



# Adaptive Design in Early Phase Clinical Trials

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Vice President, Strategic Consulting

# Console Overview

**\*Configurable windows – expand or contract as needed**

The screenshot shows a webinar console interface with a central slide titled "Adaptive Design in Early Phase Clinical Trials" by James Matcham. The slide content includes the Cytel logo, the title, and the speaker's name and title: "James Matcham, Vice President, Strategic Consulting".

Surrounding the central slide are several configurable windows:

- Media Player:** A window for video playback, currently showing a black screen.
- Speaker Bio:** A window displaying the speaker's profile, including a photo and a detailed biography of James Matcham.
- Resource List:** A window containing links for "Download Today's Slides" and "Subscribe to the Cytel Blog!".
- Q&A:** A window for audience questions, featuring a text input field labeled "Enter your question" and a "Submit" button.
- Survey:** A window titled "Feedback Survey" with two questions: "1. Please rate the overall quality of this webinar." (with a dropdown menu) and "2. Please share any additional feedback and suggestions for future webinar topics." (with a text input field).

Media Player

Speaker Bio

Resources

Questions

Survey

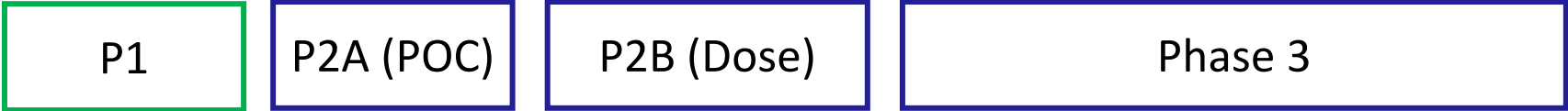
# Agenda

- Background
- Dose Escalation
- Decision Making
- Combination Studies
- Dose Finding
- Enrichment
- Q&A



