DECISION ANALYSIS IN ECONOMIC EVALUATIONS

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INTRODUCTION

Decision analysis is a technique that can be used to incorporate information and estimates in a systematic way to compare different options.

Decision analysis is being used more commonly in pharmacoeconomics evaluations.

Decisions are made all the time in healthcare where the results of those **decisions** are **not certain**.

INTRODUCTION

For example, if you treat a person with pneumonia using an antibiotic, there may be an **80% chance it will work**.

However, you cannot be **100% sure** that it will work, so there is ***uncertainty*** about the effectiveness of that antibiotic.

Therefore, the decision to treat that patient is made under conditions of ***uncertainty***.

WHAT ARE THE SOURCES OF UNCERTAINTY?

When a **decision** is made in **healthcare**, there is uncertainty around the outcome of that decision. There are lots of ways in which uncertainty can exist:

- **Diagnosis**: for example, diagnostic tests do not always give the correct result.
- **Natural history of the disease**: not everyone with the same disease will feel the same way or will suffer the same ill effects of that illness; for example, not everyone with hypertension will eventually have a myocardial infarction.

WHAT ARE THE SOURCES OF UNCERTAINTY?

- **Treatment efficacy and effectiveness**: no treatment is 100% effective, so there is always a chance it will not work in everyone; for example, as antidepressant drugs.

- **The development of adverse events**: some people show side effects or allergic responses to drugs, such as penicillins.

- **Unit cost of resources**: the price of services changes over time and between places; for example, drugs, staff time.

WHAT ARE THE SOURCES OF UNCERTAINTY?

The common theme in these examples is that you **can never predict exactly** what is going to happen when you make a decision, but a **decision must be made**.

This is what is meant by **decision-making** under conditions of **uncertainty**.

In fact, **most decisions** we make are made under **conditions** of **uncertainty**, whether they are about healthcare or other aspects of our lives.

PROBABILITY: THE LANGUAGE OF UNCERTAINTY

It is not possible to remove uncertainty from the decision-making process, but it is possible to quantify it.

Knowing the level of uncertainty can influence our decision.

For example, if you were about to cross a road and you were told that you had a **20% risk of death**, would you still cross?

In decision analysis we represent uncertainty by using **probabilities**.

PROBABILITY: THE LANGUAGE OF UNCERTAINTY

Probability can have many related meanings:

- Number between 1 and 0 expresses likelihood of event:

for example, what is the probability of successfully treating a urinary tract infection (UTI) with trimethoprim?

- Probability as proportion in a population:

for example, what is the probability of having appendicitis if you are between 11 and 16 years old?

PROBABILITY: THE LANGUAGE OF UNCERTAINTY

- Probability as a measure of strength of belief:

we all use the words **'possibly'** and **'probably'** as subjective measures of probability.

The sum of probabilities of all possible outcomes of a chance event is always **1**.

If the probability of an antibiotic successfully treating a case of pneumonia is 0.8, then the probability that it will **not work** must be **0.2**.

PRINCIPLES OF PROBABILITY

There may be three or more possible outcomes of a decision.

For example, the possible outcomes of a total hip replacement operation may be

- *survival with improved mobility*
- *survival with **no** improvement in mobility*
- *perioperative death*

PRINCIPLES OF PROBABILITY

If

- the probability of perioperative death is 1% (0.01)

and

- the probability of survival with improved mobility is 85% (0.85),

then

- the probability of survival with no improvement in mobility must be 14%

(1 - (0.01 + 0.85) = 0.14)

WORKED EXAMPLE 8.1

What is the probability of picking a man from the population in Baghdad who is both hypertensive [p = 0.09) and has arthritis (p = 0.02)?

The probability of this happening is

0.09 X 0.02 = 0.0018 (0.18%)

WORKED EXAMPLE 8.1

What is the probability of picking a man from the population in Baghdad who is not hypertensive (p = 1 - 0.09) and has arthritis (p = 0.02)?

The probability of picking a man from the population in Baghdad who is not hypertensive (p = 1 - 0.09) and has arthritis (p = 0.02) is:

(1 - 0.09) x 0.02 = 0.0182 (1.82%).

USE OF DECISION ANALYSIS TO DESIGN ECONOMIC EVALUATIONS

The aim of economic analysis of an intervention is to determine whether, under specified conditions, it is cost-effective. Economic evaluation can be considered to consist of many stages.

