Clinical decision analysis: an alternate, rigorous approach to making clinical decisions and developing treatment recommendations

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A difficult decision

A 60-year-old male truck driver presents to his family physician for relief of neck pain which is impeding his ability to work. As well as being a smoker and overweight, he has other cardiac risk factors, including elevated blood pressure and cholesterol levels. He wants a prescription for a COX-2 inhibiting non-steroidal anti-inflammatory drug (NSAID), having heard from his friends that this drug works well for neck and shoulder pain. His physician, however, is reluctant to prescribe such a drug, in light of recent evidence associating serious cardiac adverse events with this class of NSAIDs. Standard NSAIDs are not an option for this patient, as he has previously suffered gastric complications with these drugs. The physician therefore suggests a consultation with a chiropractor. The patient, however, is reluctant to consider neck manipulation as a treatment option. He has recently read about a chiropractic patient who reportedly suffered from paralysis as a result of stroke following neck manipulation. Being paralyzed represents one of the truck driver's worst fears. Furthermore, drug treatment is more convenient given that he is on the road for weeks at a time, and he knows from previous experience that NSAIDs have been effective in alleviating his neck pain. The physician points out that the risk of stroke associated with neck manipulation is likely to be exceedingly small and that a heart attack could be equally devastating. The physician is therefore faced with the difficult decision of deciding between two treatment options for her patient's neck pain: a COX-2 inhibiting NSAID or neck manipulation.

What makes a decision difficult?

There are many reasons that a decision can be difficult. First, a decision can be difficult because of its complexity. In the above, highly simplified example, the physician must consider many different issues: the risk of myocardial infarction associated with COX-2 inhibiting NSAIDs, the risk of stroke associated with neck manipulation, the relative rates of effectiveness associated with these treatments, and her patient's attitudes towards the adverse events associated with these treatments. Second, a decision can be difficult because of the inherent uncertainty in the situation. In the above case, uncertainty stems from the poorly established rates of effectiveness and rates of complications associated with these treatments. Third, a decision maker may have multiple objectives, yet pursuing one objective may hinder progress towards another. In the case above, important trade-offs must be made: is the greater ease of administering a drug treatment to this patient worth the potential increased risks of myocardial infarction associated with COX-2 inhibiting NSAIDs? Finally, a decision can be difficult when different perspectives are considered. Here, the truck driver is unwilling to consider any treatment associated with even a slight risk of paralysis as a result of stroke, whereas the risk of a heart attack seems less frightening to him.

What is clinical decision analysis?

Decision analysis is a formal, mathematical approach to analyzing difficult decisions faced by clinical decision makers (*i.e.* patients, clinicians, policy-makers). At the individual patient level it can be used to decide on appropriate treatment. At the group level it can be used to develop treatment guidelines and recommendations. Most clinical decision analyses are based on a 'decision tree'. Describing the basic elements of a decision tree is the easiest way to understand clinical decision analysis.

Performing a clinical decision analysis

Step 1: Constructing a decision tree

Decision analysis begins with formulating the clinical problem using a *decision tree.* A decision tree is the structure into which data about treatment effectiveness and treatment complications are integrated. Below is a simplified decision tree for the neck pain patient in our example (Figure 1) which will be used to explain the basic structural elements of a decision tree.

A decision tree is a horizontal structure. Time flows from left to right, with each successive set of branches representing the outcomes of a decision or event.

Several types of *nodes* are used in a decision tree. Each branch in the tree has an associated node located at its right-hand end. Each node represents an event, either a decision, an uncertain event, or a final outcome. A *decision* node (square) is used to represent the choice facing the decision maker which will be made based on a strict interpretation of the *expected value* of each treatment alternative (more on expected value later). A *chance* node (circle) is used to represent an uncertain event with multiple possible outcomes. A *terminal* node (triangle) is used to represent a final treatment outcome, that is, the end of the path in the decision tree, often referred to as a health state outcome. All of the right-most nodes in a decision tree must be terminal nodes.

