Evidence-based decisions: the role of decision analysis

11

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CHAPTER CONTENTS

KEY ISSUES

- What is a decision analysis?
- How to undertake a decision analysis:
  - structuring a question
  - designing a decision tree
  - extracting probabilities
  - gathering utilities
  - combining information on probability and utility in the process of 'rolling back' a decision tree
- The strengths and weaknesses of decision analysis

INTRODUCTION

The components of an evidence-based decision include the results of research, a patient's values or preferences for particular choices, an awareness of available resources, and the experience and expertise of the decision maker (DiCenso et al 1998). Having made it this far in the text, you will have grasped that making evidence-based decisions in practice can sometimes be difficult; requiring the use of complex, often incomplete information, and with uncertain decision outcomes (Hunink et al 2001, Tavakoli et al 2000). Paying attention to and integrating the volume of information in practice can often seem overwhelming. Nurses, like all human beings, have limited capacity to manage all of the different components of a complex decision at the same time (Hunink et al 2001, Sarasin 2001). Decision analysis is one approach that can help systematically combine the elements required for an evidence-based decision.

WHAT IS DECISION ANALYSIS?

Decision analysis is based on the normative expected utility theory (EUT; see Chapters 2 and 5; Elwyn et al 2001, Tavakoli et al 2000, Thornton 1996). Decision analysis is used prescriptively as a way of assisting decision makers with their choices. Underpinning the process is the assumption that humans are rational, logical decision makers. A rational decision, in the context of decision analysis, is one that results in the outcome with the greatest usefulness to the individual (Elwyn et al 2001).

Carrying out a decision analysis involves breaking a decision problem down into its component parts. For decision analysis, these component parts are the probability of different outcomes occurring and the value or preference an individual attaches to those outcomes. Synthesising the value of these component parts guides you toward the 'best' decision option (Dowie 1993, Tavakoli et al 2000) given your goal to maximise the decision maker's utility (more on utility in a moment). Breaking the decision problem down in this way provides an explicit and transparent map of how a decision has been taken:

> "Decision analysis is a systematic, explicit, quantitative way of making decisions in healthcare that can . . . lead to both enhanced communication about clinical controversies and better decisions. (Hunink et al 2001 p 3)"

Decision analysis is not a suitable tool to be used for all decision situations. It is, however, a technique particularly suited to *complex* decision situations: those choices in which the 'best' option is not readily available. Complexity can be due to different options carrying different risks or benefits, or because how a patient views different outcomes is particularly important.

THE STAGES IN A DECISION ANALYSIS

The stages involved in carrying out a full decision analysis are outlined in Box 11.1.

Structuring the decision

The first thing that you need to do when planning or managing patient care, is to outline the decision problem you are faced with; a process known as *structuring* the decision problem. Structuring a decision involves translating an ill-defined problem into a set of well-defined elements (von Winterfeldt 1980). As a starting point, take the clinical scenario described in Box 11.2.

Box 11.1 Stages in carrying out a decision analysis

- Define the decision problem
- Structure the decision: construct a decision tree
- Assess the probability of different outcomes: add probability to the decision tree
- Measure patient utility: add utility to the decision tree
- Calculate the 'expected value' of a decision tree: identify the 'best' option
- Assess the sensitivity of the decision model

Box 11.2 Clinical scenario

You are a practice nurse who runs a women's health clinic. You provide advice to women on a variety of different health issues, including women who are experiencing menopausal symptoms. In your clinic this morning, you see a 51-year-old woman who is experiencing considerable distress from a number of menopausal symptoms. You discuss at some length with the woman the potential choices available to her to aid the symptoms, including taking hormone replacement therapy (HRT), non-HRT therapies, and doing nothing. There are associated risks and benefits with all of the different choices that she has open to her, and no particular option seems to be the most appropriate.

In this instance, you are faced with an uncertain and complex decision situation. The woman has a number of choices available to her. You are aware that there are risks and benefits associated with those decision choices and need to help the woman make a decision about what to do.

Balance sheets

One strategy to help define the decision problem is to list all the different options or actions you can think of that the woman could choose, and consider the possible benefits and risks of each choice; an approach known as constructing a 'balance sheet' (Hunink et al 2001).

Identifying the options for a particular decision can be made easier by examining the research literature. Using the '5S' approach to looking for evidence, the first place we might look are decision support systems (Haynes 2006). Systems such as NHS Clinical knowledge summaries (CKS) (http://CKS.library.nhs.uk/home) and Clinical Evidence (www.clinicalevidence.com), which provide evidence-based guidance on interventions, also illustrate common management options for conditions. In this instance, both Clinical Evidence and CKS provide guidance on the management of menopausal symptoms. The options available to the woman are: (1) do nothing or receive/provide lifestyle advice; (2) taking hormone replacement therapy (HRT); (3) non-hormonal alternatives to HRT. Clinical evidence also gives details on the benefits and risks of the different interventions. You could use this information to construct a balance sheet like the one in Table 11.1.

Decision trees

Another way of structuring the decision is to represent the choices in the form of a 'decision tree', which provides the structure for a decision analysis. A decision tree represents both the decision options you have available to you (represented in a tree as a square node between branches) and the uncertainty associated with each decision option (represented in a tree as a circular node) (Dowie 1993). When structuring a decision problem in the form of a tree, the model needs to be complex enough to represent all the important events that might happen to an individual, whilst simple enough

Table 11.1 Balance sheet for menopausal decision

Intervention	*Benefit*	*Harm*
Provide lifestyle advice	Might be sufficient to help manage hot flushes and anxiety symptoms	None from intervention itself. Long-term consequences of the menopause: increased risk of osteoporosis, urogenital atrophy, cardiovascular disease, stroke
Hormone replacement therapy (provision of oestrogen with a progestogen in women with a uterus)	Relief of menopausal symptoms; hot flushes, night sweats, urogenital atrophy Decreased risk of osteoporosis Decreased risk of colorectal cancer	Increased risk of breast cancer Increased risk of stroke Increased risk of venous thromboembolism
Non-hormonal alternatives that contain phytoestrogens (e.g. soy foods)	May reduce symptoms such as hot flushes	None known

to be understandable (Detsky et al 1997). The decision tree will always be a simplified model of the actual decision situation, but should still incorporate the risks and benefits associated with the decision you are faced with (Detsky et al 1997). Figure 11.1 shows the information in the balance sheet of Table 11.1 as a decision tree.

The structure of the tree reflects the key elements of the decision problem: the choices available to the woman and the risks and benefits of each option. To simplify the model, only the most important potential benefits and risks of different interventions have been included: relief of menopausal symptoms, decreased risk of osteoporosis, and increased risk of breast cancer. If we modelled all of the potential risks/benefits for each option, then the model might better reflect the decision situation but might not be so understandable.

The importance (to the person making the choice) of the different elements in a decision will determine the shape of the tree. For some decisions, just identifying the different options available, and their associated benefits and risks, might provide enough of a structure to make a decision on the best option for this particular individual.

Assessing the probability of different outcomes

An important dimension of any decision is the likelihood that events you would like to see happen actually happen. Rejecting a decision option on the basis that there is a one in a million chance of an outcome occurring might not be that rational, but we can only judge the adequacy of a choice if we make such information explicit.

