



Howard Thom

With Gianluca Baio, Nathan Green, Anthony Hatswell,
Claire Williams, Nicky Welton, Pedro Saramago, Marta
Soares, Padraig Dixon, James O'Mahony

(Scientific Committee of the R for HTA organization)

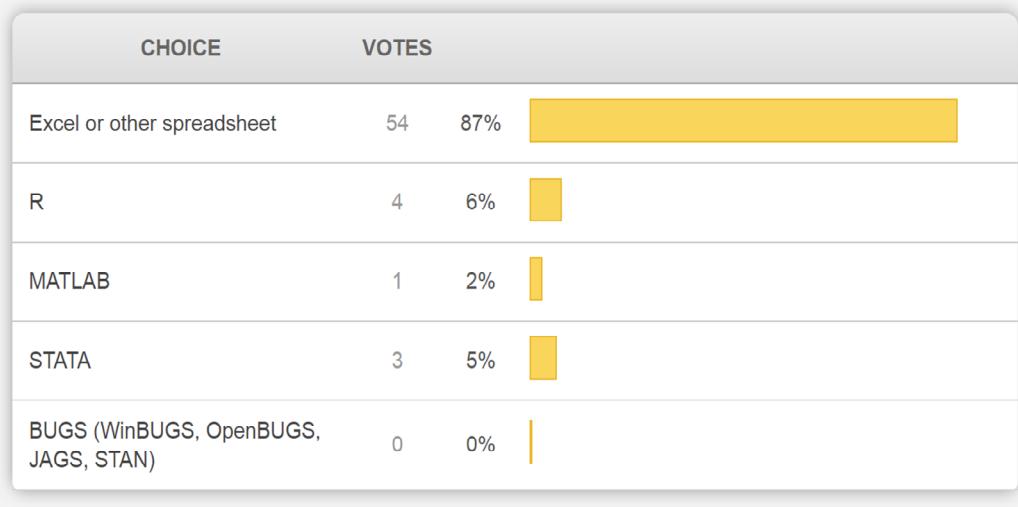
bristol.ac.uk



Background

- Majority of cost-effectiveness analysis (CEA) conducted in Excel
 - Computationally slow
 - Inflexible so limited to simple models
 - Calculations are opaque
 - Limited statistical analysis
- R statistical programming language overcomes these issues
- In this presentation, I'll give a tour of the advantages of R
- I'll briefly show how to implement a decision tree in R
- I'm keen for your feedback on advantages and disadvantages of R

What software do you mostly use for cost-effectiveness analysis?



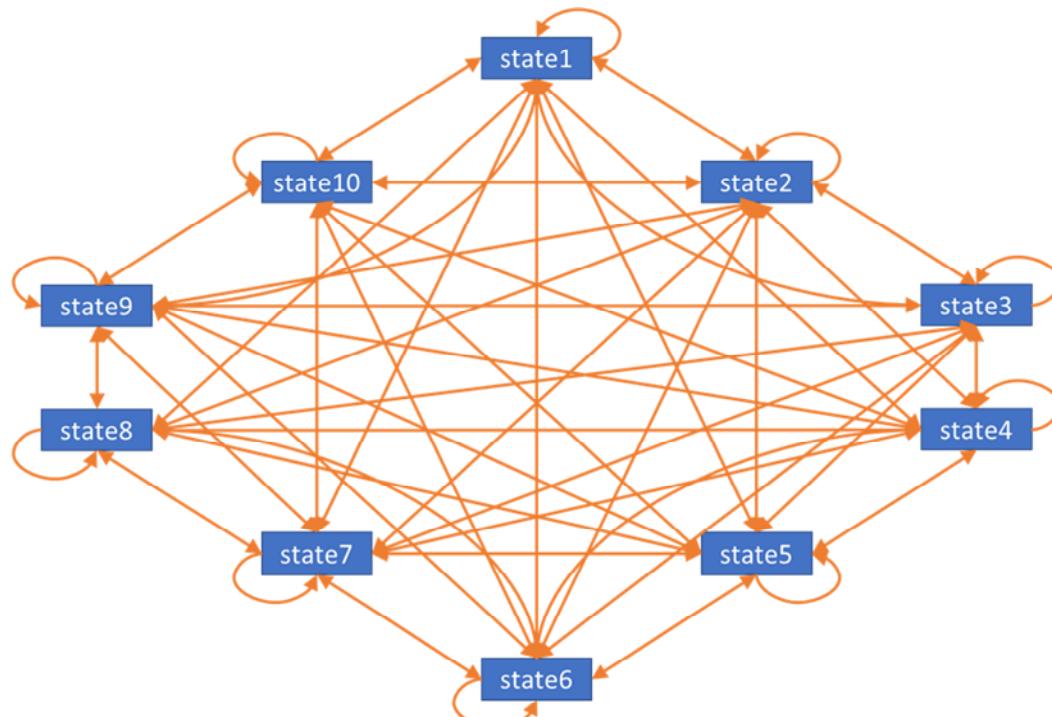
ANSWER CHOICES	RESPONSES
▼ Excel or other spredsheet	60.61%
▼ R	18.18%
▼ Matlab	0.00%
▼ STATA	18.18%
▼ BUGS (WinBUGS, OpenBUGS, JAGS, STAN)	3.03%
TOTAL	

Why R?

- Very fast, particularly with matrix operations common in cost-effectiveness analysis (CEA) modelling
- One-step analysis: all data analysis and economic modelling can be conducted in the same script.
- Packages: R is hugely extensible with thousands of packages.
 - These include many for HTA purposes, which I'll briefly review.
- All analyses, including sensitivities and scenario analyses, can be run from a single script.
 - This ensures reproducibility.
- Transparent: Excel formulae are hidden and tracing the web of dependencies is difficult.
- Flexible: R is a programming language (syntax is similar to C/C++) with functions, program flow, and object oriented features.
 - This enables much more ambitious economic models to be implemented, such as individual level simulations, discrete event simulation, and value of information analysis

Speed comparisons

- We'll start with the obvious advantage: speed.
- We'll show the same CEA model implemented in Excel and R
- This is a live demonstration
- 10-state Markov model, two treatments, 1000 samples.
 - Costs, utilities, and transition probabilities are random



Excel version

AutoSave (● off) 10_state_draft_VBA_20200210 Excel Search

File Home Insert Draw Page Layout Formulas Data Review View Developer Help

Cut Copy Paste Format Painter Arial 10 A A Wrap Text General Conditional Formatting Table Cell Styles Insert Delete Format AutoSum Fill Clear Sort & Filter Selection