# Clinical Development Plans

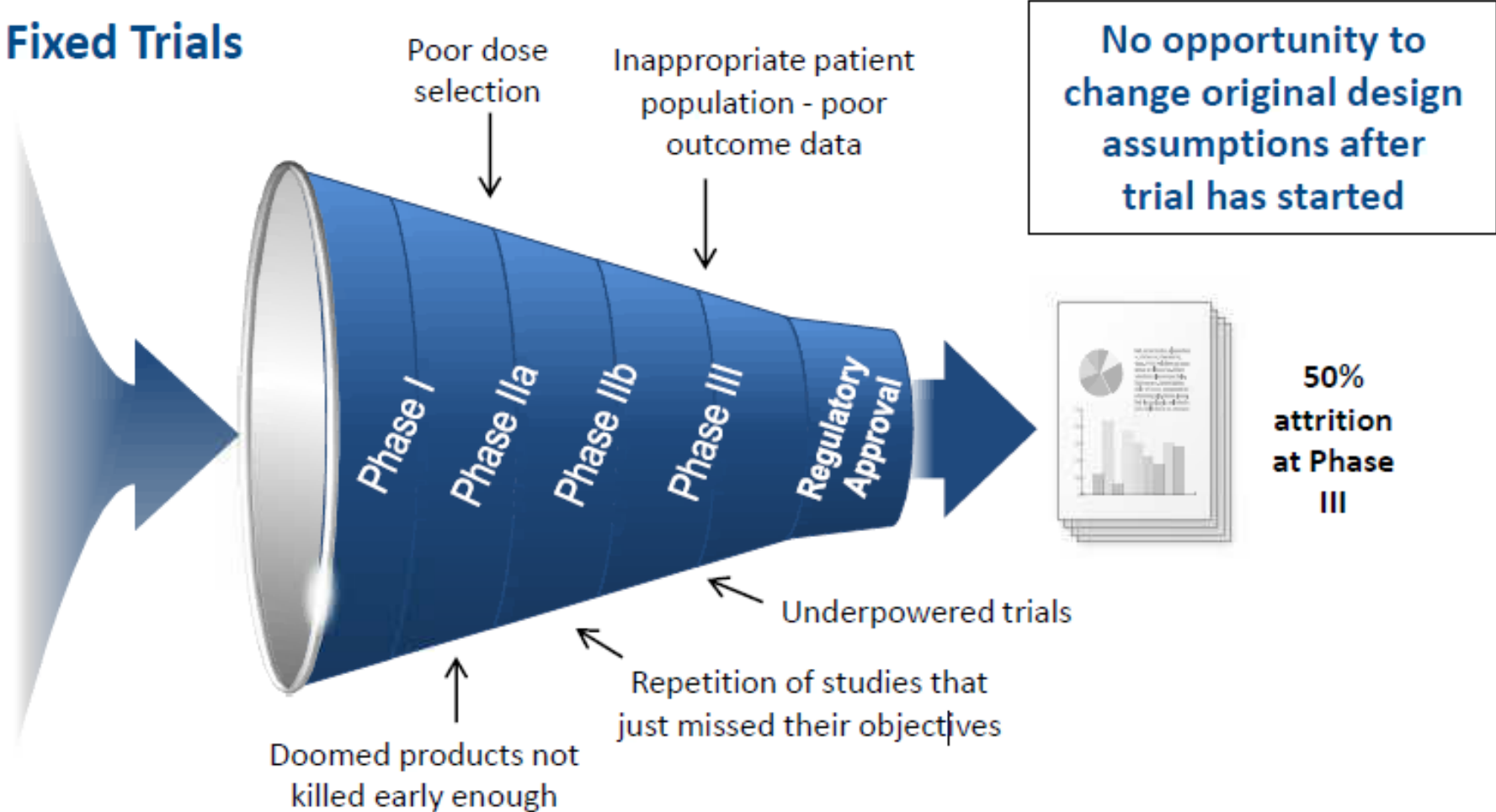
## Non-Oncology



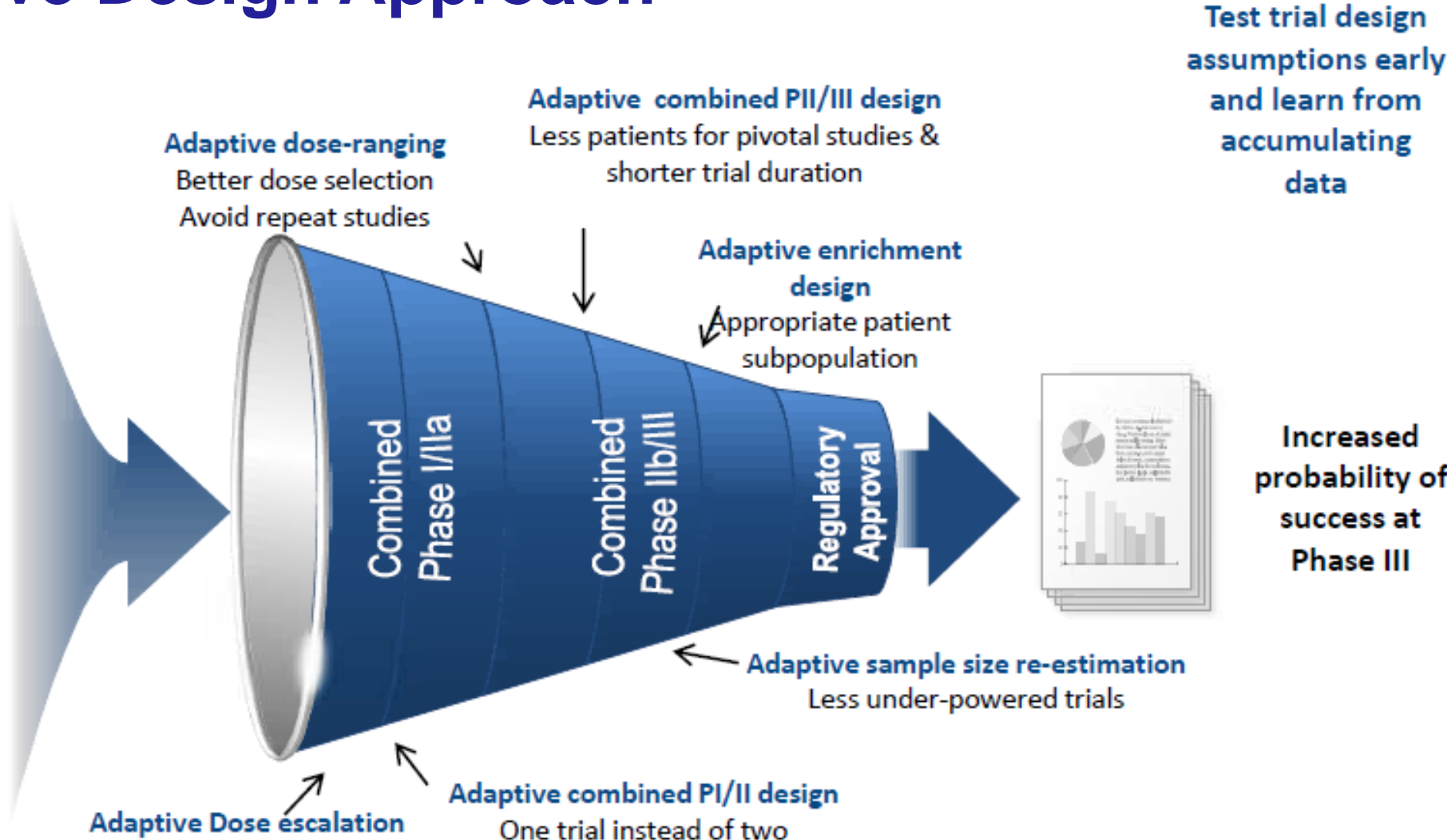
