



Use of Conditional Assurance for Decision Making in Phase 1 Dose Escalation in Early Oncology

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Conditional Assurance and Bayesian Borrowing



Deep Dive into the Framework



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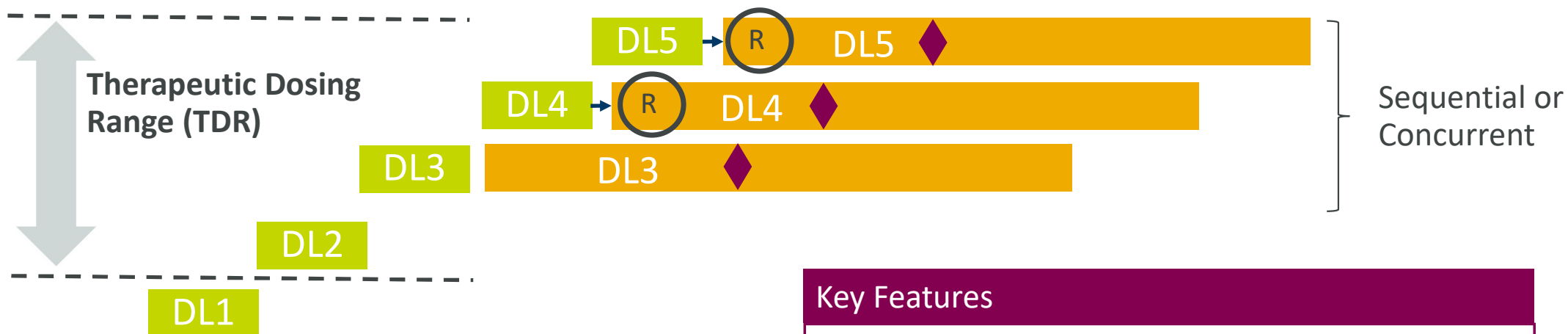
Take Home Messages



Early Oncology Two-Step Dose Optimisation Schematic

Escalation Cohorts

Optimization/Expansion Cohorts



Key Features

- **Primary Endpoints:** e.g. Safety, PK, PD, preliminary efficacy, etc.
- **Variable** Sample Size
- **Heterogeneous** Population

Esc. N = 3-12 Exp. N = 20-40

◆ Early/multiple interim analyses

3 (R) Partial randomisation, when >1 DL in Exp.



Decision Gate to Consider Conditional Assurance of Expansion

Conditional Assurance

The **predictive probability of success** in optimisation or expansion cohorts conditional on the data observed during dose escalation

The Question it Answers

How much has the **emerging escalation data** increased or decreased chance of expansion success relative to what we believed before we started?



Opportunities Built on Consistency, Speed and De-risking

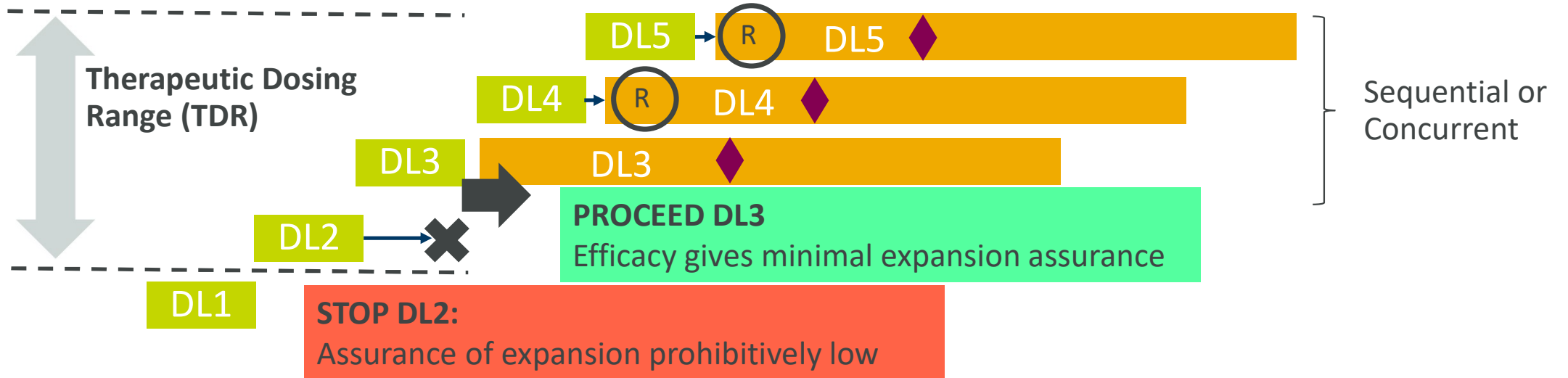
- ✓ Consistent **quantitative** statistical thinking using assurance to quantify risk of inadequate efficacy and plan to de-risk accordingly
 - Estimate and **control risk** of 'false-stop' for a given dose level
- ✓ Answers questions of **when and how**
 - Enables seamless expansion
 - Optional acceleration
- ✓ **Flexible** in meeting project specific need



Enabling Seamless Clinical Development Plan

Escalation Cohorts

Optimization/Expansion Cohorts



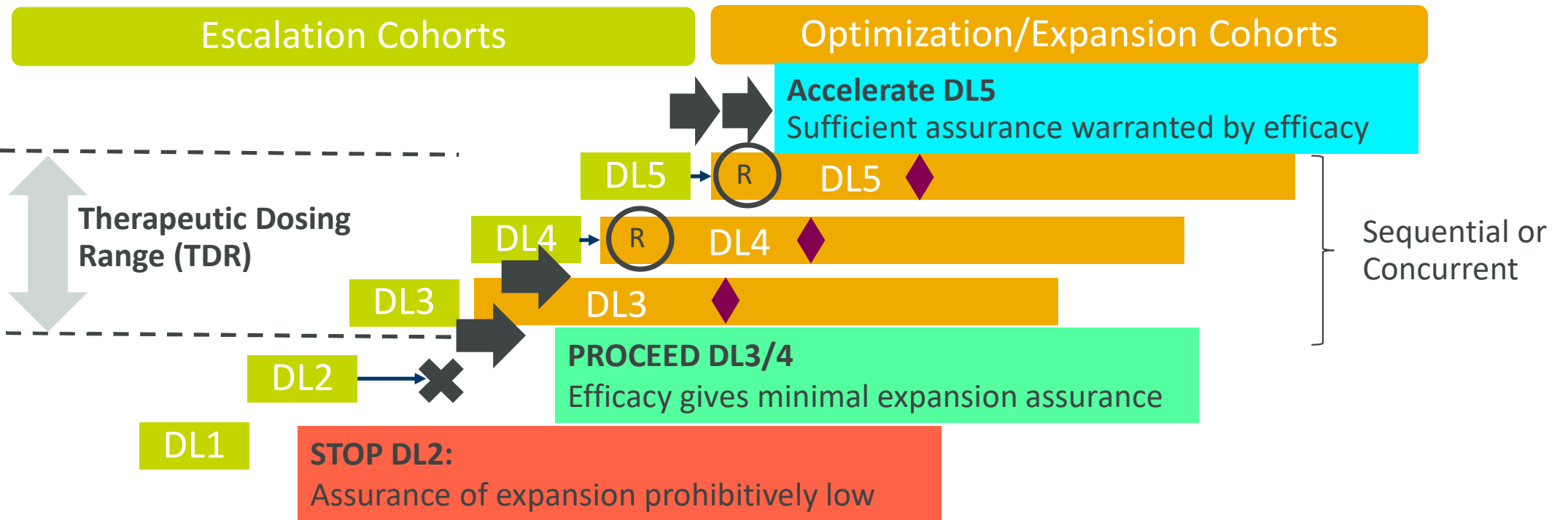
Esc. N = 3-12 Exp. N = 20-40

◆ Early/multiple interim analyses

Ⓡ Partial randomisation, when >1 DL in Exp.



