Looking sharp!

Applying cutting-edge SHapley Additive exPlanation (SHAP) approaches to cost-effectiveness modelling in contrast to one-way sensitivity analysis

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Stefano Perni[1], Jackie Vanderpuye-Orgle[2], Jean-Etienne Poirrier[3]

[1]Parexel International, London, UK [2]Parexel International, Los Angeles, USA [3]Parexel International, Wavre, Belgium

Background

Knowledge and understanding of why a model reaches a certain outcome is defined as model explainability; this considers the relative weight of each variable in reaching the final outcome. The explainability of a cost-effectiveness model is often limited to the use of one-way and probabilistic sensitivity analysis (OWSA and PSA). However, OWSA and PSA are also limited to the estimation of the variation of the model output based on a certain percentage variation of a single (for OWSA) or all (for PSA) input parameters. By its nature, OWSA and PSA do not account for neither correlations between input parameters nor non-linear relationships between input parameters and model outputs. An optimal alternative to assessing explainability is the SHAP (SHapley Additive exPlanations) approach derived from coalitional game theory. This method is also increasingly employed to explain the output of machine learning models. SHAP values represent the individual contribution of each model parameter to the model prediction, similar to the coefficients of each variable in a linear regression.

Methods

We present the use of SHAP in explaining a theoretical cost-effectiveness model outcomes.

For this purpose, the results of the probabilistic sensitivity analysis (PSA) of a Markov model (Figure 1) with input values presented in Table 1 were used to calculate SHAP for the estimated ICER and compared to the results of a classical OWSA changing the parameters ±10%.

The time horizon was 20 years and the cycle length = 6 months.

Figure 1. Scheme of a general Markov model.

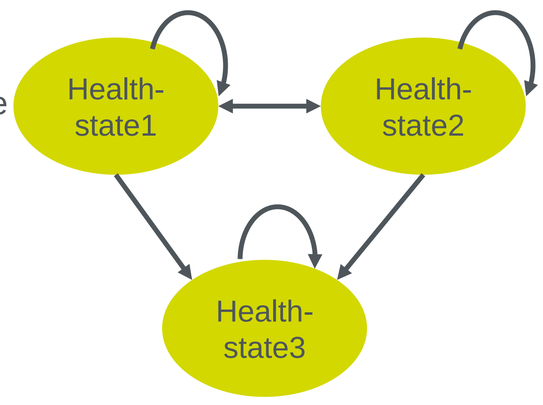

Table 1. Input parameters values for base-case

Transition matrix for Intervention

	Health-state1	Health-state2	Health-state3
Health-state1	0.9	0.1	0.0
Health-state2	0.3	0.6	0.1
Health-state3	0.0	0.0	1.0

Transition matrix for Comparator

	Health-state1	Health-state2	Health-state3
Health-state1	0.5	0.1	0.4
Health-state2	0.1	0.4	0.5
Health-state3	0.0	0.0	1.0

QoL	QALY
Health-state1	0.9
Health-state2	0.5
Health-state3	0.0

Therapy cost	£/cycle
Intervention	6.000
Comparator	2.000

Results

- The base-case had an ICER of 15.5772 $/QALY
- The most impactful parameters identified by OWSA was the cost the intervention drug and the QoL of Health-state1 (Figure 2)
- SHAP average contributions on PSA results, also representing the average input parameter importance, showed a different ranking than OWSA. Particularly for discount rate, QoL of health-state2 and the transition probability of remaining in Health-state1 for the intervention (Figure 3)
- The model input parameters in the base case with the greatest SHAP values (contribution to the model estimated ICER) were the discount rate and the transition probability from Health-state2 to Health-state1 for the intervention (Figure 4)

