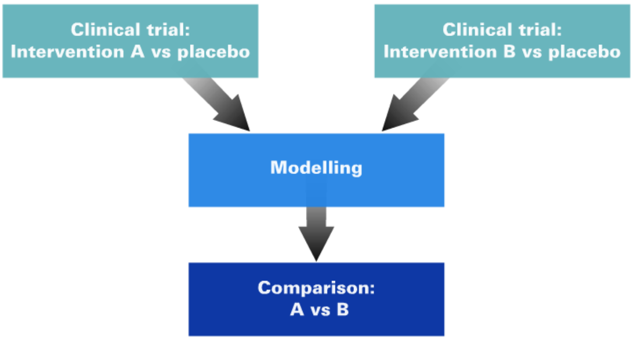
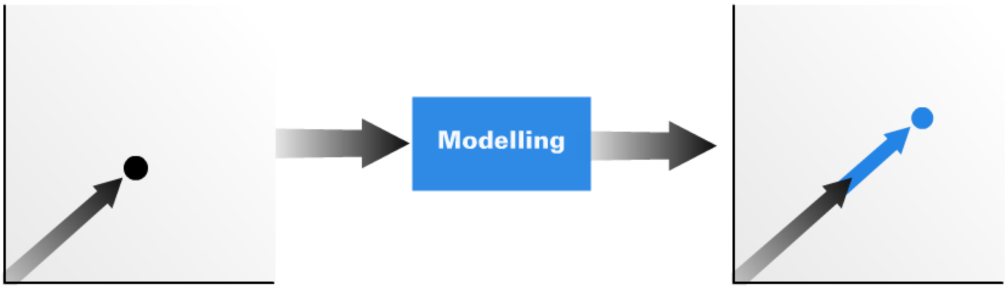
Health Economics Learning Tool
Modelling

A model is simply a simulation of events or situations that have not been observed in reality. Modelling is a widely used predictive tool in many disciplines and is often employed in economic evaluation.

One use of modelling is to integrate data from multiple sources – for example, if separate placebo-controlled trials of two interventions have been carried out rather than a single trial comparing them directly.



Another use is to extrapolate, or make predictions from, data – for example, if the timeframe of a clinical trial is too short to capture all the effects of an intervention; or if intermediate endpoints have been measured rather than a final outcome, such as cholesterol elevation rather than death from heart attack.



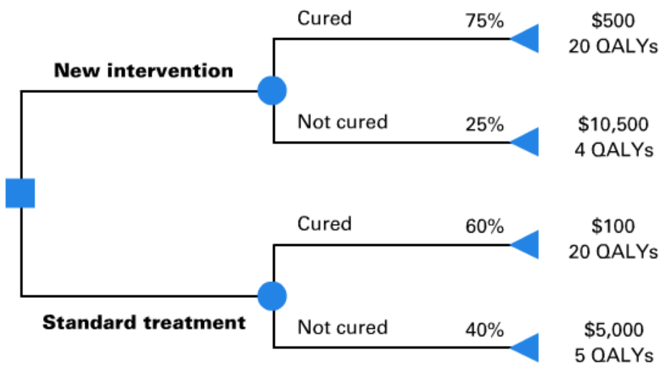
In economic evaluation, decision modelling is commonly used. This is a systematic, quantitative approach for assessing the relative value of different options. A decision model tracks the course of a disease to compare alternative interventions, with the objective of summarising relevant advantages and informing the management of patient populations. The model should reflect reality, but justifiable simplifications may be made to keep it manageable and comprehensible. It is also important to remember that a model developed for one population may need to be adapted for use in a different population – for example, because costs and resource use may vary.

Two of the most commonly used types of decision model are decision trees and Markov models.

Let's first look at decision trees.

Decision trees

With any model, the first stage is to identify and bound the problem. It can then be structured using a decision tree, which is a visual map of all the possible paths associated with the problem. It is built up of nodes and branches.



