

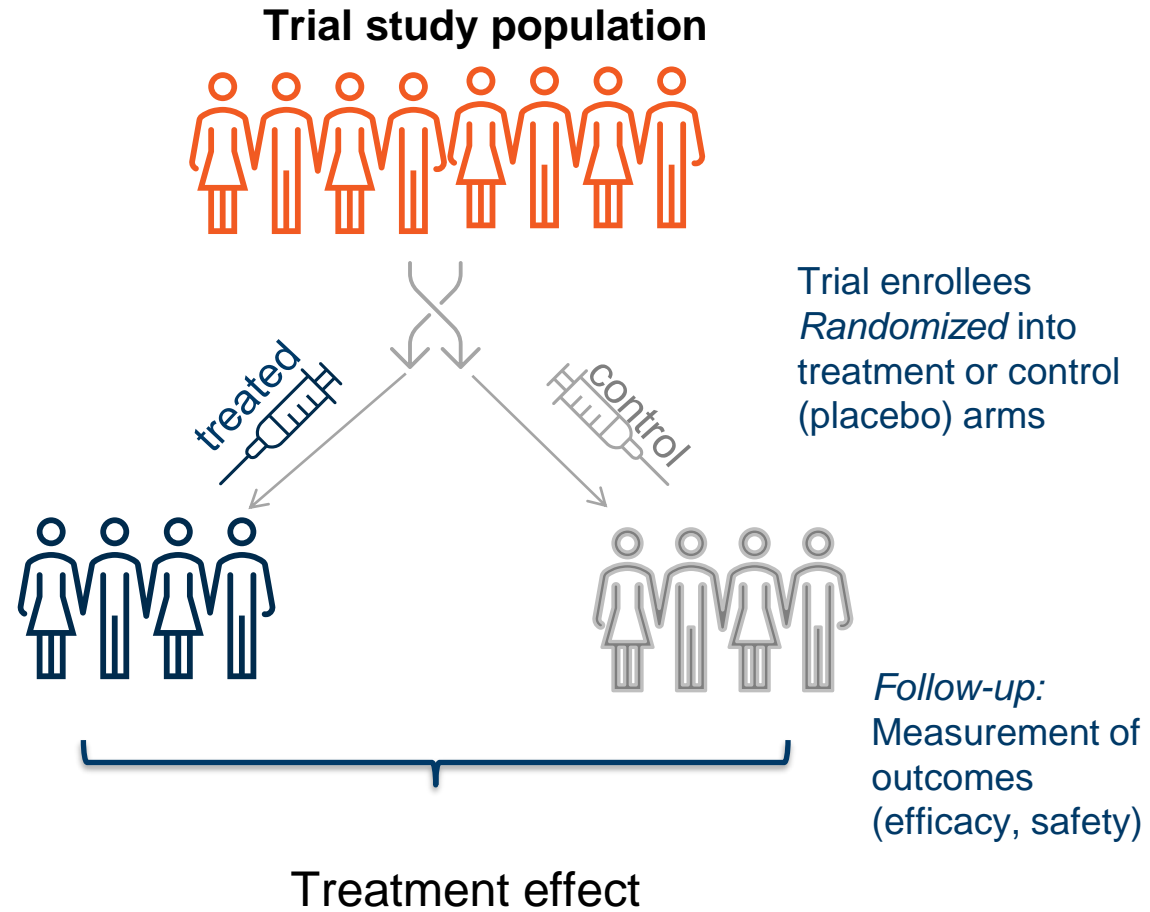


# Brief Overview of Methods for Bayesian Power Borrowing

