



# The value-driven adaptive design

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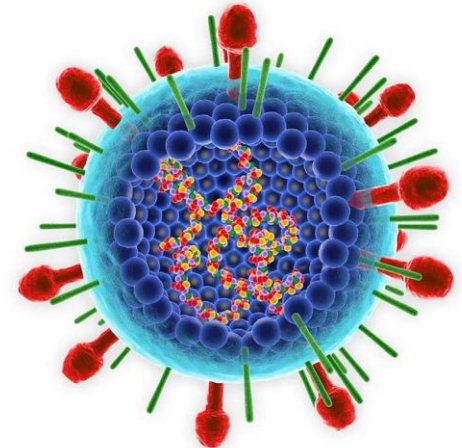


# Outline

- RSV case study
- Traditional approach to trial design
- Value-based approach to trial design (including adaptive extension)
- Value-driven adaptive design (including implementation)
- Demonstration

# RSV Case Study

- Respiratory syncytial virus (RSV) infection accounts for approximately 3.6 million hospitalisations and over 100,000 deaths each year, globally
- 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 of the strategies and the effectiveness in preventing medically attended RSV events (MA-RSV) in the first 12 months of life





## Traditional approach

- Define primary outcome (e.g., MA-RSV), statistical model and parameter/s of interest
- Construct hypothesis test comparing interventions MV and II
- Estimate a required sample size based on power, type one error rate, etc.
- Choose a trial design that meets feasibility 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



## Limitations to translation

- 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

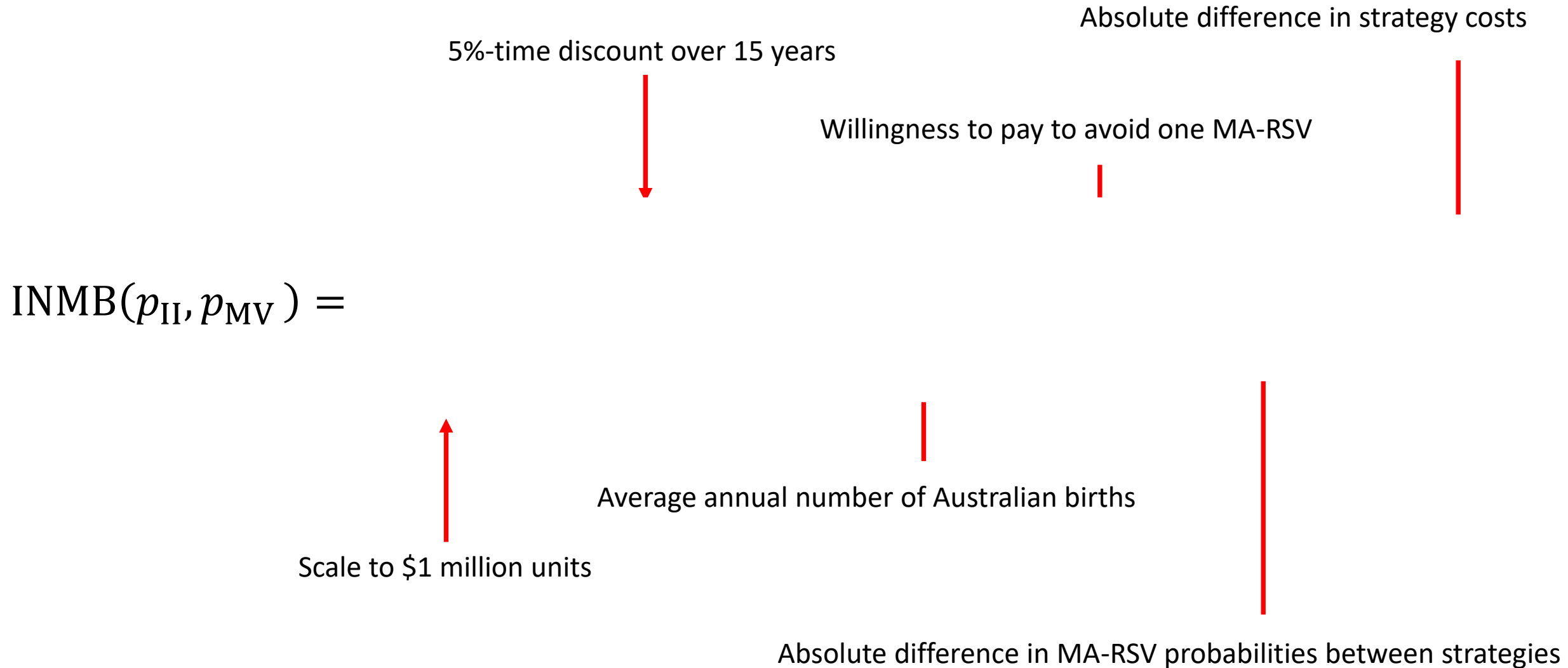
## What if we did it differently?



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



# The (simplified) decision function





## Value of information (VOI)

- Suppose you have decision function  $U(d, \Theta)$  for decision  $d$  and parameters  $\Theta$
- Given our current uncertainty, what decision is better in expectation?

$$\operatorname{argmax}_d E_{\Theta}[U(d, \Theta)]$$

- What is the expected value of reducing parameter uncertainty (with data)?

$$\text{EVSI} = E_X \left[ \max_d E_{\Theta|X} [U(d, \Theta)] \right] - \max_d E_{\Theta} [U(d, \Theta)]$$





## Value based approach

- We can estimate if data collection is **valuable** using EVSI
- If EVSI exceeds the cost of data collection, then the trial may be justified
- Choose a design that optimises this trade-off
- But the first EVSI term is computationally challenging
  - Requires simulation over potential datasets (e.g., 10,000)
  - Requires statistical model and decision model to be evaluated each time
- But there are recently developed approximation methods that work very well
- Still rarely implemented in practice (usually supporting information)



## Extensions to adaptive designs



- Could we use a value-based decision rule to drive trial adaptations?
- Revise VOI calculation at interims and stop if no longer sufficiently valuable
- Flight et al. found that no one had implemented this before
  - VOI had been estimated at interims but never used to drive decisions
  - No trial has been prospectively designed using a value-based rule
- There are methods to compute iterative VOI
  - i.e., recruit one more participant, compute VOI, stop or continue, repeat
  - BUT the assumptions required are unreasonable

# Value-driven adaptive design



- Our value-driven adaptive design using 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.