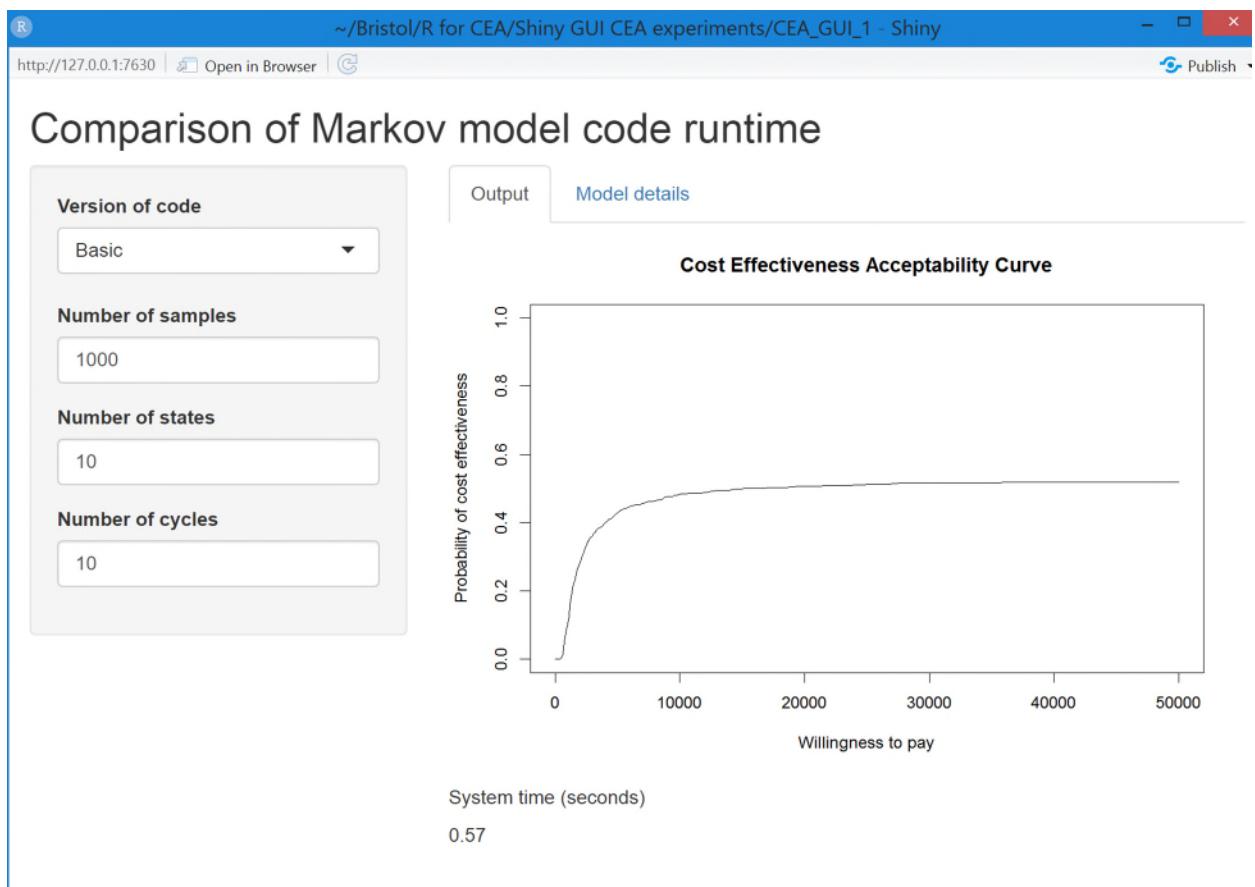
H17

Summary of variables in the model												
			Run Probabilistic Sensitivity Analysis				Press to run 1,000 simulation trials (recorded from A38 below)					
Name	Value	Variable description	Restore	low	high	Stochastic	est. sd.	alpha	beta	Comment	State 1-10 cc	
cAsymp	100	Cost of one cycle in the asymptomatic disease state	100	-	-	111	10.00				Modelling it c	
cDrug	50	Cost of drug for one cycle	50	40	60	46	5.10				Assumed all	
uAsymp	0.80	Quality of life weight for one cycle in state 1-10	0.80	-	0.81172	-		80	20	10Feb2020 C		
uAsymp_treat	0.80	Quality of life weight for one cycle in state 1-10 for treatment group	0.80	-	0.78827	-		80	20	10Feb2020 C		
cycle	1	Length in years of one cycle										
cDR	3.5%	Discount rate for costs										
oDR	3.5%	Discount rate for outcomes										
Analysis												
Strategy	Eff	Cost										
No drug	22.12	£ 2,766										
Drug	22.12	£ 2,814										
difference	-	£ 48	#DIV/0!	ICER								
Probabilistic Sensitivity Analysis results												
Trial	inc.Effect	inc.Cost	ICER									
1	1.33	£51	£38		min	-£10,834						
2	1.12	£50	£45		median	£12						
3	0.99	£42	£42		max	£7,437						
4	0.02	£53	£2,604		mean	-£10						
5	0.82	£46	£56		stdev	£632						
6	2.50	£46	£18			2.50%	-£472					
7	0.36	£43	£119			97.50%	£407					
8	1.00	£60	£60									

Introduction Parameters and Analysis Transition Probability Matrix Markov Model Markov Figure

R version

- The interface was coded in R Shiny (more on this later)

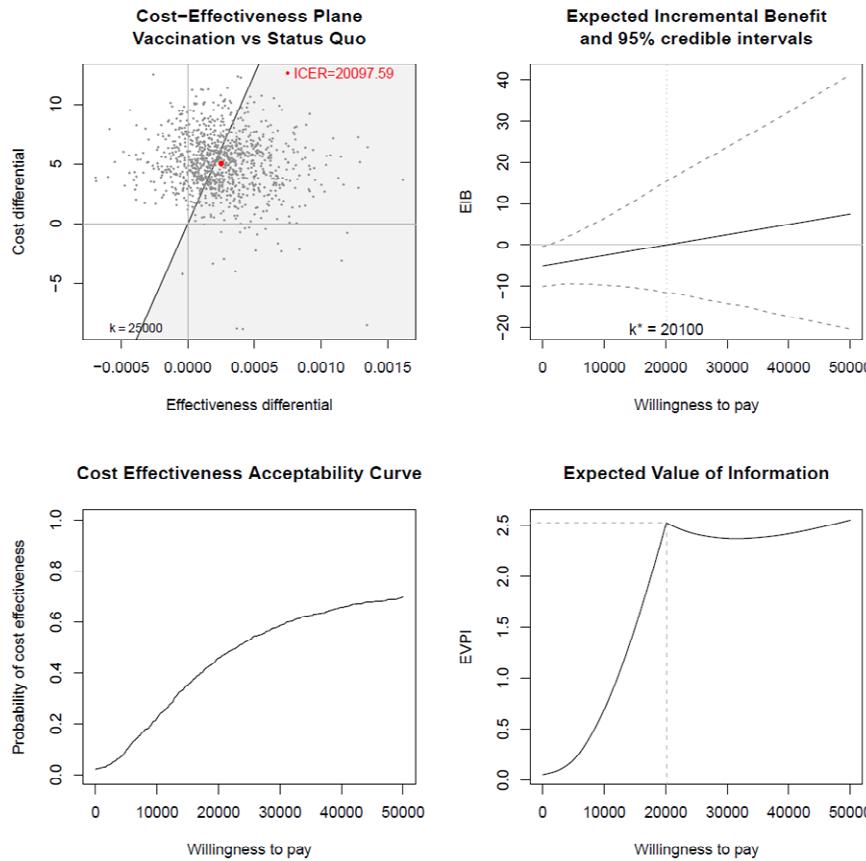


BCEA – Gianluca Baio, UCL

- As noted, the CEAC in the R Shiny version of the model was generated by the BCEA package.
- “Bayesian Cost-Effectiveness Analysis”
- BCEA is a suite of tools for post-processing results of a probabilistic sensitivity analysis
- Does not build CEA models for you. You must give it simulated costs and effects
 - Although these can be from any software, including Excel.