Having structured the decision problem and identified the *potential* benefits and risks associated with each option, we need to consider in detail how

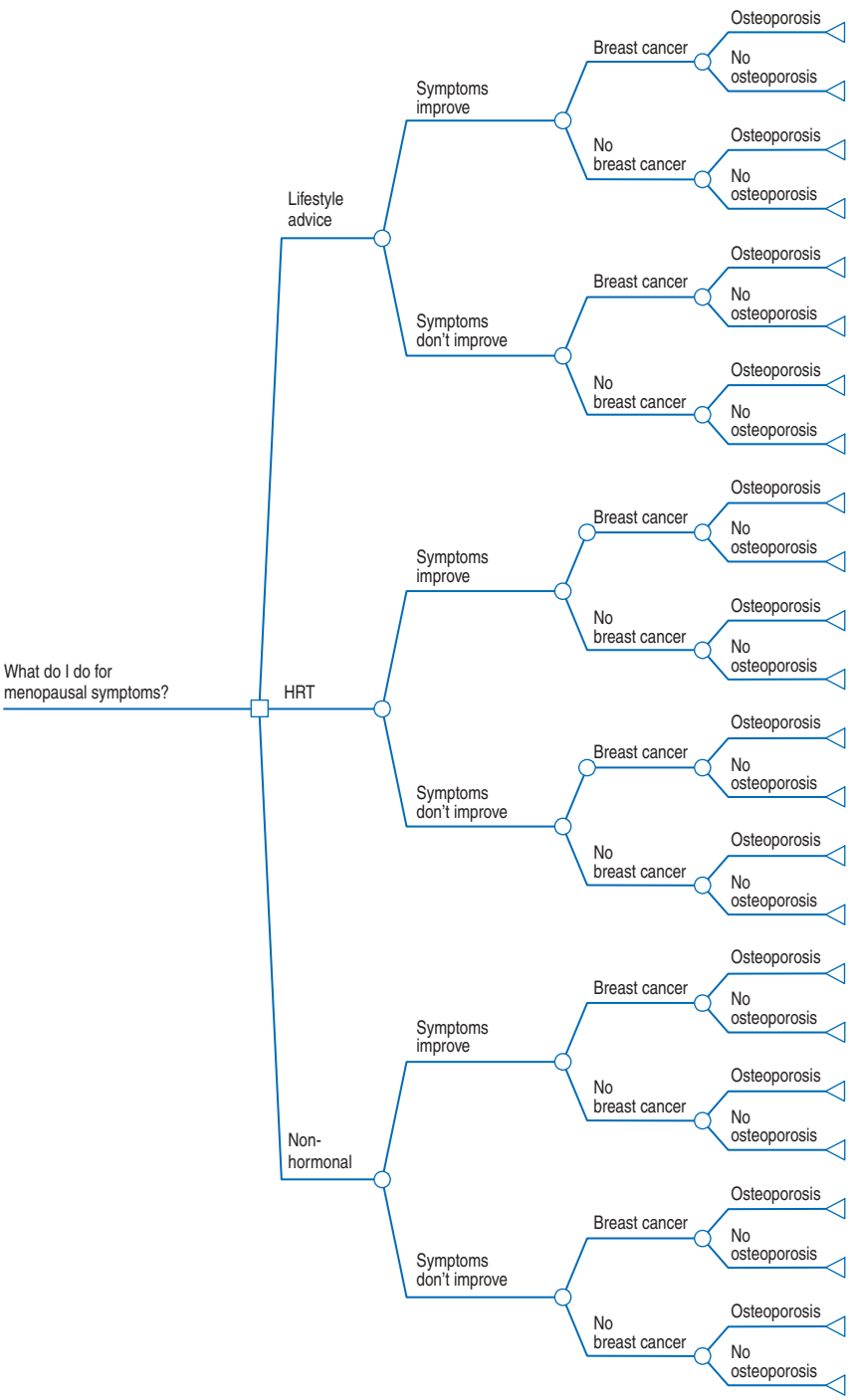

Figure 11.1 Structure of a decision tree.

likely those outcomes are to occur. As decision analysis is commonly associated with decisions to intervene or treat, then the data needed to estimate such probabilities should come from good quality research evidence. The best kinds of research design to provide unbiased treatment or intervention probabilities are well conducted randomised controlled trials (RCTs) or – preferably – meta-analyses of good-quality RCTs (Richardson & Detsky 1995a, 1995b). Whereas research-based estimates are preferable to experience for ascertaining probabilities, even experience expressed explicitly in the form of a numeric estimate is preferable to keeping such estimates implicit and hidden from patients and colleagues when making choices.

Using research evidence

For each potential outcome within your decision problem, we need the probability of that outcome occurring for your patient or patient group, together with an estimate of the uncertainty surrounding this probability. The less confidence you have in your estimate of probability (i.e. the greater the uncertainty), the wider the range of your estimate of uncertainty should be (Naglie et al 1997).

To find these probabilities, we conduct a search for research evidence (see Chapter 4). As with any evidence-based decision, any evidence we find needs to be appraised critically. If, following our search, we find one study that is better in terms of its methodological quality than the other retrieved studies (it might be a good-quality systematic review/meta-analysis as opposed to a single, small trial), then this can be used to provide our probability estimates. If we find several relevant studies, then we need to assess them for methodological quality, eliminate those of poor quality, and use the average of the results of the remaining studies to estimate our values (Naglie et al 1997).

Study results can be reported as dichotomous or continuous measures. For the purpose of basic decision analysis, you need an estimate of how likely an outcome is to occur *or* not occur. This dichotomous outcome can be expressed as a probability, percentage or fraction (see Chapter 3). Sometimes, papers give raw figures for the number of participants who experienced an outcome. In this case, you can calculate the probability yourself.

However, studies sometimes report outcomes as continuous measures (i.e. the mean decrease in pain as measured on a pain score). Results presented in this way provide the overall effect of an intervention (e.g. giving pain relief decreased mean pain scores compared to control), but do not tell you the number/percentage of individuals experiencing the outcome (i.e. it doesn't whether 40% or 60% of the subjects in the intervention group had improved pain). This is the information we need to estimate the likelihood of an event occurring within a decision model.

One way to convert continuous probability data into a format you can use in a decision model is to use 'mean effect sizes' (Tickle-Degnen 2001). The effect size (*d*) is the difference between mean outcomes for two conditions in *standard deviation units*. An effect size that is reported in standard deviation units can be used to calculate the proportion of individuals for whom an intervention succeeded or failed (Tickle-Degnen 2001). We will

Table 11.2 Effect sizes and success rates

Magnitude of effect	d	Success rates: Control (%)	Success rates: Intervention (%)	Success rates: Change (%)	r	Success rates: Control (%)	Success rates: Intervention (%)	Success rates: Change (%)
Zero	0	50	50	0	0	50	50	0
Small	0.20	46	54	8	0.10	45	55	10
Medium	0.50	40	60	20	0.24	38	62	24
Large	0.80	34	66	32	0.37	32	69	37
Very large	2.00	16	84	68	0.71	15	86	71

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All calculations and estimations are based on the assumption of a binomial distribution of the outcome measure, with approximately equal number of cases and approximately equal variances within each condition. All rates here are success rates. To calculate failure rates, subtract any success rate from 100%.

not discuss how to calculate mean effect sizes (for an outline and Excel spreadsheet, see: www.cemcentre.org/renderpage.asp?linkID=30325015) and Table 11.2.

What if there is no evidence?