Branches emanating from a decision node represent the treatments under consideration. Branches emanating from the chance nodes represent the possible outcomes of a treatment.

Using our example, the physician must decide between neck manipulation and a COX-2 NSAID for her patient's neck pain, represented by the decision (square) node (Figure 1). If neck manipulation is administered, there is a chance that neck manipulation will or will not resolve her patient's neck pain, represented in Figure 1 by a chance node (circle), just right of the decision node. Similarly, there is a chance that a stroke will or will not occur, represented by two other chance nodes. Therefore, one possible path following treatment with neck manipulation is that the patient will experience resolution of his neck pain, but experience a stroke. The health state outcome for this path is 'No neck pain, stroke', represented by the upper terminal (triangle) node. Hence, there are four possible outcomes to treatment with neck manipulation in this decision tree.

Step 2: Assigning probabilities and outcome values

Once the structure of the decision tree is completed, one must assign numerical estimates to the tree. There are two types of estimates to consider: probabilities and outcome values. Probabilities are assigned to the chance nodes (a probability is a quantitative estimate of the likelihood that a given outcome depicted in the decision tree will occur). Outcome values are assigned to the terminal nodes (an outcome value is a quantitative expression of

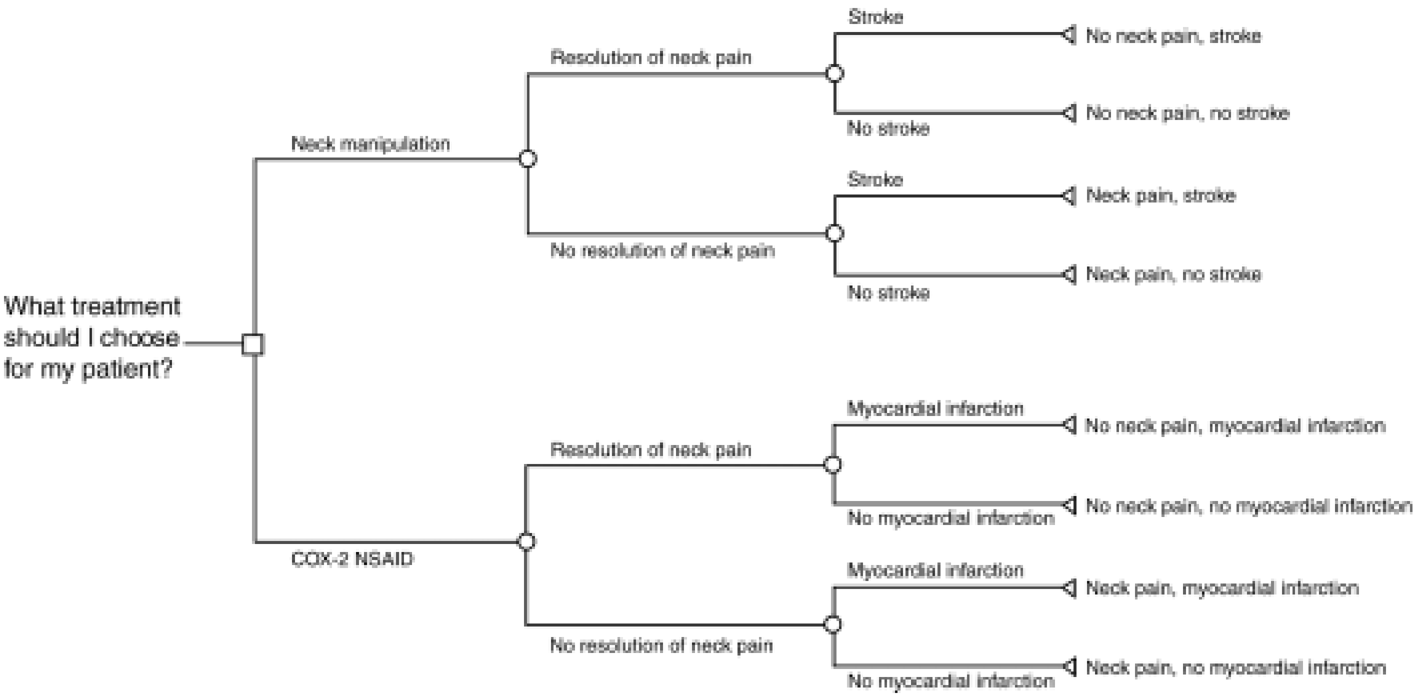

Figure 1. A simplified decision tree for a patient with neck pain.