Enriching Clinical Development Plan via Opportunity of Early Acceleration



Esc. N = 3-12 Exp. N = 20-40

◆ Early/multiple interim analyses

Ⓡ Partial randomisation, when >1 DL in Exp.



Efficacy Gatekeeper Complements Optimization Designs

Stage 1: Multi-dimensional data determines TDR in Escalation Cohorts



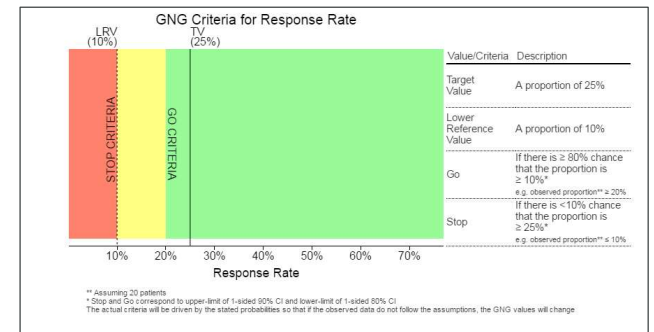
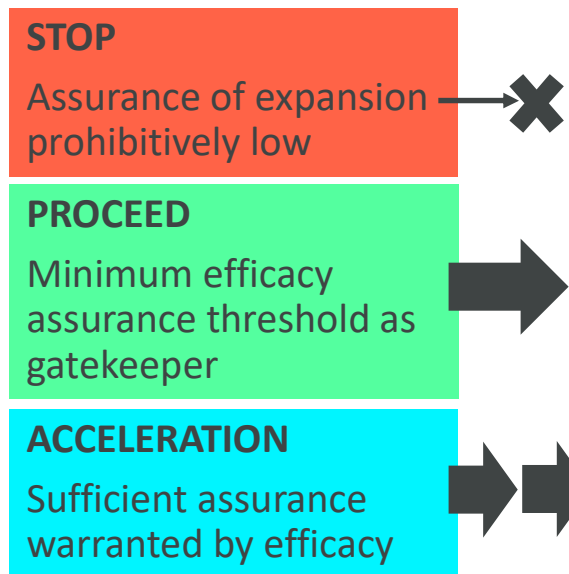
Designs to Consider:

Safety only: mTPI-2, CRM

Safety and PK and/or PD: DROID

Safety and Efficacy: BOIN12

Stage 2: Determine Optimal Dose in Optimization/Expansion Cohorts



Designs to Consider:

Lalonde Go-NoGo

Continuous Monitoring

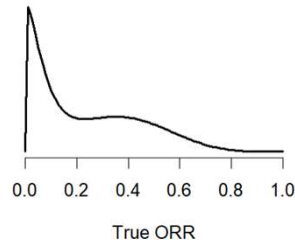
Assurance, BOIN12, DROID



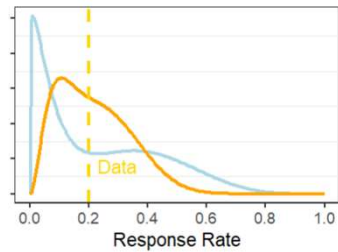
TV = 0.4, LRV = 0.15, n2 = 30

Expansion Assurance And Conditional Assurance

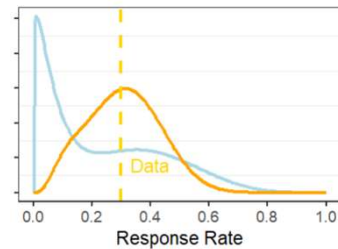
No Escalation phase data



= 2/10 responders



= 3/10 responders



Go Assurance = 37.7 %

Minimum Conditional Go Assurance = 30.0 %

Minimum Conditional Go Assurance = 54.4 %

7.7 %
↓
Minimum Derisked Assurance

Escalation Phase

Expansion phase

↑ 16.7%
Minimum Derisked Assurance



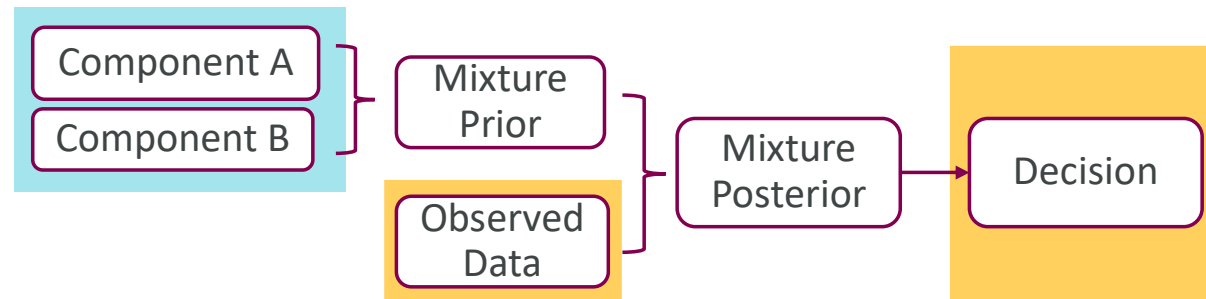
Use Bayesian Borrowing to Inform Minimum Conditional Assurance