Step 1 : Identify the research question

The specific decision to be evaluated should be clearly defined by answering the questions: **What is the objective of the study**?

For example the decision is whether to add a new antibiotic to an institutional formulary to treat infections.

USE OF DECISION ANALYSIS TO DESIGN ECONOMIC EVALUATIONS

Step 2: Specify alternatives

Ideally the most effective treatments or alternatives should be compared.

In pharmacotherapy evaluations, makers of new products may compare or measure themselves against a standard (i.e., older, more well-established) therapy.

USE OF DECISION ANALYSIS TO DESIGN ECONOMIC EVALUATIONS

Decision analysis could compare more than two treatment options

(e.g., it could compare the five most common statins)

or an intervention versus **no** intervention

(e.g., a diabetes clinic versus no clinic).

For the example problem, the use of the new medication (antibiotic A) will be compared with that of the current standard (antibiotic B).

USE OF DECISION ANALYSIS TO DESIGN ECONOMIC EVALUATIONS

Step 3: Draw the decision analysis structure or tree

Once these stages have been completed, we can build our decision tree. A decision tree has five principal components:

1. **Starting point**: at which point in the process we begin the evaluation of the intervention.

2. All **treatment alternatives** under **investigation**: the different strategies under investigation.

USE OF DECISION ANALYSIS TO DESIGN ECONOMIC EVALUATIONS

3. **Decision nodes** ■: there should only be one decision node: the policy decision of whether to use one strategy or the other.

4. **Chance nodes** ●: these are uncertain events and will have probability values attached to them.

5. **Outcome/time horizon** ◀: the outcome being used must be defined and the point at which evaluation ends (time horizon).

USE OF DECISION ANALYSIS TO DESIGN ECONOMIC EVALUATIONS

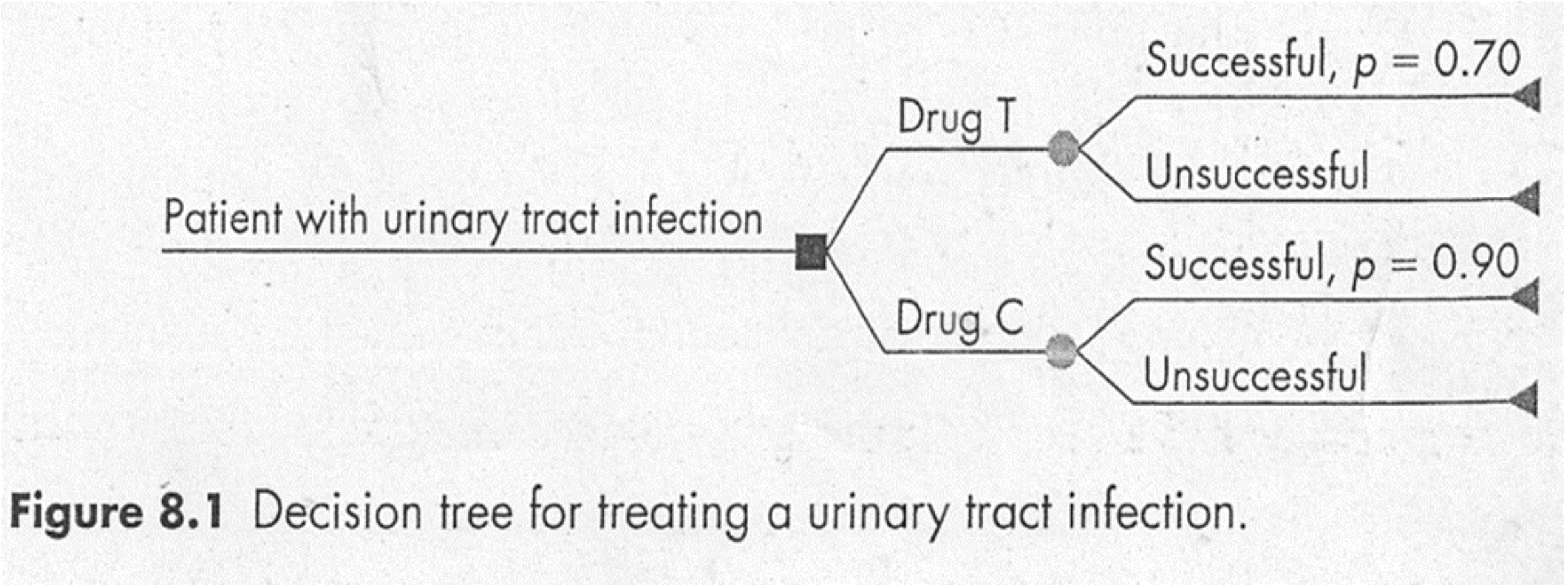

Figure 8.1 Decision tree for treating a urinary tract infection.

