47th ANNUAL INTERNATIONAL CONGRESS
EHS 2025 JUNE 4-6
PARIS - FRANCE

Incisional Hernia

Enhanced Prediction of Incisional Hernia in Liver Transplant Patients:
A comparative Analysis of Logistic Regression and Machine Learning Models

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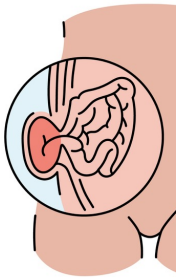
BACKGROUND

- **Incisional hernia (IH)** is a common complication **after liver transplantation** (LT).
- LT patients face **increased risk** due to large incisions, immunosuppression and specific comorbidities.
- IH significantly **impacts quality of life** and creates health/financial burdens.
- Accurate **IH risk prediction** is essential to guide preventive strategies and improve outcomes.



METHODES

Study Design:

- Retrospective cohort (2010-2019)
- 308 LT patients

Outcome:

Incisional hernia requiring repair (17.9% incidence)

Analysis:

1. External validation of Penn Hernia Risk Calculator
2. Development of LT-specific logistic regression model
3. Comparison with 10 machine learning methods

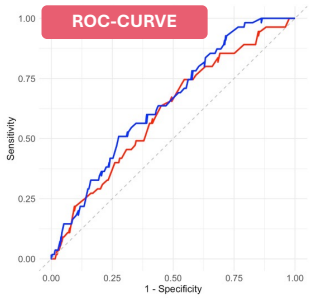
RESULTS

External Validation

PREDICTORS

Age
BMI
Smoking
Anemia
Hypertension
Diabetes
Elixhauser Comorbidity score ≥2
History of cancer
History of acute infection
History of drug abuse
History of abdominal surgery

ROC-CURVE



AUC : General Penn Hernia Model
0.612
POOR DISCRIMINATION

AUC : Transplant Penn Hernia Model
0.649

Observed / Expected: General Penn Hernia Model
<0.001
POOR CALIBRATION

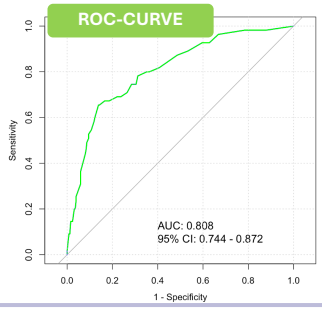
Observed / Expected: Transplant Penn Hernia Model
<0.001

LT-specific revision

PREDICTORS

Hypertension
History of abdominal surgery
Age: 60+
Preoperative functional class 2
History of herniation
Re-transplantation
Polycystic Liver Disease

ROC-CURVE



AUC : Revised LT-specific model
0.808
SIGNIFICANT IMPROVEMENT

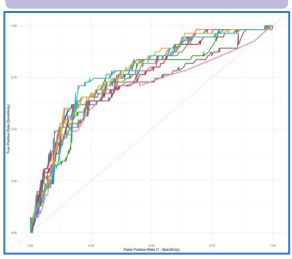
Observed / Expected: Revised LT-specific model
1.021

Machine Learning Models

MODELS

Model (AUC)
- Logistic Regression (0.776)
- LDA (0.775)
- QDA (0.746)
- SVM Linear (0.777)
- SVM RBF (0.782)
- SVM Polynomial (0.779)
- Decision Tree (0.733)
- Random Forest (0.778)
- GBM (0.773)
- XGBoost (0.781)

ROC-CURVE



PERFORMANCE METRICS

Model	AUC (95%CI)	Sensitivity	Specificity	PPV	NPV	Brier score	O/E (95% CI)
Logistic Regression	0.776 (0.702-0.850)	0.807	0.739	0.482	0.948	**0.127**	1.016 (0.742-1.281)
LDA	0.775 (0.702-0.848)	0.840	0.716	**0.508**	0.962	0.129	**1.003 (0.733-1.266)**
QDA	0.746 (0.679-0.812)	0.753	0.774	0.476	0.938	0.153	0.833 (0.603-1.042)
SVM Linear	0.777 (0.705-0.849)	0.800	0.728	0.444	0.944	0.130	0.943 (0.692-1.196)
SVM RBF	**0.782** (0.711-0.853)	**0.857**	0.700	0.456	**0.964**	0.127	0.982 (0.727-1.256)
SVM Polynomial	0.779 (0.712-0.847)	0.803	0.759	0.478	0.948	0.134	0.931 (0.697-1.204)
Decision Tree	0.733 (0.641-0.824)	0.697	**0.786**	0.445	0.926	0.143	1.009 (0.742-1.282)
Random Forest	0.778 (0.712-0.843)	0.803	0.755	0.428	0.947	0.129	0.997 (0.746-1.289)
GBM	0.773 (0.698-0.849)	0.787	0.771	0.492	0.948	0.140	2.236 (1.629-2.814)
XGBoost	0.781 (0.702-0.861)	0.823	0.778	0.491	0.955	0.142	2.266 (1.652-2.855)

CONCLUSION

- **Penn models** do not adequately account for LT-specific risk factors, leading to poor calibration and discrimination.
- **Revised logistic regression model** offers the best overall balance between sensitivity, specificity, and calibration.
- **Machine learning models**, though promising, require refinement for clinical utility.