External data

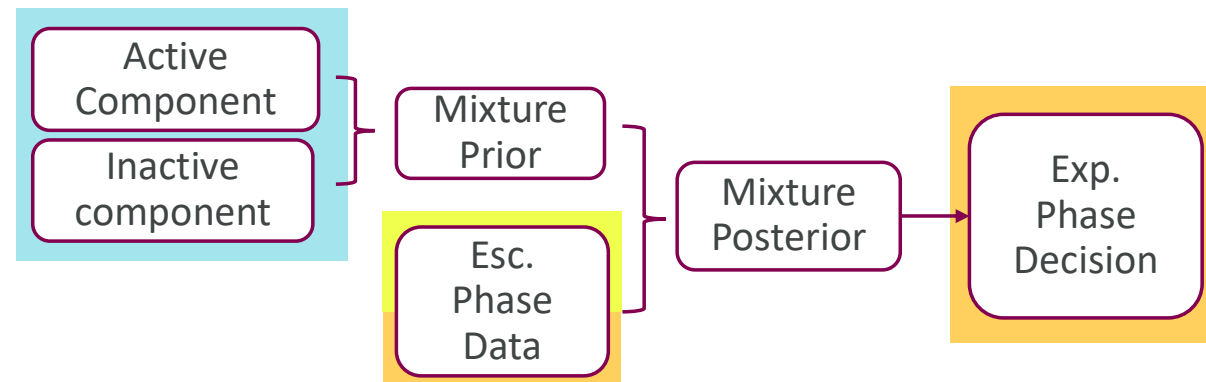
A homogenous population

A heterogenous population

Bayesian borrowing

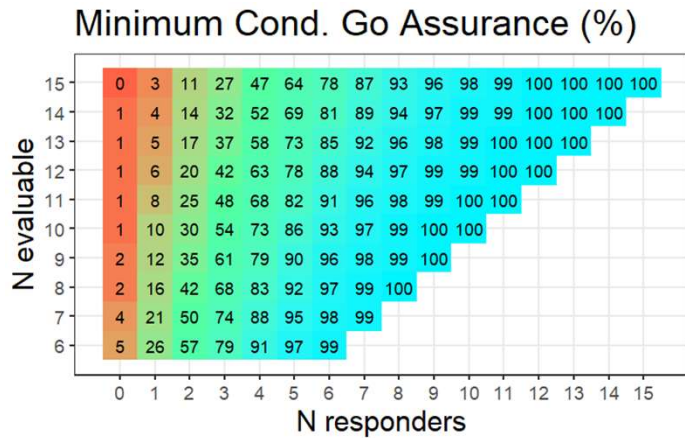


Ph1/2 decision making



Example: Dynamic Decision Making

TV = 0.4, LRV = 0.15, n2 = 30

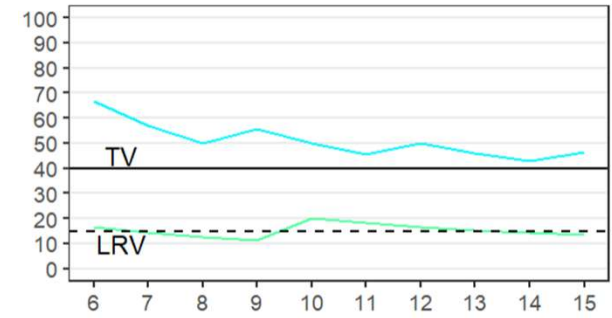


STOP
A < 10% assurance to meet Expansion Go or Consider

PROCEED
A ≥ 10% assurance to meet Expansion Go or Consider

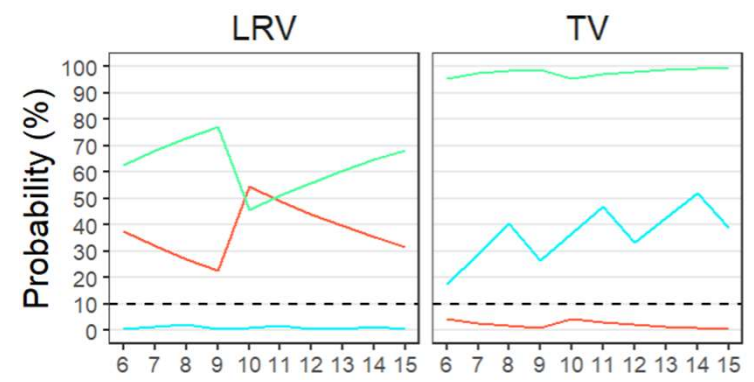
ACCELERATION
A ≥ 80% assurance to meet Expansion Go

Decision Criteria



Emerging Data: N Patients

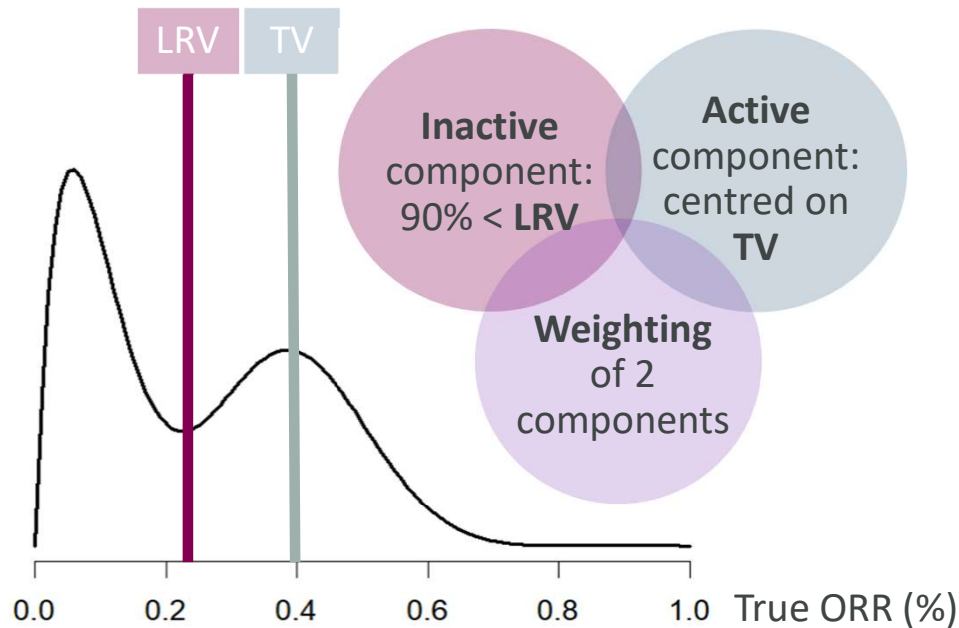
% of Outcome Given True Drug Effects



Emerging Data: N Patients



Bayesian Mixture Design Prior: Rule Of Thumb Components

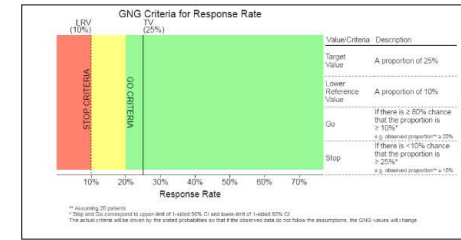


Inactive component:
90% < LRV

Active component:
centred on TV

Weighting of 2 components

- Points of consideration**
- Pre-clinical evidence: PD-efficacy translation
 - External evidence: MoA/Treatment modality
 - Population

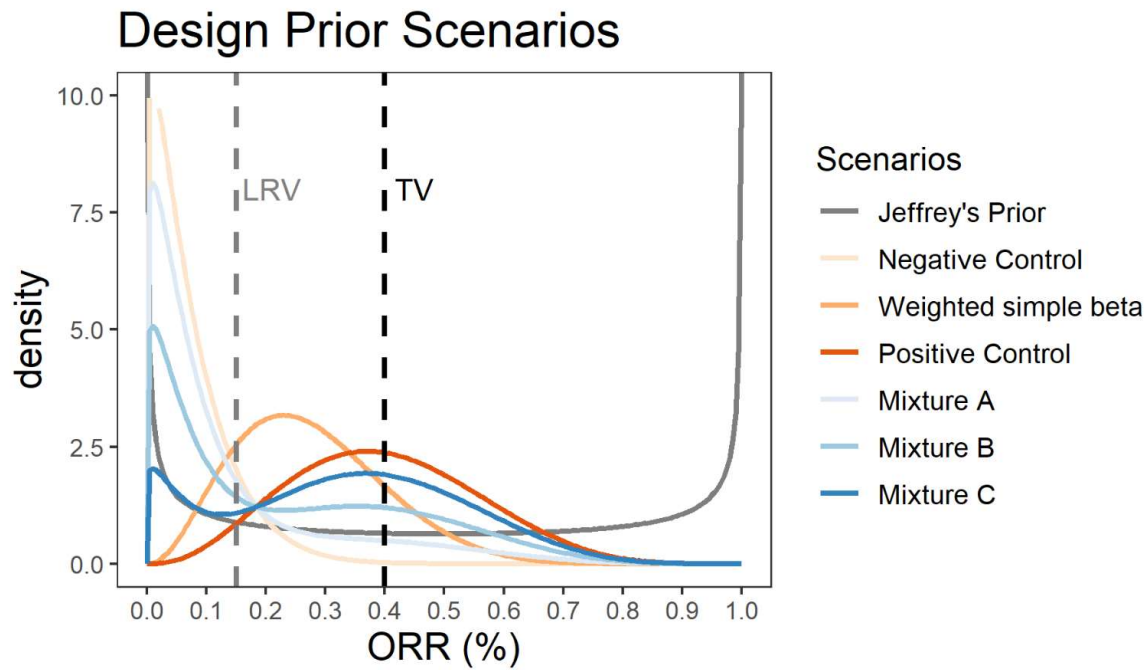


1. Calibrates Ph1 expansion conditional assurance given underlying uncertainty in early development
2. Provides a framework to estimate de-risking potential of upcoming studies
3. Offers robust efficacy cut-offs
4. Prevents over-reaction to small emerging datasets



