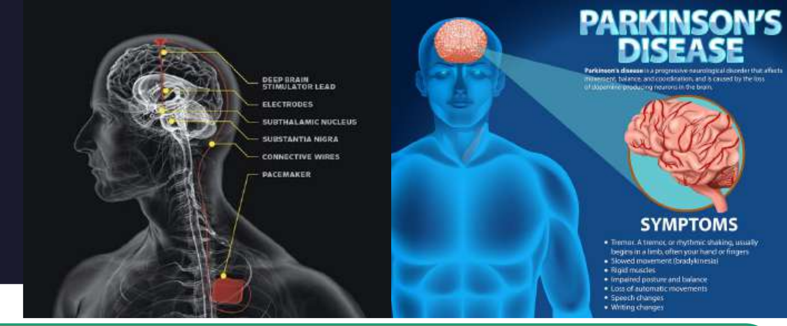
Seven Patients Found: The Case for Decision Theoretic Diagnosis

Data: Kaggle Parkinson's Disease Dataset (n=2,105). Methods: rstanarm HMC 4 chains × 2,000 iterations. Analysis: R 4.3 & Python.



1) Introduction, Data, Methodology

Parkinson's Disease (PD) affects ~10 million people worldwide. Early, accurate diagnosis enables timely intervention: yet clinical assessment alone yields up to 25% misclassification rates. This study applies Bayesian logistic regression to 2,105 patients from the Kaggle PD dataset to model diagnosis probability across 15 clinical predictors, incorporating decision-theoretic threshold optimization to maximize sensitivity for a disease where missed diagnoses carry higher cost than false alarms.

Research Question: Can a Bayesian framework with decision-theoretic thresholding outperform standard logistic regression for PD early detection?

Dataset: Kaggle PD dataset, n = 2,105 patients. 80/20 train/test split → 1,684 train, 421 test.
Outcome: Binary PD diagnosis (1 = positive). Prevalence = 28.5% in test set.

15 Clinical Predictors — Organized by Category

Odds ratios from Bayesian logistic regression posterior means

Motor Symptoms
Tremor · Rigidity
Bradykinesia · Postural
OR up to 6.82×

Clinical Assessments
UPDRS (0-199)
MoCA (0-30) · Functional
OR up to 1.27×

Demographics
Age · Gender
BMI · Ethnicity
OR up to 1.20×

Medical History
Family Hx · Hypertension
Diabetes · Smoking
OR up to 1.56×

Methodological Framework

2,105 Patients
Kaggle PD dataset · 15 clinical predictors

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Classical GLM Baseline
Logit · Probit · CLogLog — AIC/BIC → Logit

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Bayesian Logistic Regression
HMC/NUTS via rstanarm · 4,000 posterior samples

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Decision Theory
c_FN = 3×c_FP → τ* = 1/(1+λ) = 0.25

