

# Decision Support Tools





## Decision Support Tools Overview

At Direct Data Analysis, we provide easy-to-use software applications that deliver actionable, product/guideline based recommendations, or probabilities of given events occurring, at the point of use.

### What are they?

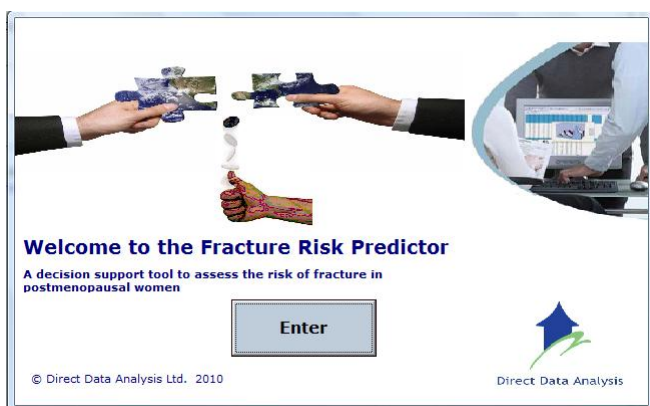
Computerised decision support tools are interactive software tools used by decision-makers to help answer questions, solve problems, and support or refute conclusions.

They can incorporate a range of data sources, such as guidelines, education, expert advice, company procedure, or statistical probabilities, into routine practice.

Our decision support tools are designed to assist, **not replace** decision-making.

### Key Functions

- **Information management** – Provides specific data and knowledge to the user at point of use.
- **Alerts and reminders** – Messages should a procedure be incorrect, or need to be reviewed.
- **User-specific recommendations** – Provides custom-tailored advice or recommendations at the point of use.
- **Quick and simple to use** – The majority of tools can be used to provide a recommendation in under one minute.



Our tools are based upon decision trees, which are populated from the chosen data source.

The user is prompted with a series of questions, following which, the software interrogates the decision tree and generates a tailor-made recommendation within seconds.



**Direct Data Analysis can help implement your decision support needs.**



## Our Decision Support Tools

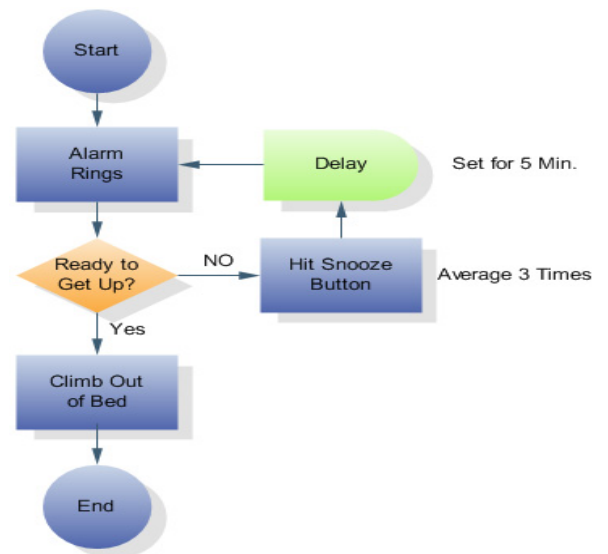
We currently offer 2 types of decision support tool, as follows:

### Product/Guidance Based

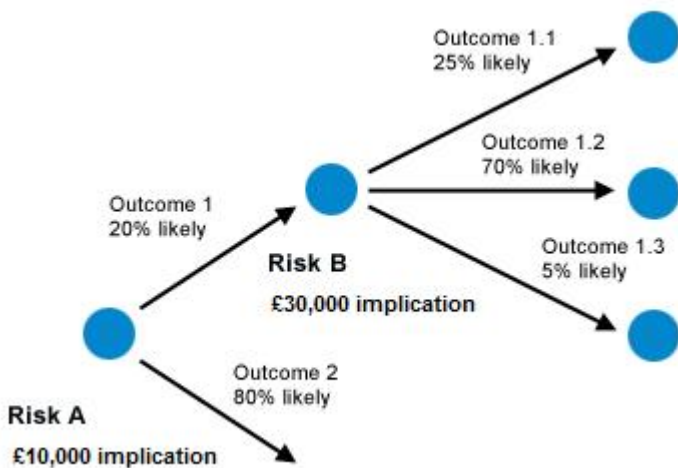
A product/guidance based decision support tool is one where a criteria hierarchy is built. This compares all the options available to the user, and provides custom-tailored assessments and advice.

This type of decision tool is based upon a decision tree to map out the decision in question, along with all the possible options available.

A very simple example is being woken up by an alarm clock. The user has two options available, either get up, or hit the snooze button. This process is then mapped out as per the flowchart opposite.