BCEA – Gianluca Baio, UCL

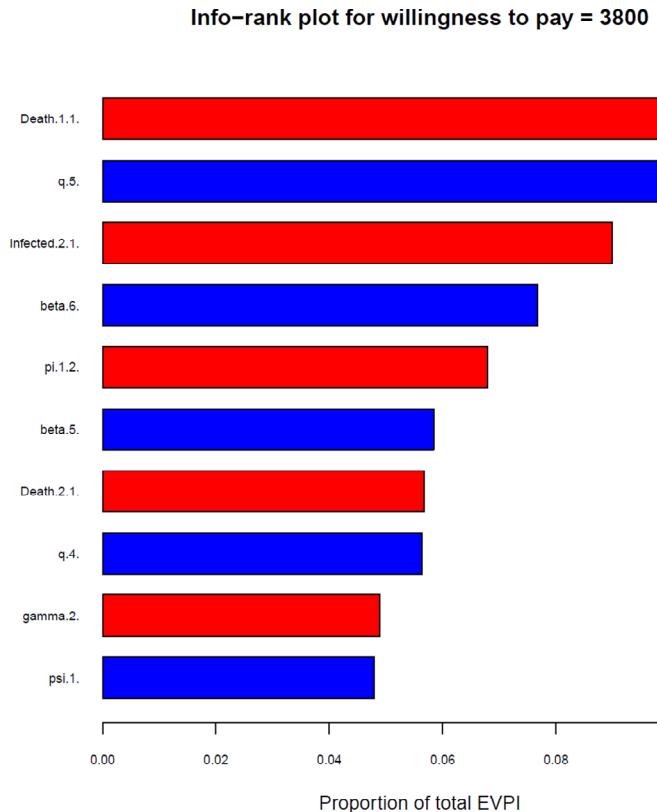
```
> m = bcea(e,c,ref=2,interventions=c("Status Quo","Vaccination"))
> plot(m)
```



BCEA – Gianluca Baio, UCL

- Includes automatic functions to estimate EVPPI.
- And what the proportion of total EVPI...
 - This is a more sophisticated analysis than one-by-one deterministic sensitivity analysis as accounts for probability that a parameter value will change

```
> ir = info.rank(inp$parameters,inp$mat,mm,howManyPars=10)
```



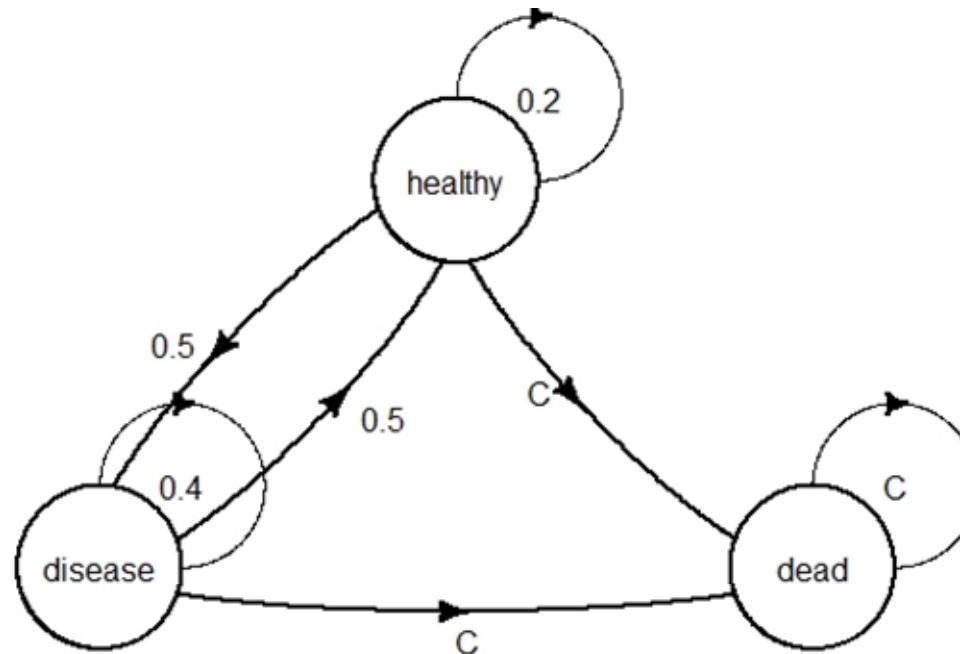
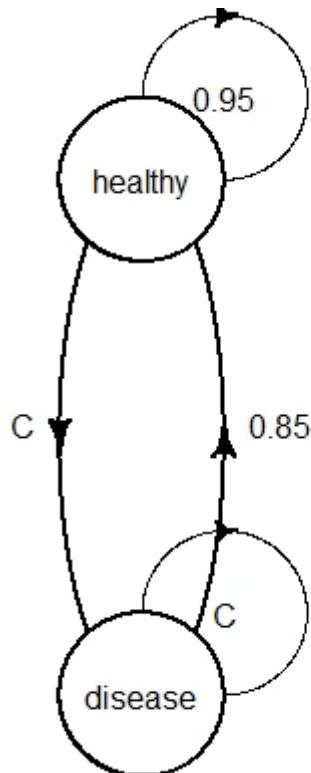
Heemod – created by Kevin Zarca, Urc Eco (France).

- Easy-to-use package for cohort multistate CEA modelling in R
- Implements modelling and reporting of Briggs textbook Decision Modelling for Health Economic Evaluation textbook.
- Deterministic and probabilistic sensitivity analysis
- Includes semi-Markov and non-homogeneous Markov models
- Has own plotting functions but can link to BCEA if preferred.

- Conversely, I've found it slow and not always flexible enough for complex modelling.
- However, has one particularly useful feature...

Heemod – created by Kevin Zarca, Urc Eco (France).

- Based on user inputs, generates a model diagram
- Not the prettiest, but useful for validation
- Examples based on Nathan Green (Imperial College) code.