TV = 0.4, LRV = 0.15, n2 = 30

A Bayesian Mixture Design Prior Enables Calibrating Ph1 Expansion Conditional Assurance



Scenario	ESS *	Baseline Go assurance
Jeffreys prior	1	64.2%
Neg. control	15	2.4%
Weighted simple beta distribution	12	44.1%
Pos. control	9	72.4%
Mixture prior A	20	16.4%
Mixture prior B	13	37.7%
Mixture prior C	9	58.3%

Simple Beta Prior

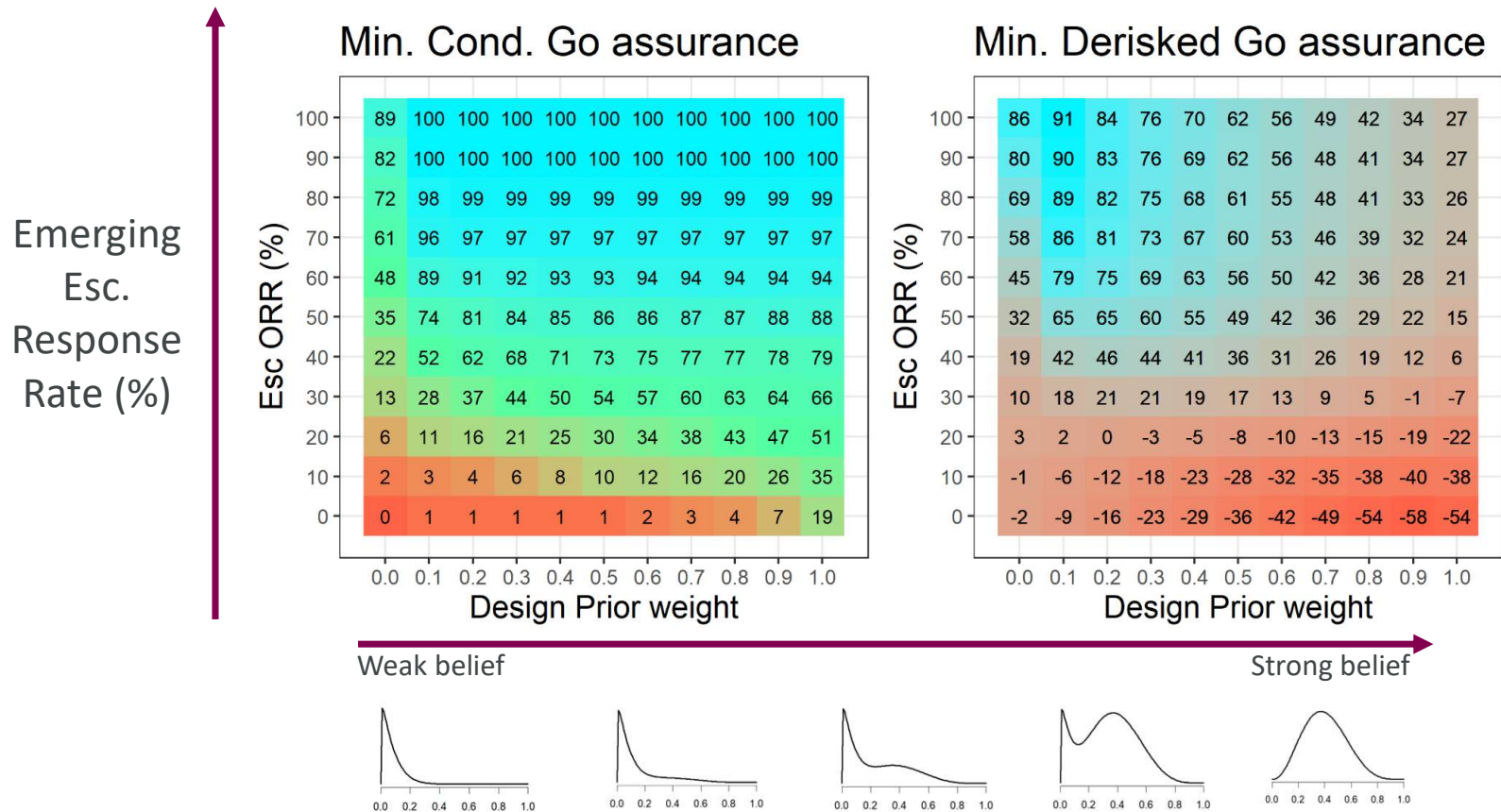
Mixture Prior

* ESS (Effective Sample Size): FDA recommend expected local-information-ratio (ELIR) method



TV = 0.4, LRV = 0.15, n1 = 10, n2 = 30

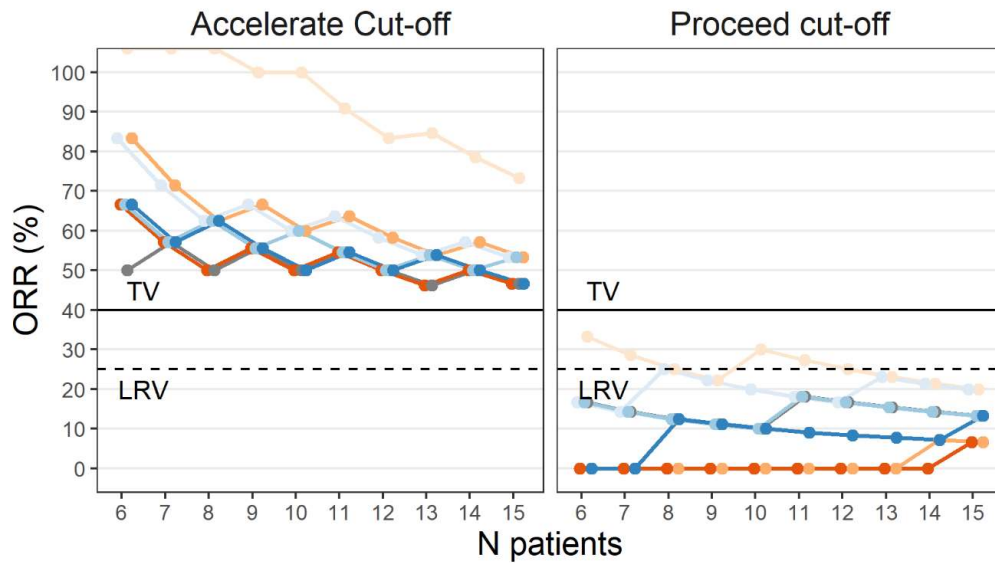
A Bayesian Mixture Design Prior Provides A Framework To Estimate De-risking Potential Of Upcoming Studies