You will not always be able to find research studies that provide you with probabilities for the outcomes you are interested in. Despite this, a decision still needs to be made (Hunink et al 2001). The most common solution is to ask an expert or experts in the clinical area to provide estimates of the likelihood of different outcomes. As highlighted in Chapter 8, expert estimates based on experience can be subject to bias and a lack of consensus (Naglie et al 1997). Because of this, it is important to ensure that your estimates of the range of uncertainty around the expert-derived probabilities reflect this uncertainty. Reflecting this uncertainty might involve using the range of estimates provided, or creating your own personal 'confidence intervals' around the estimates.

Adding probabilities into the decision model

Having identified the likelihood of different outcomes occurring, together with an estimate of the uncertainty around this figure, you need to add it to your decision model. Sometimes it helps to list all of the possible outcomes that may occur within the decision situation together with your probability estimates and their source in a table. An example of this for the menopause decision is given in Table 11.3. The probability estimates in this table were identified from CKS or from references in Clinical Evidence. We have assumed that the woman will be considering using HRT that contains both oestrogen and progestogen (combined HRT therapy) as she still has a uterus. All the data are given for a 5-year period. The likelihood of developing osteoporosis is measured by the likelihood of having a fractured

Table 11.3 Probability table for menopausal decision

Outcome	*Probability estimate*	*Range*
Symptoms improve with lifestyle advice*	0.55	0.2–0.705
Symptoms improve with HRT	0.86	0.706–0.96
Symptoms improve with non-hormonal treatment	0.43	Not known
Risk of developing breast cancer over 5 years with no treatment	0.014	0.013–0.014
Risk of developing breast cancer over 5 years with HRT	0.028	0.028–0.031
Risk of developing breast cancer over 5 years with non-hormonal treatment	0.014	0.013–0.014
Risk of hip fracture (osteoporosis) over 5 years with no treatment	0.0015	0.0005–0.0025
Risk of hip fracture (osteoporosis) over years with HRT	0.0012	0.0002–0.0022
Risk of hip fracture (osteoporosis) over 5 years with non-hormonal treatment	0.0015	0.0005–0.0025

There is no evidence to suggest that using non-hormonal therapies for menopausal symptoms affects either the overall risk of developing breast cancer or osteoporosis, so the incidence rates for women who don't take hormone-replacement therapy (HRT) have been used.
*The values for this outcome were the ones for the placebo group.

neck of femur (which is the most common outcome associated with osteoporotic disease).

Having listed the likelihood or probability of different outcomes occurring in this way, the values can then be added in to the decision tree (Figure 11.2). For each branch in the tree, the probability values should add up to 1. This is because the outcomes are mutually exclusive; meaning that you cannot have more than one outcome for each branch simultaneously. For example, if there is a 25% chance that the menopause will lead to a fractured neck of femur there is a complementary 75% chance that it will not. You cannot have a fractured neck of femur on one leg, and at the same time *not* have one.

Assessing patient values or preference: measuring utility

A key challenge for evidence-based decision makers is incorporating a patient's preferences for different decision options (DiCenso et al 1998) into the decision-making process. In decision analysis, patient values or preferences are explicitly considered in the form of measures of utility. Utility is a numeric or quantitative measure of the value an individual or group place on the different outcomes or consequences of a decision (Richardson & Detsky 1995b). The aim of many decisions in healthcare is to improve an individual's state of health. For this reason, utility might also be referred to as 'health state preference' and reflects how an individual values a given state of health. This is not the same as measures of quality of life, which focus on the characteristics of that health state (Hunink et al 2001).

Utility is measured on an interval scale, from 0 to 1 (or 100). Zero equates to the worst possible health state *for that individual* and 1 or 100 represents the best possible health state *for that individual*. You might find in some publications that 0 is equal to death and 1 or 100 perfect health. The problem

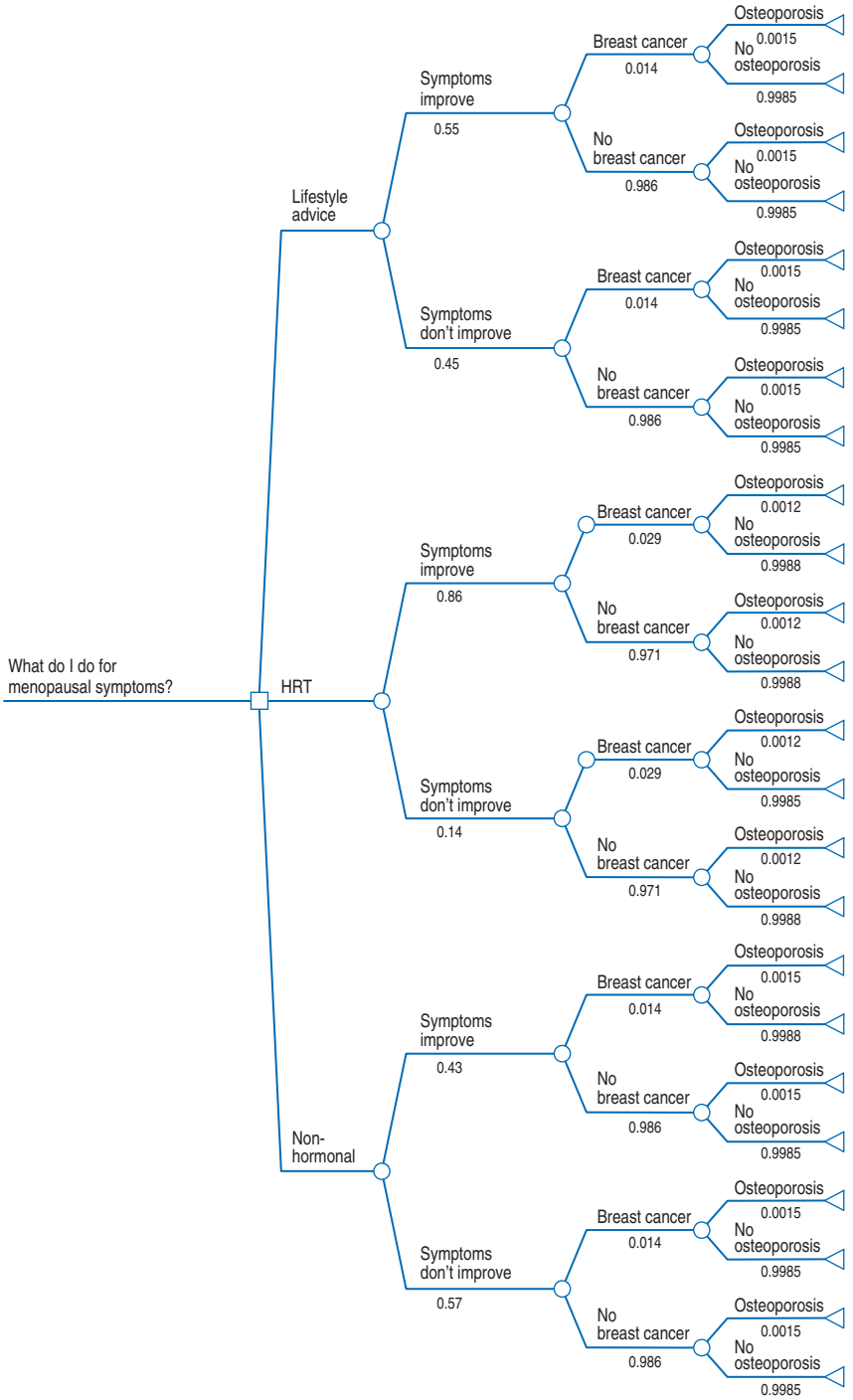

Figure 11.2 Probability values added to decision tree.

with this convention is that it fails to recognise that, *for some individuals*, there are health states that are worse than death *for them*; far *better* to refer to them as 'worst' and 'best' health states (Drummond 1993). Utility can be measured at the individual patient level for individual clinical decisions, or at a population level for societal decisions. This chapter focuses on individual-level decisions between patients and professionals.