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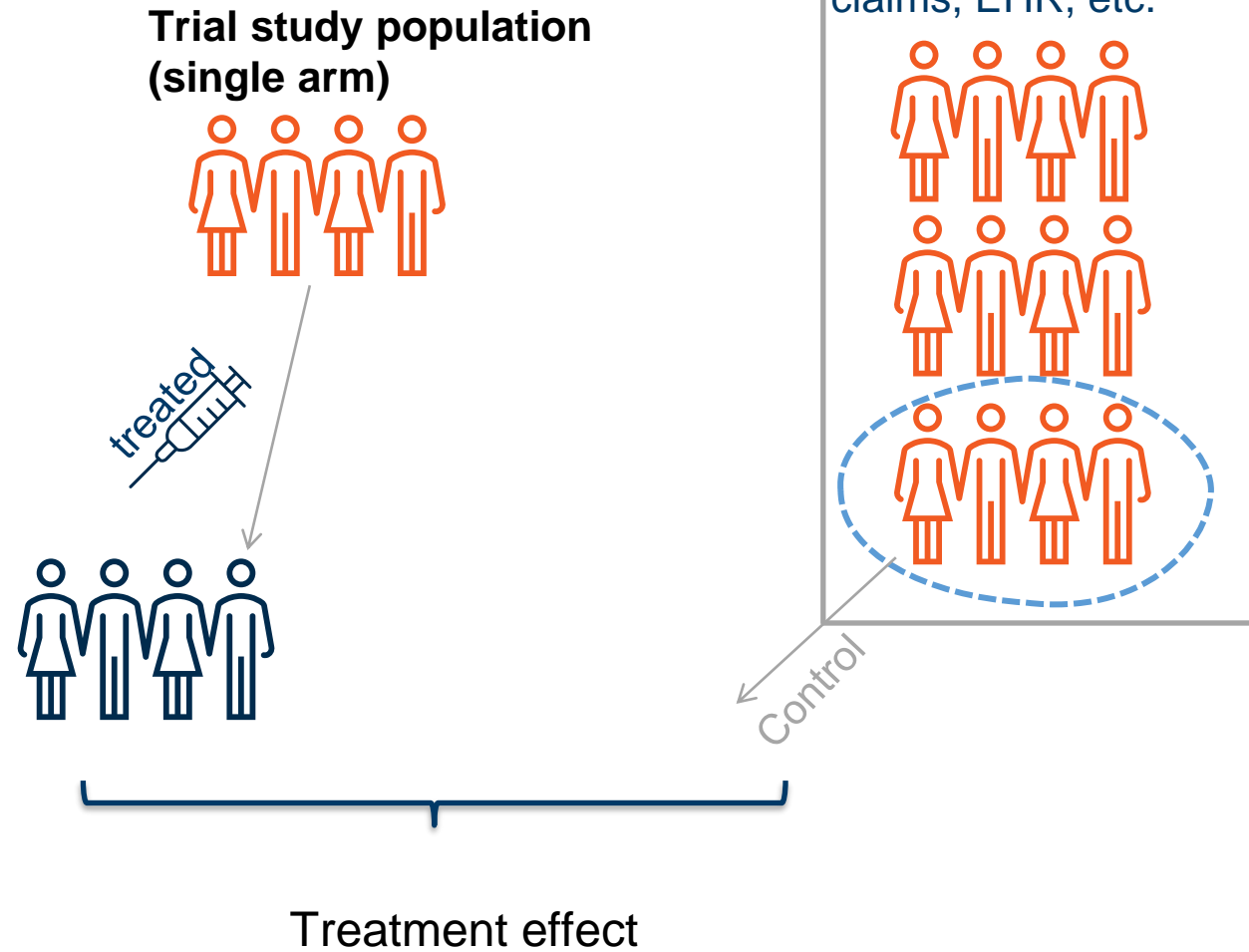


