

Interpretable pretreatment prediction of adaptive replanning needs in head and neck cancer radiotherapy

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SUMMARY

Purpose: To identify pre-treatment clinical predictors of Head and Neck Cancer (HNC) radiotherapy replanning and develop an interpretable model¹⁻³ to predict it.

Methods: In 547 HNC patients (437 train / 110 test), we performed statistical analysis on 22 pretreatment clinical variables to determine which factors impact replanning. Based on these predictors, we built a points-based scoring system where points are assigned to each variable according to its replanning rate. Patients scoring above a threshold were flagged for replanning. For comparison, classical machine learning models were trained on the same data.

Results: The overall replanning rate was 48%. The strongest independent predictors, subsequently used in our models, were N stage, chemotherapy, tumour site, and PTV volumes. The points-based system achieved a test AUC of 0.794, comparable to the best machine learning model (logistic regression, test AUC = 0.789), despite being simpler.

Conclusion: Our interpretable risk-scoring system can support early identification of HNC patients likely to need replanning, enabling proactive scheduling of rescans and reducing workflow disruptions.

REFERENCES

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INTRODUCTION

- **Head and neck cancer (HNC)** patients undergoing radiotherapy often require **replanning due to anatomical changes**.
- However, replanning is **resource-intensive** and typically decided on **short notice**, causing workflow disruptions and treatment delays.
- Therefore, we aimed to identify pretreatment **clinical predictors of replanning** and develop an **interpretable prediction model**¹⁻³ using them.

OBJECTIVES

- (1) **Find Predictors:** Determine which variables impact replanning via statistical analysis.
- (2) **Build Points Model:** Create simple points-based scoring system from the strongest predictors.
- (3) **Compare to ML:** Benchmark the points model against classical machine learning models.

METHODS

Dataset

- **Patient Cohort:** 547 HNC patients treated with radiotherapy between 2017 and 2024 at the McGill University Health Centre.
- **22 pre-treatment variables:** sex, age, tumour site, TNM staging, overall stage, p16 status, pathology, laterality, grade, chemotherapy, immunotherapy, surgery, BMI, neck volume, smoking history, PEG use, PTV volumes, diagnosis-to-treatment delay.
- **Split:** training (n=437) and testing (n=110) sets, balanced for replan rate, sex, diagnosis, and fractionation.

(1) Find Predictors

- Univariate screening (χ^2 , Mann-Whitney U).
- Redundancy check (VIF, spearman, Cramer’s V).
- Multivariable logistic regression (odds ratios).
- Select independent predictors for models.

(2) Build Points Model

Derived on training set

- Compute baseline replan rate: 48%.
- Compute replan rate for each predictor.
- Convert each rate to integer points relative to baseline:
 $points = [(category\ rate - 48\% \ baseline) \div 10\%]$
*Ex: N3 Stage (69% replan) $\rightarrow$ +2;
 No chemo (29% replan) $\rightarrow$ -2*
- A patient’s score is the sum of their points. They are flagged for replanning if the score ≥ 0 .

(3) Compare to ML

- Train models: logistic regression, decision tree, random forest, SVM, k-NN, and naïve bayes.
- Compare AUC results against points-model.

RESULTS

(1) Find Predictors

- **Overall replanning rate:** 48%
- **Univariate analysis:** 13 of 22 variables significant ($p < 0.05$)
- **Strongest independent predictors** (used in both models): Low-, mid- and high- dose PTV volumes, chemotherapy, N stage, and tumour site.

(2) Build Points Model

- The final score card is shown in Fig.1. A patient is flagged for replanning if their total score ≥ 0 .
- The magnitude of each point value reflects how strongly that factor raises or lowers replanning risk. Higher total scores correspond to progressively higher replanning rates (Fig. 2).
- On a hold-out test set, the points model achieved **AUC 0.794**.

Variable	Category	Points
N Stage	N0	-2
	N1	1
	N2 or N3	2
Chemotherapy	No	-2
	Yes	1
Tumour Site	Larynx	-2
	Nasopharynx	3
	Other	0
High-Dose PTV Volume	≤ 76 cc	-2
	76 to 135 cc	-1
	> 135 cc	1
Mid-Dose PTV Volume	≤ 31 cc	-2
	31 to 208 cc	0
	> 208 cc	1
Low-Dose PTV Volume	0 cc	-2
	0 to 242 cc	1
	> 242 cc	2

Figure 1. Points-based scoring card.