Utilities can be estimated in a number of ways:

- Arbitrarily assign a value according your own judgement: this is by far the most common approach in healthcare. For example, statements such as, 'there is no point in discussing compression (therapy) for his leg ulcer as he won't tolerate it' represent an arbitrarily assigned value statement.
- Ask a group of experts to reach a consensus on their estimates of utility.
- Use relevant utility values published in the literature.
- Measure utility values directly using reliable and valid measures (Naglie et al 1997, Sarasin 2001). Methods for measuring utility directly include rating scales, the use of a technique known as the 'standard gamble' and 'time-trade off'.

Rating scales

With a rating scale, an individual is asked to evaluate the utility of different outcomes on a line between 0 and 10 or 100. The scale is anchored with the most preferred health state at one end and the least preferred at the other. The remaining health states are placed on a line between them, reflecting differences in the preferences of the individual (Drummond 1993).

Standard gamble

The standard gamble involves examining an individual's valuation of health states compared with death. The individual is offered two alternatives: a gamble with two possible outcomes (death or return to normal health), or the certain outcome of remaining in the health state being valued for the rest of his or her life. The probability of the outcomes occurring in the gamble is altered until the individual is 'indifferent' (has no clear preference). This state of indifference represents the preference value (Thornton et al 1992).

Time trade-off

In the time trade-off approach the individual is asked to consider the relative amounts of time he or she would be willing to spend in a given health state. For each health state for which you need a utility, the individual is offered a choice: to stay in this health state for the rest of his or her life, or return to perfect health but for a shorter period of time. The amount of time the patient is willing to 'trade' is used to calculate the value for the health state (Drummond 1993).

An example of how the same health state would be elicited from an individual using the different methods is shown in Box 11.3.

Different methods of eliciting utility use different approaches, and produce different values for the *same health state* in the *same individual*

Box 11.3 Examples of utility elicitation using different methods

RATING SCALE

On a scale where 0 represents death and 100 represents excellent health, what number would you say best describes how you would feel about developing breast cancer over the next 5 years (Figure 11.3)?

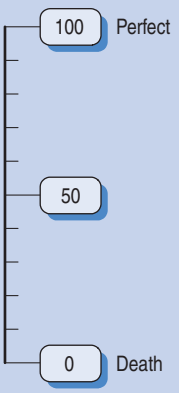

Figure 11.3 Rating scale.

STANDARD GAMBLE

Imagine that you will develop breast cancer over the next 5 years. You are told that there is a new treatment available to you, which has a 50% probability of completely curing you of cancer. However, the treatment also has a 50% probability of causing immediate death. Would you have the treatment (Figure 11.4)?

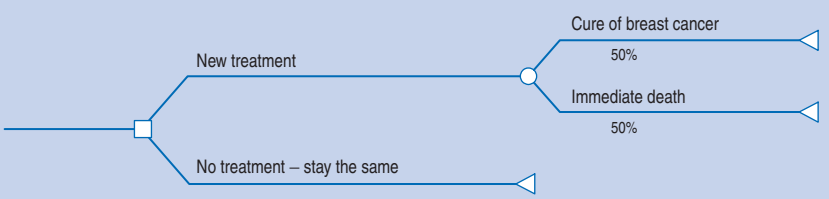

Figure 11.4 Standard gamble.

DEPENDING ON YOUR ANSWER

If your answer was 'No', would you be prepared to have the new treatment if there was a 60% chance of the cure and a 40% chance of death?

If your answer was 'Yes', would you be prepared to have the new treatment if there was a 40% chance of the cure and a 60% chance of death?

Alter the values up or down until the person is at a point where she cannot decide (i.e. both options are equal). The person's utility for having breast cancer is the probability of having a cure for breast cancer. So say, for instance, that the patient would accept the treatment when it had a 90% chance of cure and a 10% chance of death, her utility for breast cancer is 0.9.

Continued

Box 11.3 Examples of utility elicitation using different methods – cont'd

TIME TRADE OFF

Imagine that you have 40 years of life expectancy, living with breast cancer. Now imagine that someone can give you a cure for your cancer but you will only live 20 more years, instead of 40. Would you take the cure?

Depending on the answer, alter the amount of time traded. So if the answer is 'No', would they accept the treatment if it cured them and they lived 39 years? If the answer was 'Yes', would the patient accept the treatment if she lived 10 more years?

Continue until the two options are the same (living with breast cancer or being cured). At this point, the utility for breast cancer would be the ratio of the length of life in perfect health to the length of life in the health state being evaluated.

(Drummond 1993). Standard gamble techniques produce higher values than other methods of utility measurement, possibly because they ask individuals to consider the risks associated with different outcomes when making choices in the gamble (Drummond 1993). They might also be subject to 'framing effects', in which the preferences are influenced by how the information and trade-off is presented. Rating scales, although easy to use, might result in values being distorted as individuals tend to avoid the extremes of the scale (Thornton et al 1992).

You also need to take into account *whose* preferences or values you are considering. Often, studies in healthcare will ask a clinician how they think their patients feel about different health states. Clinician's evaluations and a patient's own views might actually be very different (Brand & Kliger 1999). Wherever possible, the utilities for each of the health states should be elicited from the person who is going to be affected most by the decision. This is not without its problems; often, patients will be asked to evaluate a health state of which they have no personal experience. Alternatively, it could be a 'hypothetical' state that could happen to them in the future; the implications of which for the here-and-now are sometimes difficult to grasp (Hunink et al 2001). Preferences or values attached to health states are not always stable. They vary across time and can alter when an individual actually experiences the health state being valued (Hunink et al 2001).

Using utility measures in a decision tree

For many decision models, the outcomes of a decision will be a combination of different health states. For instance, we could evaluate how a woman feels about taking HRT (i.e. taking a tablet for a period of time), her symptoms improving, developing breast cancer, and having osteoporosis. In these circumstances, utility can be measured as a whole, or in parts, which are then combined to provide an overall evaluation (Naglie et al 1997). If you are estimating utility for different outcomes as a whole, then you would use a utility measure to do this. If you are using a 'decomposed' approach, you would firstly assess the utility of each separate outcome (e.g. utility for symptoms improving, utility for taking a tablet, and utility for developing breast cancer) and then combine them. Naglie et al (1997) suggest that, to combine