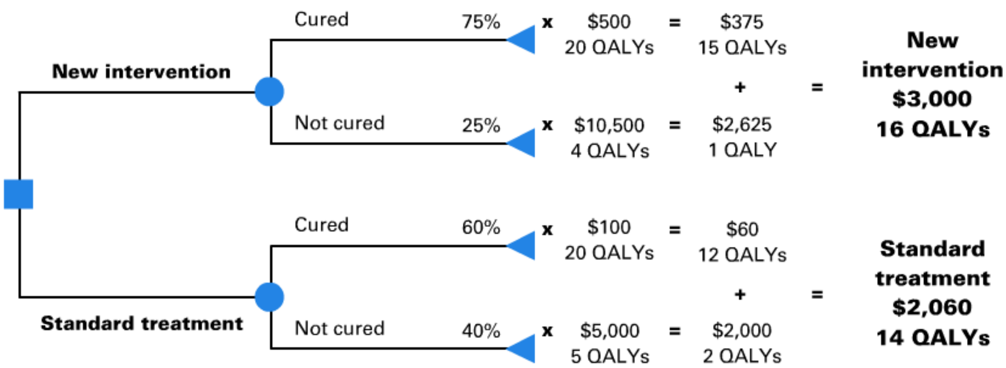
Decision nodes are represented by squares and indicate a choice that is made – each branch represents one of the options. Here, the decision is between treating patients with the new intervention or standard treatment.

Chance nodes are represented by circles and indicate events not under the control of the decision maker – branches represent the possible outcomes.

Terminal nodes are represented by triangles and indicate the end of a path.

Once the tree has been constructed, probabilities are assigned to chance events and payoffs are assigned to each path. The values for each path are then weighted by the probability of them occurring. The average – or expected – payoff for each decision is calculated by summing the results.

In this case, this gives the costs and quality-adjusted life years – or QALYs – associated with the new intervention and standard treatment. These results can then be used to calculate the economic evaluation results – for example, the incremental cost-effectiveness ratio, or ICER.



$$\text{ICER} = \frac{\text{Incremental cost}}{\text{Incremental outcome}} = \frac{\$3{,}000 - \$2{,}060}{16 - 14} = \$470/\text{QALY}$$

Sensitivity analysis is also important to investigate how uncertainty about parameters in the model impacts the results – this will be covered later.

Now let's turn to Markov models.

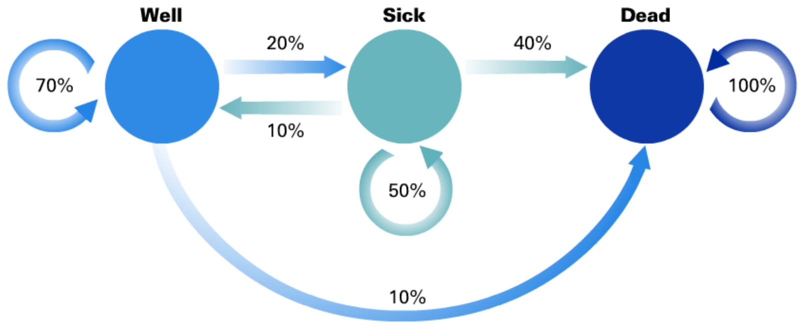
Markov models

These are often used when the timing of events is important or when patients move in and out of a health state over time.

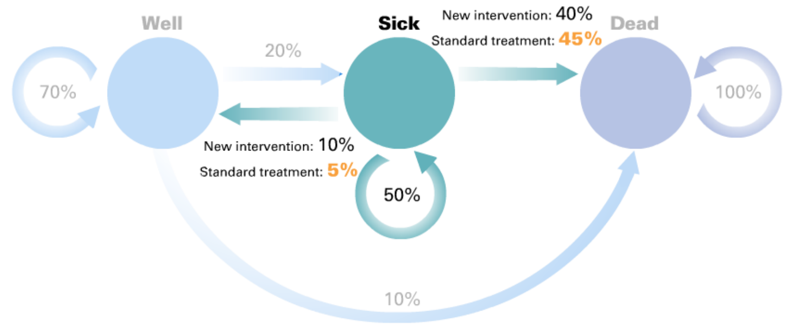
In a Markov model, a set of health states are defined that represent the course of a disease – in this simple example there are three states: well, sick and dead.

People in the model can only exist in one health state at a time, but can move – or transition – between the health states at regular time intervals, known as cycles. Here, people who are well can stay well, become sick, or die; people who are sick can get better, stay sick, or die; and people who are dead can only remain dead!