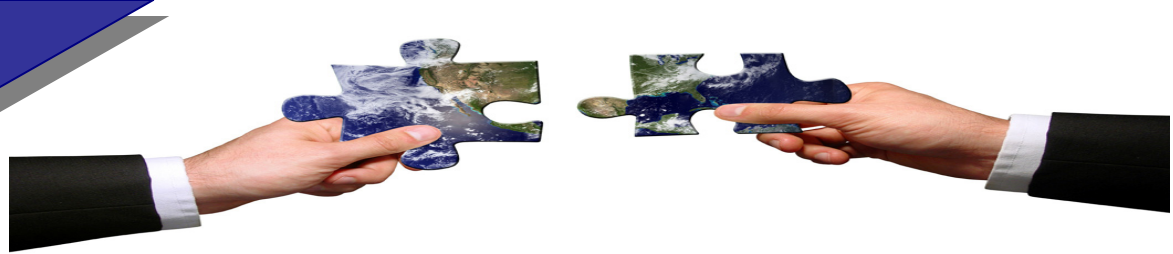


### Statistical/Evidence Based



This type of tool uses a decision tree to compare the probability of given events, based upon individual characteristics. It is used to model future actions with uncertain consequences, and provide formal methods to choose amongst alternatives. Our example shows how this is implemented in practice.

In the example opposite, we have two risks to choose from. Risk A occurs 80% of the time and carries a £10,000 implication, or risk B, which carries a £30,000 implication, but only occurs 20% of the time. However, risk B has a further subset of probable options.



## Product/Guidance Example Managing High Blood Pressure

For the product/guidance based example, we have taken the UK guidance\* for the management of hypertension (high blood pressure) and produced a decision support tool to implement this guidance.

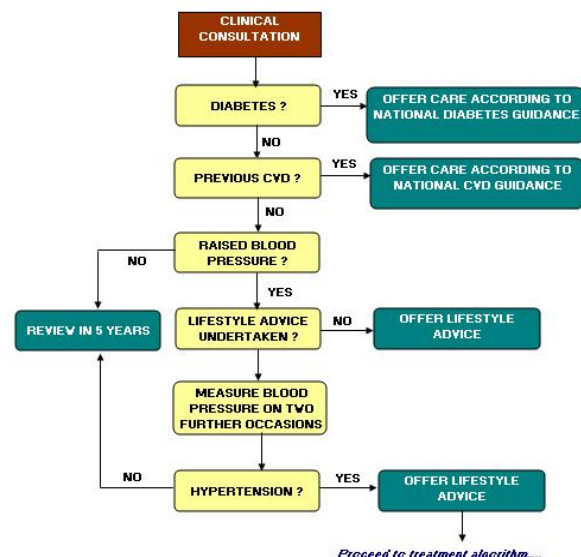
### The first task is to map the product/guidance and all possible decisions

Here we have applied the guidance to a flowchart, which lists all possible situations, along with what options, or path to proceed at each point.

The user proceeds through the flowchart until they arrive at a decision (the green boxes).

In this example, the most important question is to find out if the patient is a diabetic. If so, the tool then informs the user that care should be undertaken in accordance with national diabetes guidelines, not the standard hypertension guidance.

The example opposite is a partially completed flowchart, a full one would also include any pharmaceutical management that may be required for the patient, based upon guidelines and their individual characteristics.



Partially completed decision tree, for the screening of patients for high blood pressure

### Next, we produce a computer program to operate the flowchart

Once the flowchart has been constructed and validated, a user interface is produced to gather data and operate the decision algorithm.

The interface prompts the user with a series of questions relevant to the decision to be made. The user selects an appropriate answer from the choices given.

The decision algorithm is then run, enabling the program to produce a tailored management recommendation.

The user needs to be able to easily and accurately answer the questions, otherwise the decision process becomes flawed.



## Product/Guidance Example Managing High Blood Pressure

### Finally, a results screen and user print out

Once the screening questions have been answered, the computer program runs the algorithm and displays the outcome on a results screen.

For this example, the screen has 3 main features:

1. Screening outcome (their blood pressure is above target)
2. Screening recommendation
3. Screening summary (copy of information input by the user)

The tool provides the user with the option to print out a summary of the screening, along with any supporting information that may be of assistance to the user.

Specific information from the screening.

The decision tool recommendation.

General information of use to the user. In this example, we provide information relating to high blood pressure (what is it, why is it a concern, how to control it)

\* National Institute for Health and Clinical Excellence (NICE). Clinical Guideline 34.



## Statistical Evidence Based Example

### Predicting Risk of Fracture

For the statistical evidence based example, we have taken data published in a scientific journal (Osteoporosis International) predicting fracture risk in postmenopausal women.