R2OpenBUGS – Andrew Gelman, Columbia University

- Run Bayesian MCMC estimation through OpenBUGS from R
 - Similar packages exist for WinBUGS, JAGS, and STAN

- First load the library

```
library(R2OpenBUGS)
```

- Then some BUGS model file (e.g. the NICE DSU TSD NMA code)

```
source("fixed_effects_binary.R")
```

- Set simulation parameters

```
n.chains<-2; num.sims<-10000*n.chains; burn.in<-50000*n.chains
```

- Call R2OpenBUGS key function

```
bugs_object<-bugs(data = bugs_data_recovery, inits = NA, model =  
fixed_effects_binary...)
```

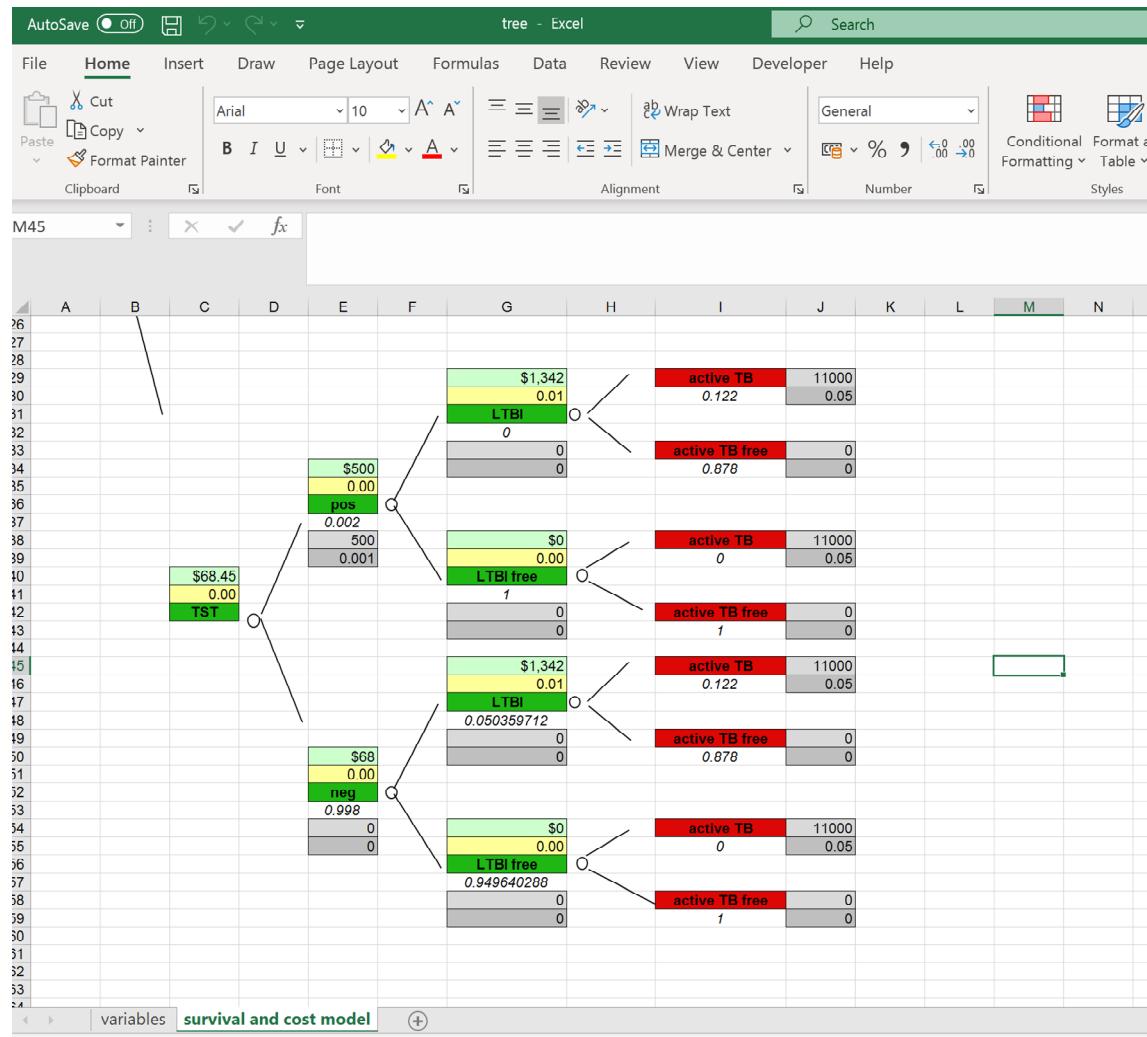
- Then get parameter samples from bugs_object\$sims.array or statistics using bugs_object\$summary

R2OpenBUGS – network meta-analysis

- I conduct all my NMAs in R.
- Automate formatting of systematic literature review data
 - Using `read.xlsx()` or `read.csv()`
- Automate model running (base case, sensitivities, and subgroups)
 - R2OpenBUGS
- Automate formatting of results (results tables, network plots, forest plots, rankograms)
 - Using `write.xlsx()` to link to Excel
 - Real example of this formatting will be shown

Xlerate – Richard Fitzjohn, Imperial College

- Proof-of-concept package to automatically convert Excel to R.
- Takes as input an Excel decision tree



Xlerate – Richard Fitzjohn, Imperial College

- You then specify the range of input and output cells

```
inputs <- xlerate::xlerate_ref( c("D3:D13", "D15:D16",
"D18:D21"), sheet = 1, label = list(col = -1))

outputs <- xlerate::xlerate_ref( c("C40", "E34", "E50",
"G29", "G38", "G45", "G54"), sheet = 2, label = list(row =
2))
```

- Using these, the package recursively searches through the Excel sheet and creates equivalent R code.
- R version is much faster and thus useful for sensitivity analyses of value of information analysis.
- Package under development and may be extended to Markov models.
- Code is available on GitHub:

<https://github.com/HealthEconomicsHackathon/xlerate#xlerate>

- And a blog entry describing the package is here:

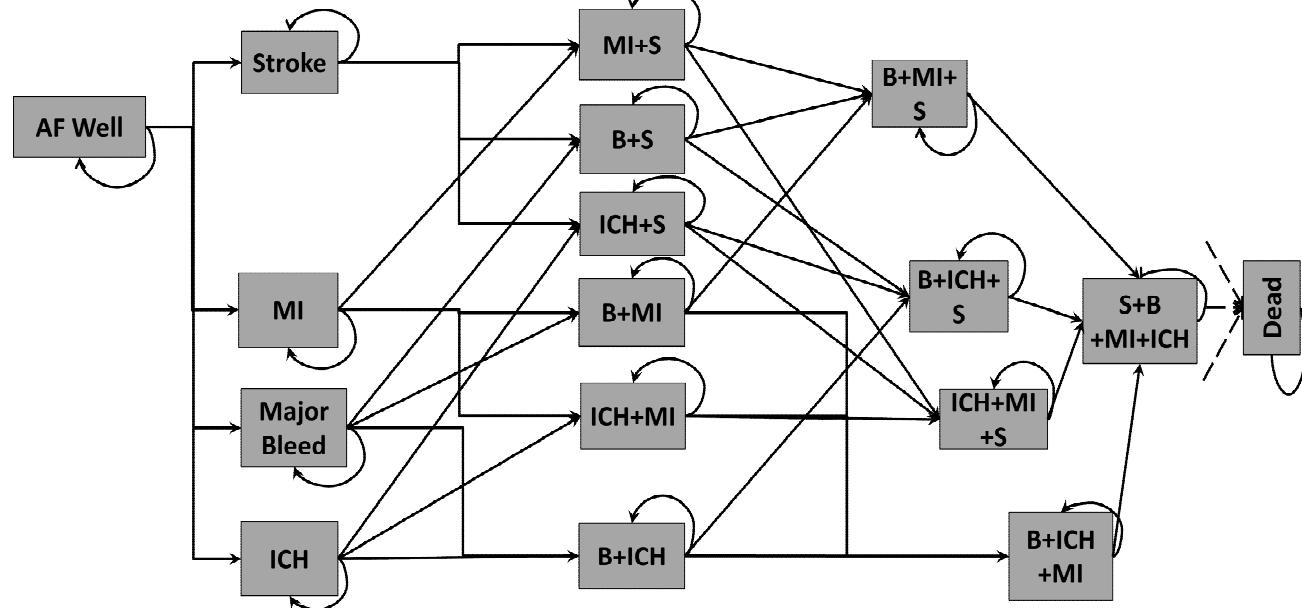
<https://reside-ic.github.io/blog/experiments-in-transforming-excel-into-r/>

Other packages

- Hesim by Devin Incerti
 - Individual level Markov and semi-Markov continuous-time multistate modelling
 - Specifically designed for CEA modelling
 - Intro available here: <https://devinincerti.com/2019/01/01/sim-mstate.html>
- Mstate by Hein Putter et al.
 - Continuous-time multistate modelling of panel data
 - Claire Williams paper on CEA modelling using mstate:
<https://journals.sagepub.com/doi/full/10.1177/0272989X16651869>
- Flexsurv – Chris Jackson
- Msm – Chris Jackson
 - Continuous-time Markov modelling of panel data
 - Includes functionality for hidden Markov models

Complex models – DOACs for AF

- The added speed and flexibility of R enables much more complex and realistic models to be implemented
- Key example is directly acting oral anticoagulants (DOACs) for atrial fibrillation (AF).
- Structure consists of 17 health states



S=Ischemic stroke, B=Major extracranial bleed, MI=Myocardial infarction, ICH=Intracranial haemorrhage

TIA and SE are transient events. Patients can switch treatment following events.

Complex models – DOACs for AF

- Structure consists of 17 health states – memory states that overcome Markov limitation
- Duplicated for 6 treatment options: coumarin, 4 DOACs, and no treatment
 - 97 states in total
 - Treatment switching included, plus transient events
- Uses 98 input parameters – including link to competing risks NMA implemented through R2OpenBUGS
 - Fully probabilistic
- Conducted EVPPI analysis using multilevel Monte Carlo modelling
 - SAVI and model regression techniques could not manage the complexity and number of input parameters
- This model will now be demonstrated live...
- Version of code available on GitHub

<https://github.com/Bogdasayen/DOACs-AF-Economic-model>

GitHub



GitHub

- Version control key to good programming practice
- GitHub is not just an online repository – it is a tool to ease collaborative working on large projects
- Updates are pulled from the repository, changes pushed back and committed.
- You can duplicate repositories (fork) or experiment with minor duplicates (branch).
- Can assign a team lead to review and accept commits.
- Interfaces easily with RStudio (more on this shortly)

Showcase – RMarkdown

bristol.ac.uk



Showcase – RShiny

- Package and extension to R that allows creation of html/JavaScript web apps.
- These can be hosted on Shiny server and made publicly available
 - For example, the NICE AF guidelines could include a link to the actual model.
 - Huge transparency benefit
- You've now seen two examples of RShiny user interfaces
 - I'm very much a novice but knocked these GUIs up in a couple of hours.
- You may also have seen the SAVI tool for value of information analysis – this is implemented in RShiny.
- Let's take a look at a fully fledged modelling example
- The Innovation and Value Initiative Rheumatoid Arthritis model (IVI-RA)
 - Devin Incerti (Genentech, formerly IVI), also created ‘hesim’ package.
<https://innovationandvalueinitiative.shinyapps.io/ivi-ra-expert/>

RStudio



- sd

bristol.ac.uk



Introduction to building decision trees in R

- Heard the wonderful things you can do in R.
- Itching to get your hands dirty?
- We'll now talk through the specifics of programming a (probabilistic) decision tree in R.

Rstudio interface

The screenshot shows the RStudio interface with the following components:

- Scripts:** A box highlighting the left pane where R scripts are written.
- List of data and functions in global environment:** A box highlighting the Global Environment tab in the top-right pane, showing objects like depression.bcea, doac.bcea, and he.
- Command line:** A box highlighting the Console tab at the bottom-left, showing the command `~/Bristol/Teaching/EE using R/Decision trees/`.
- Plots, packages, files, help:** A box highlighting the bottom-right pane, which contains a "Cost effectiveness plane" plot comparing Antidepressant vs CBT, showing an ICER of -1924.13.

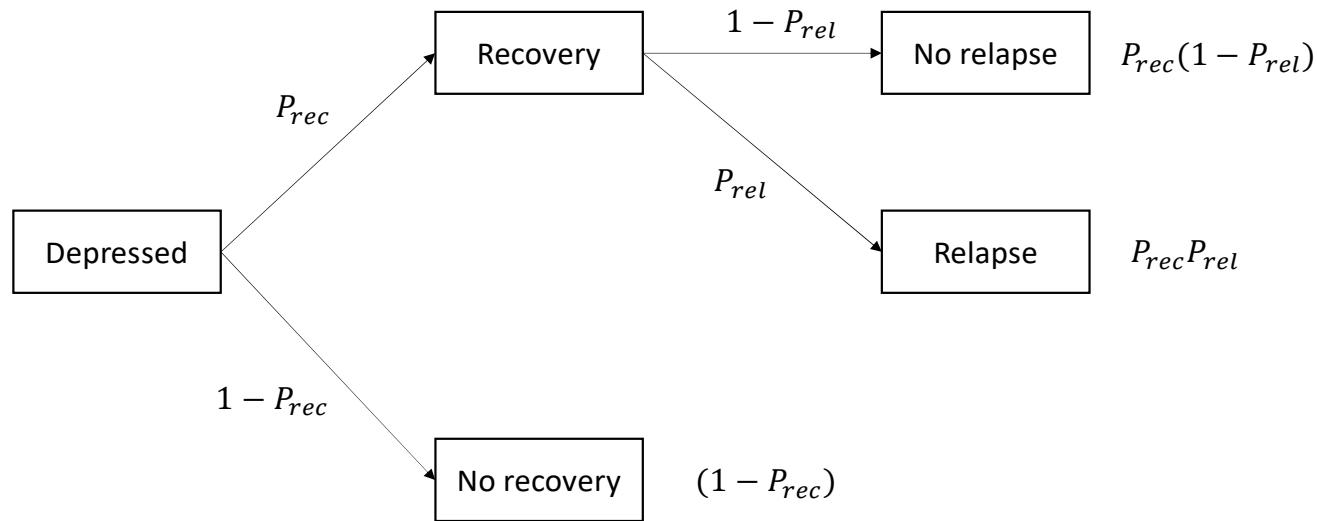
Simple functions – logit and its inverse

```
# Logistic link function
logit <- function(x) {
  return(log(x / (1 - x)))
}

# Inverse of logit
expit<-function(x) {
  return(1 / (1 + exp(-x)))
}
```