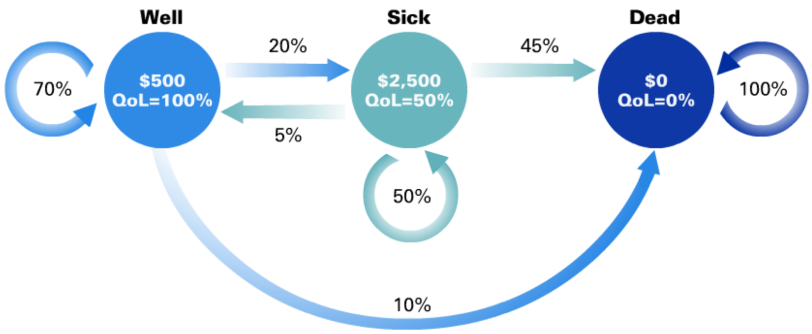
The model is run in repeated cycles over a fixed time horizon or until all people in the model are dead. How people transition between the states during each cycle is determined by probabilities. These depend only on the current health state of the individual and not on any previous health states they have been in – this is the 'Markovian assumption'.



Each intervention in the evaluation will have a different set of transition probabilities – here, sick people who receive standard treatment are less likely to get well and more likely to die than with the new intervention.



Each health state is also assigned a value – for example in terms of cost per cycle and quality of life – these are used when evaluating the model to generate results.

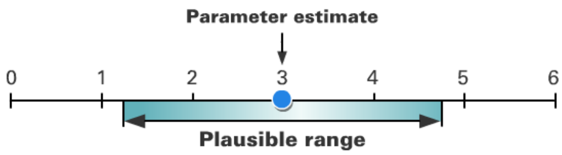


Evaluation may be carried out using cohort simulation – where people pass through the model as a group – or patient-level simulation – where people move through the model one at a time. The model is evaluated twice – once for each intervention under comparison. The results can then be used to calculate the economic evaluation results – for example, the ICER.

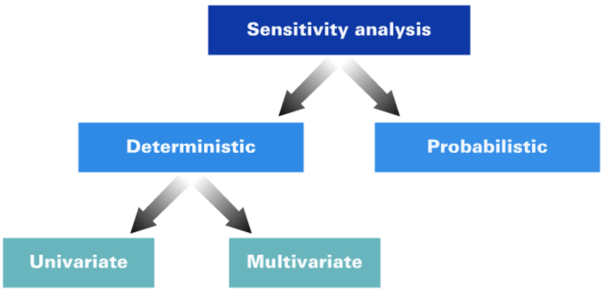
As with decision trees, sensitivity analysis is also important to investigate how uncertainty impacts the Markov model results – let us now look at this in more detail.

Sensitivity analysis

Sensitivity analysis involves varying parameters within a plausible range and recalculating the model results. Ways of determining a plausible range include carrying out a literature review, gathering expert opinion, or using a statistical confidence interval.



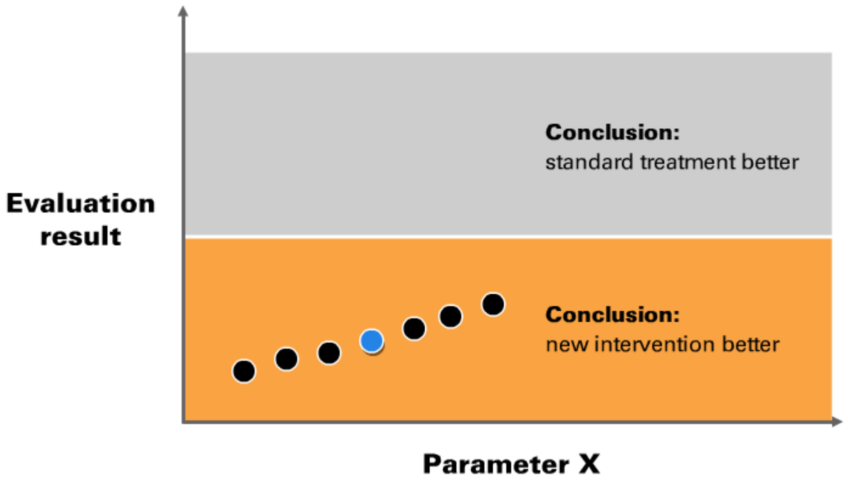
There are two key approaches to sensitivity analysis: deterministic methods, where the researcher selects values within the plausible range and varies either one parameter at a time or a combination; and probabilistic sensitivity analysis, which involves simultaneous random sampling of all uncertain parameters.