## Oncology



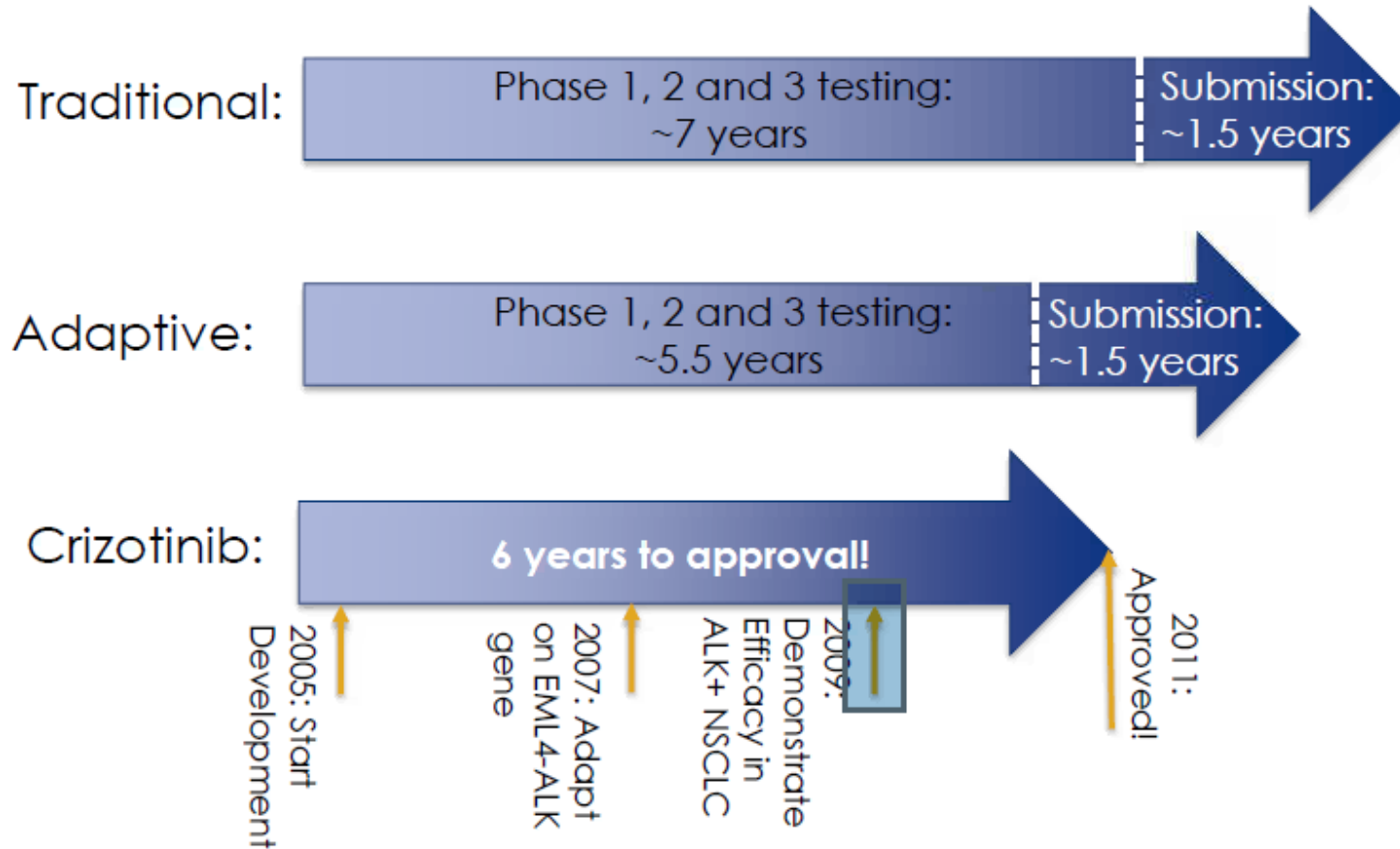
# Traditional Approach



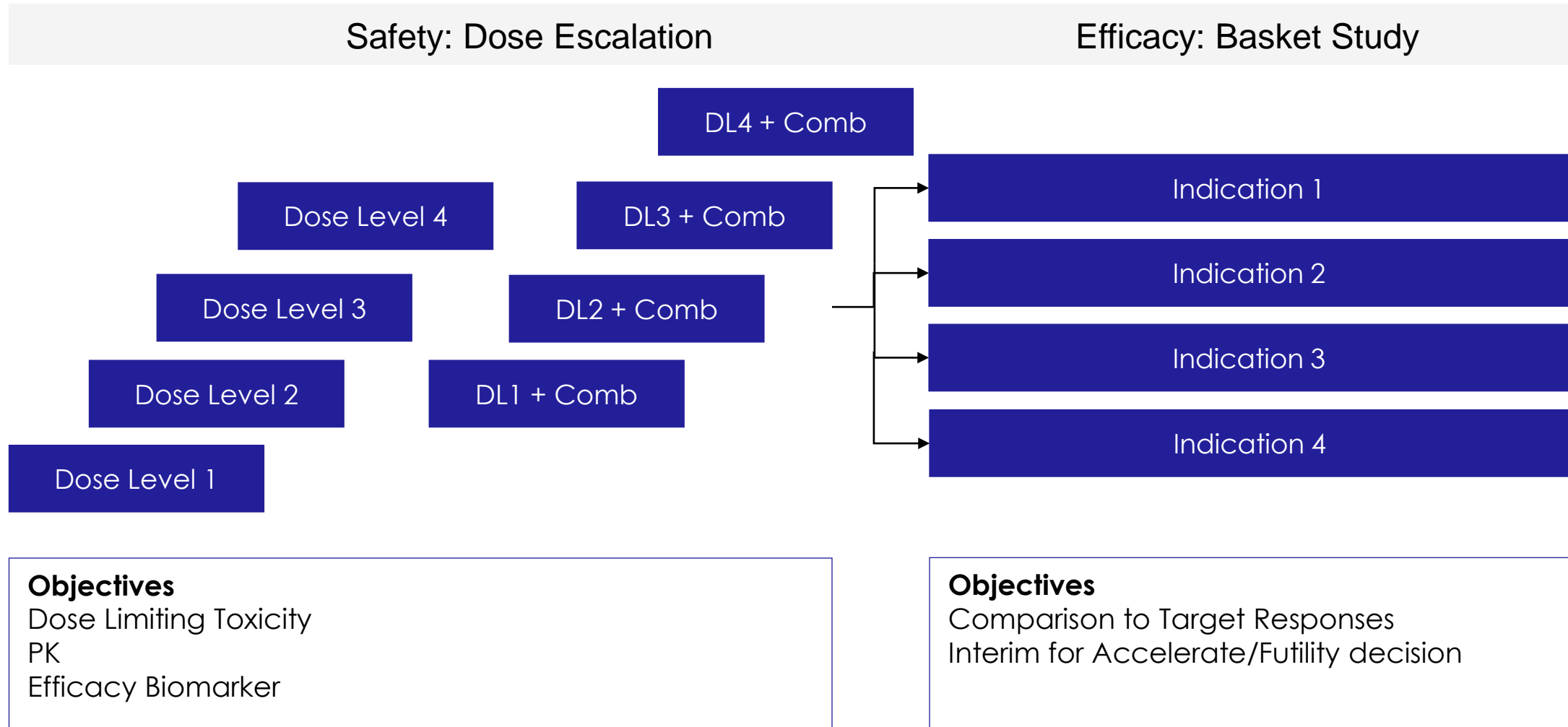
# Adaptive Design Approach



# Benefit of