



# Rethinking Clinical Trial Design

## Should We Consider the Value of Information?

**Michael Dymock, Julie A Marsh, Mark Jones, Anna Heath, Kevin Murray and Tom Snelling**



# A confession

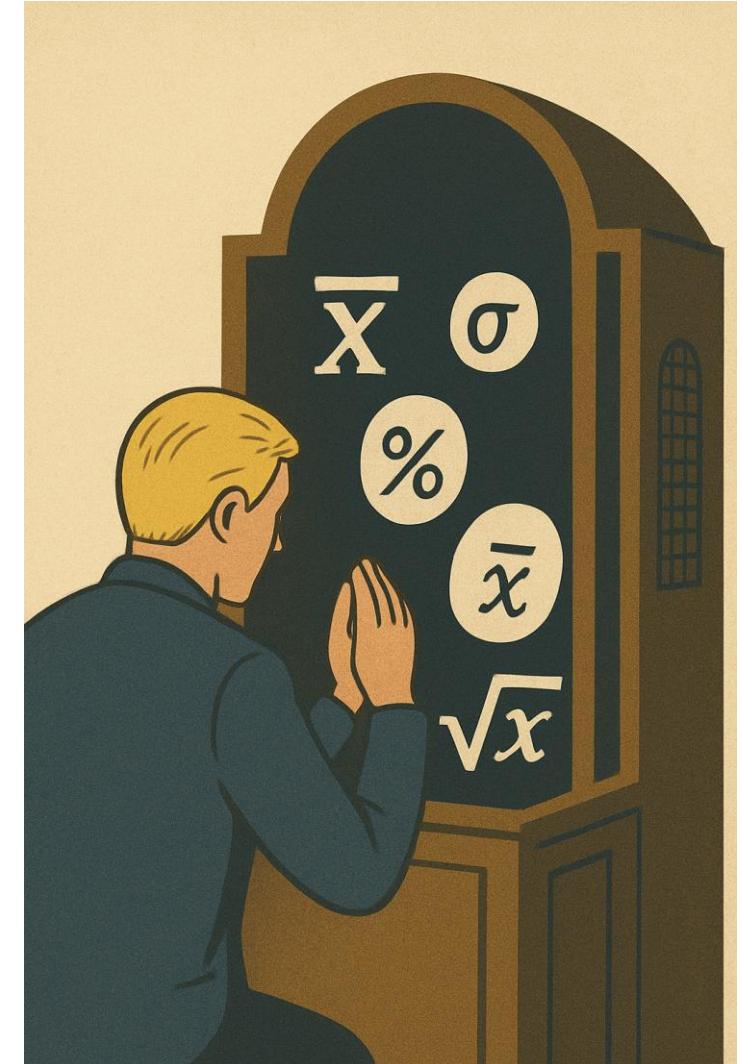
This is a statistics talk...

AND a philosophy of science talk!

It may be (a little) provocative...

so, if any content concerns you....

good! Let's discuss afterwards!





## Some questions to ponder

### **Clinical trials produce useful evidence**

- Do they always?
- How often do results inform policy and practice?

### **Hypothesis testing is central to clinical trial design**

- Why?
- Should it *always* be?



## The traditional approach

- Define primary outcome, statistical model and parameter/s of interest
- Construct hypothesis test
- Estimate a required sample size based on power, type one error rate, etc.
- Choose a trial design that meets feasibility, ethical and **statistical** criteria
- Conduct the trial
- Hope you meet a decision rule and publish the results
- Hope that the results **translate** into policy and practice



## What are (some) limitations?

- Decision-makers consider multiple clinical and health economic outcomes
- But the design was driven only by the primary outcome (for statistical reasons)
- Results from secondary analyses may be highly uncertain
- Perhaps we could have collected more data to resolve this uncertainty
- Perhaps we collected too much data and could have decided earlier



## What if we did it differently?



- What if we **knew** what the decision-maker needed and designed a trial to answer this question **directly**?
- Suppose we had a function to represent their decision-making process
- Could we collect **just** enough information to **sufficiently** inform the decision?
- Could we “**bridge**” the gap (abyss) between clinical research and translation?
- No longer concerned with statistical errors because we have no interest in making declarations about the value of the effect parameter

Can we do it?