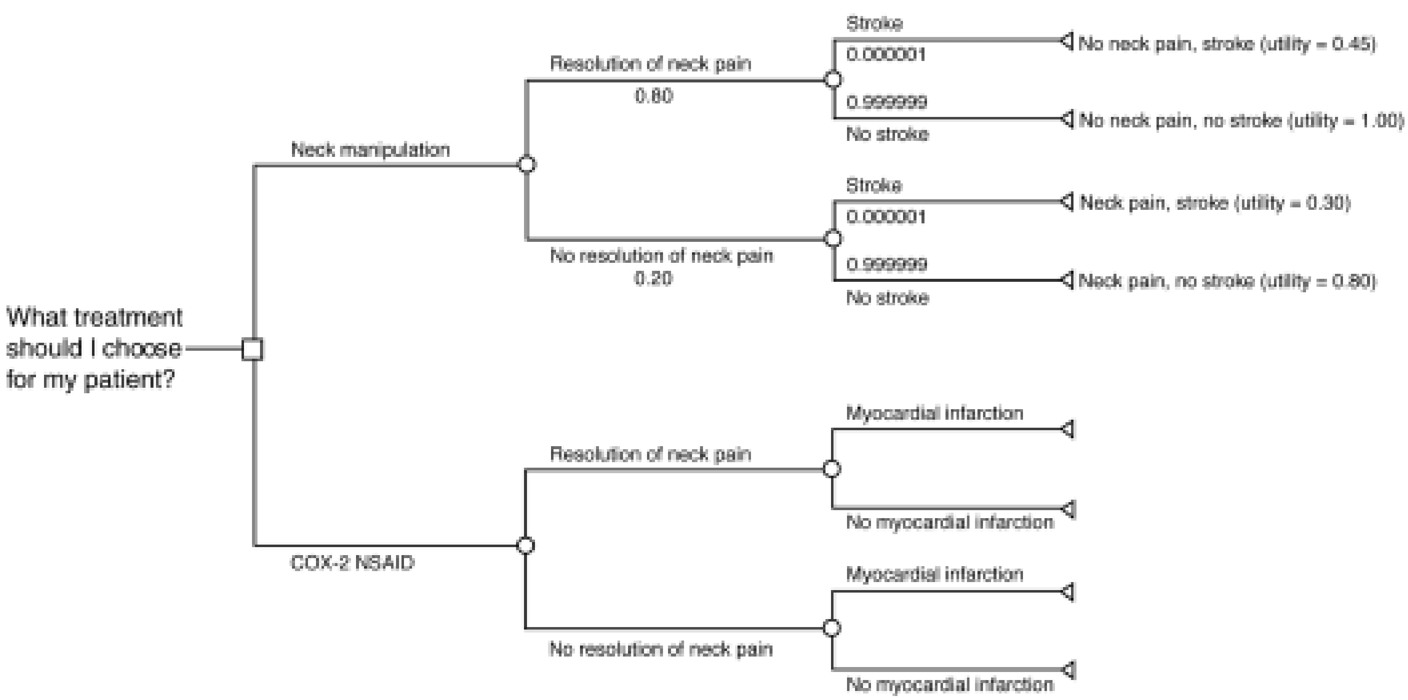

Figure 2. Decision tree with probabilities and utilities included for the neck manipulation arm.

the desirability of such an outcome). The validity of a decision analysis depends to a large degree on the accuracy of these estimates.