Adaptive Designs

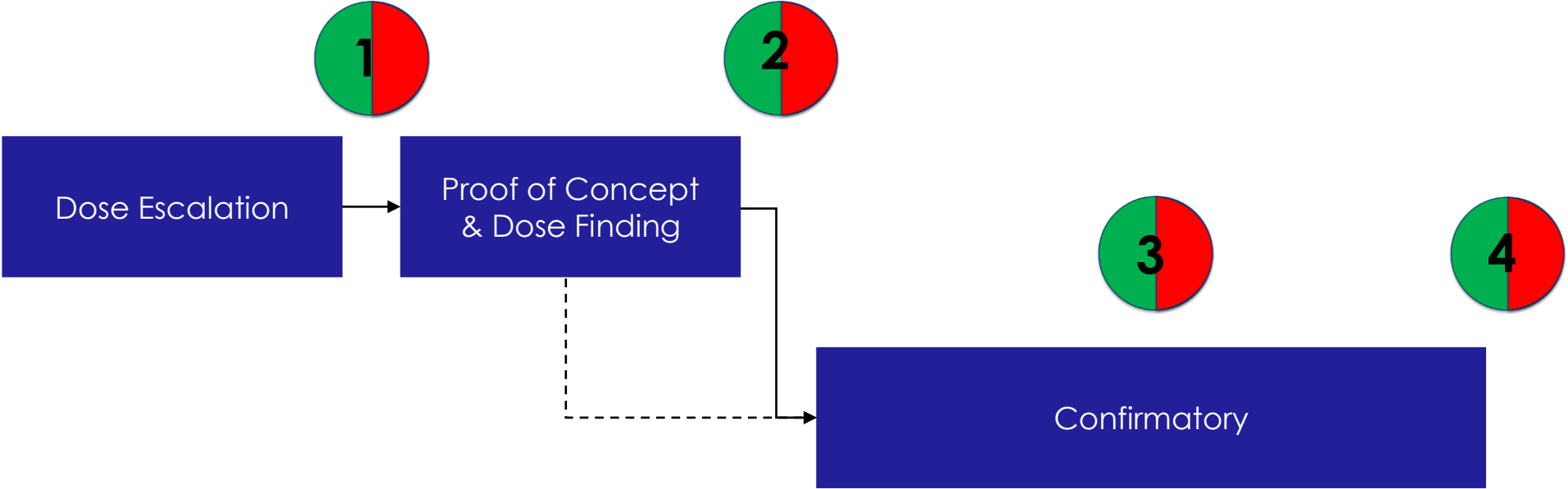


# Example Adaptive Phase 1/2 Design





# Clinical Development Decision Points