Table 11.4 Calculation of utility scores for menopausal decision

Short-term outcomes	*Utility value*	*Disutility*
HRT*	0.98	0.02
Non-hormonal therapy*	0.99	0.01
Symptoms improve	1	0
Menopausal symptoms (Brazier et al 2005)	0.81	0.19
Long-term outcomes	Utility value	
Breast cancer	0.8 (CEAR)**	
Fractured hip	0.63 (CEAR)†	
Lifestyle branch – outcomes	Utility	
Symptoms improve, breast cancer, fractured hip	$(0.8 \times 0.63) - 0 = 0.504$	
Symptoms improve, breast cancer	$0.8 - 0 = 0.8$	
Symptoms improve, fractured hip	$0.63 - 0 = 0.63$	
Symptoms improve	1	
Symptoms the same, breast cancer, fractured hip	$(0.8 \times 0.63) - 0.19 = 0.314$	
Symptoms the same, breast cancer	$0.8 - 0.19 = 0.61$	
Symptoms the same, fractured hip	$0.63 - 0.19 = 0.44$	
Symptoms the same	0.81	
HRT branch – outcomes	Utility	
Take HRT, symptoms improve, breast cancer, fractured hip	$(0.8 \times 0.63) - (0.02 + 0) = 0.484$	
Take HRT, symptoms improve, breast cancer	$0.8 - (0.02 + 0) = 0.78$	
Take HRT, symptoms improve, fractured hip	$0.63 - (0.02 + 0) = 0.61$	
Take HRT, symptoms improve	0.98	
Take HRT, symptoms the same, breast cancer, fractured hip	$(0.8 \times 0.63) - (0.02 + 0.19) = 0.294$	
Take HRT, symptoms the same, breast cancer	$0.8 - (0.02 + 0.19) = 0.59$	
Take HRT, symptoms the same, fractured hip	$0.63 - (0.02 + 0.19) = 0.42$	
Take HRT, symptoms the same	$1 - (0.02 + 0.19) = 0.79$	
Non-hormonal therapy branch – outcomes	Utility	
Take non-hormonal therapy, symptoms improve, breast cancer, fractured hip	$(0.8 \times 0.63) - (0.01 + 0) = 0.494$	
Take non-hormonal therapy, symptoms improve, breast cancer	$0.8 - 0.01 = 0.79$	
Take non-hormonal therapy, symptoms improve, fractured hip	$0.63 - 0.01 = 0.62$	
Take non-hormonal therapy, symptoms improve	0.99	
Take non-hormonal therapy, symptoms the same, breast cancer, fractured hip	$(0.8 \times 0.63) - (0.01 + 0.19) = 0.304$	
Take non-hormonal therapy, symptoms the same, breast cancer	$0.8 - (0.01 + 0.19) = 0.6$	
Take non-hormonal therapy, symptoms the same, fractured hip	$0.63 - (0.01 + 0.19) = 0.43$	
Take non-hormonal therapy, symptoms the same	$1 - (0.01 + 0.19) = 0.8$	

*This is 'author judgement' on the assumption that having both will be worse than either by themselves.

**Five studies had examined the utility of breast cancer. Three used time trade-off (TTO) and two used clinician/author judgement to estimate utility. The value given is the mean of the five values.

†Nine studies estimated the utility of fractured hip, some after 1 year, others after 2 years. Two studies used standard gamble, one time trade-off, and one a mixture of TTO and rating scales. The other studies were all author judgement. The value given is the mean of the nine values.

utilities, you first need to divide them into short-term and long-term outcomes. You would then convert the utilities of all your short-term outcomes into 'disutility' values, by subtracting them from 1. For each branch of the tree, you would then multiply the utility values of all the long-term states together, before subtracting the disutility values for the short-term states to provide you with your overall utility rating. Finally, you should rank the utility values for each tree branch, to ensure that they make sense.

An example of how to do this is given in Table 11.4, for the possible outcome states for the decision model given in Figure 11.1.

Where possible, the utility values for each individual health state have been taken from the Cost Effectiveness Analysis Registry (CEAR) at the New England Medical Centre (www.research.tufts-nemc.org/cear/default.aspx) and a study estimating the utility of menopausal symptoms (Brazier et al 2005). The CEAR gives the preference scores derived from empirical studies for a number of health states, listed by disease. This is a useful resource to estimate utility measures for health states when eliciting utility measures from individual patients is not possible. We failed to find published utility values associated with taking HRT and non-hormonal therapies, therefore these values are the authors' own estimations.

For each branch of the decision tree in Figure 11.2, we calculated the utility value, using the approach suggested by Naglie et al (1997). For instance, the outcome for the top branch of the tree is not having an intervention, symptoms improving, but over the long term developing breast cancer and osteoporosis. The short-term states in this case are symptom improvement (with a disutility score of 0) and long-term states of breast cancer and fractured hip (with utilities of 0.8 and 0.63 respectively). The overall utility for the outcome of this branch is therefore:

$$(0.8 \times 0.63) - 0 = 0.504$$

Once you have calculated the utility for each outcome in your decision model, you can add the values to your decision tree at the appropriate point. An example of how to do this for the menopausal decision is given in Figure 11.5.

Identifying the 'best' option

When both probabilities and utilities have been added to the decision tree, the 'expected utility', or value of each decision option, needs to be calculated. The eventual value represents both the probability of an outcome occurring and the value/utility the decision maker attaches to that outcome. If you are a logical, rational decision maker, you would select the decision option that has the highest numerical value. The expected utility represents the option that maximises the decision maker's values and the likelihood of a particular outcome occurring (Hunink et al 2001).

Calculating the decision tree

Calculating the expected utilities is called 'folding back' a tree. Starting from the left hand side of the tree, for each branch you multiply the probability by the utility, and then add each result together, at each stage, until you reach the decision branch. Figure 11.6 shows the full calculation for the menopausal decision tree.