In our example, the key probability estimates for the decision tree are: the probability of stroke associated with neck manipulation, the probability of a myocardial infarction associated with COX-2 NSAIDs, and the probabilities of spinal manipulation and a COX-2 NSAID resolving the patient's neck pain. The best available evidence in the scientific literature should be used as a basis for these probabilities. Hence, probability estimates for treatment effectiveness and risks should be obtained from rigorously conducted systematic reviews, whose results were based on high-quality trials and observational studies. However, as is often the case, poor-quality studies may be the only evidence available on which to base probability estimates. In this case, other sources of information are used, including expert opinion. Probability estimates range from 0.0 (impossible) to 1.0 (absolute certainty). Probabilities are assigned to each branch emanating from a chance node and they must sum to 1.0.

Outcome values for each health state outcome must then be assigned at end of each branch of the decision tree. Outcome values can be expressed in several ways, including: number of deaths, years of life, quality-adjusted life years, complications prevented, or *utilities.* A 'utility' is a measure of the desirability of a health state outcome. It is a quality-of-life measure expressed as a single value between 0.0 and 1.0. Utilities for health state outcomes are assessed relative to two extreme health scenarios: death (which is assigned a utility of 0.0) and good health (which is assigned a utility of 1.0). Hence, health outcomes are anchored between two anchor states, death and good health. Utility values provide summary scores that aggregate the positive and negative aspects of quality-of-life.

Utilities can be estimated in many ways. The best approach is to measure them directly from appropriate subjects using valid and reliable scaling methods. Scaling methods for measuring utilities from subjects include standard gamble, rating scale, and time-trade off. Describing utility scaling methods is beyond the scope of this article. However, interested readers may refer to a recent publication in the journal *Spine* for further information (Tosteson, 2000). Since directly measuring utilities is time consuming and costly, alternatives to estimating utilities include having content experts achieve consensus on the required utility estimates or searching the literature for relevant, published 'off the shelf' utilities.

To illustrate the above discussion, consider the probabilities and outcome values depicted in Figure 2 for the neck manipulation branch. The probability of experiencing resolution of neck pain is assumed to be, for the purpose of this example, 0.80 (that is, 80 of 100 individuals who receive neck manipulation are assumed to experience resolution of their neck pain). Since probabilities assigned to each branch must sum to 1.0, the probability of not experiencing resolution of neck pain is 1.0 – 0.80 = 0.20. Similarly, in Figure 2, the risk of experiencing stroke following neck manipulation is assumed here to be 1 stroke *per* 1,000,000 neck manipulations. Hence, the probability of a stroke is 0.000001, whereas the probability of no stroke is 0.999999. In Figure 2, outcome values, or utilities, have also been assigned to the health state outcomes at the terminal nodes. For the purpose of this example, the utility for having no neck pain, but suffering from neurological deficits as a result of a stroke is assumed to be 0.45 (*i.e.* No neck pain, stroke). The health state outcome associated with less quality-of-life (*i.e.* Neck pain, stroke) has a lower utility, whereas those with greater quality-of-life (*i.e.* No neck pain, no stroke; Neck pain, no stroke) have higher utilities.

Step 3: 'Folding back' the decision tree

To calculate a decision tree, one works backwards, from right to left. For this reason calculating a decision tree is often referred to as 'folding back' or 'rolling back' the tree. The value of each node (*i.e.* decision, chance, terminal) is calculated as follows. As described above, the value of a terminal node is its outcome value, in this case, its utility. The value of a chance node is equal to its *expected value.* Expected value is calculated by weighting (*i.e.* multiplying) the values of each of its branches by their respective probabilities and summing the results. The value of a decision node is equal to the value of its best treatment option, that is, the treatment with the highest expected value.