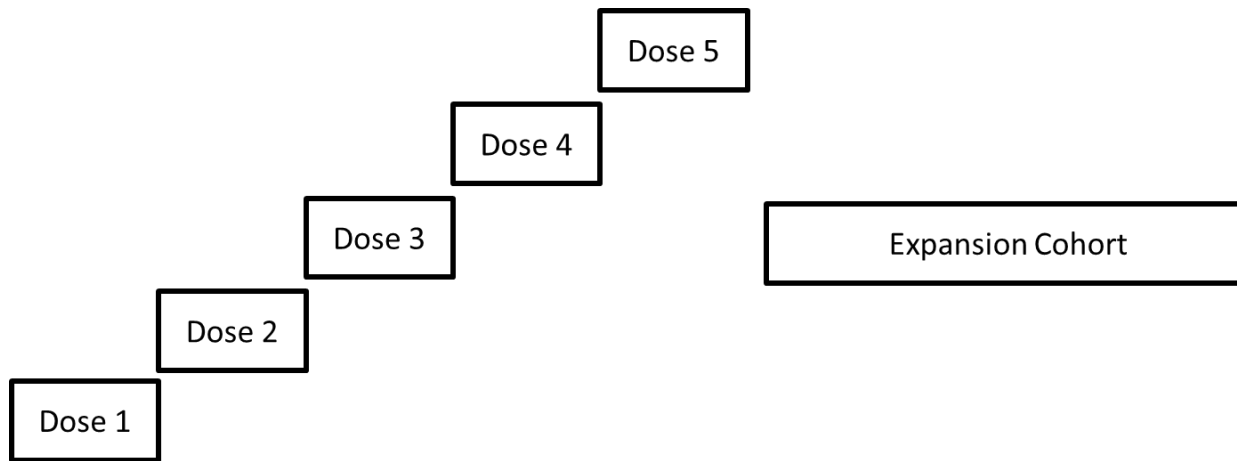


# Agenda

- Background
- **Dose Escalation**
- Decision Making
- Combination Studies
- Dose Finding
- Enrichment
- Q&A