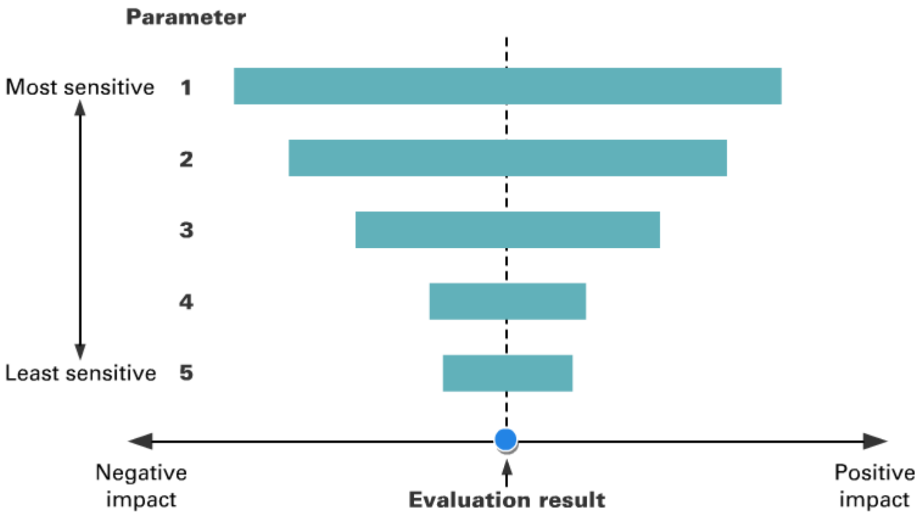
Let us now examine these techniques in more detail.

Univariate

The simplest method is one way – or univariate – sensitivity analysis, where a single parameter is adjusted whilst others are kept constant. The degree of variation in the evaluation result gives an indication of sensitivity to the parameter. If the conclusion remains the same, then the evaluation's robustness is strengthened.

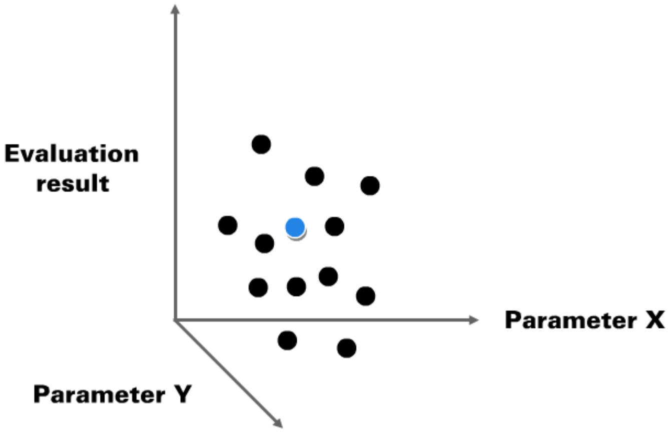


Univariate analysis might be used before carrying out a more sophisticated form of sensitivity analysis. For example, parameters in the model might be varied one at a time, and the results used to construct a 'tornado diagram' ranking parameters by their sensitivity to uncertainty. This allows the researcher to identify where to focus further efforts to reduce uncertainty in the evaluation.