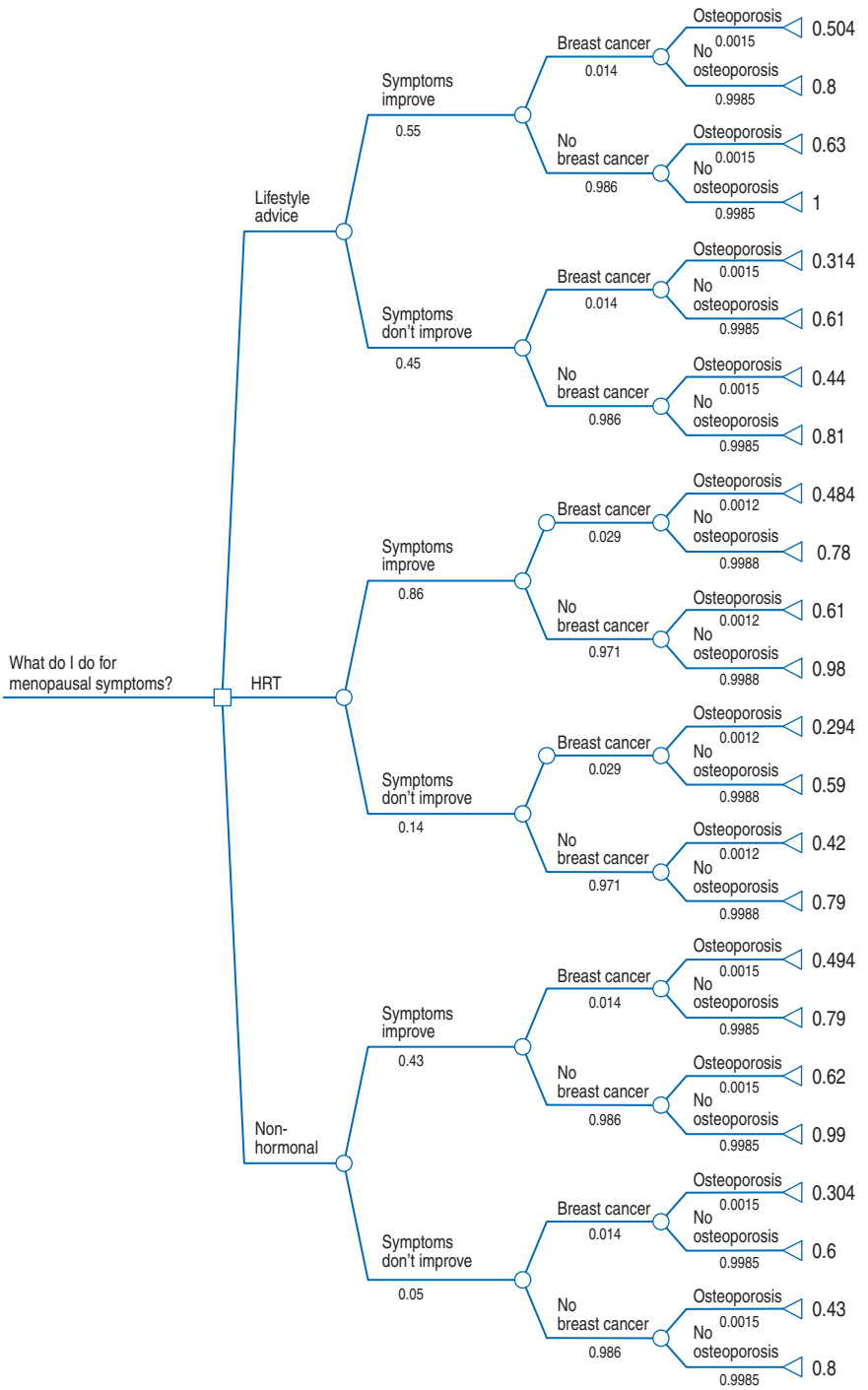

Figure 11.5 Decision tree for menopausal decision with utilities.

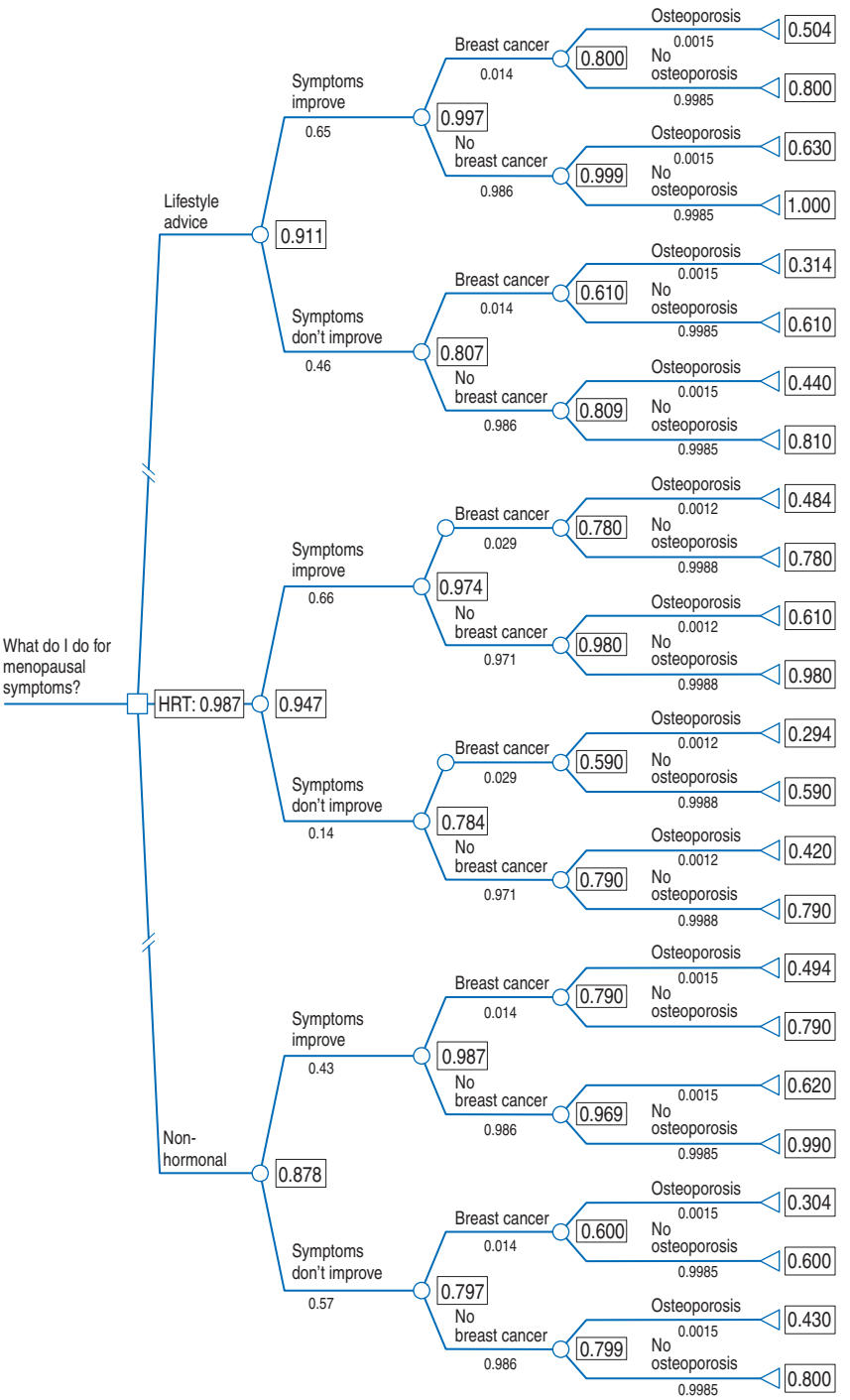

Figure 11.6 Full calculation of the decision tree.

An example of how to calculate the expected utility (EU) for each branch is given for the lifestyle part of the tree as follows:

1. Multiply the utility of the outcome for the top branch (0.504) with the probability of osteoporosis (0.002), which equals 0.001.
2. Multiply the utility of the outcome for the second branch (0.8) with the probability of no osteoporosis (0.999), which equals 0.799.
3. Add these figures together ($0.001 + 0.799 = 0.8$) and multiply this by the probability of having breast cancer ($0.8 \times 0.014 = 0.011$).
4. Follow the same procedure for the next two end points of the tree branch: $((0.63 \times 0.002) + (1 \times 0.999)) \times 0.986 = (0.001 + 0.999) \times 0.986 = 0.986$.
5. Add the results of c) and d) together: $0.011 + 0.986 = 0.997$.
6. Multiply this by the probability of symptoms improving ($0.997 \times 0.55 = 0.548$).
7. Follow the same procedure for the 'symptoms don't improve' branch, starting from the furthest branches and working backwards:
   a. $(0.314 \times 0.002) + (0.61 \times 0.999) = 0.61$
   b. $(0.44 \times 0.002) + (0.81 \times 0.999) = 0.809$
   c. $(0.61 \times 0.014) + (0.809 \times 0.986) = 0.807$
   d. $0.45 \times 0.807 = 0.363$.
8. Add together the two values from the symptoms improve (0.548) and symptoms don't improve (0.363) branches to give the overall expected value for the lifestyle advice option ($0.548 + 0.359 = 0.911$).

Carry out the same calculations for each branch of the decision tree, folding back from right to left, until you have an overall value for each decision option in the model. In this instance, the option with the highest value, of 0.947 (or 0.95) is HRT, so (if she were a logical, rational decision maker) the woman should choose to take HRT for her menopausal symptoms.

Sensitivity analysis

Sensitivity analysis is a way of assessing the 'robustness' of your decision analysis (Dowie 1993). Like all models, the results are dependent on the numbers that go in. There are some situations where either the research evidence is very uncertain (perhaps the estimates of likelihood of certain outcomes have a wide range) or individual values/preferences for certain outcomes vary considerably. In these instances, if you alter the probability or utility estimates in the model, the results might be different. This is important, as you might want to use the decision model with another individual. Different patients might have different probabilities (due to differing prognostic factors) or have varying values/preferences for outcomes.