#### First we model the probability of the event in question happening

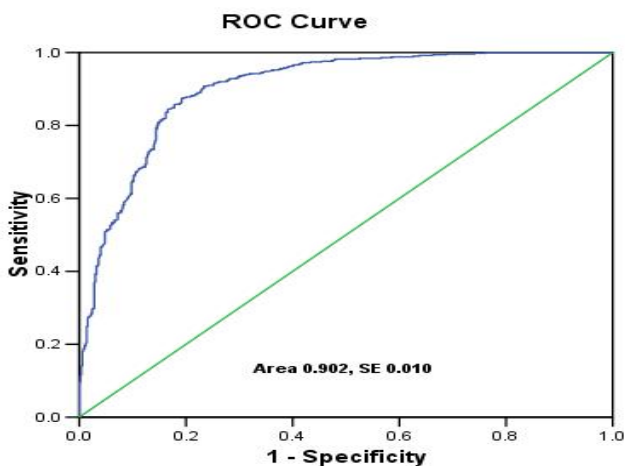
The first step in creating this type of tool is to analyse a set of data, appropriate to the event in question.

In this example, the dataset would contain information known to be risk factors for postmenopausal fracture. This dataset is then analysed, usually using logistic regression modelling. The risk factors shown to be the most statistically significant from the analysis are used in the model. The table below shows the completed analysis, listing the most significant predictors for the 5-year risk of fracture.

Multivariable model for prediction of 5-year risk of hip fracture without and with BMD assessment

Predictor	Assessment without BMD evaluation <sup>a</sup>	Co-efficient	Assessment with BMD evaluation <sup>a</sup>	Co-efficient
Age (per 5 years after 65)	1.6 (1.4–1.8)	0.095	1.4 (1.3–1.6)	0.073
Fracture after age 50	1.7 (1.3–2.3)	0.529	1.5 (1.1–2.0)	0.387
Maternal hip fracture after age 50	1.5 (1.0–2.3)	0.407	1.4 (0.9–2.1)	0.347
Weight ≤ 125 lbs (57 kg)	1.8 (1.4–2.5)	0.608	1.2 (0.9–1.7)	0.195
Current smoker	1.5 (0.9–2.5)	0.429	1.3 (0.8–2.2)	0.289
Uses arms to stand from a chair	2.5 (1.6–3.8)	0.910	2.3 (1.5–3.5)	0.819

We then apply a formula to the value of each predictor, in order to create a model which will calculate the probability of fracture, based upon the individual characteristics of each screening.



We assess the model's performance by plotting a ROC curve with the data. ROC curves with values  $>0.75$  are generally considered to represent good performance of the model. If the curve value was  $<0.50$ , then you would be better off tossing a coin. In this example, the ROC curve value of our model is 0.902.



# Statistical Evidence Based Example

## Predicting Risk of Fracture

We then produce a computer program to gather data and present the results

Screening information is collected from the user, in order to operate the tool and calculate (in this example), the probability of a fracture over the next 5 years.

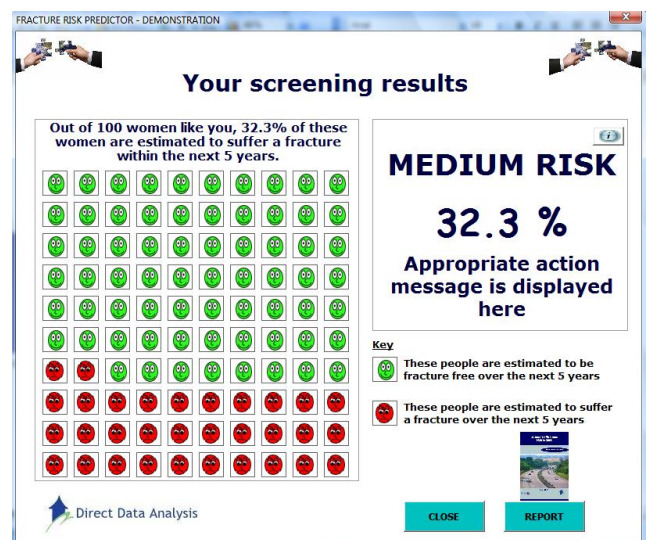
The questions asked are ones which our analysis has previously identified as being significant in predicting the probability of fracture.



The results screen on the statistical model differs slightly from the product/guidance tool, in so far as we now display the probability of the person being screened, suffering a fracture in the next 5 years.

Here, the probability on it's own is meaningless. Is 32.3% good, or should I be worried? In this example, clinical expertise is used to classify the probabilities into Low, Medium, and High Risk. We can then display an appropriate message, dependant on the risk level.

We can also visually represent the risk. In this example we have used 100 faces. What we are saying here to the user, is that this represents 100 people who have entered exactly the same information as you.



The green faces are persons not suffering a fracture, the red ones those that will suffer a fracture over the period. This is just one example, the risk can be presented in many ways.

