5 Computational methods for value of information analyses (A8)

Expected Value of Perfect Information (EVPI)

The formula for EVPI is:

$$EVPI = E\left[\max_t \{NB(t,\theta)\}\right] - \max_t \left\{E_\theta\left[NB(t,\theta)\right]\right\}$$

where $NB(t,\theta)$ is the net-benefit function for intervention option t and input parameters θ.

EVPI is straightforward to compute given a set of simulations from the joint distribution of θ (see for example Welton et al. (2012)).[1]

Expected Value of Partial Perfect Information (EVPPI)

The formula for EVPPI for a subset of focal parameters φ, where the non-focal parameters are ψ so $\theta = \{\varphi, \psi\}$:

$$EVPPI(\varphi) = E_\varphi\left[\max_t \left\{E_{\psi|\varphi}\left(NB(t,\theta)\right)\right\}\right] - \max_t \left\{E_\theta\left[NB(t,\theta)\right]\right\} \qquad \text{(A2.1)}$$

EVPPI is more complex to compute, due to the inner expectation in (A2.1). Our net benefit function is:

$$NB_k = -\left(dressingcost_k + pSSI_k * \left(SSIcost + SSIQALYloss * WTP\right)\right)$$

To compute $EVPPI\left(SSIcost\right)$, we can simply "plug-in" the means of the $pSSI_k$ to obtain the inner expectation (A2.1).[2]

The SSI risk under intervention k satisfies:

$$logit\left(pSSI_k\right) = \mu + \left(d_k - d_S\right)$$

where μ is the log-odds of an SSI under the reference dressing (Simple, k=S), and is the log-odds ratio of intervention k relative to the reference (Simple, k=S). Therefore, net-benefit

is a non-linear function of μ and d_k. To find EVPPI(μ) and EVPPI(d_k), we need to rely on a Taylor series approximation to enable us to evaluate the inner expectation (A2.1).[2]

Expected Value of Sample Information

The formula for EVSI is:

$$EVSI = \underset{y,\theta}{E}\left[\max_t \left\{\underset{\theta|y}{E}\left(NB(t,\theta)\right)\right\}\right] - \max_t \left\{\underset{\theta}{E}\left[NB(t,\theta)\right]\right\}$$

The outer expectation averages over potential new datasets y that may be collected for given study design, based on our current belief of parameters, θ. The inner expectation averages over the posterior distribution of parameters θ given observed data, y, to form an updated expected net benefit and optimal intervention given data y.

EVSI for a trial collecting information on the relative effectiveness of different dressing types is computed using the following steps:

1. Approximate the joint posterior for relative intervention effects (log-odds ratios) compared with the reference dressing (Simple, k=S) using a multivariate Normal distribution.
2. Simulate log-odds ratios $\left(d_k - d_S\right)$ from multivariate normal distribution.
3. Form covariance matrix for likelihood of a new study with sample sizes (n_E, n_S, n_G, n_A) on each group (E=Exposed, S=Simple, G=Glue, C=Complex). We assume a standard deviation for the log-odds on a given group, based on the Cochrane review Simple wound dressing groups only, giving an estimated standard deviation, s=3.7 (note this is comparable, but more conservative, than the estimate obtained by averaging the standard deviation of log-odds ratio's from the Cochrane review, divided by 2 to obtain estimates on log-odds scale, which gave s=3.125). Taking advantage of the linearity of relative effects on log-odds scale, and assuming standard deviation on log-odds scale is the same for each intervention, it can be shown that the covariance for the likelihood is:

$$V_{lik} = \begin{pmatrix} \frac{s^2(n_S+n_E)}{n_S n_E} & \frac{s^2}{n_S} & \frac{s^2}{n_S} \\ \frac{s^2}{n_S} & \frac{s^2(n_S+n_G)}{n_S n_G} & \frac{s^2}{n_S} \\ \frac{s^2}{n_S} & \frac{s^2}{n_S} & \frac{s^2(n_S+n_A)}{n_S n_A} \end{pmatrix}$$

4. Simulate from a multivariate likelihood:

$$y \sim MVN\left(\begin{pmatrix} d_E - d_S \\ d_G - d_S \\ d_A - d_S \end{pmatrix}, V_{lik}\right)$$

5. Form the posterior for parameters $(d_k - d_S)$ using multivariate Normal conjugacy.
6. Find the posterior expected net-benefit given simulated data y. Because the net-benefit is linear in SSI costs, the mean for $SSIcost$ can be plugged into the inner expectation as for EVPPI, but the net-benefit function is non-linear in the probability of an SSI, $pSSI_k$, and so a Taylor series approximation is necessary to obtain the posterior expected net-benefit given data y [Madan et al][2].
7. Identify the intervention maximising posterior expected net-benefit given y, and save the value of expected net-benefit for the optimal intervention.
8. Average over simulated data-sets y to obtain: $\underset{y,\theta}{E}\left[\max_t \left\{\underset{\theta|y}{E}\left(NB(t,\theta)\right)\right\}\right]$
9. Subtract $\underset{y,\theta}{E}\left[\max_t \left\{\underset{\theta|y}{E}\left(NB(t,\theta)\right)\right\}\right]$ to obtain EVSI.

We only considered balanced designs in our results, and only considered studies that included Simple dressings as one of the groups, since this represents current practice. We explored studies with different numbers of groups and different numbers of included interventions by setting the sample size of omitted groups to 0.001. Results are presented for total sample size which is distributed evenly across the included groups, so all designs are balanced.

References

1. Welton NJ, Sutton AJ, Cooper NJ, Abrams KR, Ades AE. Evidence synthesis for decision making in healthcare: Wiley; 2012.

2. Madan J, Ades AE, Price M, Maitland K, Jemutai J, Revill P, et al. Strategies for Efficient Computation of the Expected Value of Partial Perfect Information. Medical Decision Making. 2014;34(3):327-42.