Clinical Evidence to Individualized Care

AI-Powered Clinical Decision Support Based on Predicted Individual Treatment Effect (PITE)

Bridging causal inference, Bayesian nonparametrics, and precision medicine

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1. Motivation & Clinical Context

Medical decisions—diagnosis, prognosis, treatment selection—are **inherently uncertain**. Clinicians integrate heterogeneous information through complex, nonlinear outcome.

The core clinical question:

> *"How much does this specific patient benefit from treatment A compared to treatment B?"*

Standard **population-level** estimates (ATE) obscure clinically meaningful heterogeneity across patients. **PITE** directly addresses this gap by providing patient-level treatment effect estimates.

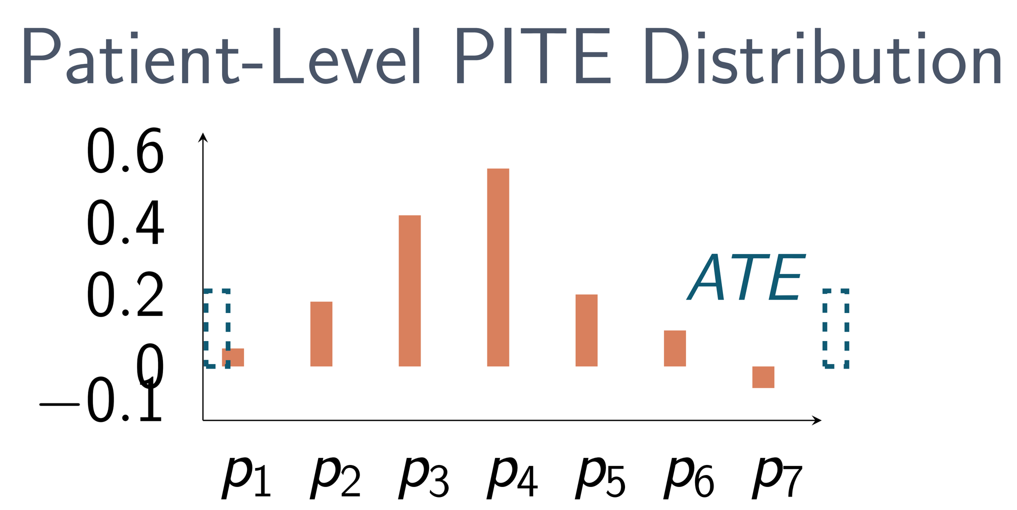
2. Methodological Innovation via PITE

Predicted Individual Treatment Effect (PITE) definition:
Let $Y_i(1)$ and $Y_i(0)$ be potential outcomes under treatment/control for patient i with covariates $\mathbf{x}_i$. The **PITE** is:

$$\hat{\tau}(\mathbf{x}_i) = \hat{Y}_i(1) - \hat{Y}_i(0)$$

- **Personalised**: one estimate per patient
- **Actionable**: directly informs treatment decisions
- **Principled**: rooted in the potential outcomes framework
- **Flexible**: continuous, binary, or bounded outcomes

ATE vs. PITE — heterogeneity revealed:



Uncertainty quantification via PITE

3 Key Methodological Contributions

(i) Clinically interpretable hurdle ordering for ZOIB modelling
(ii) Shared-forest BART enabling information borrowing across outcome components
(iii) Scalable Beta-likelihood approximation for efficient posterior computation
(iv) Effective Clinical Decision Support requires data management + modelling + XAI + validation

4 Shared-Forest Hurdle BART with PITE

1. The Framework: Bayesian Additive Regression Trees

Nonparametric Power: Harnesses an ensemble of sum-of-trees to map complex, non-linear relationships without rigid distributional assumptions.

Regularizing Priors: Effectively preventing overfitting in high-dimensional noise.

2. The Innovation: Shared Tree Structure in a Hurdle Model

Dual-Task Efficiency: A unified forest simultaneously models the binary hurdle (zero vs. non-zero) and the continuous continuous intensity.

Enforced Consistency: Ties the structural covariate space splits together, dramatically stripping out unnecessary parameter complexity.

Component Differentiation: Keeps tree structures shared across tasks while scaling leaf predictions using component-specific parameters β_c:

$$f_c(x) = \sum_{t=1}^{T} g_{t,c}(x)$$

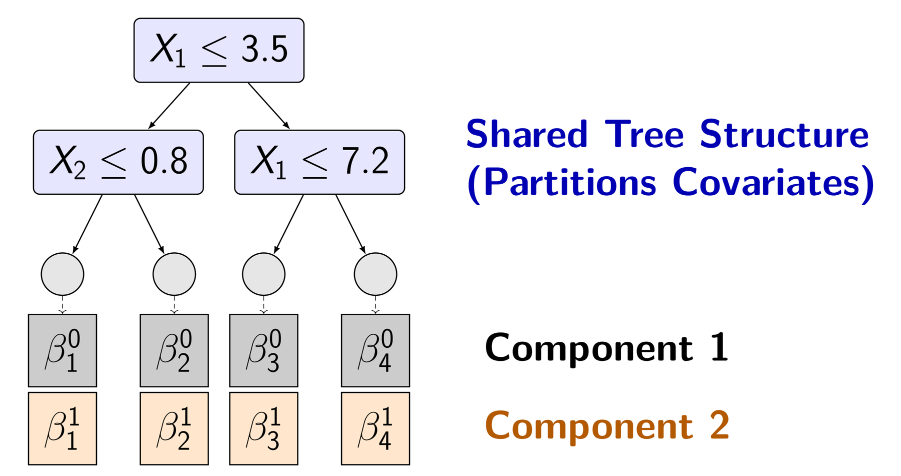
3. The Guarantee: Uncertainty Quantification and PITE

PITE validation: Counterfactual information is calculated based on model predictions that capture and isolate uncertainty across different components.

5 PITE — Illustrative Example

A single illustrative tree shows patient partitioning based on clinical biomarkers. The full **BART ensemble** computes averages across hundreds of these trees.

Root: All Patients ($n = 580$) ⟶ High Risk Stratum ($n = 112$) ⟶
Age ≤45 | Age >45
$\hat{\tau} = +\mathbf{0.41}$ (High Benefit)
Low Risk Stratum ($n = 152$)
$\hat{\tau} = -\mathbf{0.04}$ (No Benefit)



- **Subgroup 1 (Age ≤ 45, Drinks > 20)**: Expected PITE $\hat{\tau} = +0.41$ (**High benefit**)
- **Subgroup 2 (Age ≤ 45, AUDIT-C ≤ 6)**: Expected PITE $\hat{\tau} = -0.04$ (**No benefit/Harm**)
- **Subgroup 3 (Age > 45, Comorbidity > 2)**: Expected PITE $\hat{\tau} = +0.33$ (**High benefit**)

Clinical Stratification Mapping:

Benefit	Equipoise	Risk / Harm
$\hat{\tau} > 0.20$	$\hat{\tau} \approx 0$	$\hat{\tau} < 0$

6 HOBZ–BART: Case Study

Alcohol Use Disorder (AUD) outcomes are *semi-continuous* on $[0,1]$: complete abstinence ($Y=0$) or persistent heavy drinking ($Y=1$), with the remainder continuously distributed in $(0,1)$.

Three-component sequential hurdle:

$$\underbrace{P(Y=0 \mid \mathbf{x})}_{\text{abstinence}} \to \underbrace{P(Y=1 \mid Y>0, \mathbf{x})}_{\text{heavy}} \to \underbrace{\text{Beta}(Y \mid \mathbf{x})}_{\text{moderate}}$$

- **Clinically interpretable**: abstinent / moderate / heavy
- **Shared-forest BART** across all three components
- **Beta-function approximation** for fast posterior computation
- **Full posterior uncertainty** — credible intervals on $\hat{\tau}(\mathbf{x}_i)$

Drinking regime mapping:

Abstinent	Moderate	Heavy
$Y = 0$	$Y \in (0,1)$	$Y = 1$

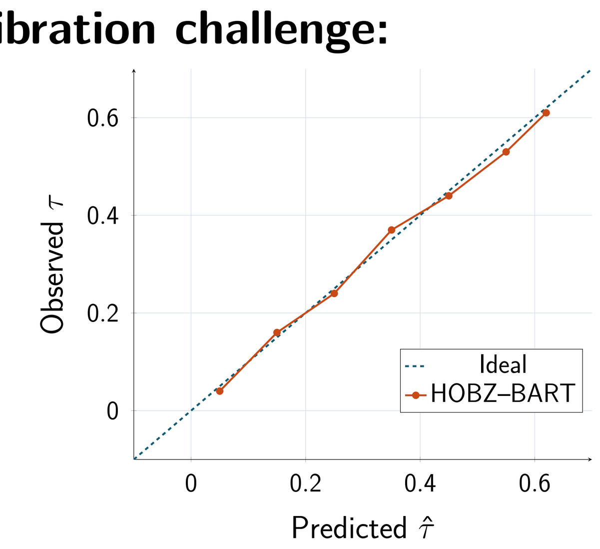
7 Validation Framework

Internal validation alone is **insufficient**:

External validation is essential for robust and reliable PITE predictions.

- **Internal**: cross-validation, WAIC, LOO
- **Calibration**: PITE calibration curves
- **External**: independent cohorts, temporal splits
- **Sensitivity**: missing data; model misspecification

PITE calibration challenge:



8 Conclusions

- PITE provides a **principled, individualised** framework for clinical decisions
- HOBZ–BART extends nonparametric methods to **semicontinuous** bounded outcomes
- **Shared-forest** BART improves stability and enables faster sampling than standard approaches.
- Effective Clinical Decision Support requires **data management + modelling + xAI + validation**

Future directions:
- Multi-disease PITE platforms: oncology, psychiatry, cardiology
- Alternative approaches to shared components

References

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