# Randomized Controlled Trial



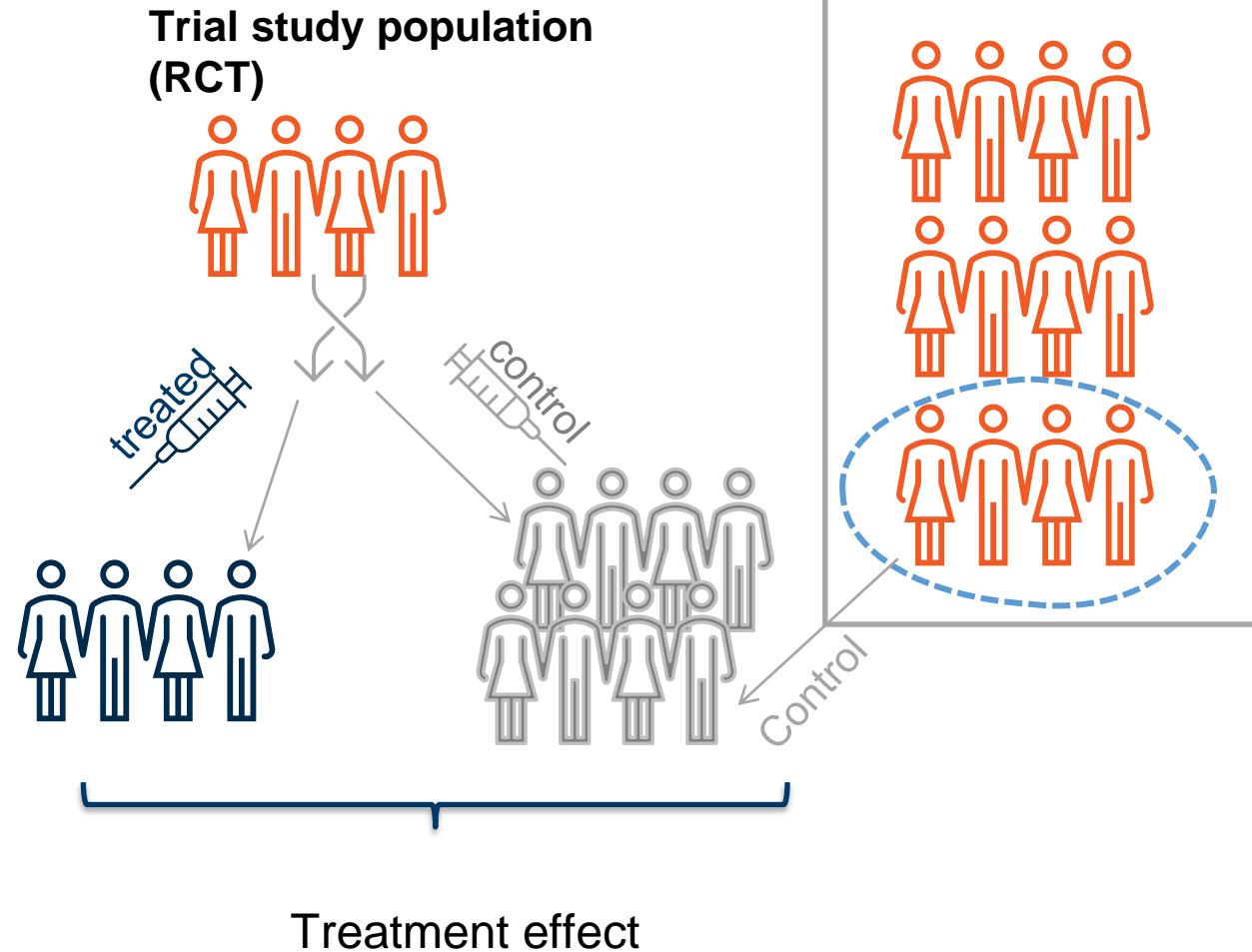


# Externally Controlled Trial





# Hybrid Trial with Historical Borrowing



# Deciding on the Hybrid Approach

## Early phase studies

- Increase power for small samples
- Generate hypotheses for later phase studies

## Unbalanced randomization

- Higher number of patients randomized to treatment

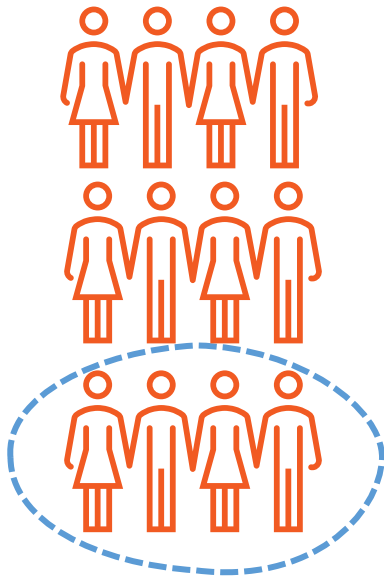
## Ethical concerns

## Recruitment challenges

- Rare diseases
- Pediatrics

# Assessing Suitability of External Data

**External data:  
Historical trial data**



Careful consideration of external data is key

- Are the datasets compatible?
  - Populations
  - Geographies
  - Temporal
  - Baseline characteristics
  - Same standard of care
- Are there notable differences?