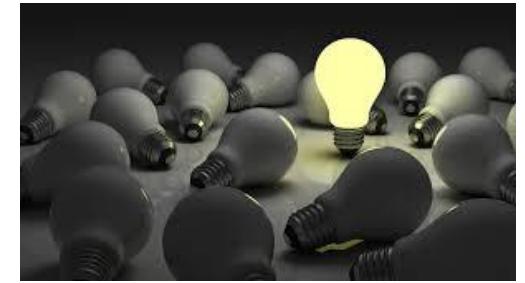
## How? Value of information (VOI) methods

- Suppose you have decision function  $U(d, \Theta)$  for decision  $d$  and parameters  $\Theta$
- We might ask:
  - Given our current uncertainty, what decision is better in expectation?
  - What is the expected **value** of eliminating parameter uncertainty?
  - What is the expected **value** of reducing parameter uncertainty?
  - Given the expected value accrued, is it worthwhile conducting my trial?



## The ~~traditional~~ value-based approach

- We can estimate if data collection is **valuable** (and therefore justifiable)
- Choose a design that optimises this trade-off
- But:
  - The methods can be computationally challenging
  - Recently developed approximation methods work well
  - Still rarely implemented in practice (usually supporting information)
  - Computational concerns? Conceptually unorthodox? Dogma?



## Extensions to adaptive designs

- Could we use a value-based decision rule to drive trial adaptations?
- Why? All designs rely on pre-trial assumptions that may be wrong
- How? Revise VOI calculation at interims and stop if no longer sufficiently valuable
- Analytical solutions exist but no trial has ever been designed this way
- Why?
  - Validity of assumptions of the current solutions in real-world settings?
  - Computational concerns? Conceptually unorthodox? Dogma?

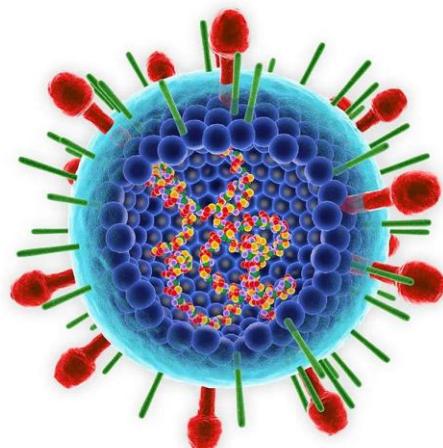


## Value-driven adaptive design

- Uses VOI as a decision rule at interims
- Repeatedly reduce parameter uncertainty and revise VOI calculation
- Applicable to trials where assumptions required by other methods do not hold
- Flexible to any statistical model, decision model and research cost function
- Extended calculation to account for value accrued external to the trial
- Methods to estimate VOI of continuing to the next analysis, or one after, etc.
  - But no free lunch! Computationally intensive to look further ahead!
- Generic methods implemented in R package (**michaeldymock25/ValueAdapt**)

# RSV Case Study

- Respiratory syncytial virus (RSV) infection accounts for approximately 3.6 million hospitalisations each year
- In Australia it is unknown whether maternal vaccination (MV) or infant immunoprophylaxis (II) will be more cost-effective
- Interested in the trade-off between the cost and effectiveness of the strategies