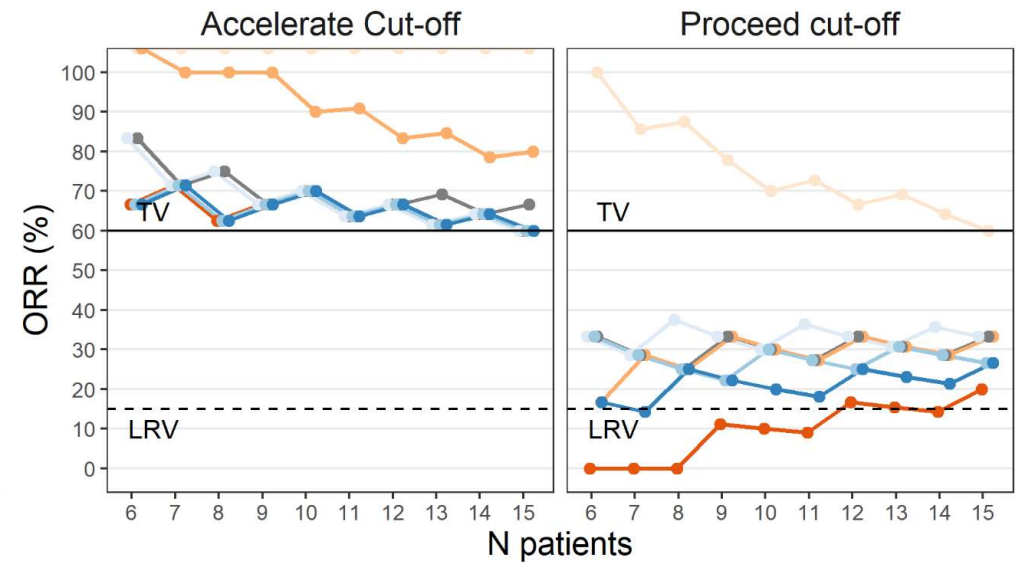
n2 = 30, proceed cut-off 10%, acceleration cut-off 80%

A Bayesian Mixture Design Prior Offers Robust Efficacy Cut-offs

TV = 0.4, LRV = 0.25



TV = 0.6, LRV = 0.15



prior

— Jeffrey's Prior

— Negative Control

— Weighted simple beta

— Positive Control

— Mixture A

— Mixture B

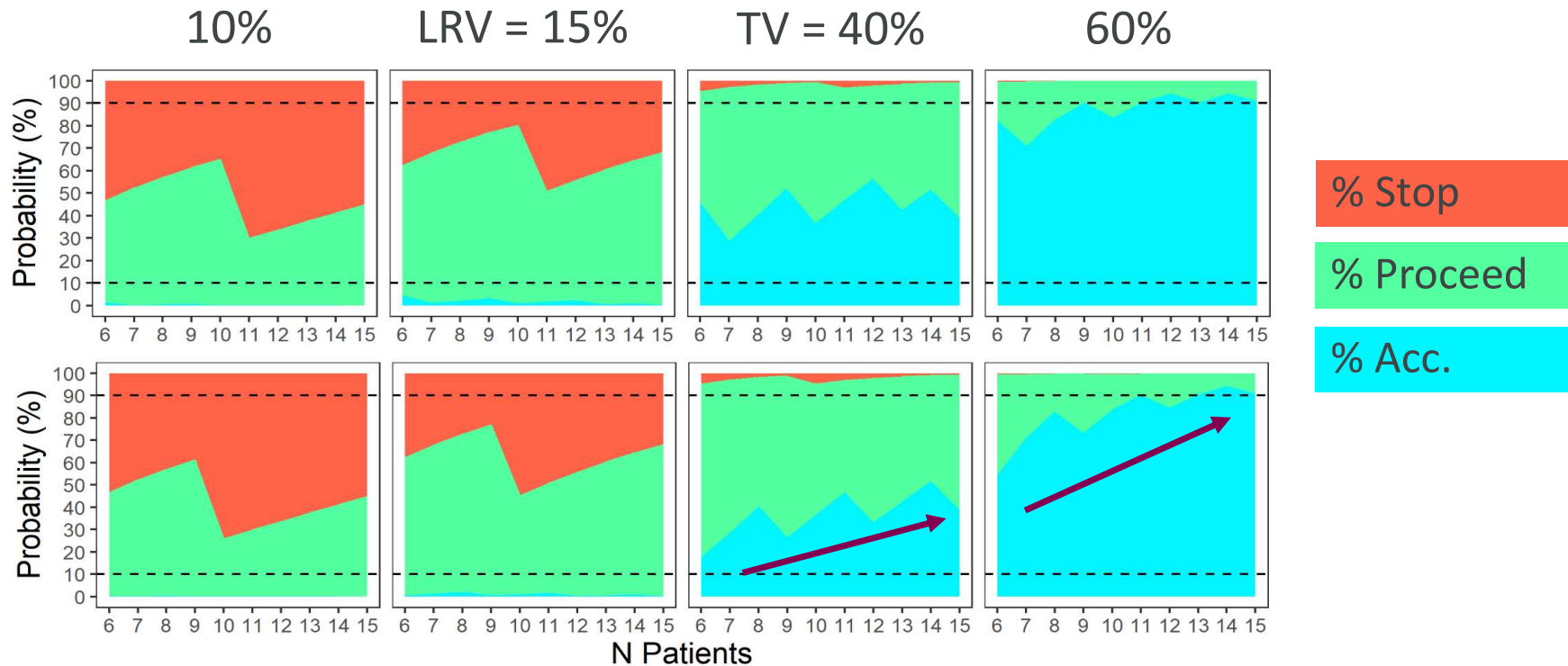
— Mixture C



TV = 0.4, LRV = 0.15, n2 = 30, proceed cut-off 10%, acceleration cut-off 80%

A Bayesian Mixture Design Prior Prevents Over-reaction To Small Emerging Datasets

Probability of Outcome for a Range of True Drug Effects



Jefferey's Prior

Mixture Prior B

% Stop

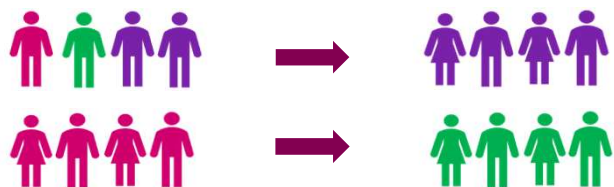
% Proceed

% Acc.