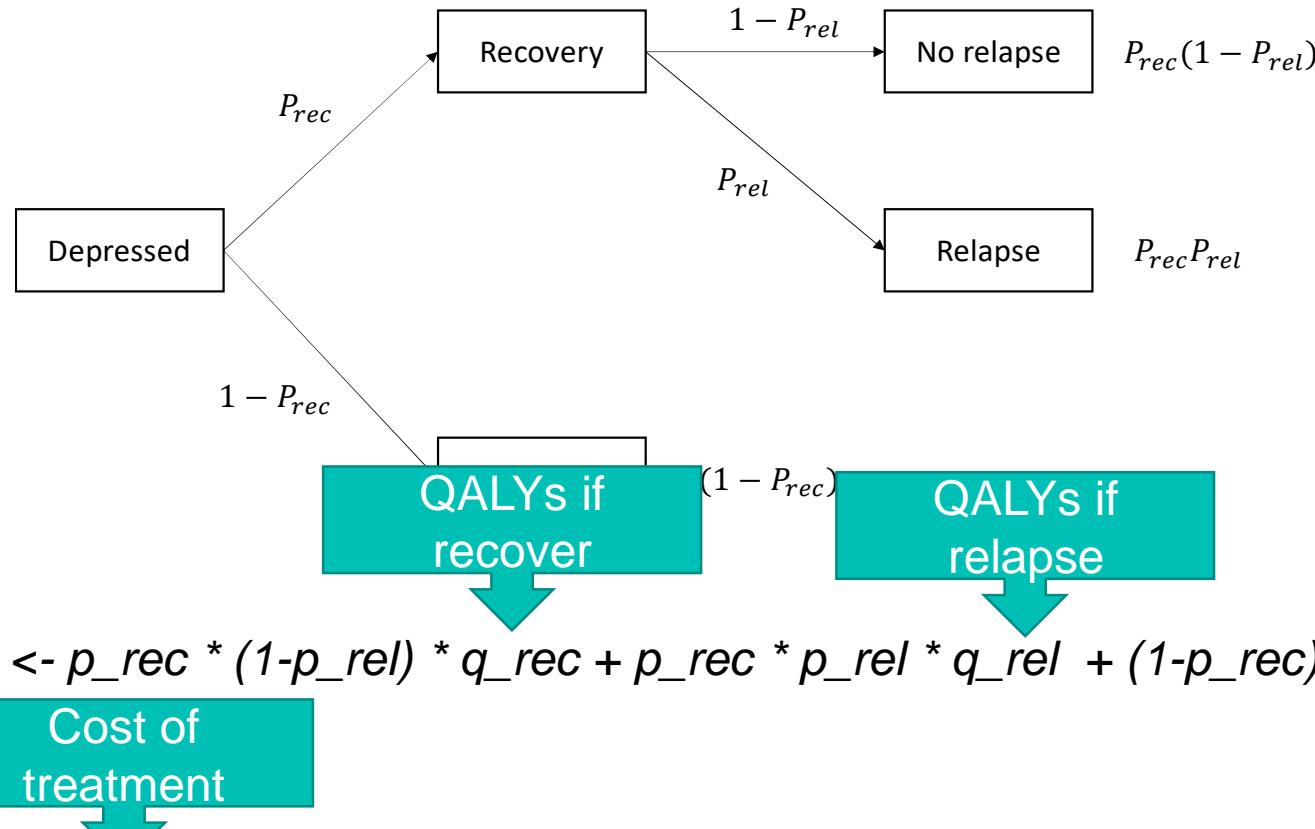
```
> logit(0)
[1] -Inf
> logit(0.5)
[1] 0
> logit(1)
[1] Inf
> expit(0)
[1] 0.5
> |
```

Simple decision tree in R



- Consider this simple decision tree with artificial input parameters.
- Probabilities of recovery and relapse for no treatment (option 1), cognitive behavioural therapy (option 2), and antidepressants (option 3).
- This toy model is available on GitHub:
<https://github.com/Bogdasayen/Depression-toy-decision-tree-in-R>

Implementing a decision tree in R



```
effects <- p_rec * (1-p_rel) * q_rec + p_rec * p_rel * q_rel + (1-p_rec) * q_norec
```

Cost of
treatment

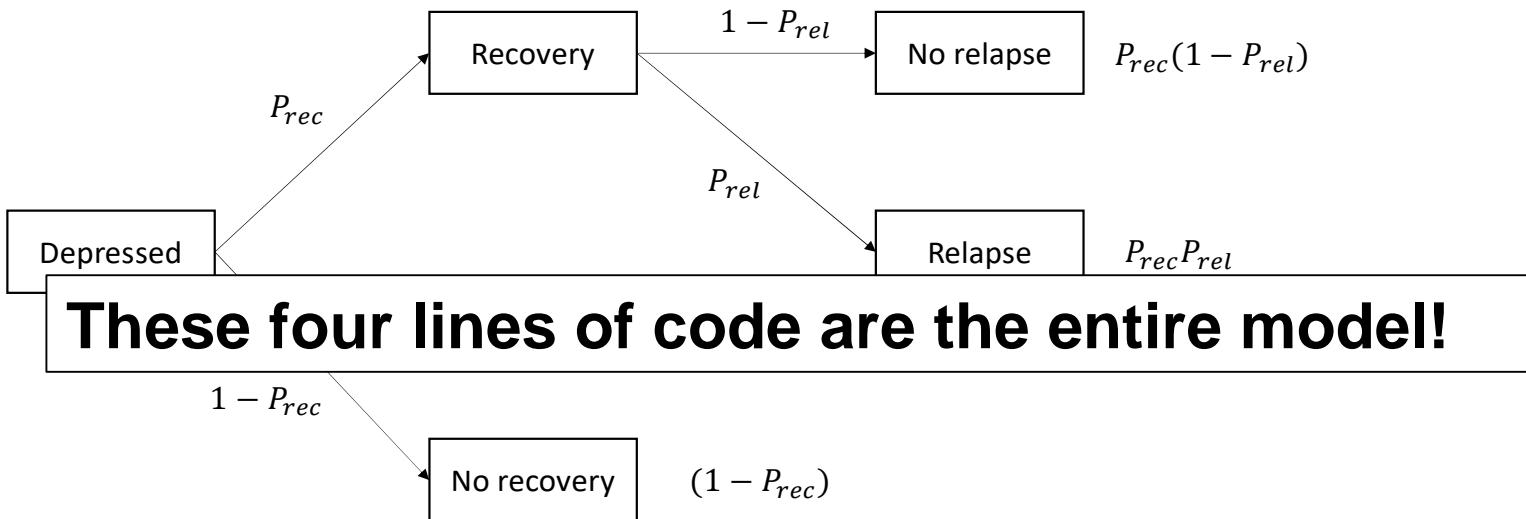
QALYs if not
recover

```
costs <- c_treat + p_rec * (1-p_rel) * c_rec + p_rec * p_rel * c_rel + (1-p_rec) * c_norec
```

```
net_benefit <- lambda_target * effects-cost
```

```
incremental_nb <- net_benefit - net_benefit[, 1]
```