Consequences:

- Well-chosen: increased power
- Poorly-chosen: bias, inflated type I error



**Statistical methods cannot rescue  
poorly chosen external data**

# What External Data to Consider?



## Historical trials are a natural choice

- Placebo group from earlier phase trial
- Placebo group from an earlier trial in the same indication with a different treatment

## Can we use real-world data?

- Challenges similar to those found in ECAs
- Weighting difficult; regression adjustment is an option



# Approaches

**We will discuss the following approaches:**

- Power prior
- Hierarchical model / meta-analytic predictive (MAP) approach
- Mixture prior





# Bayesian Method #1: Power Prior

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# How Does the Bayesian Power Prior Work?

Incorporates individual patient data from external data source

Amount of borrowing controlled by a parameter  $\alpha$  which downweights the influence of the external data

- Higher values = more borrowing
- Lower values = less borrowing

# Analysis without the External Data

$$\underbrace{\pi(\theta | D)}_{\text{Posterior distribution for } \theta} \propto \underbrace{L(\theta | D)}_{\text{Likelihood (model + data for current trial)}} \underbrace{\pi(\theta)}_{\text{Prior distribution for } \theta}$$

# Components of the Bayesian Power Prior

$$\pi(\theta \mid D, H, \alpha) \propto L(\theta \mid D)L(\theta \mid H)^\alpha \pi(\theta)$$

# Isolating the Effect of the External Data

$$\pi(\theta \mid D, H, \alpha) \propto L(\theta \mid D) \underbrace{L(\theta \mid H)^\alpha}_{\text{External data discounted by } \alpha} \pi(\theta)$$

External data  
discounted by  $\alpha$

# Isolating the Effect of the External Data

$$\pi(\theta \mid D, H, \alpha) \propto L(\theta \mid D) L(\theta \mid H)^\alpha \pi(\theta)$$

It must be that  $0 \leq \alpha \leq 1$ .

If  $\alpha = 1$ , complete pooling of current and external data

If  $\alpha = 0$ , external data are ignored

# Choosing $\alpha$

## How to choose $\alpha$

- Set  $\alpha$  yourself (fixed power prior)
- Use the data to set a fixed value for  $\alpha$  (empirical Bayes power prior)
- Use the data to adaptively choose  $\alpha$  (modified power prior)

Note: using a fixed value of  $\alpha$  significantly simplifies calculations.





# **Bayesian Method #2: Hierarchical Model / Meta- Analytic Predictive Approach**

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# Hierarchical Model / MAP approach

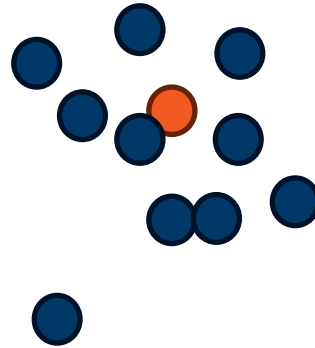
Hierarchical models are common in Bayesian methodology

- Allow us to “**borrow**” information from the external data and apply it to our current trial
- The amount of borrowing is controlled by a variance parameter
- Useful when there are several external datasets

# Hierarchical Model / MAP approach

- **Low heterogeneity** between studies (low variance)
- **High** amount of borrowing