When you carry out a sensitivity analysis, you alter the probabilities and/or utilities in your decision model to explore the impact these alterations have on the expected value of different branches and whether the optimum decision changes as a result. The point at which the optimum decision switches given the probability or utility values is known as its 'threshold'. If you subsequently have a patient with probabilities above or below that threshold then *their* optimum decision might be different from the initial model.

Let us alter the probability and utility values for the variables in our menopausal treatment decision analysis. The probability values were altered using the estimates of uncertainty in Table 11.3. Utilities were altered at points between 0 and 1. The results of the analysis can be seen in Figure 11.7. These two graphs illustrate that our decision model is sensitive to changes in the probability of symptoms improving with non-hormonal therapy, and the utility of taking HRT and symptoms improving. The threshold for the probability of symptoms improving with non-hormonal therapy is 0.8. This means that if the probability of this therapy improving symptoms is above 0.8 (i.e. if 80% or more of individuals who take the therapy experience an improvement in symptoms), then this becomes the preferred decision option. The threshold for the utility of taking HRT and symptoms improving is 0.9. This means that if a woman has a utility value of above 0.9 for taking HRT *and* having improved symptoms, then HRT is her preferred option. However, if her utility value is below 0.9, then lifestyle advice is her preferred option.

If the decision model is relatively insensitive to changes in either probability or utility, then you can be confident with the preferred options it suggests

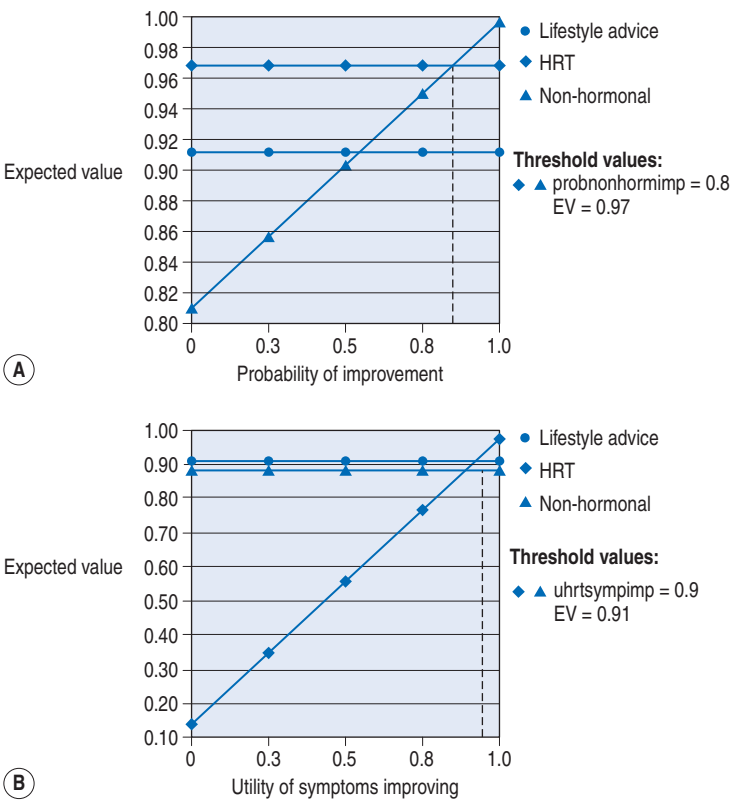

Figure 11.7 Results of one-way sensitivity analysis on menopausal decision tree: a) sensitivity analysis on probability of improvement with non-hormonal therapy, b) sensitivity analysis on symptoms improving with HRT.

(Naglie et al 1997, Richardson & Detsky 1995b). If the model is extremely sensitive to changes in these values then there is a high degree of uncertainty surrounding the decision and the recommendations of the model should be treated cautiously (Naglie et al 1997). In those situations in which the decision model is sensitive to utilities alone it is important to ensure that the utilities used accurately reflect the views of the individual making the decision.

BENEFITS AND LIMITATIONS OF DECISION ANALYSIS

Decision analysis is clearly not an approach for handling uncertainty in all clinical decisions. However, it is a useful technique for assisting complex and uncertain decisions, where the best option is not immediately obvious. By specifically including the results of research studies in the decision model, it can help a practitioner make evidence-based decisions. Often, the decision models used in a decision analysis are based on a wider range of information than would be used in a more unstructured approach to decision making (Elwyn et al 2001).

Decision analysis provides an explicit and systematic approach to decision making, which enables clinicians to explain both to patients and colleagues how a particular decision has been reached (Elwyn et al 2001, Richardson & Detsky 1995b, Tavakoli et al 2000). By incorporating patient values into the decision model, it also enables patients to be more involved in the decision process and to directly influence the final decision (Elwyn et al 2001).

Decision analysis has some potent limitations. Sometimes the probability estimates necessary to populate a tree do not exist in the research literature; a situation that necessitates using subjective estimates of probability (Naglie et al 1997). Such estimates are subject to a number of forms of bias (see Chapter 7).

Utility measurement itself may also be questioned as an approach. Is it possible, or indeed appropriate, to try and quantify something which is so subjective and emotional (Tavakoli et al 2000)? As we saw earlier, utility values depend on the method by which they are measured and are subject to framing. Asking individuals to evaluate a health state of which they have no experience, and might not be able to understand (Dowding & Thompson 2002), is not only counterintuitive but also fundamentally flawed. Hastie & Dawes (2001) highlight the anomaly whereby individuals asked to rate a health state before diagnosis (e.g. being HIV positive) were more negative about the state than when asked to rate the same state a year after being diagnosed. People adapt.

Decision analysis is often criticised for being too time consuming and artificially simplifying complex decision problems (Tavakoli et al 2000). However, all forms of decision making are open to criticism and limited by the amount of data available to the clinician. What makes decision analysis a different approach is that these weaknesses are explicit and open to debate (Dowding & Thompson 2002).

CONCLUSION

When faced with a decision situation in which complexity, uncertainty and the lack of an optimum choice are all present, decision analysis may help. Decision analysis helps structure your evaluation of the evidence base and relate it directly to the decision options you face. Perhaps the biggest contribution decision analysis makes is the explicit and systematic incorporation of the preferences of the patients whose lives will be most affected by the decisions taken.

Combining preferences for outcomes *and* the likelihood of those outcomes occurring goes a long way to answering the frequently asked question, 'How exactly do I practice evidence-based decision making? Although there is no escaping the fact that for many clinicians decision analysis represents a 'black-belt' decision technique, it should be part of the armoury for those nurses who strive to be truly advanced decision makers.

EXERCISES

Exercise 1. Structuring decisions

Try to identify a recent decision that you have made in practice that you found difficult. Perhaps this was because it was very complex or uncertain, or because you and your patient had different views about what might be the best thing to do. (Remember a *decision* is made when you have to choose between different options):

1. Write a description of the decision situation, trying to identify the key features that made it difficult.
2. Now list all the different options you had open to you, and the risks and benefits associated with each option. You might need to think about whether there are options available to you for that decision which you didn't consider at the time.
3. Put this into a balance sheet (see Table 11.1)
4. Now try to represent your decision situation as a decision tree (see Figure 11.1).
5. Remember that decision nodes in a tree are represented by a square box, and chances by a circle node. You might need to simplify the decision situation by focusing on the key outcomes that might happen as a result of different actions you could take.