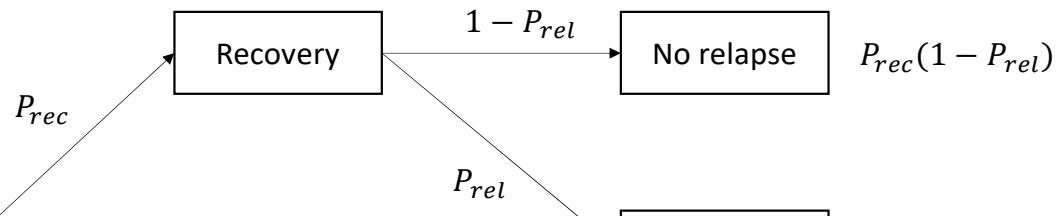
Implementing a decision tree in R



```
effects <- p_rec * (1-p_rel) * q_rec + p_rec * p_rel * q_rel + (1-p_rec) * q_norec  
costs <- c_treat + p_rec * (1-p_rel) * c_rec + p_rec * p_rel * c_rel + (1-p_rec) *  
c_norec  
net_benefit <- lambda_target * effects - costs  
incremental_nb <- net_benefit - net_benefit[, 1]
```

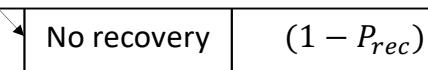
And now we make it probabilistic...

Making it probabilistic (model code)



See any difference?

R performs the same calculations whether the p.rec and other variables are vectors or scalars



```
effects <- p_rec * (1-p_rel) * q_rec + p_rec * p_rel * q_rel + (1-p_rec) * q_norec  
costs <- c_treat + p_rec * (1-p_rel) * c_rec + p_rec * p_rel * c_rel + (1-p_rec) * c_norec  
net_benefit <- lambda_target * effects - costs  
incremental_nb <- net_benefit - net_benefit[, 1]
```

Making it probabilistic (Costs, Utilities)

Outcome	Costs	QALYS
Recovery, no relapse	$C_{rec} = N(\mu = 1000, \sigma = 50)$	$Q_{rec} = N(\mu = 26, \sigma = 2)$
Recovery, relapse	$C_{rel} = N(\mu = 2000, \sigma = 100)$	$Q_{rel} = N(\mu = 23, \sigma = 3)$
No recovery	$C_{no\ rec} = N(\mu = 2500, \sigma = 125)$	$Q_{no\ rec} = N(\mu = 20, \sigma = 4)$

Costs for recovery, relapse, and no recovery over 30 year horizon

```
c_rec <- rnorm(n = n_samples, mean = 1000, sd = 50)
c_rel <- rnorm(n = n_samples, mean = 2000, sd = 100)
c_norec <- rnorm(n = n_samples, mean = 2500, sd = 125)
```

QALYs for recovery, relapse, and no recovery over 30 year horizon

```
q_rec <- rnorm(n = n_samples, mean = 26, sd = 2)
q_rel <- rnorm(n = n_samples, mean = 23, sd = 3)
q_norec <- rnorm(n = n_samples, mean = 20, sd = 4)
```

Making it probabilistic (Treatment effects)

- Log odds ratios follow multivariate normal

Recovery:
$$\begin{pmatrix} lor_{2,rec} \\ lor_{3,rec} \end{pmatrix} \sim MVN \left(\begin{pmatrix} 0.99 \\ 1.33 \end{pmatrix}, \begin{pmatrix} 0.22 & 0.15 \\ 0.15 & 0.20 \end{pmatrix} \right)$$

Relapse:
$$\begin{pmatrix} lor_{2,rel} \\ lor_{3,rel} \end{pmatrix} \sim MVN \left(\begin{pmatrix} -1.48 \\ -0.40 \end{pmatrix}, \begin{pmatrix} 0.14 & 0.05 \\ 0.05 & 0.11 \end{pmatrix} \right)$$

- As it's a statistical language, the multivariate normal is implemented simply in R:

```
lor_rec <- mvrnorm(n = n_samples, mu = c(0.99, 1.33),  
                     Sigma = matrix(c(0.22, 0.15, 0.15, 0.20), nrow = 2))  
  
lor_rel <- mvrnorm(n = n_samples, mu = c(-1.48, -0.40),  
                     Sigma = matrix(c(0.14, 0.05, 0.05, 0.11), nrow = 2))
```

Instead MCMC via R2OpenBUGS

- Can run the NMA each time you run the model
- Or (more likely) load precalculated log odds ratios for recovery (similarly for relapse)

```
mcmc_recovery <- read.csv(file = "lor.recovery.bugs.csv")
```

- Can use just the first n_samples of the matrix

```
lor_rec <- mcmc_recovery[1:n_samples, ]
```

Making it probabilistic (Reference probabilities)

Parameter	No Treatment (Option 1)
P_{rec}	$P_{1,rec} = Beta(\alpha = 6, \beta = 200)$
P_{rel}	$P_{1,rel} = Beta(\alpha = 2, \beta = 100)$

- The beta distribution is another of many implemented in base R.
- Note however the idiosyncratic naming convention of the parameters.
- α is *shape1* and β is *shape2*.

```
p_rec[, 1] <- rbeta(n = n_samples, shape1 = 6, shape2 = 200)
p_rel[, 1] <- rbeta(n = n_samples, shape1 = 2, shape2 = 100)
```

Making it probabilistic (Comparator probabilities)