**A user print out is also available, as the previous example.**

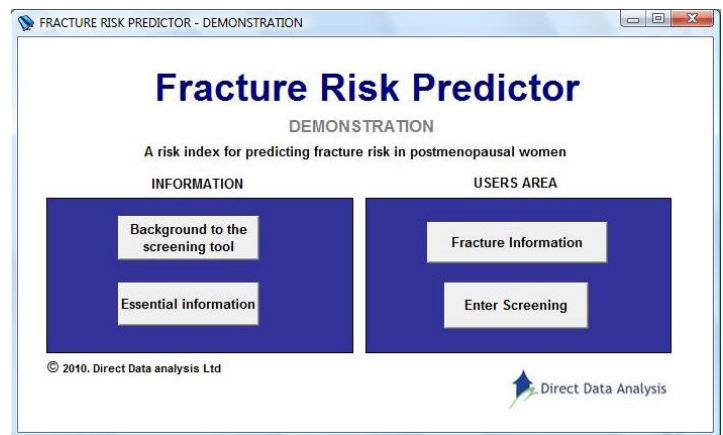


## Additional Features

All our decision support tools include the following as standard:

### User Help and Information Screens

All decision support tools contain a menu page. Here the user has options to view information such as how to use the tool, supporting information regarding the product/guidance, and any other information you wish to include.



### User Manual

In addition to the help and information screens within the decision support tool, we produce a 'user manual' which explains topics such as what the tool is to be used for, how to install onto a computer, how to use the tool, etc.

The user manual is produced as a pdf file, for ease of distribution.

### CD and Case

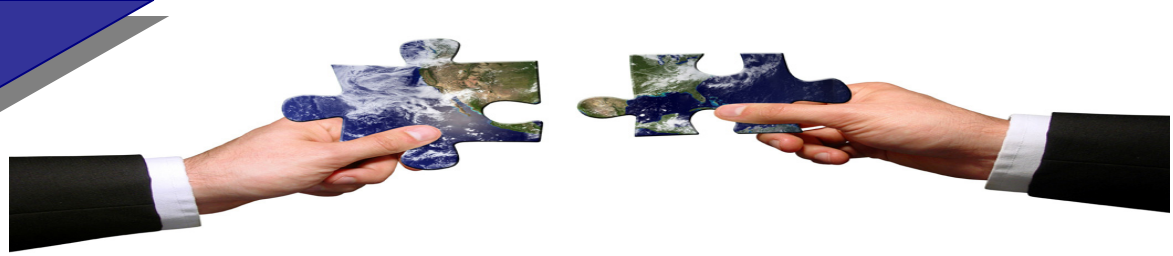
All our decision support tools are distributed via CD and printed case. We can produce as many of these as you require, in order to forward to your clients.

### Automatic Data Collection and Storage (OPTIONAL)

We can provide the option to collect and store all data that is input into the tool. This option can be beneficial if you wish to:

- Have auditable records. In the example opposite, we can see that G Smith, underwent a screening on the 10/7/2010, and we can view full details of that screening.
- Have records for analysis of data. View trends, time of day tool is used, outcomes, etc.

Name	Sex	Age	Is the patient a diabetic ?	History of CVD ?	Tried diet & lifestyle ?	BP Systolic	BP Diastolic	Date of Consultation
G Smith	Male	57	No	Yes	No	145	84	10/07/2010
J Smith	Male	45	No	No	Yes	162	92	05/07/2010
P Green	Female	53	No	No	No	138	80	06/07/2010
B Wright	Male	64	Yes	No	No	151	79	07/07/2010
A N Other	Male	62	No	Yes	No	147.5	77	08/07/2010
J Smith	Male	64.9	No	No	Yes	146.9	74.3	09/07/2010
P Green	Female	67.8	No	No	No	146.3	71.6	10/07/2010
B Wright	Male	70.7	Yes	No	No	145.7	68.9	11/07/2010
A N Other	Male	73.6	No	Yes	No	145.1	66.2	12/07/2010
J Smith	Male	76.5	No	No	Yes	144.5	63.5	13/07/2010
P Green	Female	79.4	No	No	No	143.9	60.8	14/07/2010
B Wright	Male	82.3	Yes	No	No	143.3	58.1	15/07/2010
A N Other	Male	85.2	No	Yes	No	142.7	55.4	16/07/2010



## For Further Information

### **For more information on our decision support tools:**

We hope that this brochure has given you an insight into the decision support process, and the tools that we offer. We also hope that the brochure has provided thought as to if, and how, decision support tools could assist your business.

If you think that a decision support tool may be of use to your business or customers, then please get in touch, where we can discuss the matter further, and provide you with a free, no obligation written quotation.

We look forward to hearing from you.

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[www.direct-data-analysis.co.uk](http://www.direct-data-analysis.co.uk)



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