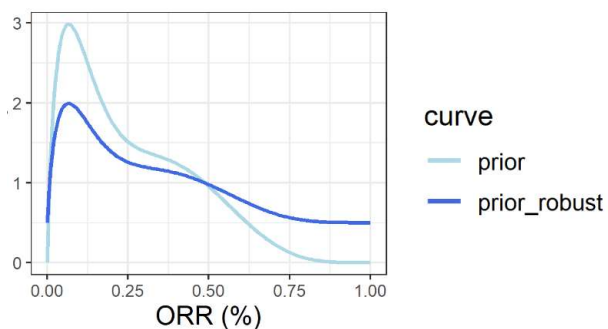


Further Opportunities

Different Population across Esc. and Exp. Phase



- ? How are Esc./Exp. population **selected**
- ? **Amount** of evidence
- **Adjust** prior components
- **Robustify** prior



Different Decision-Making Endpoints across Esc. and Exp. Phase

RECIST
ORR

ctDNA

PSA50

PD
biomarker

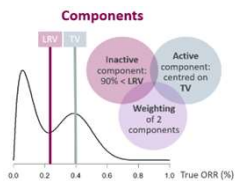
- **Types** of endpoints
- **Correlation** between the surrogate outcome and the clinically meaningful outcome
- Clinical relevance of a **composite** endpoint



Take Home Messages

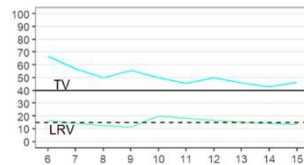
Quantitative Decision Framework

- Bayesian Borrowing
- Mixture Prior



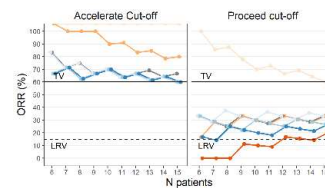
Dynamic Decision Making

- When
- How

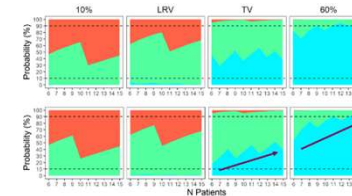


Robust Framework

- Decision criteria
- O/C

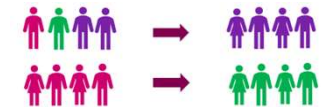


Controlling False Stop and False Acceleration



Flexibility

- Design Prior
- Threshold
- Different Population/Endpoints



References

- Jeanne Fourie Zirkelbach et al., **Improving Dose-Optimization Processes Used in Oncology Drug Development to Minimize Toxicity and Maximize Benefit to Patients.** JCO 40, 3489-3500(2022).
- Temple, J. R., & Robertson, J. R. (2021). **Conditional assurance: the answer to the questions that should be asked within drug development.** Pharmaceutical Statistics, 20(6), 1102-1111.
- O'Hagan, A., Stevens, J. W., & Campbell, M. J. (2005). **Assurance in clinical trial design.** Pharmaceutical Statistics: The Journal of Applied Statistics in the Pharmaceutical Industry, 4(3), 187-201.
- Chen, D. G., & Ho, S. (2017). **From statistical power to statistical assurance: It's time for a paradigm change in clinical trial design.** Communications in Statistics-Simulation and Computation, 46(10), 7957-7971.
- Best, N., Price, R. G., Pouliquen, I. J., & Keene, O. N. (2021). **Assessing efficacy in important subgroups in confirmatory trials: An example using Bayesian dynamic borrowing.** Pharmaceutical statistics, 20(3), 551-562.
- Kopp-Schneider, A., Calderazzo, S., & Wiesenfarth, M. (2020). **Power gains by using external information in clinical trials are typically not possible when requiring strict type I error control.** Biometrical Journal, 62(2), 361-374.



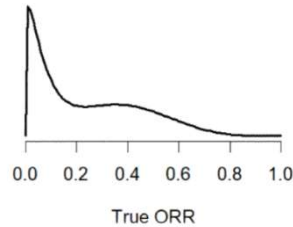
Back-ups



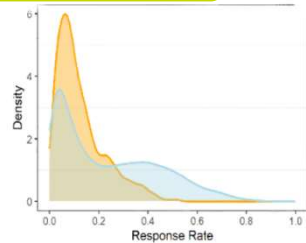
TV = 0.4, LRV = 0.15, n2 = 30

Expansion Assurance And Conditional Assurance

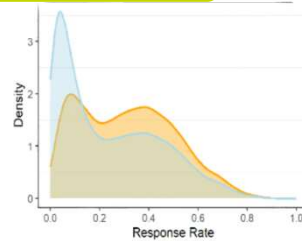
No Escalation
phase data



= 2/10 responders



>= 2/10 responders



Go Assurance = 37.7 %

Minimum Conditional
Go Assurance = 30.0 %

Conditional Go
Assurance = 66. %

7.7 %
↓
Minimum
Derisked
Assurance

Escalation Phase

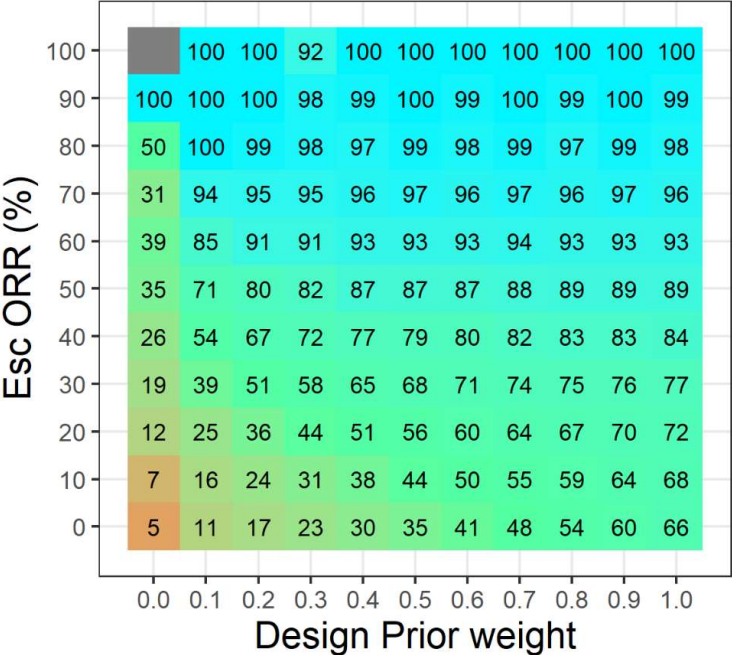
Expansion phase

↑ 29.2 %
Derisked
Assurance

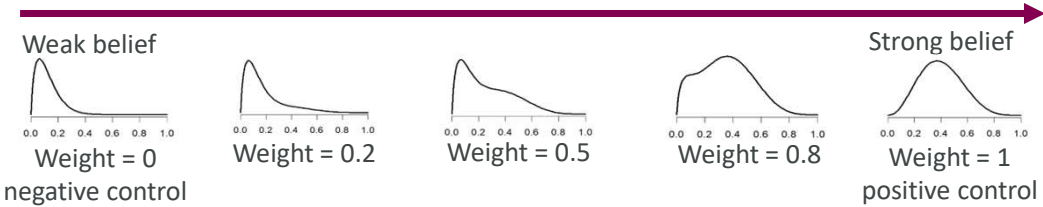
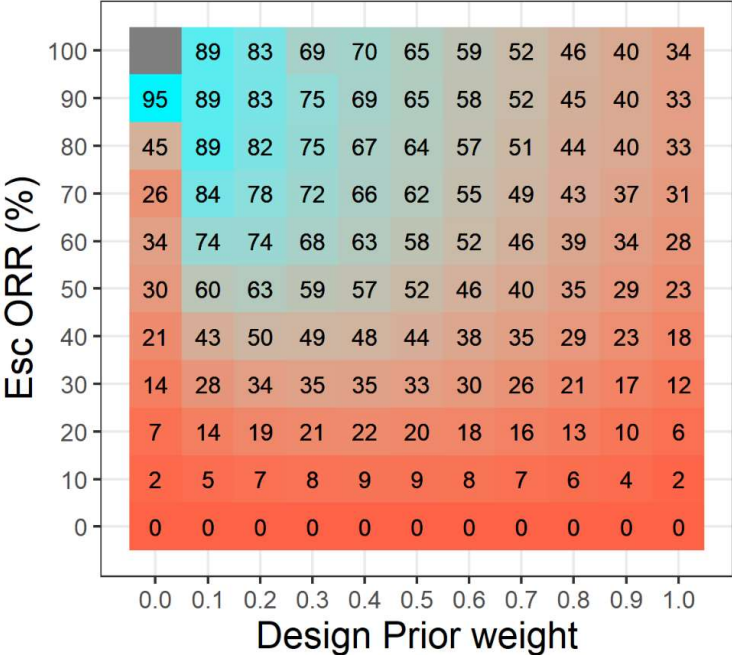