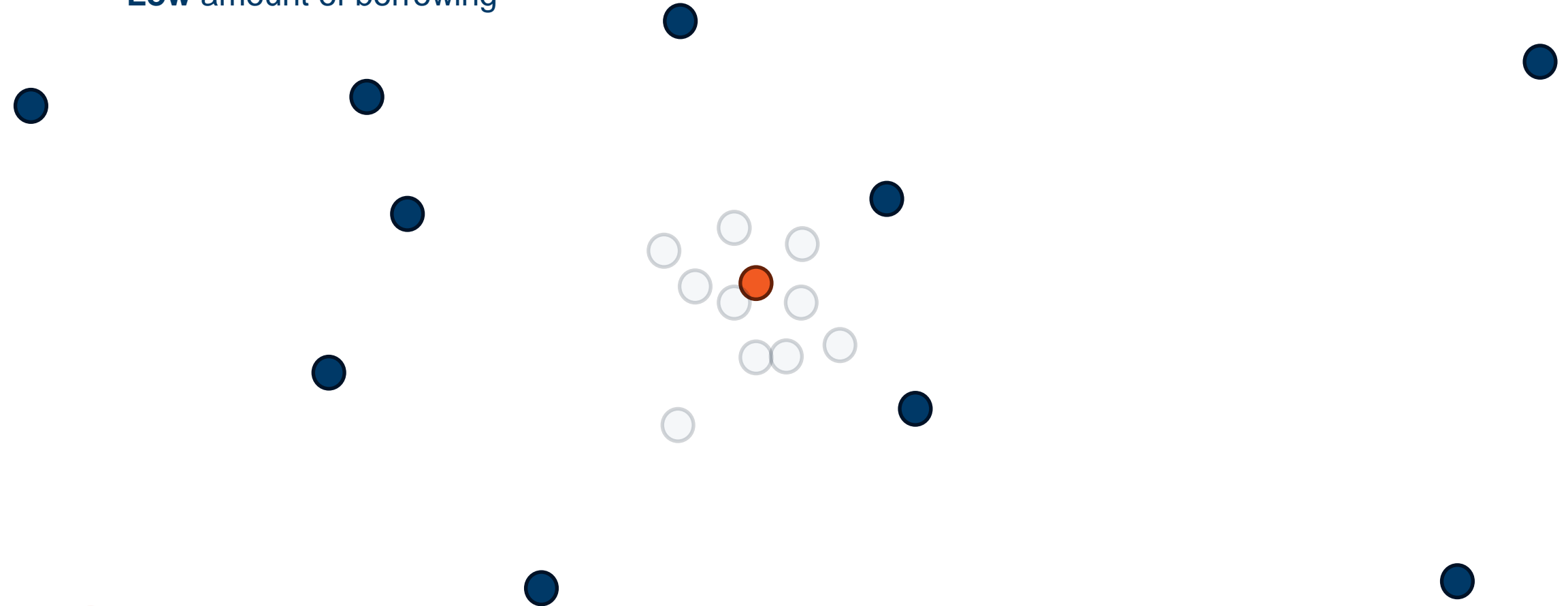
Orange dot = Current study  
Blue dots = External studies



# Hierarchical Model / MAP approach

- **High heterogeneity** between studies (high variance)
- **Low** amount of borrowing

Orange dot = Current study  
Blue dots = External studies





# Bayesian Method #3: Mixture Prior

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# What is a Mixture Prior?

A mixture prior is a prior composed of more than one component.

Component #1: A general, non-informative prior distribution for the current trial

Component #2: An informative prior distribution determined by external data

$$P(\theta) = (1 - a) \cdot P_{\text{current}}(\theta) + a \cdot P_{\text{external}}(\theta),$$

where  $0 \leq a \leq 1$ .



## CASE STUDY

# Belimumab for the treatment of systemic lupus erythematosus



**Disease:**

**Systemic lupus erythematosus (SLE)**

**Population:** Pediatric (ages 5-17)



**Drug:**

**Benlysta® (belimumab)**

**Sponsor:** Glaxo-Smith-Kline



**Endpoint:**

**Response at week 52**

Source: [BLA 125370/s-064 and BLA 761043/s-007 Multi-disciplinary Review and Evaluation Benlysta® \(belimumab\) for Intravenous Infusion in Children 5 to 17 Years of Age with SLE](#)





## CASE STUDY



# Belimumab for the treatment of systemic lupus erythematosus



### Unmet Need in Pediatrics:

“[T]here is a high unmet medical need for efficacious and safe treatments for pediatric patients with SLE.”

“There are currently no treatments specifically approved for this subpopulation.”



### Enrollment Difficulties:

“...the Applicant requested to ... lower the overall target enrollment from 100 to 70 subjects due to difficulties enrolling pediatric patients between 5 and 17 years of age.”