Score	≤ -7	-6 to -3	-2 to 2	3 to 6	≥ 7
Observed Replan Rate	8%	28%	53%	71%	77%

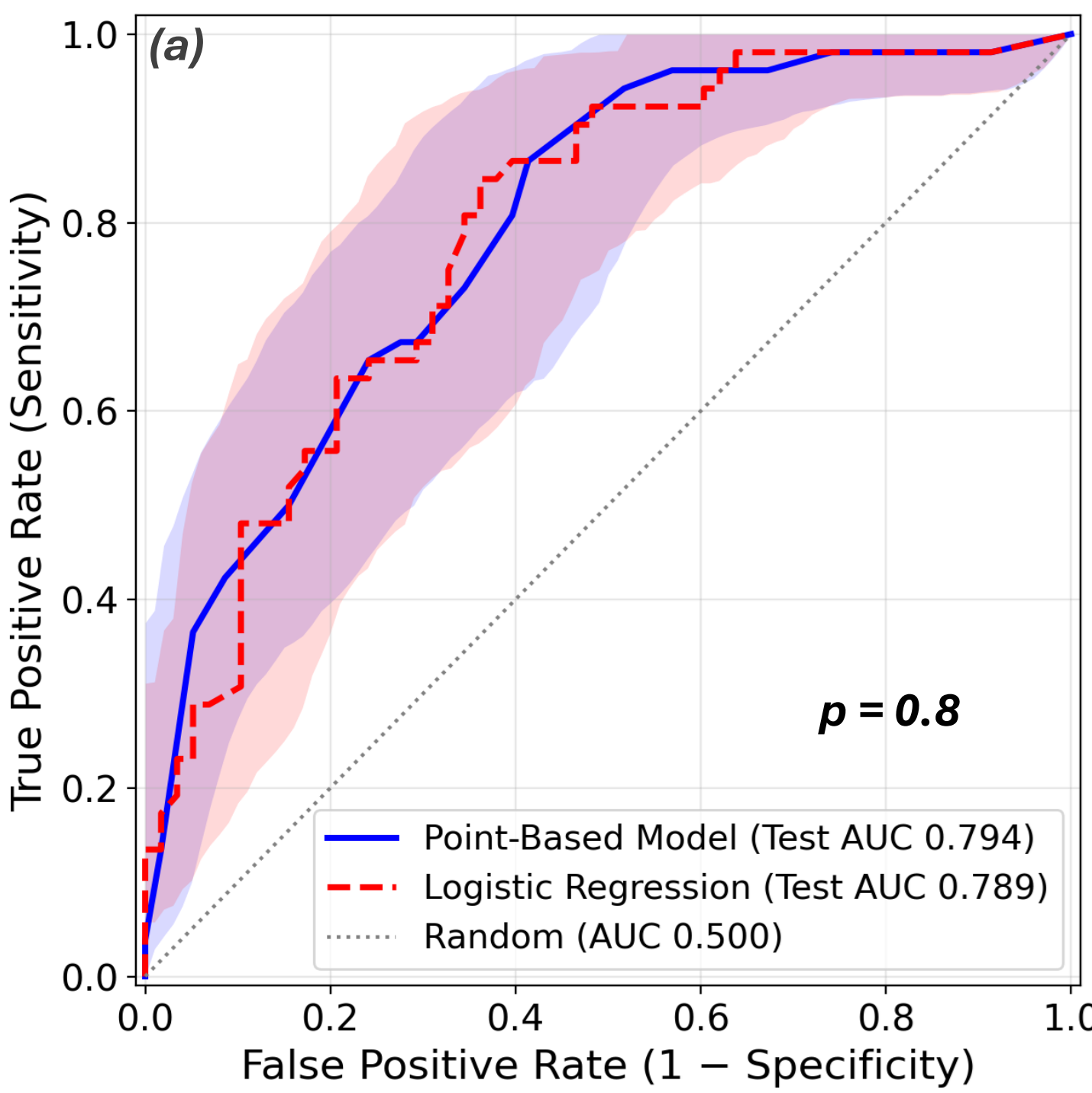
Figure 2. Observed replanning rate by total score.

Variable Tested	Value	Points Added
N Stage	N1	+1
Tumour Site	Larynx	-2
Chemotherapy	Yes	+1
Volume of High Dose PTV	140 cm ³	+1
Volume of Mid Dose PTV	215 cm ³	+1
Volume of Low Dose PTV	350 cm ³	+2
TOTAL SCORE		+4 $\rightarrow$ FLAG

Figure 3. Example patient prediction.

(3) Compare to ML

- The best machine learning model (logistic regression) achieved a test AUC of **0.789**.
- This result is statistically indistinguishable from the points model ($p > 0.5$), indicating that the simple scoring system does not sacrifice meaningful accuracy.



Point-Based Model		Logistic Regression	
Sens: 0.73, Spec: 0.66		Sens: 0.71, Spec: 0.67	
True Label	No Replan	38	14
	Replan	20	38
Predicted Label		Predicted Label	
True Label	No Replan	39	19
	Replan	15	37
Predicted Label		Predicted Label	

Figure 4. Model comparison: (a) ROC curves and (b) confusion matrices for the points model vs logistic regression.

DISCUSSION & CONCLUSIONS

- We developed an interpretable risk-scoring system for HNC radiotherapy replanning based on pre-treatment variables.
- The simple points card performs comparably to ML models.
- This tool can support early identification of patients likely to require replanning, enabling proactive scheduling of rescans and reducing workflow disruptions.

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