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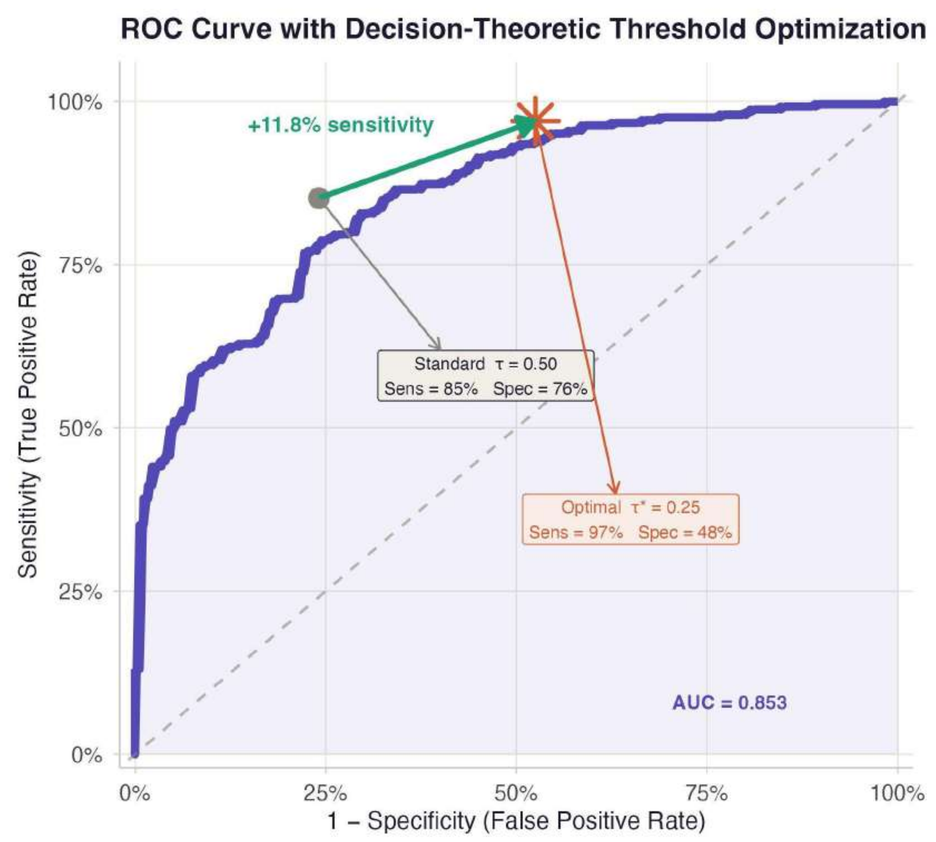
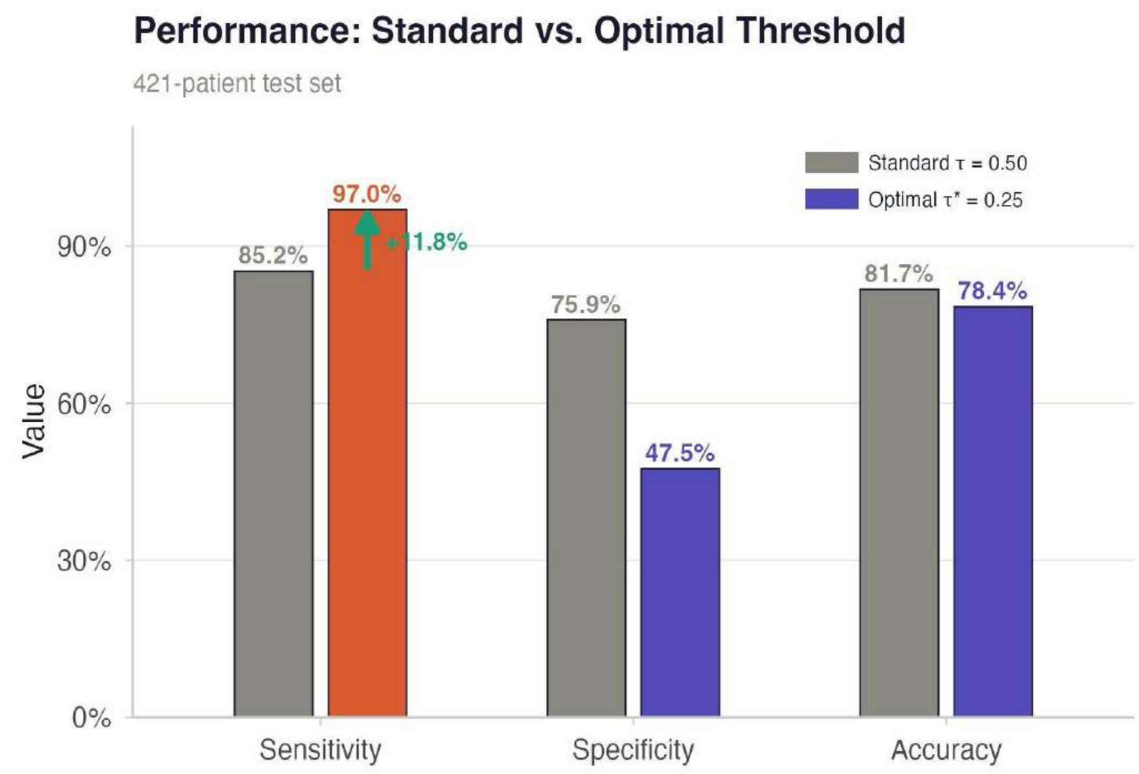
Optimal Threshold τ* = 0.25
97% sensitivity · full uncertainty quantification

Our main emphasis is on using a combination of Bayesian Logic and Decision Theory (false negatives are much worse than false alarms) to detect Parkinson's Disease at a higher clip. We see that throughout the next few sections, we take an increase in false positives to significantly tank false negatives and guarantee a high sensitivity to provide clinical aid.

2) Side by Side Model Improvements and Comparisons





The Bayesian model correctly distinguishes PD from non-PD patients 85% of the time. This is well above random chance. The star marks where our optimized threshold sits.

Standard $\tau = 0.50$

52 TP	9 FN
87 FP	273 TN

Optimal $\tau^* = 0.25$

59 TP	2 FN
189 FP	171 TN

At the standard threshold, 9 patients with PD are falsely undiagnosed. The Bayesian threshold catches 7 of them. This doesn't require much change, just an emphasis on minimizing false negatives.