USE OF DECISION ANALYSIS TO DESIGN ECONOMIC EVALUATIONS

The **starting point** is the patient group who have been **diagnosed** with a **UTI** that now needs to be treated.

At the **decision node**, the policy decision is whether to treat this group of patients with the standard current treatment (Drug T) or whether to use a newer, more costly agent, Drug C.

USE OF DECISION ANALYSIS TO DESIGN ECONOMIC EVALUATIONS

There is **no** 'do nothing' option here because current practice is to treat symptomatic UTIs, to alleviate symptoms, and also to prevent complications such as pyelonephritis.

It would, however, be possible to include **more antibiotics** in the model and have more arms in the tree, if it were felt to be necessary.

The **probabilistic event** here is whether or not the antibiotic is successful in treating the infection.

USE OF DECISION ANALYSIS TO DESIGN ECONOMIC EVALUATIONS

It would also be possible to expand the tree by including the probabilistic events of side effects and withdrawal from treatment.

The endpoint of the evaluation is whether the antibiotic is successful or not

The time horizon would probably be quite short- about 7 days in this intervention.

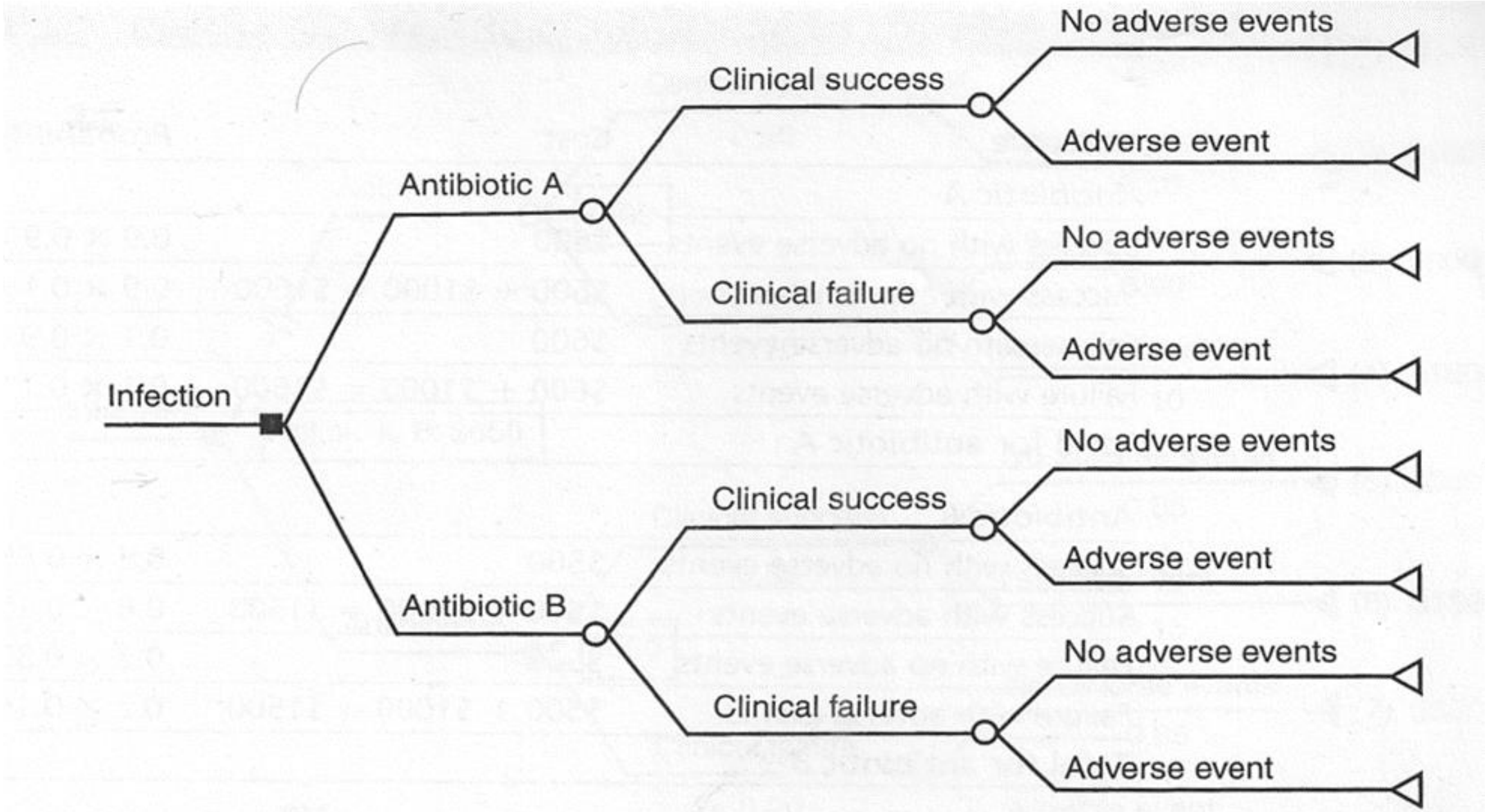

Figure 9.1. Decision tree structure for the antibiotic example.

Figure 8.2 show decision tree for the treatment of depression using selective serotonin-reuptake inhibitors (SSRIs) or tricyclic antidepressants (TCAs).