Overall Cond. Assurance

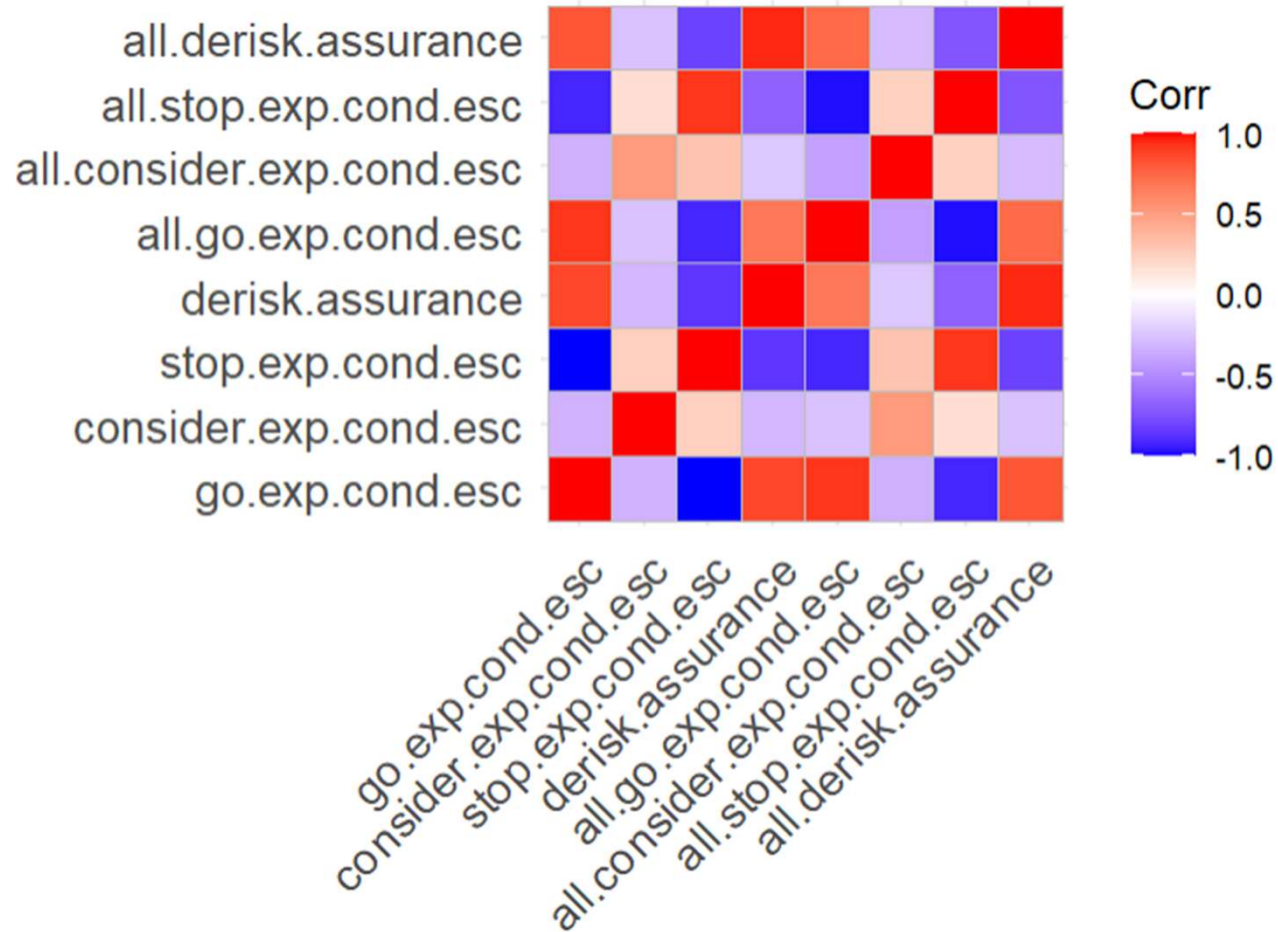
Cond. Go Assurance



Derisked Go Assurance



Min. VS Cond. Assurance



TV = 0.4, LRV = 0.15, n2 = 30, proceed cut-off 10%, acceleration cut-off 80%

A Bayesian Mixture Design Prior Prevents Over-reaction To Small Emerging Datasets

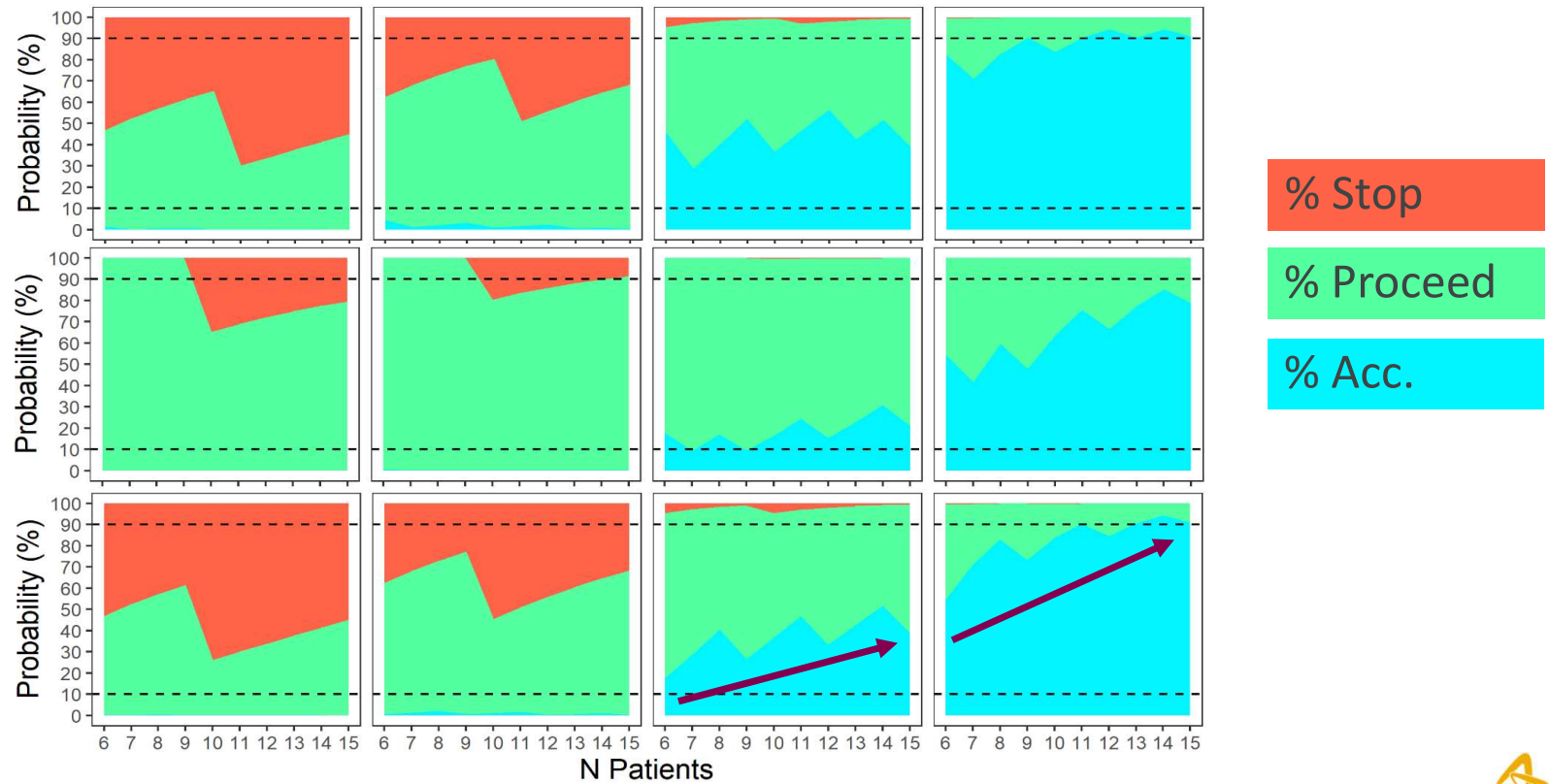
Probability of Outcome for a Range of True Drug Effects