Parameter	CBT (Option 2)	Antidepressant (Option 3)
P_{rec}	$P_{2,rec} = \text{expit}(\text{logit}(P_{1,rec}) + lor_{2,rec})$	$P_{3,rec} = \text{expit}(\text{logit}(P_{1,rec}) + lor_{3,rec})$
P_{rel}	$P_{2,rel} = \text{expit}(\text{logit}(P_{1,rel}) + lor_{2,rel})$	$P_{3,rel} = \text{expit}(\text{logit}(P_{1,rel}) + lor_{3,rel})$

- We can use a loop over the number of treatments $n.treat$
`for(i in 2:3){
 p_rec[, i] <- expit(logit(p_rec[, 1]) + lor_rec[, i - 1])
 p_rel[, i] <- expit(logit(p_rel[, 1]) + lor_rel[, i - 1])
}`

Making it probabilistic - vectorise

Parameter	CBT (Option 2)	Antidepressant (Option 3)
P_{rec}	$P_{2,rec} = \text{expit}(\text{logit}(P_{1,rec}) + lor_{2,rec})$	$P_{3,rec} = \text{expit}(\text{logit}(P_{1,rec}) + lor_{3,rec})$
P_{rel}	$P_{2,rel} = \text{expit}(\text{logit}(P_{1,rel}) + lor_{2,rel})$	$P_{3,rel} = \text{expit}(\text{logit}(P_{1,rel}) + lor_{3,rel})$

- Or we can vectorise, which is much faster than a loop

```
p_rec[, c(2:n_treat)] <- expit(logit(p_rec[, 1]) + lor_rec[, c(2:n_treat) - 1])
```

```
p_rel[, c(2:n_treat)] <- expit(logit(p_rel[, 1]) + lor_rel[, c(2:n_treat) - 1])
```

The expit and logit functions work on vectors and matrices.

- Can set n.treat to any number without having to duplicate code.

Formatting results

- Use `paste("string1", "string2")` function for string concatenation
- Use `round(x,digits=3)` for numeric formatting

```
format_results<-function(x, n_digits = 2) {  
  paste(round(mean(x), digits = n_digits),  
        " (", round(quantile(x, probs = 0.025), digits = n_digits), ", "  
        ", round(quantile(x, probs = 0.975), digits = n_digits), ") ", sep = "")  
}
```

```
> paste("string1", "string2", sep = "+")  
[1] "string1+string2"  
> round(3.141592, digits = 3)  
[1] 3.142  
> format_results(c_rec)  
[1] "999.46 (907.56, 1094.33)"  
>
```

Decision tree results

- Build a results matrix

```
results_matrix <- matrix(NA, nrow = 6, ncol = n_treat)
```

- Name the rows and columns

```
rownames(results_matrix) <- c("Total costs", "Total QALYs", "Incremental costs",  
"Incremental QALYs", "Net Benefit", "Incremental NB")
```

```
colnames(results_matrix) <- t_names
```

- Then calculate summaries

```
for(i_treat in 1:n_treat)
```

```
{
```

```
  results_matrix["Total costs", i_treat] <- format_results(x = costs[, i_treat])
```

```
  results_matrix["Total QALYs", i_treat] <- format_results(x = effects[, i_treat])
```

```
  results_matrix["Incremental costs", i_treat] <- format_results(x = incremental_costs[,  
i_treat])
```

```
  results_matrix["Incremental QALYs", i_treat] <- format_results(x = incremental_effects[,  
i_treat])
```

```
  results_matrix["Net Benefit", i_treat] <- format_results(x = net_benefit[, i_treat])
```

```
  results_matrix["Incremental NB", i_treat] <- format_results(x = incremental_nb[, i_treat])
```

```
}
```

Exporting the results matrix to Excel

- Export as a csv

```
write.csv(results_matrix, file = "depression_results.csv")
```

- Or as an Excel file

```
library(xlsx)
```

```
write.xlsx(results_matrix, file = "depression_results.xlsx", sheetName = "CEA results")
```

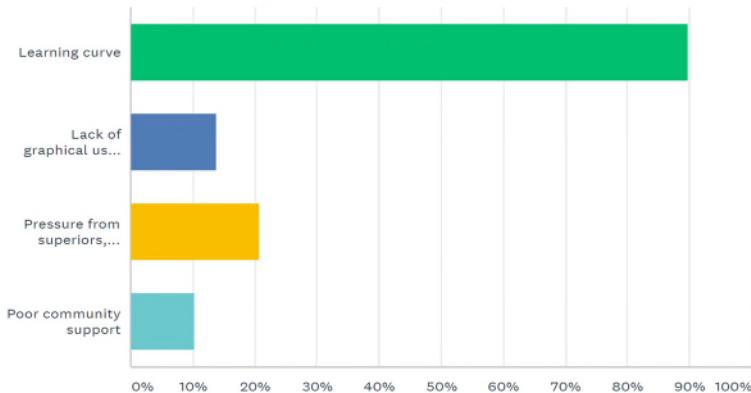
	No treatment	CBT	Antidepressant
Total costs	2458.08 (2216.38, 2692.91)	2678.9 (2424.37, 2937.03)	2366.58 (2087.97, 2621.49)
Total QALYs	20.09 (12.87, 27.59)	20.41 (13.54, 27.56)	20.59 (14.02, 27.52)
Net Benefit	399358.81 (254931.73, 549117.1)	405521.49 (267937.64, 548404.61)	409355.48 (277952.91, 548049.21)
Incremental NB	0 (0, 0)	6162.68 (-1978.38, 26095.58)	9996.67 (-2660.86, 36001.2)

What are the barriers to using R

- ISPOR and R for HTA surveys

Learning curve is main barrier to adopting R

SurveyMonkey Analyze - R for CEA pre-workshop survey



ANSWER CHOICES

▼ Learning curve

▼ Lack of graphical user interface

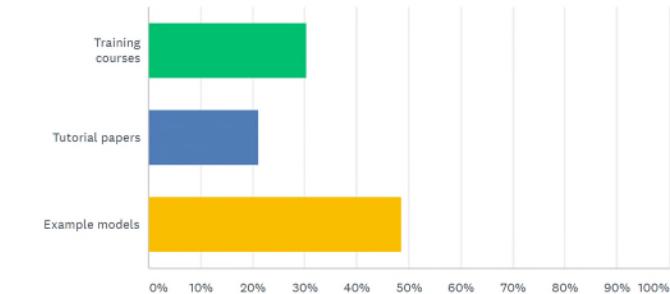
▼ Pressure from superiors, clients or assessors

▼ Poor community support

Total Respondents: 29

What would be most helpful to ease transition to R?

Answered: 33 Skipped: 0



ANSWER CHOICES

▼ Training courses

▼ Tutorial papers

▼ Example models

TOTAL

Training opportunities

- EE modelling in R (Bristol)
- R for HTA training day
- Erik in Netherlands DES
- Tutorial papers and websites
- Intro to R (various, including DARTH)

Invitation to panel discussion

- 30th June 2020, London.