## CASE STUDY



# Belimumab for the treatment of systemic lupus erythematosus



### Inadequate Power:

“[The trial] was not adequately powered to make a formal statistical inference on its own due to ... enrollment limitations and the rarity of disease in pediatric subjects....”



### Similarity with Adults:

“The clinical review team believes that the disease and patient response to treatment are likely to be similar between the adults and pediatric subjects.”

# Bayesian Mixture Prior

**Idea:** Analyze the pediatric study using a mixture prior informed by the adult study

Pediatric study prior:

$$P(\theta) = (1 - a) \cdot P_{peds}(\theta) + a \cdot P_{adult}(\theta)$$



# Bayesian Mixture Prior

**Idea:** Analyze the pediatric study using a mixture prior informed by the adult study

Pediatric study prior:

$$P(\theta) = (1 - a) \cdot P_{peds}(\theta) + a \cdot P_{adult}(\theta)$$



Non-informative  
prior



# Bayesian Mixture Prior

**Idea:** Analyze the pediatric study using a mixture prior informed by the adult study

Pediatric study prior:

$$P(\theta) = (1 - a) \cdot P_{peds}(\theta) + a \cdot P_{adult}(\theta)$$



Informative prior  
based on adult study



# Bayesian Mixture Prior

$$P(\theta) = (1 - a) \cdot P_{peds}(\theta) + a \cdot P_{adult}(\theta)$$



**If  $a = 0$ ,** only noninformative prior is used.

**If  $a = 1$ ,** only informative prior based on adult study is used.

## **Additional steps:**

- Vary  $a$  between 0 and 1 in steps of 0.05.
- Find the minimum value of  $a$  such that credible interval of efficacy parameter does NOT contain 0, i.e., statistical significance.



# Bayesian Mixture Prior

Weight (a)	Mean Log Odds	Median Log Odds	95% Credible Interval	Posterior Probability of Efficacy
0.00	0.36	0.36	(-0.46, 1.18)	0.81
0.05	0.39	0.42	(-0.41, 1.13)	0.85
0.10	0.41	0.44	(-0.36, 1.08)	0.89
0.15	0.42	0.45	(-0.32, 1.04)	0.91
0.20	0.43	0.46	(-0.27, 1.00)	0.93
0.25	0.44	0.46	(-0.23, 0.95)	0.94
0.30	0.44	0.46	(-0.19, 0.91)	0.95
0.35	0.45	0.46	(-0.15, 0.87)	0.96
0.40	0.45	0.46	(-0.11, 0.84)	0.96
0.45	0.45	0.47	(-0.06, 0.80)	0.97
0.50	0.46	0.47	(-0.01, 0.78)	0.97
0.55	0.46	0.47	(0.04, 0.76)	0.98
0.60	0.46	0.47	(0.09, 0.75)	0.98
0.65	0.46	0.47	(0.14, 0.74)	0.98
0.70	0.46	0.47	(0.17, 0.73)	0.99
0.75	0.47	0.47	(0.19, 0.72)	0.99
0.80	0.47	0.47	(0.21, 0.72)	0.99
0.85	0.47	0.47	(0.22, 0.71)	0.99
0.90	0.47	0.47	(0.23, 0.71)	1.00
0.95	0.47	0.47	(0.24, 0.70)	1.00
1.00	0.47	0.47	(0.24, 0.70)	1.00

Source: [BLA 125370/s-064](#) and [BLA 761043/s-007 Multi-disciplinary Review and Evaluation Benlysta® \(belimumab\) for Intravenous Infusion in Children 5 to 17 Years of Age with SLE](#)





## Why choose each method?



### Power prior

- ✓ Most studied
- ✓ Relatively easy to fit models with fixed weights

### Hierarchical/MAP

- ✓ Convenient when you are incorporating several datasets

### Bayesian mixture prior

- ✓ Has been used in regulatory settings
- ✓ Don't need IPD

# Recommendations



Always do a sensitivity analysis



Simulation to determine Type I error and power



- Varying treatment effects
- Varying degrees of heterogeneity
- Varying sample sizes