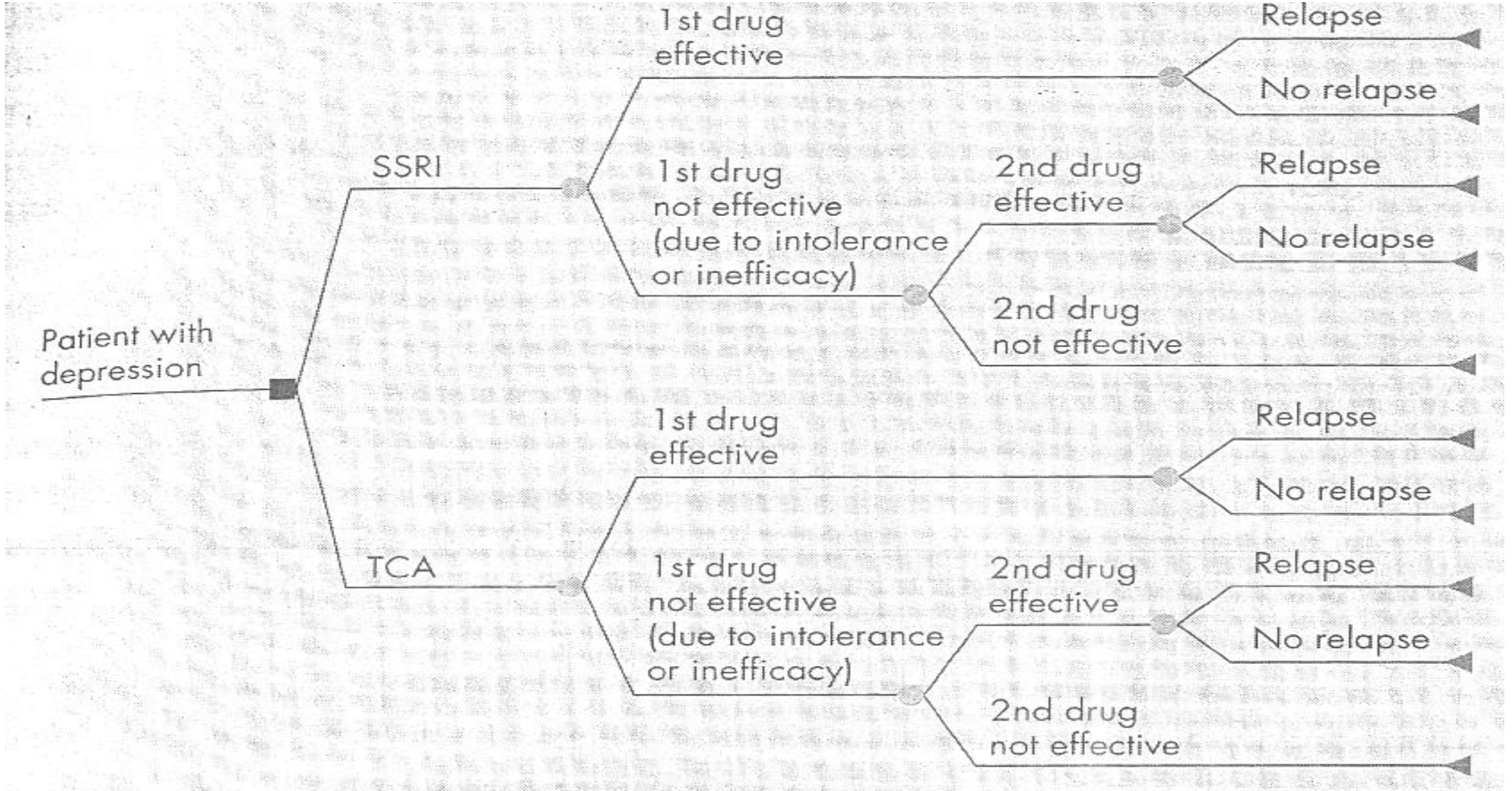

Figure 8.2 Decision tree (decision-analytical model) of SSRI versus TCA in the treatment of depression.

USE OF DECISION ANALYSIS TO DESIGN ECONOMIC EVALUATIONS

Step 4: Specify possible costs, outcomes, and probabilities

For each option, information should be obtained for the probability of occurrence and the consequences of the occurrence.

Probabilities are assigned for each branch of the chance nodes, and the sum of the probabilities for each branch must **add up to 1.00**.

Consequences are reported as monetary outcomes, health-related outcomes, or both.

USE OF DECISION ANALYSIS TO DESIGN ECONOMIC EVALUATIONS

Table 9.1 lists these data for the antibiotic example.

Table 9.1. Estimates for the antibiotic example

	Antibiotic A	Antibiotic B
Probability of clinical success	90%	80%
Cost of antibiotic per course of therapy	$600	$500
Probability or adverse events	10%	15%
Cost of treating adverse events	$1000	$1000

USE OF DECISION ANALYSIS TO DESIGN ECONOMIC EVALUATIONS

Step 5: Perform calculations

At each terminal node, the probability of a patient having that outcome is calculated by multiplying the probability of each arm from the choice node to the terminal node.

The total costs for each terminal node are calculated by adding up the costs over all of the branches from the choice node to the terminal node.

The product of the costs multiplied by the probability (C X P) is calculated for each node, and then summed for each option.