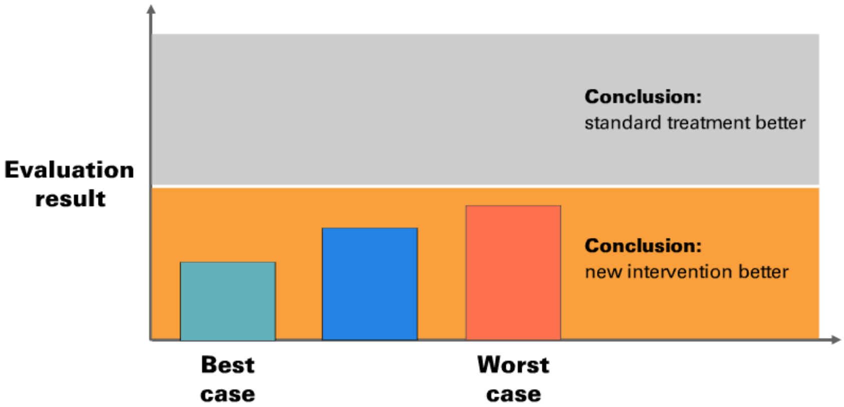


Multivariate

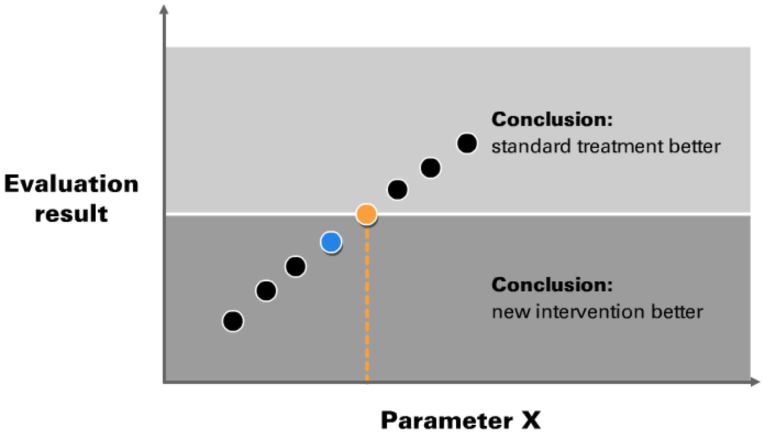
Multivariate analysis is used to investigate the effect of varying more than one parameter at a time. This is more realistic, although can be complex if there are many parameters.



Multivariate analysis might be used to generate a best and worst-case scenario; as with univariate sensitivity analysis, if the conclusion remains the same, then the evaluation's robustness is strengthened.



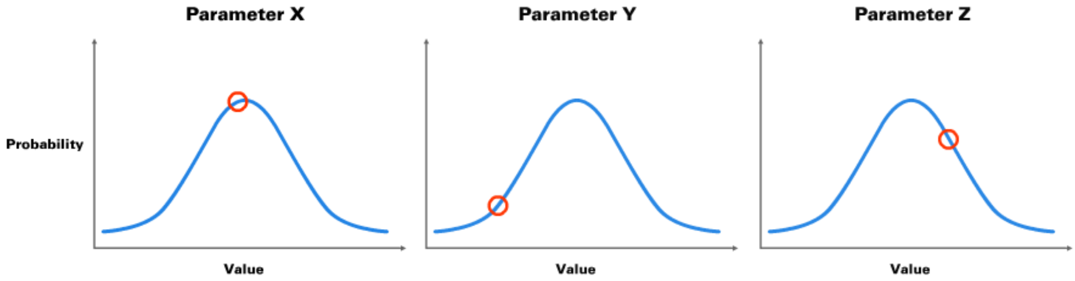
Either technique can also be used to carry out a threshold analysis to identify the critical parameter value or sets of values that cause the conclusion to change.



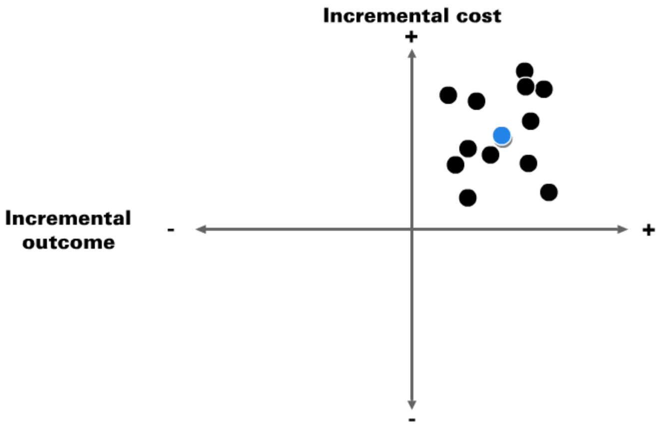
Probabilistic

Probabilistic sensitivity analysis is also used to investigate the effect of varying multiple parameters, and allows uncertainty to be quantified. However, it is more complex and time-consuming, and in practice is not always necessary.

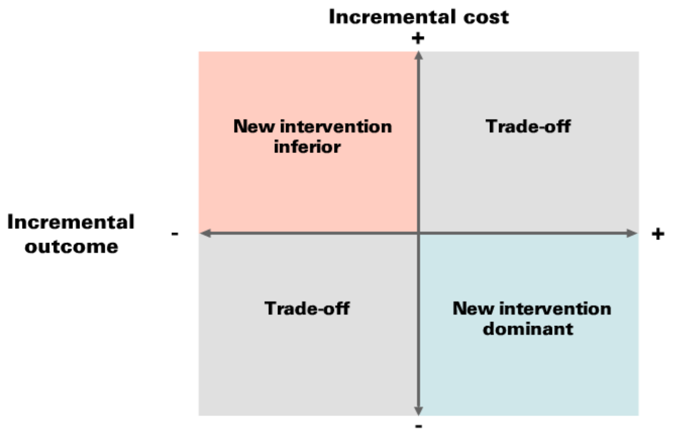
Probabilistic sensitivity analysis is carried out by assigning probability distributions to uncertain parameters to describe how they vary. Parameter values are selected at random from these and used to recalculate the evaluation results. This process is repeated perhaps a thousand times.