Applying this calculation to our example in Figure 2 and working backwards from the right-most terminal nodes, the total expected value of neck manipulation treatment is: $[(0.45 \times 0.000001) + (1.0 \times 0.999999)] \times 0.80 + [(0.30 \times 0.000001) + (0.80 \times 0.999999)] \times 0.20$

= 0.96 (rounded to two decimal points). Hence, on a utility scale of 0.0 (death) to 1.0 (good health), the expected value of neck manipulation treatment is 0.96. That is, *on average*, the expected value of receiving neck manipulation is 0.96. Depending on the probabilities assigned to the COX-2 NSAID branches, NSAID treatment would be considered superior or inferior to neck manipulation. Thus, if the total expected value of the COX-2 NSAID branches was > 0.96 on the utility scale, this treatment would be considered superior to neck manipulation. A rational decision maker would therefore decide on COX-2 NSAID treatment for this patient. If the total expected value of the COX-2 NSAID branches was < 0.96, this treatment would be considered inferior to neck manipulation. Hence a rational decision maker would decide on neck manipulation.

Sensitivity analyses

The probability and outcome value estimates assigned to a decision tree may be biased if the only sources of evidence available in the published literature are low-quality studies. Furthermore, there may be a high degree of uncertainty surrounding the estimates if, for example, published data vary significantly (as is the case with most estimates required to conduct a decision analysis of neck pain treatments). Hence, a wide range of possible probabilities and outcome values are considered in an analytic step called 'sensitivity analyses'. Sensitivity analysis is the process of repeatedly folding back a decision tree using a range of probability and outcome value estimates. If the results of the decision model are shown to be sensitive to a probability value associated with a high degree of uncertainty, then the answer to the decision problem will remain uncertain until evidence from high-quality studies becomes available. Thus, sensitivity analyses help to identifying pressing issues which need to be addressed in future studies, thereby prioritizing future research. For example, if the results of our decision analysis were sensitive to poorly established neck manipulation effectiveness rates, this would suggest a critical research objective for future studies.

Applications of clinical decision analysis

Decision analysis was first used in health care to assist physicians to make treatment decisions about individual patients. It was later used by health economists to analyze decisions for the purpose of evaluating and economically appraising health care programmes at the group patient level. Hence, when a decision analysis includes costs, it becomes an economic evaluation summarizing the tradeoffs between changes in health and health care spending. Examples of such evaluations include cost-effectiveness analysis and cost-utility analysis.

Limitations of decision analysis

Clearly, the decision trees presented in Figures 1 and 2 are oversimplified examples. For example, in real life, patients may experience multiple short-term health outcomes, such as a temporary resolution of neck pain, followed by re-exacerbation. Similarly the outcome of stroke may vary from minor residual neurological symptoms to locked-in syndrome. For this reason, decision analysts use software that simulate what would occur to large cohorts of patients receiving treatments by allowing patients to move from one health state to another. These 'Markov state transition models' allow more realistic representations of real life. However, even these complicated decision analytic models are simplifications of real life.

Readers should also understand that the expected value of a decision tree does not mean that by choosing neck manipulation, as in our example, the patient is guaranteed a final outcome with a utility value equal to 0.96. It simply means that, based on the decision model, 0.96 would be the *average* utility if one were to repeat neck manipulation on a large number of identical patients. For this reason, it has been suggested that clinical decision analysis is best applied at the group, rather than individual, patient level.

It is equally important to understand that the validity of a decision analysis rests to a large degree on the validity of the data underlying the assigned probabilities and outcome values. As most readers know, the current scientific literature for many health conditions, spinal disorders included, has significant limitations. These limitations include a lack of high-quality trials, as well as widespread clinical heterogeneity among studies which invalidates synthesis of their results into aggregate estimates.

A complete discussion of the limitations of clinical decision analysis is beyond the scope of this article. Despite its limitations, however, clinical decision analysis can represent a valuable scientific undertaking. One of its greatest potential contributions is identifying which variables (*i.e.* rates of effectiveness, rates of complications) a decision is most sensitive to, thereby highlighting the most pressing issues which need to be addressed in future research.

Summary

Decision analysis is the application of quantitative methods to analyze decisions under conditions of uncertainty. It provides a formal structure for thinking about a treatment decision in a systematic manner, by integrating the evidence about the beneficial and harmful outcomes associated with treatments, as well as patient and societal values associated with those treatment outcomes.

References

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