Cost Assumption

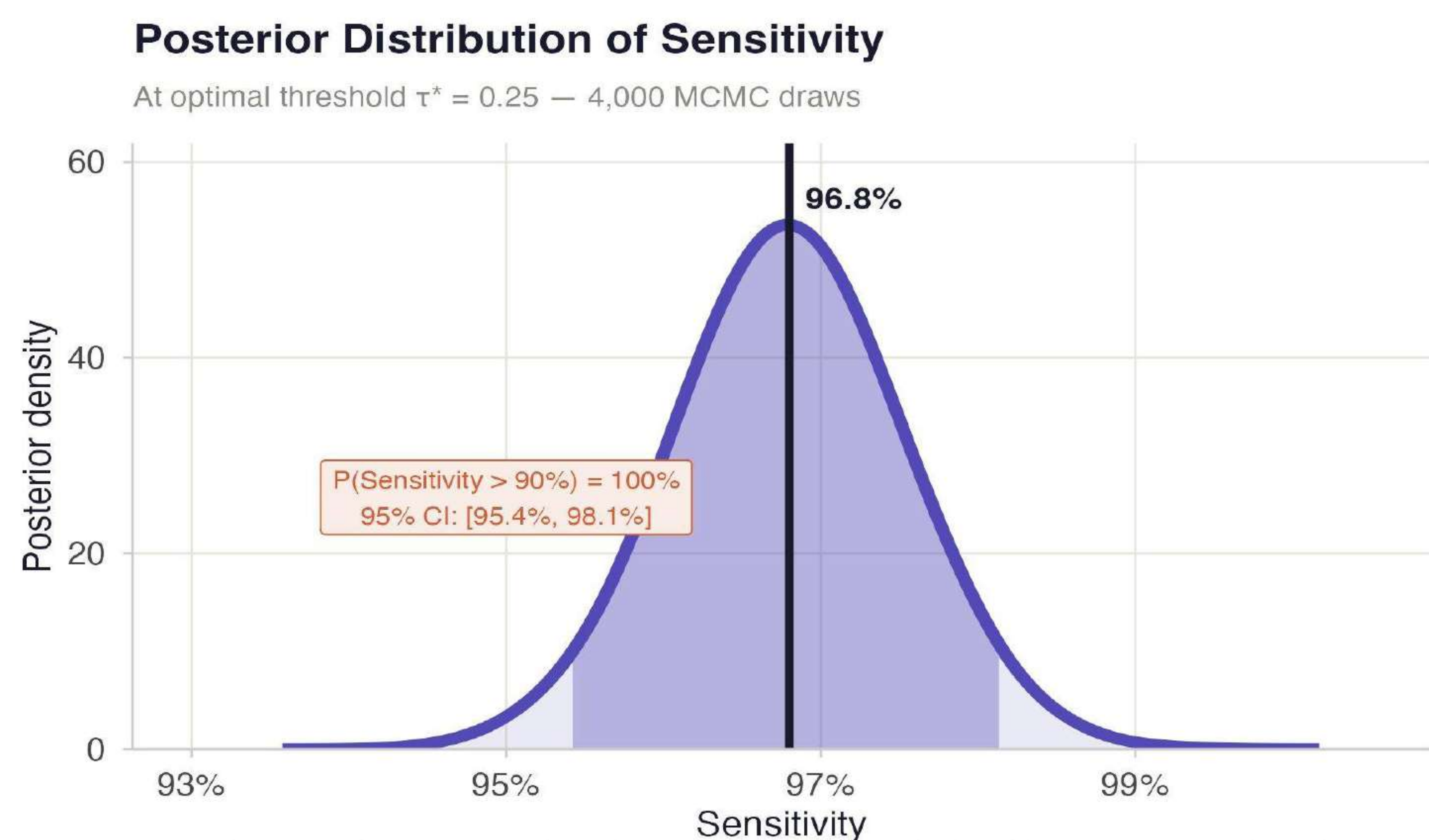
$c_{FN} = \lambda \times c_{FP} \quad (\lambda = 3)$