USE OF DECISION ANALYSIS TO DESIGN ECONOMIC EVALUATIONS

In our example, each of the two options (antibiotic A versus antibiotic B) have four possible terminal endpoints: success/no adverse events, success/adverse events, failure/no adverse events, failure/adverse events.

Table 9.2 and Figure 9.2 show the calculations used to estimate the average expected cost per treatment.

Note that the sum of the probabilities for the four terminal endpoints equals 1.00.

TABLE 9.2. CALCULATIONS FOR THE ANTIBIOTIC EXAMPLE

Outcome	*Cost*	*Probability*	*Cost × Probability*
Antibiotic A			
Success with no adverse events	$600	0.9 × 0.9 = 0.81	$486
Success with adverse events	$600 + $1000 = $1600	0.9 × 0.1 = 0.09	$144
Failure with no adverse events	$600	0.1 × 0.9 = 0.09	$54
Failure with adverse events	$600 + $1000 = $1600	0.1 × 0.1 = 0.01	$16
Total for antibiotic A		1.00	$700
Antibiotic B			
Success with no adverse events	$500	0.8 × 0.85 = 0.68	$340
Success with adverse events	$500 + $1000 = $1500	0.8 × 0.15 = 0.12	$180
Failure with no adverse events	$500	0.2 × 0.85 = 0.17	$85
Failure with adverse events	$500 + $1000 = $1500	0.2 × 0.15 = 0.03	$45
Total for antibiotic B		1.00	$650

USE OF DECISION ANALYSIS TO DESIGN ECONOMIC EVALUATIONS

For patients taking **antibiotic A**, the costs can range from $600 (for medication and no adverse events) to $1600 (for medication and treatment of adverse events), and the average cost is $700 per patient.