For help structuring the tree, refer to the article by Detsky et al (1997).

Exercise 2. Assessing the probability of different outcomes

Take the decision tree that you constructed in Exercise 11.1:

1. List all of the possible outcomes in a table like the probability table in Table 11.3.
2. Carry out a search to try and find research evidence to tell you what the probability or likelihood of each of those outcomes happening might be. Places you could look include:
   a. published evidence-based guidelines
   b. systematic reviews of available evidence

c. pre-appraised studies (such as those available via evidence-based nursing: www.ebn.bmjjournals.com/)
d. searching for randomised trials/research studies in available databases (such as CINAHL and Medline).

3. Summarise the evidence you have found. Discard poor-quality studies where appropriate. Use the average result of studies to give you your overall estimate. Remember that you might need to convert the figures for continuous outcomes into a probability estimation using mean effect sizes.
4. Put in estimates of the range of uncertainty (probability) for your figures into the table – this could be confidence intervals from published studies, or the full range of estimation from a number of published studies.
5. If you can't find any evidence for your probability estimations then you will need to estimate them. You could do this by asking an expert (if you have access to one) or carry out an estimation based on your own experience. Remember that this type of estimation may be open to bias, so perhaps put in a broader probability range.
6. Put your probability estimates into the decision tree you constructed in Exercise 1. Make sure that the probabilities for each branch add up to 1.

Exercise 3 Measuring utility

Take the decision tree you have constructed from learning Exercises 1 and 2:

1. List all the possible outcomes that could occur to the person who is making the decision.
2. Separate the outcomes into short-term outcomes (which could happen to the person straight away, such as side effects from a drug therapy) and long-term outcomes (which might happen over a longer period of time, such as developing an illness such as heart disease).
3. Try to estimate the value or preference individuals attach to these health states. Ask a friend or colleague to evaluate your different health states, using a rating scale approach, or a standard gamble (see Box 11.3). See if you get different responses using different methods.
4. If you estimate values from different people, then take the average utility, and give each outcome a utility value.
5. List all of the possible combinations of outcomes that could occur in your decision model in a table (like the list in Table 11.4)
6. Calculate the 'disutility' of all of your short-term health states, by subtracting your utility value from 1.
7. Calculate the utility for each possible combination of outcomes. Multiply the utility values of all the relevant long-term states together, and then subtract the disutility values for the short-term states.
8. You should have a utility value for each possible health state for each branch of your tree – add these values to your decision tree.

Continued

EXERCISES – CONT'D

Exercise 4 Calculating a decision tree

Take the decision tree with both your probability and utility values that have been constructed following learning Exercise 3:

1. Calculate the 'expected utility' for each choice option in your tree. You do this by working systematically back from left to right, multiplying utility by probability and then adding branches together. Use the example calculation in the chapter to help you.
2. When you have calculated the values for each branch, look to see which branch has the highest value. This is the option that you should choose, if you are a logical rational decision maker.
3. How does this option compare with the decision you actually took? Is it the result you expected? Why?
4. Identify the branch of the tree where your probability estimates are the most uncertain. Alter these values, perhaps first to represent the lowest possible value you think is reasonable, and then the highest value. Recalculate your values for each branch.
5. How does this affect what you should do? Has the decision option you should choose altered? How? What do you think this tells you about your decision model?

Did one particular outcome cause disagreement between individuals (or where the value someone else gave you and your value were different) when you were measuring utility? Alter the values in your tree for this utility value and see if it affects what decision you should take. What does this tell you about your decision model?

RESOURCES

www.treeage.com/ A decision analysis software package that can be used to construct and calculate decision trees. Has a 30-day trial download that students can use to help them with the process. Students do need to be reasonably computer literate to make full use of the program.

SOURCES

Clinical knowledge summaries (http://cks.library.nhs.uk/menopause) 2008.

Detsky A S, Naglie G, Krahn M D et al 1997 Primer on medical decision analysis: Part 1 – getting started. Medical Decision Making 17:123–125

MacLennan A, Broadbent J, Lester S et al 2004 Oral oestrogen and combined oestrogen/progestogen therapy versus placebo for hot flushes. In: Cochrane Database of Systematic Reviews, Issue 4

Morris E, Rymer J 2006 Menopausal symptoms. Clinical Evidence 15. Mean value of the trial results reported in the guidance

REFERENCES

Brand D A, Kliger A S 1999 Planning for a kidney transplant: is my doctor listening? The Journal of the American Medical Association 282:691–694

Brazier J E, Roberts J, Platts M et al 2005 Estimating a preference-based index for a menopause specific health quality of life questionnaire. Health and Quality of Life Outcomes 3:13

Detsky A S, Naglie G, Krahn M D et al 1997 Primer on medical decision analysis: Part 1 – getting started. Medical Decision Making 17:123–125

DiCenso A, Cullum N, Ciliska D 1998 Implementing evidence based nursing: some misconceptions. Evidence Based Nursing 1:38–39

Dowding D, Thompson C 2002 Decision analysis. In: Thompson C, Dowding D (eds) Clinical decision making and judgement in nursing. Churchill Livingstone, Edinburgh

Dowie J 1993 Clinical decision analysis: background and introduction. In: Llewelyn L, Hopkins A (eds) Analysing how we reach clinical decisions. Royal College of Physicians of London, London, p 7–26

Drummond M. 1993 Estimating utilities for making decisions in healthcare. In: Llewelyn L, Hopkins A (eds) Analysing how we reach clinical decisions. Royal College of Physicians of London, London, p 125–143

Elwyn G, Edwards A, Eccles M et al 2001 Decision analysis in patient care. Lancet 358:571–574

Hastie R, Dawes R M 2001 Rational choice in an uncertain world. Sage, London

Haynes B R 2006 Of studies, syntheses, synopses, summaries, and systems: the '5S' evolution of information services for evidence-based healthcare decisions. Evidence-Based Medicine 11:162

Hunink M, Glasziou P, Siegel J et al 2001 Decision making in health and medicine. Integrating evidence and values. Cambridge University Press, Cambridge

Naglie G, Krahn M D, Naimark D et al 1997 Primer on medical decision analysis: Part 3 – estimating probabilities and utilities. Medical Decision Making 17:136–141

Richardson W S, Detsky A S 1995a Users' guides to the medical literature VII: how to use a clinical decision analysis A. Journal of the American Medical Association 273:1292–1295

Richardson W S, Detsky A S 1995b Users' guides to the medical literature VII: how to use a clinical decision analysis B. Journal of the American Medical Association 273:1610–1613

Sarasin F P 2001 Decision analysis and its application in clinical medicine. European Journal of Obstetrics and Gynecology and Reproductive Biology 94(2):172–179

Tavakoli M, Davies H T O, Thomson R 2000 Decision analysis in evidence-based decision making. Journal of Evaluation in Clinical Practice 6:111–120

Thornton J G 1996 Decision analysis. Clinical Obstetrics and Gynaecology 10:677–695

Thornton J G, Lilford R J, Johnson N 1992 Decision analysis in medicine. British Medical Journal 304:1099–1103

Tickle-Degnen L 2001 From the general to the specific. Using meta-analytic reports in clinical decision making. Evaluation and the Health Professions 24:308–326

von Winterfeldt D 1980 Structuring decision problems for decision analysis. Acta Psychologica 45:73–93