A missed diagnosis is 3× costlier than a false alarm

Optimal Threshold

$\tau^* = \frac{1}{1+\lambda} = \frac{1}{4} = \mathbf{0.25}$

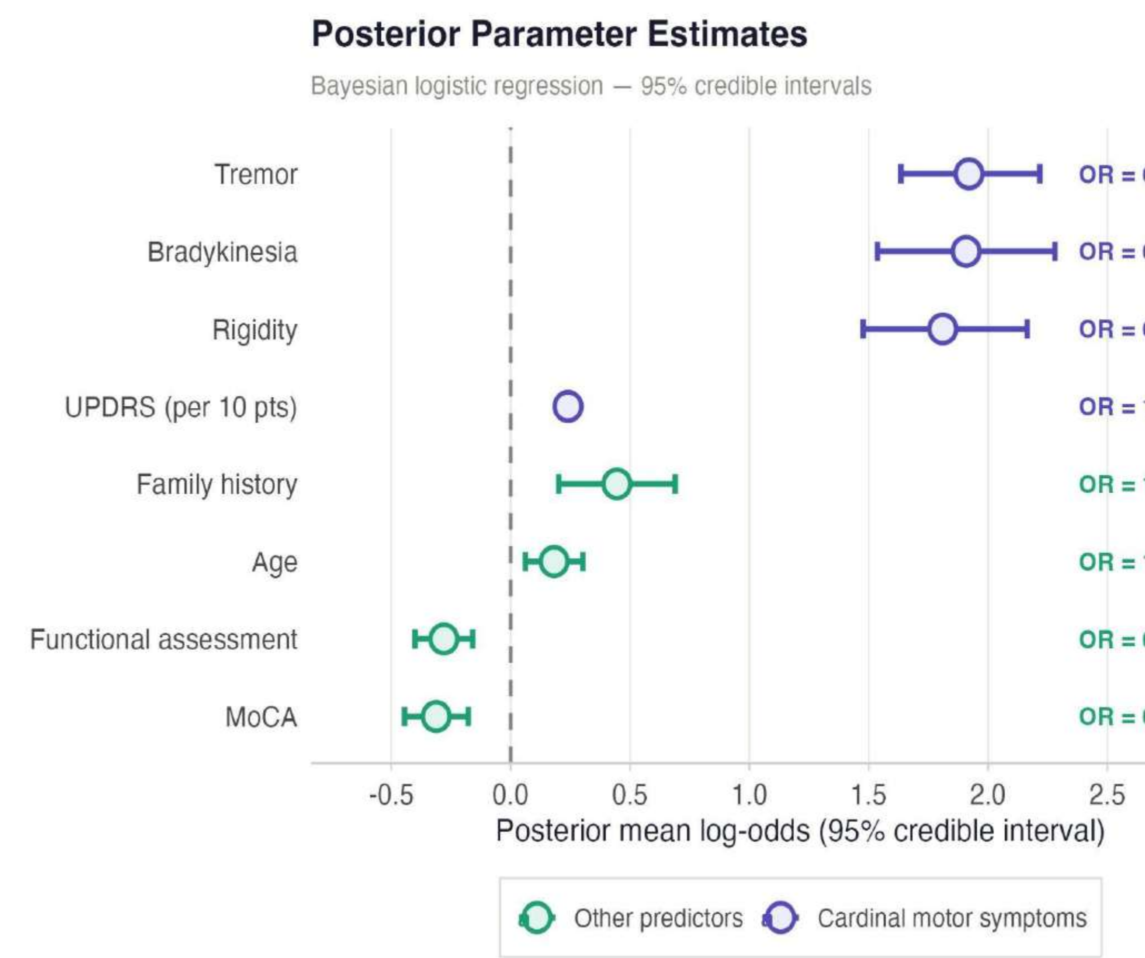
Derived by minimizing expected misclassification cost