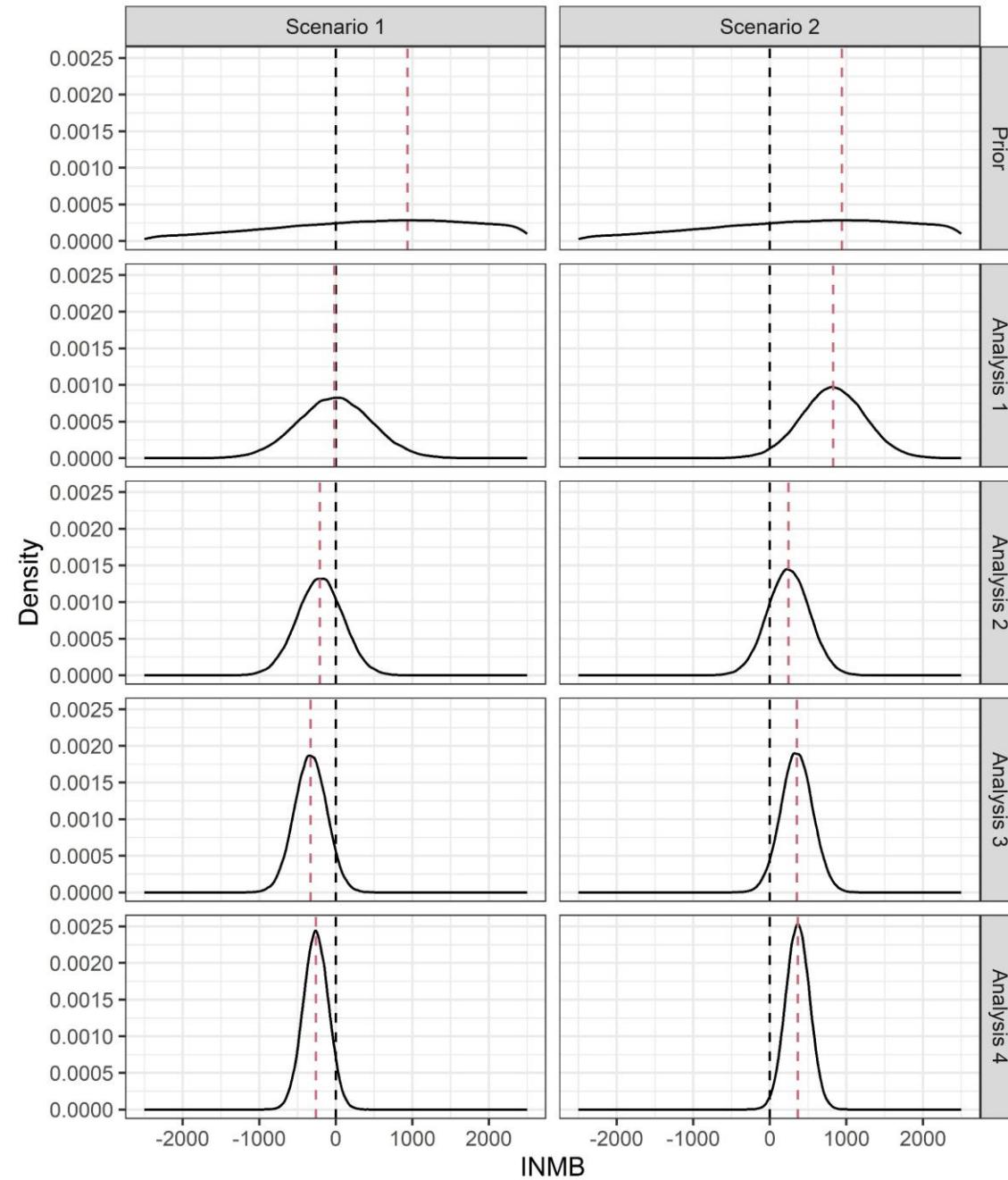




## Scenarios for illustration

- 1) The incremental effectiveness of II compared to MV is **large** (i.e., II is preferred)
- 2) The incremental effectiveness of II compared to MV is **small** (i.e., MV is preferred)

- For both scenarios we estimate the initial VOI to be \$121 million
- This exceeds the initial trial cost (e.g., \$2 million) so we proceed
- Recruit 500 participants, compute the VOI, compare the cost (e.g., \$1 million), repeat





# Summary

## **Clinical research should\* be designed to inform decision-making**

The value-driven adaptive design is fundamentally different to traditional designs (adaptive or not) in its philosophy

- Not based on a hypothesis test (i.e., no statistical error)
- Focused on the value of reducing a decision-maker's uncertainty

There are further complexities to consider (an adaptive design may not be appropriate, the decision model may be more complex, etc.)

Future direction is to design a hypothetical RSV trial using a transmission decision model



# Acknowledgements

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- References:
  - Too many: available on request



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EVIDENCE IN ACTION

# The decision function

$$\text{INMB}(p_{\text{II}}, p_{\text{MV}}) = \frac{1}{1,000,000} \times \sum_{t=0}^{14} 1.05^{-t} \times 300,000 \times (5200(p_{\text{II}} - p_{\text{MV}}) + 260)$$

5%-time discount over 15 years

Average annual number of Australian births

Willingness to pay to avoid one MA-RSV

Absolute difference in MA-RSV probabilities between strategies

Absolute difference in strategy costs

Scale to \$1 million units

The diagram illustrates the components of the INMB formula. Red arrows point from descriptive text labels to specific parts of the equation. The label '5%-time discount over 15 years' points to the term  $1.05^{-t}$ . The label 'Average annual number of Australian births' points to the term  $300,000$ . The label 'Willingness to pay to avoid one MA-RSV' points to the term  $5200(p_{\text{II}} - p_{\text{MV}})$ . The label 'Absolute difference in MA-RSV probabilities between strategies' points to the term  $(p_{\text{II}} - p_{\text{MV}})$ . The label 'Scale to \$1 million units' points to the coefficient  $\frac{1}{1,000,000}$ . The label 'Absolute difference in strategy costs' points to the constant term  $260$ .



## A final confession: abstract amendment

*“We will investigate scenarios where a traditionally designed trial stops too early (i.e., collects insufficient data) and stops too late (i.e., wastes resources collecting unnecessary data) and show how a value-driven adaptive design would have outperformed its traditional counterpart.”*

If you read my abstract and you were hoping to see this, I am sorry!

Upon reflection, this makes no sense!

The goal posts can be moved arbitrarily!