Similarly, for patients taking **antibiotic B**, the costs can range from $500 (for medication and no adverse events) to $1500 (for medication and treatment of adverse events), and the average cost is $650 per patient.

USE OF DECISION ANALYSIS TO DESIGN ECONOMIC EVALUATIONS

These calculations show that antibiotic B is less expensive even when including the costs of treating adverse events.

But because **antibiotic A** is a better clinical option (higher probability of success and lower probability of adverse events), decision makers could use the incremental cost-effectiveness ratio (ICER) to determine whether to add antibiotic A to the formulary.

USE OF DECISION ANALYSIS TO DESIGN ECONOMIC EVALUATIONS

The calculated ICER would be:

$$\text{ICER} = \frac{\Delta\text{Costs}}{\Delta\text{Outcomes}} = \frac{\$700 - \$650}{0.90 - 0.80} = \$500 \text{ more per extra success}$$

If it is decided that each extra successful outcome is worth at least $500 (patient discharged from the hospital faster, prevention of second round of treatment costs with another antibiotic, and so on), then antibiotic A would be added to the formulary.

USE OF DECISION ANALYSIS TO DESIGN ECONOMIC EVALUATIONS

Step 6: Conduct a sensitivity analysis

Because some uncertainty surrounds the estimates used to construct these models, a sensitivity analysis is conducted.

WORKED EXAMPLE 8.8

Theoretical example of use of a decision tree in an incremental economic analysis of the treatment of blue finger syndrome

Several drugs are indicated for a very distressing condition known as **'blue finger syndrome'**, where patients' fingers turn dark blue for no reason.

The drugs used are associated with lots of side effects.

Some people cannot tolerate the drugs (this means they have side effects that are so bad they have to stop taking them) or the drugs may not work.

WORKED EXAMPLE 8.8

If these things happen, they will be referred to their local outpatient clinic to see a finger specialist.

This may be an important factor in the ultimate choice of therapy. You are the adviser to your local healthcare provider.

They want to know whether to use **indigociliin** or **navytriptyline** when a person presents to their GP with blue finger syndrome. About **200** people per year present with blue finger syndrome.

WORKED EXAMPLE 8.8

You have the following information from a trial:

Agent	*Withdrawal rates due to intolerance or inefficacy (%)*	*Normal treatment cost per patient per year (£)*
Indigocillin	40*	250.00
Navytriptyline	60*	10.00

*Significant difference in efficacy.

The additional cost of treating a patient who withdraws from either drug per year is £ 500.

WORKED EXAMPLE 8.8

Figure 8.3 shows the decision-analytical model for this intervention.

The information above allows us to calculate how many of the 200 patients will go down each arm of the model .

We also know how much each arm costs for one patient. Therefore, we can calculate how much each arm costs in total