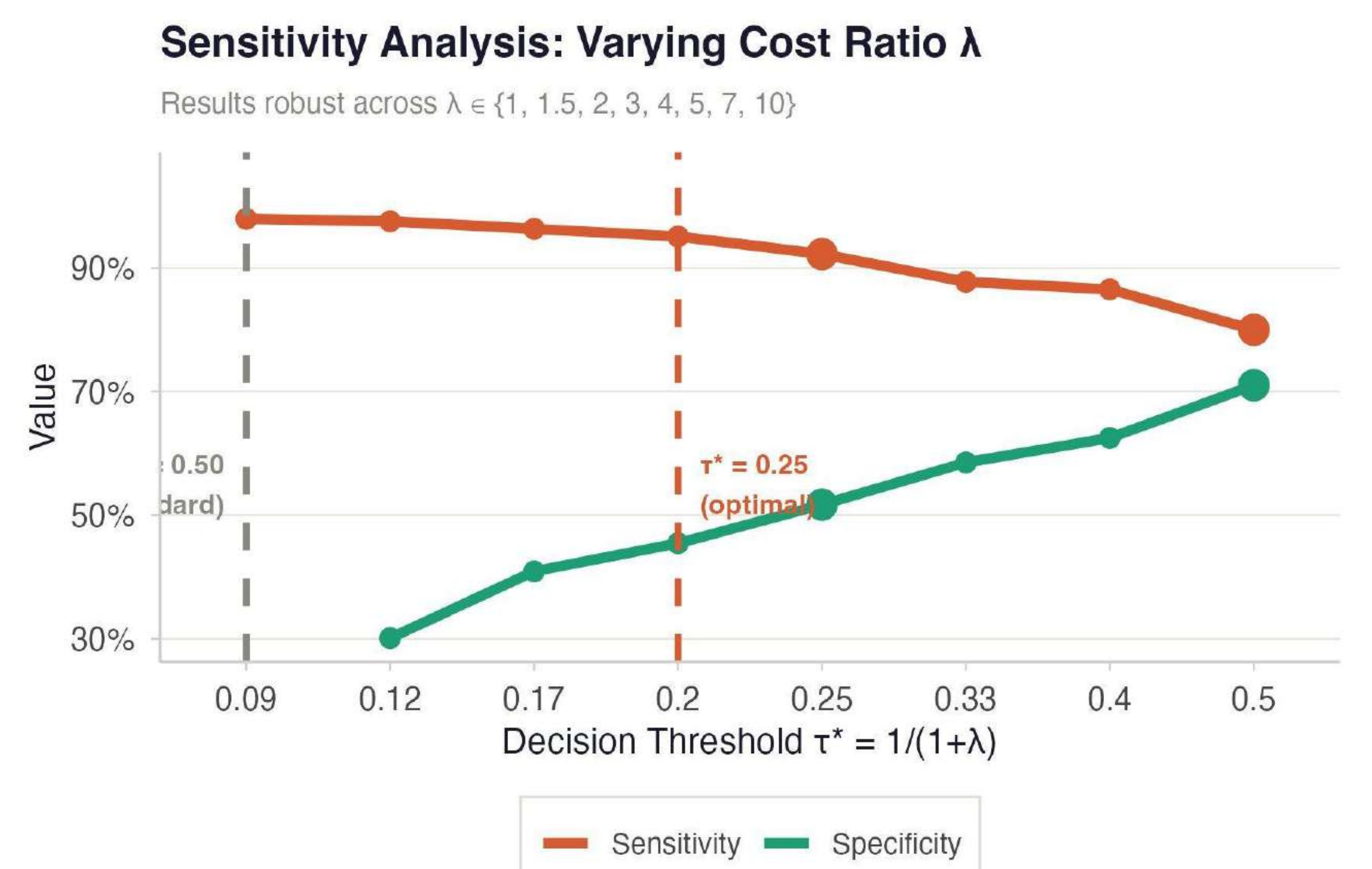
Every single one of 4,000 simulated model runs exceeded 90% sensitivity. This showcases how our threshold minimizes false negatives and helps guarantee early treatment.

3) Clinical Significance

97% Sensitivity τ* | **0.853** AUC (ROC) | **100%** P(Sens > 90%)



- **+11.8% sensitivity gain** (85% → 97%) at $\tau^* = 0.25$ vs. standard $\tau = 0.50$
- **7 fewer missed diagnoses** per 421 patients in the test set
- AUC = 0.853 — strong overall discriminative ability
- P(Sensitivity > 90%) = **100%** across all 4,000 MCMC draws
- Results robust across $\lambda \in \{1, 1.5, 2, 3, 4, 5, 7, 10\}$



Tremor, Bradykinesia, and Rigidity dominate. Patients with these symptoms are 6× more likely to have PD. UPDRS and family history add meaningful but secondary signal. MoCA and functional assessment contribute least. Together these results confirm the Bayesian model isn't just marginally better, more so that it's clinically meaningfully better, catching patients that standard logistic regression systematically loses. Even if we assume a missed diagnosis is only 1.5× costlier than a false alarm, the optimal threshold stays well below 0.50. The 7-patient gain is not sensitive to our cost assumption . It holds across every scenario tested.

CONCLUSIONS

1) Lowering the classification threshold from 0.50 to 0.25 raises sensitivity from 85% to 97%. This catches 7 additional PD patients per 421 who would have been sent home undiagnosed under standard logistic regression.

2) What our model provides is a safer, more conservative alternative to traditional diagnosis. One can be pre-screened by anyone with marginal training, and the high sensitivity sends those prone to receive more care. The most important predictors are the physically obvious ones: tremors, bradykinesia, rigidity. It's not hard to spot these.

3) Next steps include validating this threshold on external PD datasets, extending the framework to multiclass severity staging, and exploring whether wearable tremor sensor data can replace clinical assessment scores in real-time diagnosis. Testing on younger or prodromal populations would further stress-test the model's generalizability.