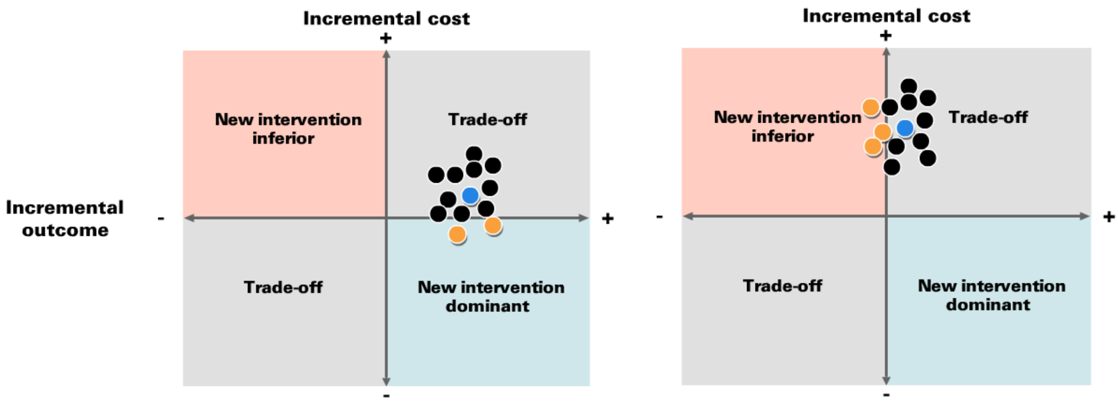
The results are often presented on what is known as the ‘cost-effectiveness plane’, where incremental cost is plotted against incremental outcome. The wider the distribution, the more uncertainty affects the economic evaluation.



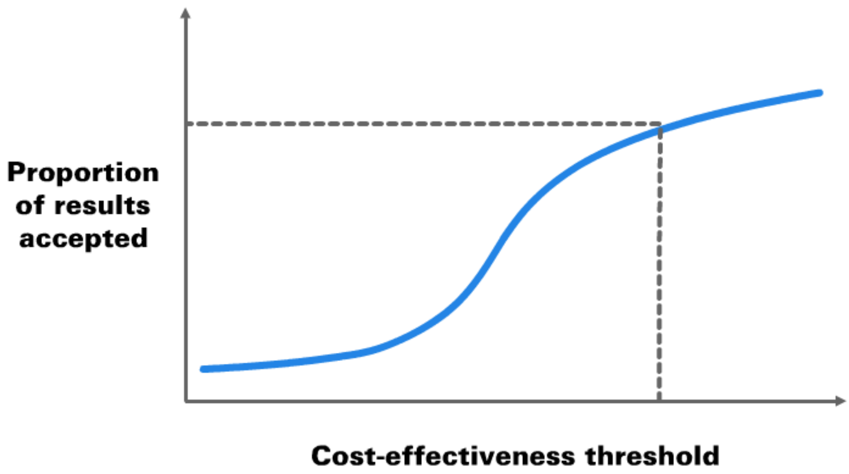
Where the results fall on the plane is also significant. Results fall in the green quadrant when the new intervention improves outcomes at a reduced cost and is therefore clearly better than – or dominant over – the comparator. They fall in the red quadrant when the new intervention worsens outcomes at increased cost and is therefore clearly worse than – or inferior to – the comparator. And results fall in the grey quadrants when a trade-off occurs – either improved outcomes at higher cost, or worse outcomes at lower cost.



If the result of an economic evaluation finds a trade-off between costs and outcomes, but the sensitivity analysis results indicate a chance of dominance, this may strengthen the case for the new intervention to be adopted. Conversely if they indicate that inferiority is possible, this may weaken the case.



A ‘cost-effectiveness acceptability curve’ could also be drawn. This shows the proportion of results that are below any given cost-effectiveness threshold – and can therefore be considered cost-effective.



Summary

This module covers the following topics:

- Decision trees
- Markov models
- Sensitivity analysis
  - univariate
  - multivariate
  - probabilistic