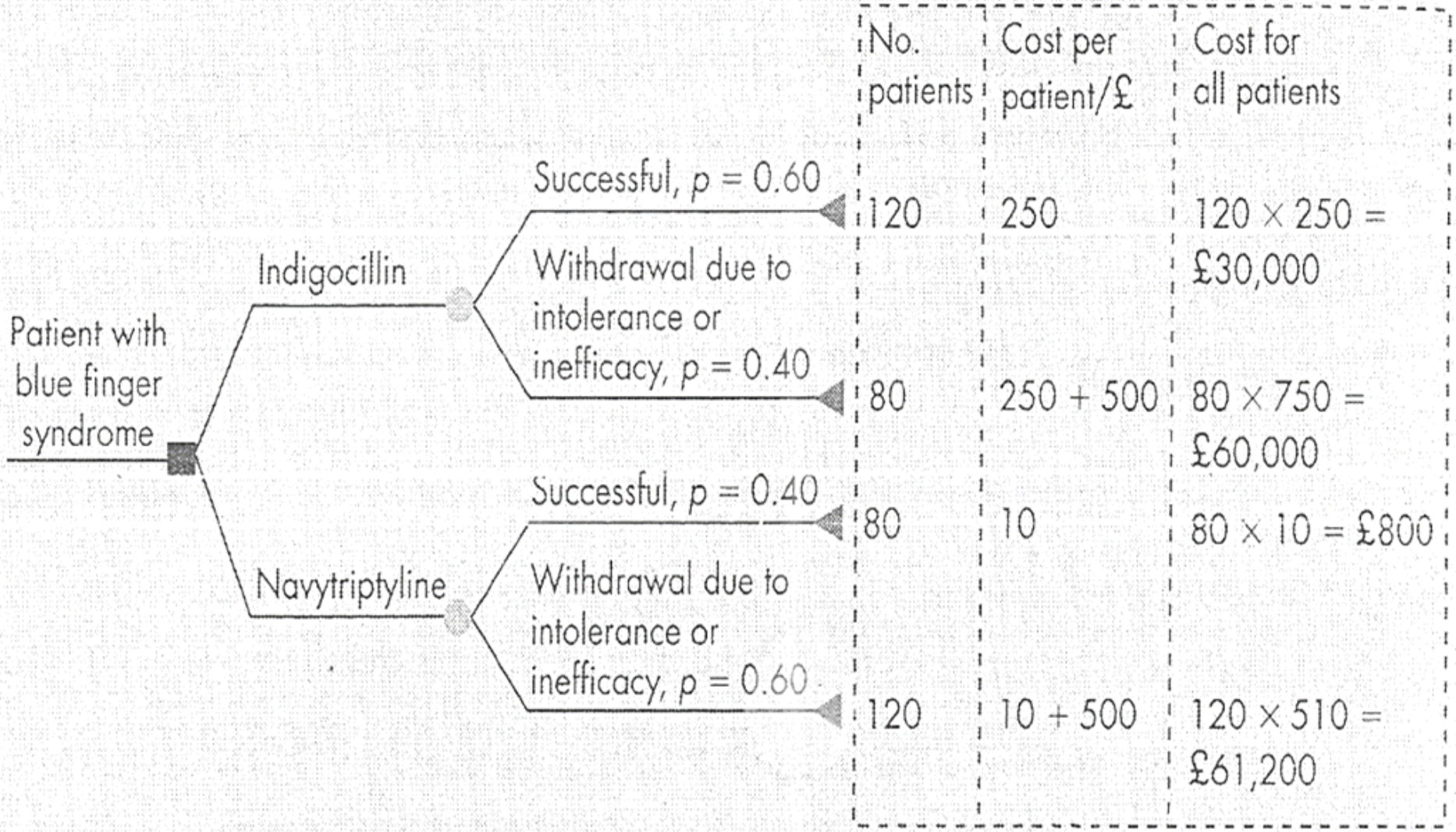

Figure 8.3 Decision-analytical model of indigocillin versus navytriptyline for blue finger syndrome.

Now we can calculate the ICER for this evaluation:

$$\text{ICER} = \frac{\text{Cost}_{\text{indigocilin}} - \text{Cost}_{\text{navytriptyline}}}{\text{Outcome}_{\text{indigocilin}} - \text{Outcome}_{\text{navytriptyline}}}$$

$$= \frac{90,000 - 62,000}{120 - 80} = \frac{28,000}{40}$$

$$= £700 \text{ per extra person successfully treated.}$$

MARKOV MODELLING

A **simple decision tree** may not be capable of **modelling** chronic disease states.

A model trying to represent a chronic disease, such as relapsing-remitting multiple sclerosis must be capable of reflecting changes in and out of health states.

These may be referred to as random processes that evolve over time. They are random because we do not know when they will occur in the disease progression.

MARKOV MODELLING

Markov models are particularly useful for representing the use of interventions to manage chronic health states.

A decision-analytical model may become unnecessarily complex, as patients will move in and out of health states many times.

An alternative method for presenting these events is shown in Figure 8.4.