## *ValueAdapt* R package

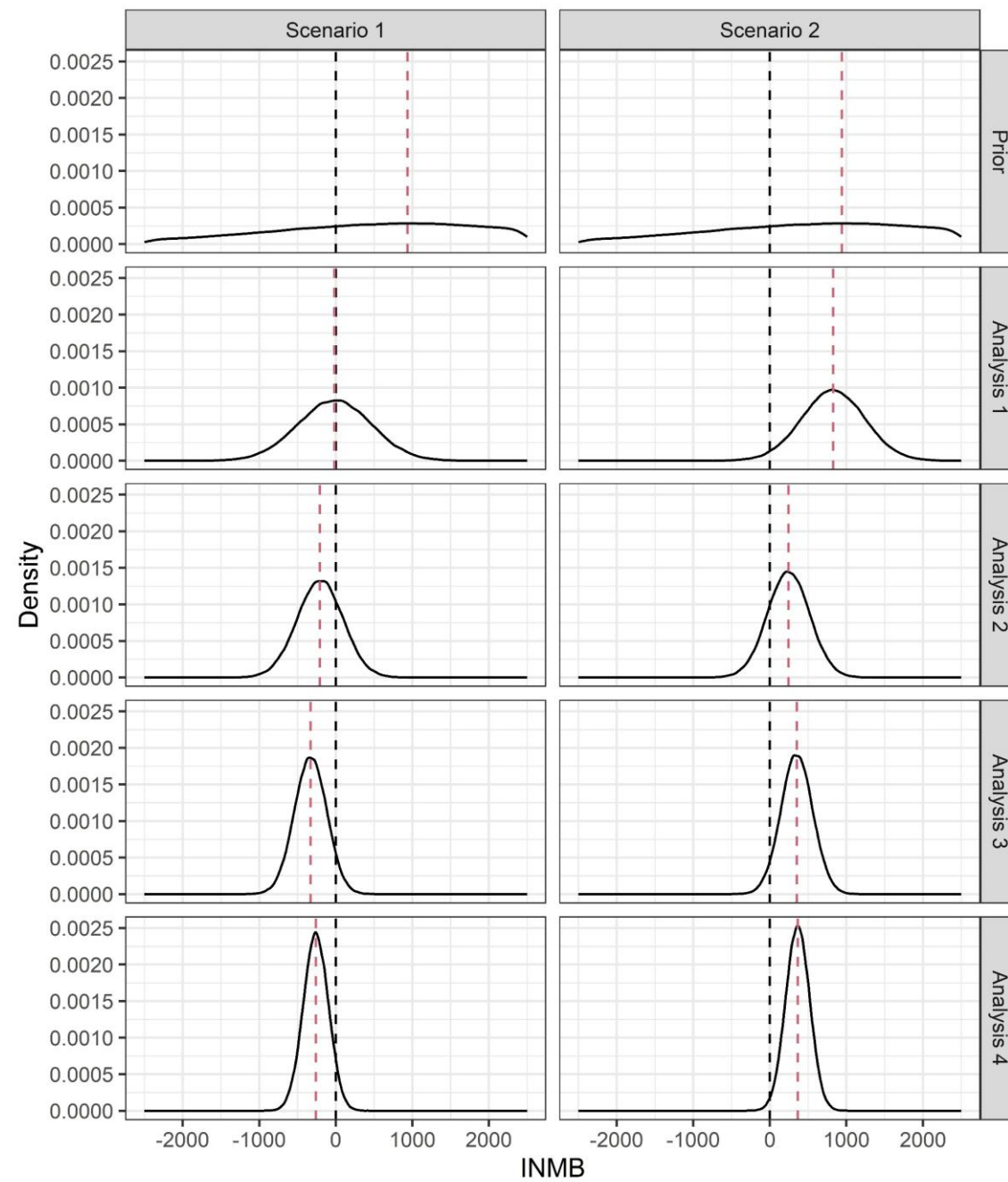
- Generic methods implemented in R package (michaeldymock25/ValueAdapt)
- User-specified:
  - Decision model, parameter uncertainty (e.g., prior distribution), external population state
  - Research cost function, approximation method (if any), sampling function
  - Statistical model (posterior), correction for future analyses, computational parameters

```
enb_sample <- function(D, U, Theta, t, prop, cost, method = "NP", K = 10000,  
  samp_args = list(), samp_fun = NULL, post_args = list(), post_fun = NULL,  
  stat_fun = NULL, model = NULL, INB_partial = NULL, Q = 50,  
  correct = NULL, num_cores = 1, num_threads = 1){
```



## Back to the RSV case study

- Consider two scenarios (for illustration):
  - 1) The incremental effectiveness of II compared to MV is large ( $p_{II} = 0.10$  and  $p_{MV} = 0.18$ )
  - 2) The incremental effectiveness of II compared to MV is small ( $p_{II} = 0.10$  and  $p_{MV} = 0.12$ )
- For both scenarios we estimate the 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



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