognitive behavior model, which believes that poor disease cognition will drive FCR[39], leading to excessive vigilance about physical sensations and catastrophic misunderstandings of normal symptoms[37]. For individuals with negative disease cognition, cognitive behavioral interventions, such as "fear-facing" techniques, have been proven to significantly and sustainably reduce FCR[40].

Financial toxicity includes not only objective economic losses but also the consequences of psychological stress, income interruption and impaired work ability caused by cancer and its treatment[18]. For GI cancer survivors, the FCR and fear of potential economic consequences are closely associated, including additional treatment costs, long-term loss of economic income, and the burden on the family. Such concerns may further exacerbate FCR. Recent dyadic research provides strong empirical support for this pathway. In a study of 196 young breast cancer patients and their family caregivers,Yang[41] found a significant correlation between financial toxicity and FCR in both patients and caregivers. notably, the financial toxicity reported by family caregivers also exerted a significant impact on patients' FCR, which shows the interpersonal chain effect of economic pressure. Furthermore, financial toxicity has been associated with specific FCR domains, Manne[42] reported that among oral and oropharyngeal cancer survivors, lower income was associated with more role and identity worries, and financial hardship was associated with more role-related fears. A systematic review confirmed that financial toxicity causes significant psychological distress and maladaptive coping strategies, requiring multilevel, coordinated efforts among stakeholders[43]. For those experiencing financial toxicity, referral to financial navigation services, social work support, and employment counseling may alleviate the economic fears that amplify recurrence-related anxiety.

4.3 The Intriguing Roles of BMI and Age

In our study, patients with higher BMI were more likely to report FCR. This association may be explained through several interconnected mechanisms. Firstly, obesity is an established risk factor for cancer development and recurrence across multiple malignancies. A meta-analysis encompassing over 6.3 million participants demonstrated that obesity was significantly associated with an increased risk of recurrence[44]. Patients may be aware of this epidemiological link, leading to heightened anxiety about their weight as a modifiable risk factor for recurrence. Secondly, overweight or obese patients may face a more severe burden of physical symptoms and functional limitations[45]. Heightened vigilance to physical sensations may cause individuals to misjudge obesity-related discomfort as signs of possible recurrence[46]. Thirdly, some cancer

treatments may lead to weight gain, and this treatment-related weight change may itself be a reminder of the disease and its potential recurrence. Therefore, BMI should be regarded as an indicator of many potential mechanisms, including metabolic factors, inflammatory processes, body image disorders, and health-related behaviors. In the future, longitudinal designs and objective body composition measurement methods should be adopted to further explore the relationships among these mechanisms.

Young age is another important predictor of FCR, which is consistent with the view of a large number of literature[47-48]. Younger cancer survivors face several unique challenges, such as concerns about fertility, career interruptions, childcare responsibilities, and unfulfilled life goals. Being diagnosed with cancer at a younger age will bring a stronger sense of life disruption and fear of future uncertainty, thus exacerbating concerns about cancer recurrence. These findings underscore the necessity of psychosocial support to reduce FCR among younger cancer survivors. Interventions should include parenting, career planning, fertility preservation, and peer support from other young people facing similar challenges.

5. Limitations

Several limitations of this study must be acknowledged. Firstly, this study adopted a cross-sectional design, and causal inference cannot be made. In the future, longitudinal research is needed to confirm whether these factors can predict FCR. Secondly, this study only selected samples from a single tertiary hospital in Guangdong Province, which limits the generalizability of the research results. Future research should verify these findings in groups of GI cancer survivors in other regions of China. Thirdly, to address the statistical issue of complete separation, we categorized the stage of cancer into early (stage I - II) and advanced (stage III - IV). This may obscure the difference in FCR between patients with stage III and stage IV disease, as these two groups of patients have different prognoses and treatment pathways. Future studies should use larger and more diverse samples and adopt finer cancer staging levels to assess the rates of complete remission to capture these potential differences.Finally, our model has not been externally validated. Although the internal verification through the division of training sets and test sets and cross-verification is reliable, the performance of the model still needs to be tested on independent datasets from other institutions and populations to ensure its universal applicability. Future research should focus on external verification of our model in larger-scale, multi-center, forward-looking cohorts.

Conclusion

This study shows that the incidence of FCR is high among GI cancer survivors. The top five variables in order of importance were advanced cancer stage, illness perception, financial toxicity, BMI , and age. Clinical nurses can identify high-risk patients early and implement effective nursing interventions based on the influencing factors of FCR in GI cancer survivors. Future research should focus on external validation of our findings in a larger, multicenter, longitudinal research cohorts in order to develop and test personalized interventions that can effectively reduce FCR and improve long-term quality of life in cancer survivorship.

Funding

No

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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