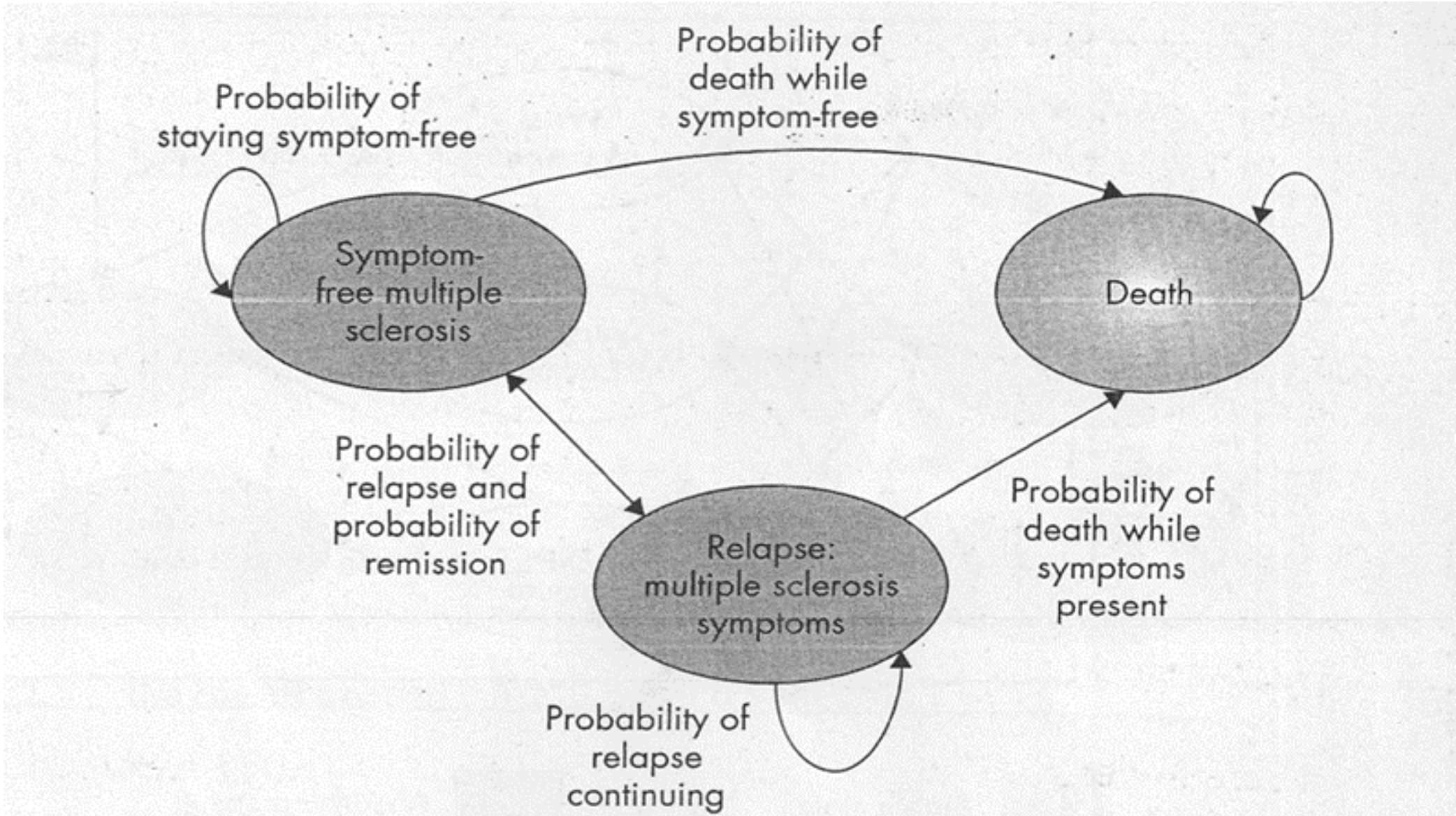

Figure 8.4 Markov model for economic analysis of the prevention and management of relapsing–remitting multiple sclerosis.

MARKOV MODELLING

This shows a simplified version of what can happen to a person with relapsing-remitting multiple sclerosis.

When they are symptom free there is a probability they will have a relapse, stay symptom free or die. When they are experiencing symptoms, there is a probability they will become symptom free, the relapse may continue, or they may die.

When a patient dies, they cannot return to the other health states. Therefore, death is referred to as the **'absorbing' state**.

MARKOV MODELLING

Markov models therefore simulate the natural history of a chronic illness such as multiple sclerosis in a population of patients over a period of time, and its associated risk of relapse, remission and death.

The population of patients moves through the model over time. The model will estimate how many patients are in remission, have relapsed or have died at any given time.

Probabilities of moving from one state to another will be obtained from clinical data sources.

Thank you