

# Evaluating the Reliability of Value of Information Methods: A Simulation-Based Comparison

Qian Xin, MSc<sup>1</sup>, Abdul-Lateef Haji-Ali, PhD<sup>2</sup>, Mark Strong, PhD<sup>3</sup>, Michael Jon O'Donnell, PhD<sup>1</sup>, Howard Thom, PhD<sup>1</sup>

<sup>1</sup>University of Bristol, Bristol, United Kingdom; <sup>2</sup>Heriot-Watt University, Edinburgh, United Kingdom; <sup>3</sup>University of Sheffield, Sheffield, United Kingdom.

## BACKGROUND

- Healthcare resource allocation is often made under **uncertainty due to imperfect information** in economic evaluations.
- Collecting additional evidence can reduce uncertainty but comes with higher costs. **Value of Information (VoI)** analysis provides a framework to assess whether reducing uncertainty is worth the investment.<sup>1</sup>
- The **Expected Value of Partial Perfect Information (EVPPi)**, the value of gaining **perfect information on a subset** of uncertain cost-effectiveness model parameters, can be estimated using Nested Monte Carlo (NMC), regression-based methods (Gaussian Process (GP), Multivariate Adaptive Regression Splines (MARS), and Bayesian Additive Regression Trees (BART)), Multi-Level Monte Carlo (MLMC), and other methods.<sup>2-3</sup>
- However, their **accuracy remains underexplored**.

## METHOD

### Model simulation

- Generic R code** was developed to generate Markov models with flexible structures, treatments, and parameters.
- Transition probabilities** generated via copulas to account for correlation.
- 12,000** simulations conducted to ensure estimate accuracy.

### Measure performance

#### Linear regression used:

- Dependent variable = NMC estimates
- Independent variables = estimates from other methods

**Stratified by** number of health states and treatment options (↑ = more complex models)

**Performance metrics:** R<sup>2</sup>, slope, coverage probability, and scatter plots.

## RESULTS

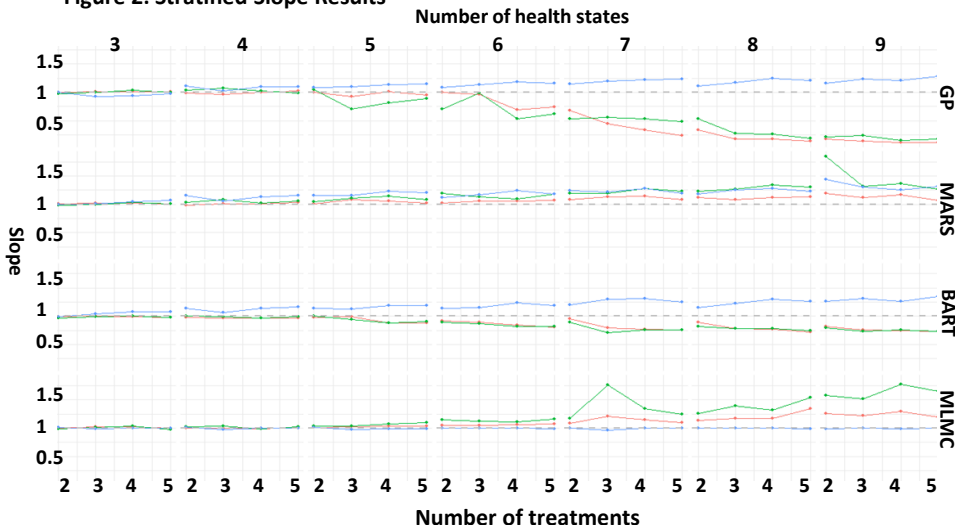
Table 1: Summary Results

variable	Method	Slope	R squared	Bias
Costs	GP	0.82	0.76	0.84
	MARS	1.03	0.93	-27.38
	BART	0.96	0.97	19.91
	MLMC	1.02	0.90	-39.18
Utilities	GP	0.71	0.65	56.53
	MARS	1.02	0.97	-22.28
	BART	0.97	0.97	37.02
	MLMC	1.01	0.96	-35.67
Transition probabilities	GP	1.08	0.91	-333.16
	MARS	1.12	0.71	-864.08
	BART	1.19	0.83	-727.17
	MLMC	1.00	0.99	8.20