10% LRV = 15% TV = 40% 60%

Jefferey's Prior

Simple Weighted Beta

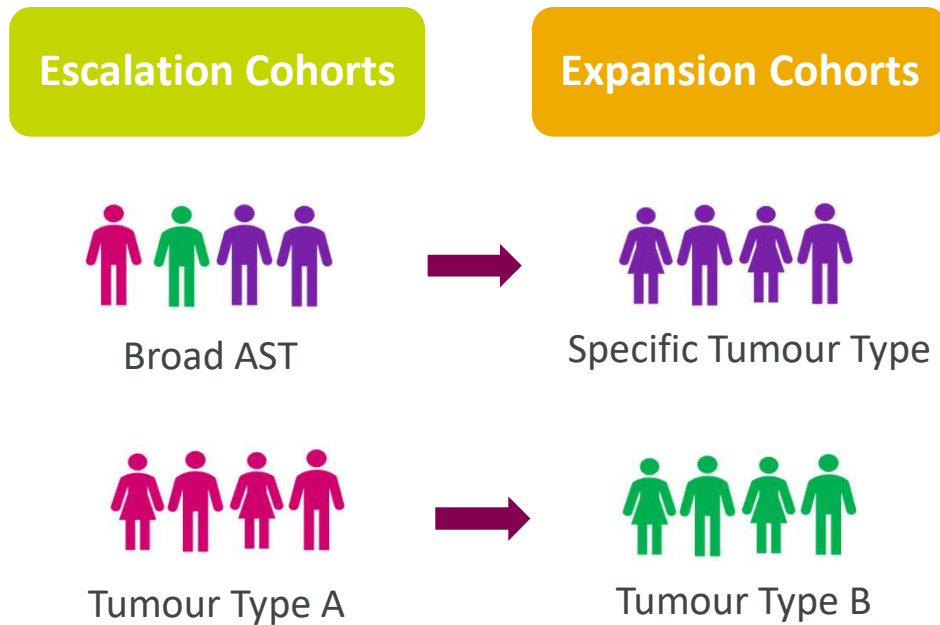
Mixture Prior B



% Stop
% Proceed
% Acc.



Different Population across Esc. and Exp. Phase

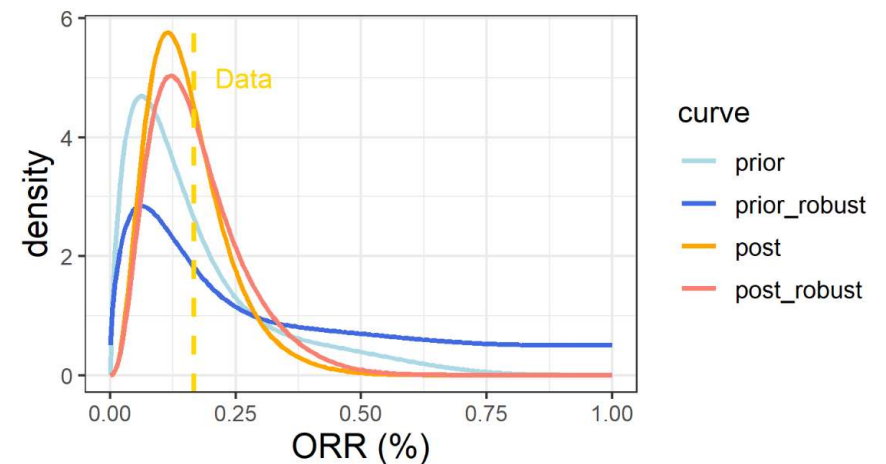


Points of consideration

- How are Esc./Exp. population selected
- Amount of evidence

Methods to consider

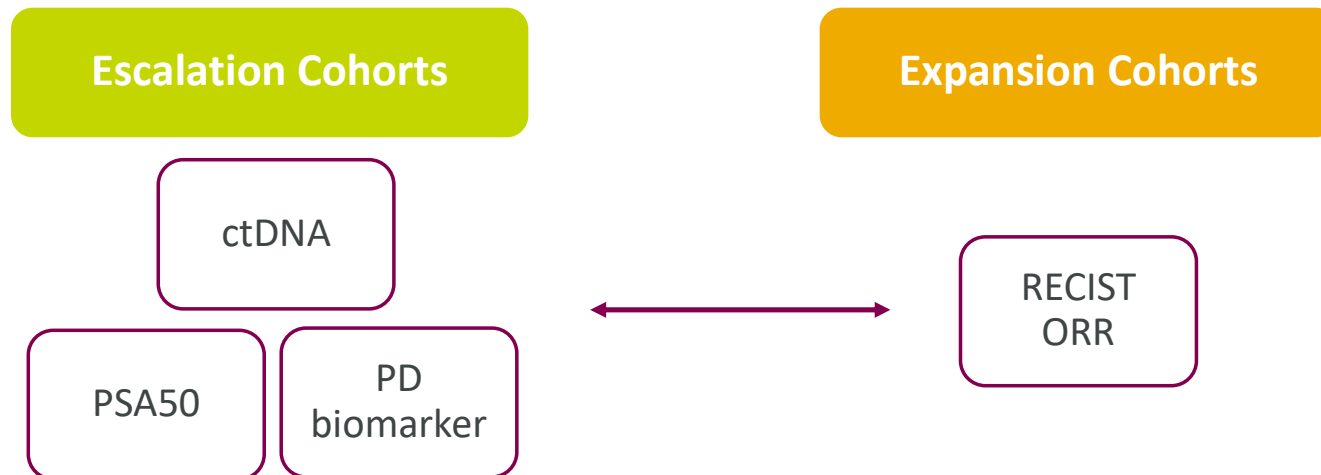
- Adjust prior components: weight, ESS, etc.
- Robustify prior



e.g. $N = 12, R = 2$



Different Decision-Making Endpoints across Esc. and Exp. Phase



Points of consideration

- Types of endpoints: binary/continuous, etc.
- Correlation between the surrogate outcome and the clinically meaningful outcome
 - Positive/Negative predictive value
 - Sensitivity/Specificity
- Clinical relevance of a composite endpoint



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