Figure 3. SHAP values for model for PSA input parameters

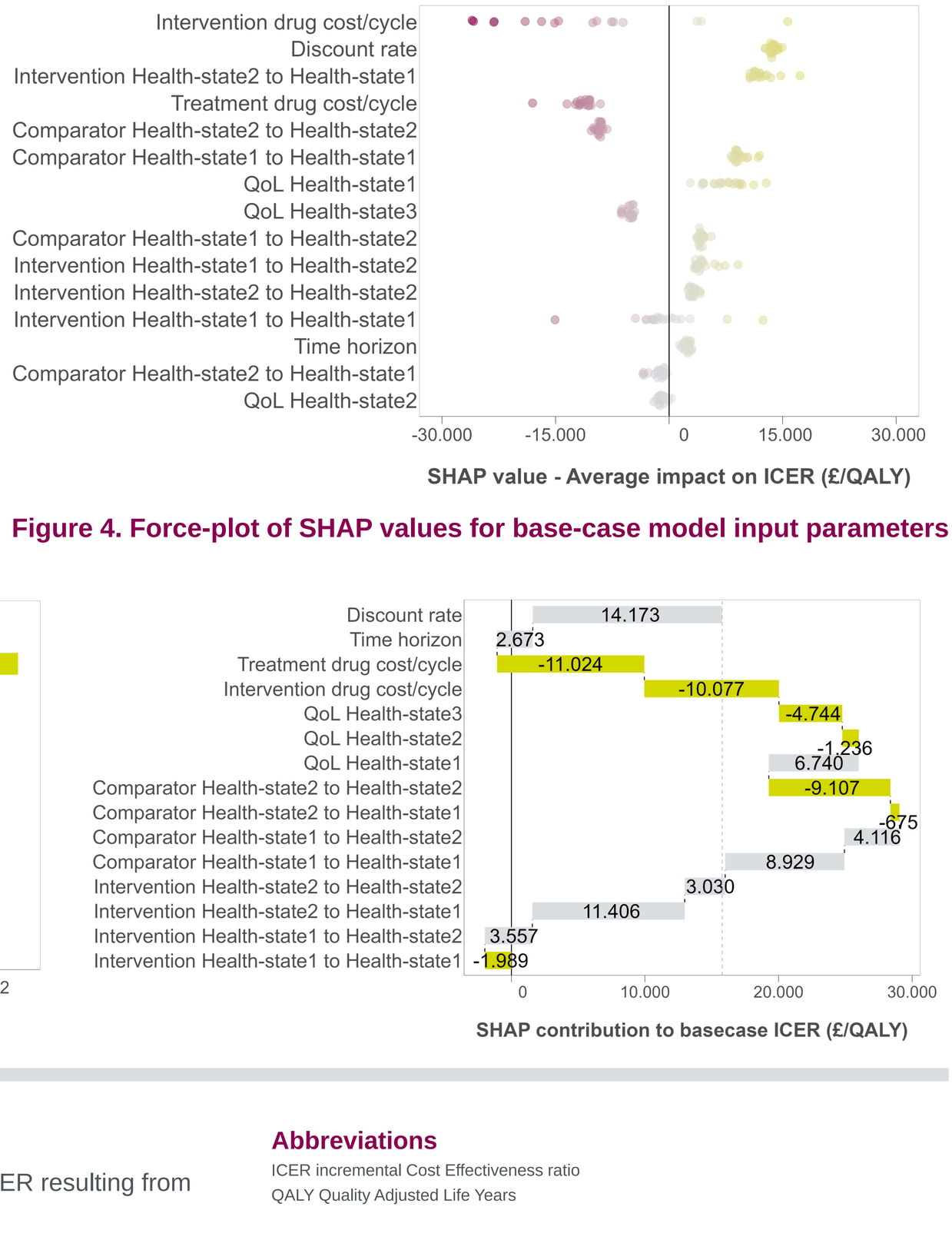

Figure 2. Results from OWSA

Figure 4. Force-plot of SHAP values for base-case model input parameters

Conclusions

- OWSA shows (and ranks) input parameters based on the variation of the ICER resulting from their individual variation
- SHAP values provide information regarding the collective contribution of each model parameter to the resulting ICER.
- Therefore, the SHAP approach could provide a new and more appropriate way than OWSA to explain the role of each variable in the calculation of cost-effectiveness model outcome.

Abbreviations

ICER incremental Cost Effectiveness ratio

QALY Quality Adjusted Life Years

REFERENCES

[1] Lundberg et al. 2017. A unified approach to interpreting model predictions. Advances in Neural Information Processing Systems.

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