**Table 1** summarizes the results for each parameter and method across all performance measures:

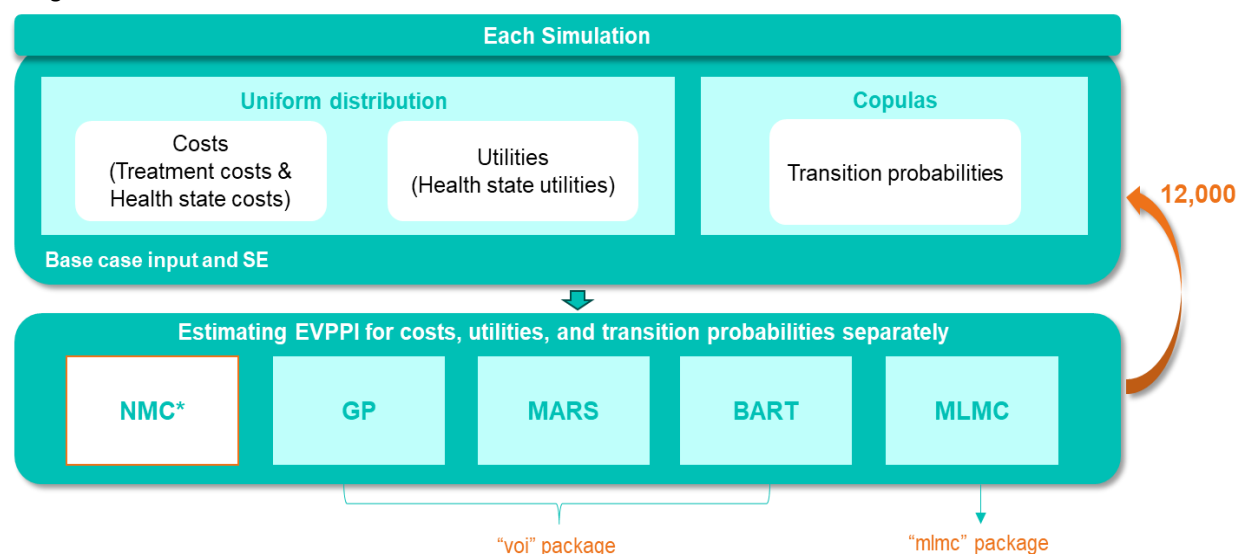
- BART** performed best for **cost**.
- MLMC** and **BART** provided the most reliable estimates for **utility**.
- MLMC** outperformed all others for **transition probabilities**.

Figure 2: Stratified Slope Results



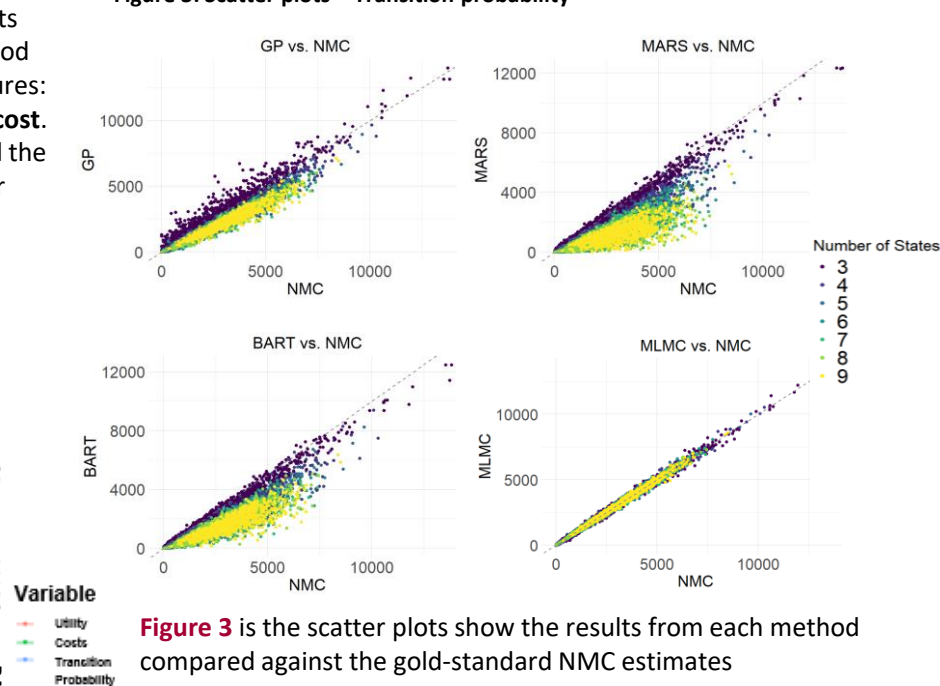
**Figure 2** shows the stratified slope results, broken down by the number of health states and treatments.

Figure 1: Method – Simulation model



Notes: \* NMC estimates are estimated based on 100 outer samples and 1000 inner samples, sufficient to ensure reasonable precision and acceptable bias. All models were developed in R 4.4.1 and executed on the high-performance computing platform. All code are provided in a GitHub repository.

Figure 3: Scatter plots – Transition probability



**Figure 3** is the scatter plots show the results from each method compared against the gold-standard NMC estimates

### When considering model complexity:

- MLMC** maintained superior performance for **transition probabilities as complexity increased**.
- BART** consistently produced the **most accurate** estimates for **cost and utility** in more complex models.

### Conclusions:

- BART** is preferred for simple models with uncorrelated parameters
- MLMC** is recommended when parameters are correlated.