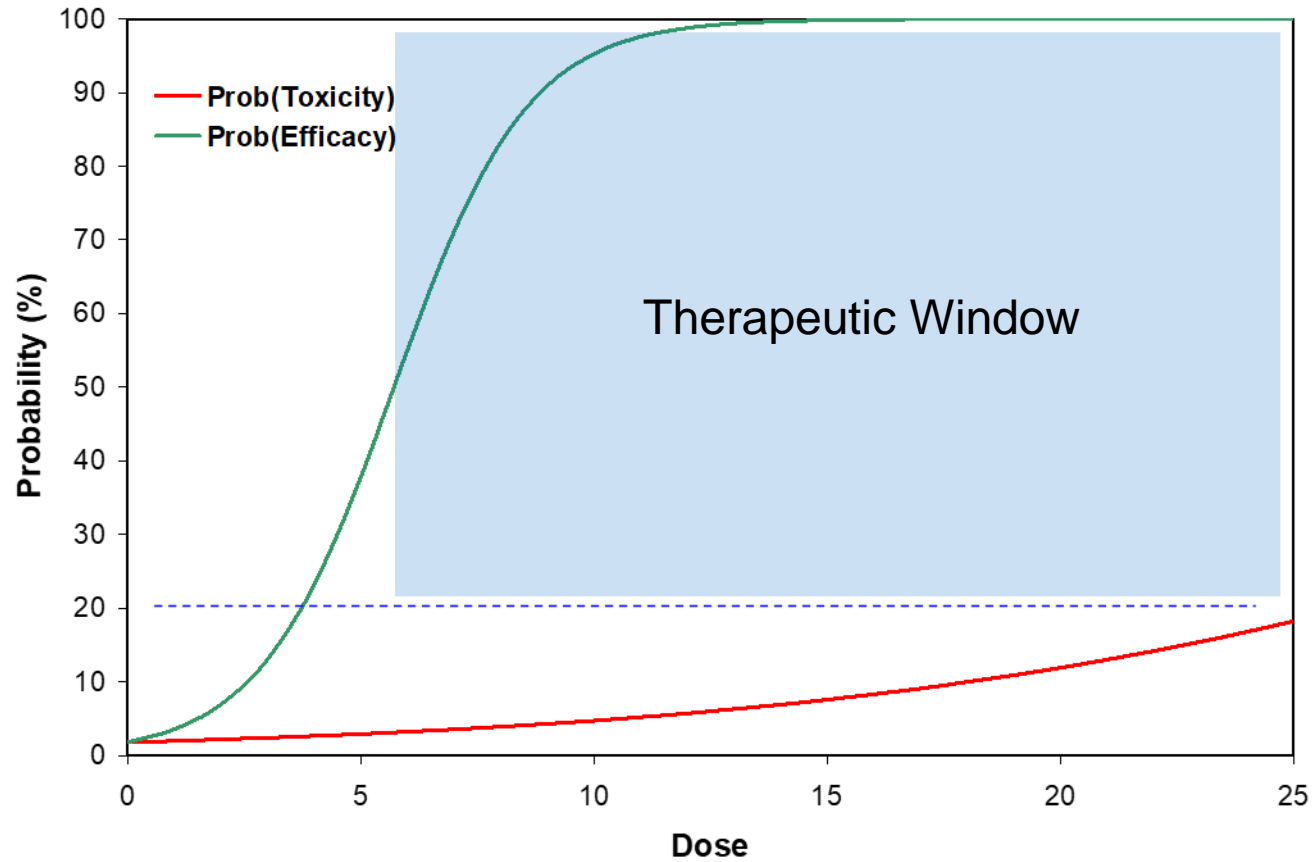


# SAD/MAD/Dose Escalation



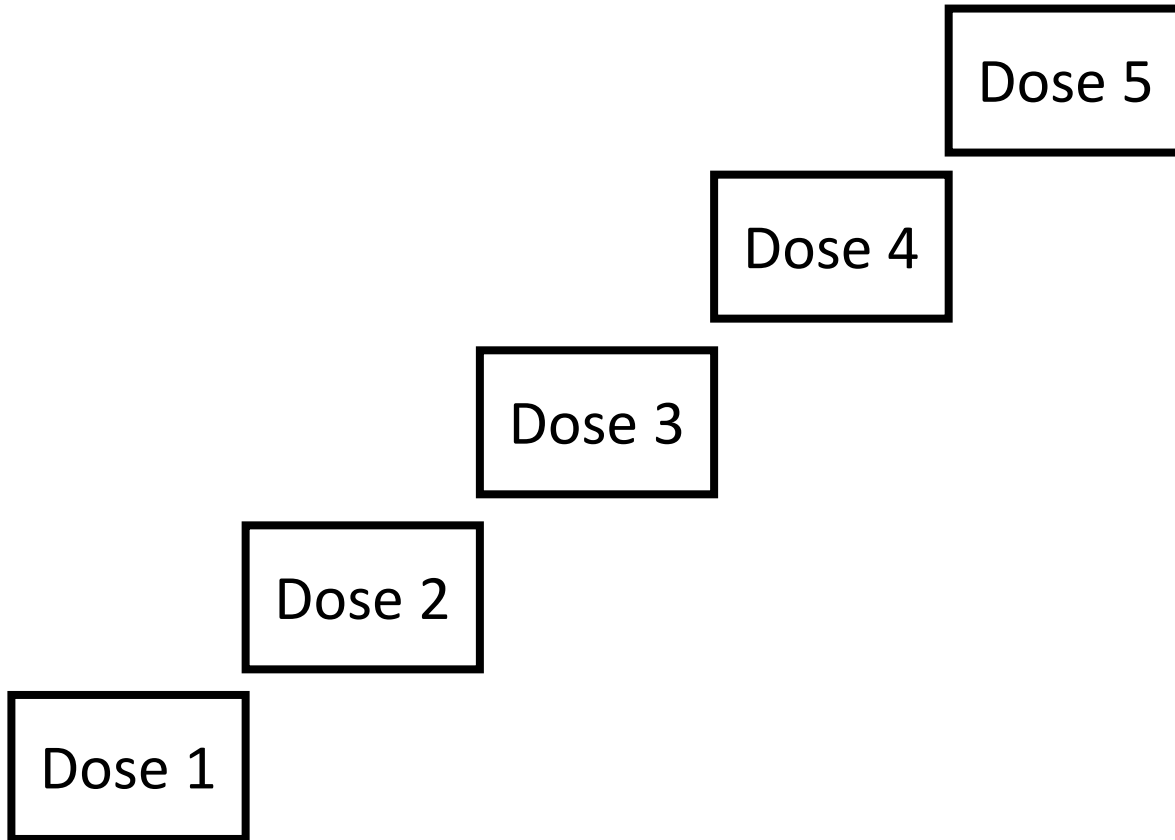
- Sequential cohorts, can repeat doses in Single Ascending Dose (SAD) and Multiple Ascending Dosing (MAD)
- Escalation is based on observing Dose Limiting Toxicities (DLT)
- Dose Escalation Committee (DEC) govern escalation decisions
- PK data collected for further dose/schedule decisions
- Response Biomarkers are valuable to determine correct activity thresholds

# Dose Ranging



Questions: Is there a range of safe doses where we can explore efficacy?  
Is there a Maximum Tolerated Dose?

# Dose Escalation



- Small cohorts with randomization to placebo
- Doses are logarithmically spaced – usually doubled
- Starting dose  $< 1/100$  predicted human dose
- At the end of each dose cohort a Data Review Committee assesses safety data and decides on dose increases
- Escalation is based on observing Dose Limiting Toxicities
- Traditional 3+3 rule common
- No statistician involved

# Escalation Rules

## Algorithm-Based

- 3+3
- mTPI
- i3+3
- Adaptive Dose Insertion
- Dual Agent PIPE

## Model-based

- CRM
- TITE-CRM
- BOIN
- BLRM
- Dual Agent BLRM



All approaches are methods to estimate the Maximum Tolerated Dose

# Documented Issues with 3+3 Design

- Chance of recommending wrong Phase 2 Dose is high, so future trials will need to dose adjust
- What happens with N=2, 4, 5 in a cohort?
- Considerable inertia amongst trialists to adopt better methods
- Cannot include intermediate doses
- No information to guide stepping from monotherapy to combination
- Need to repeat recommended dose with additional cohort to confirm safety outcome

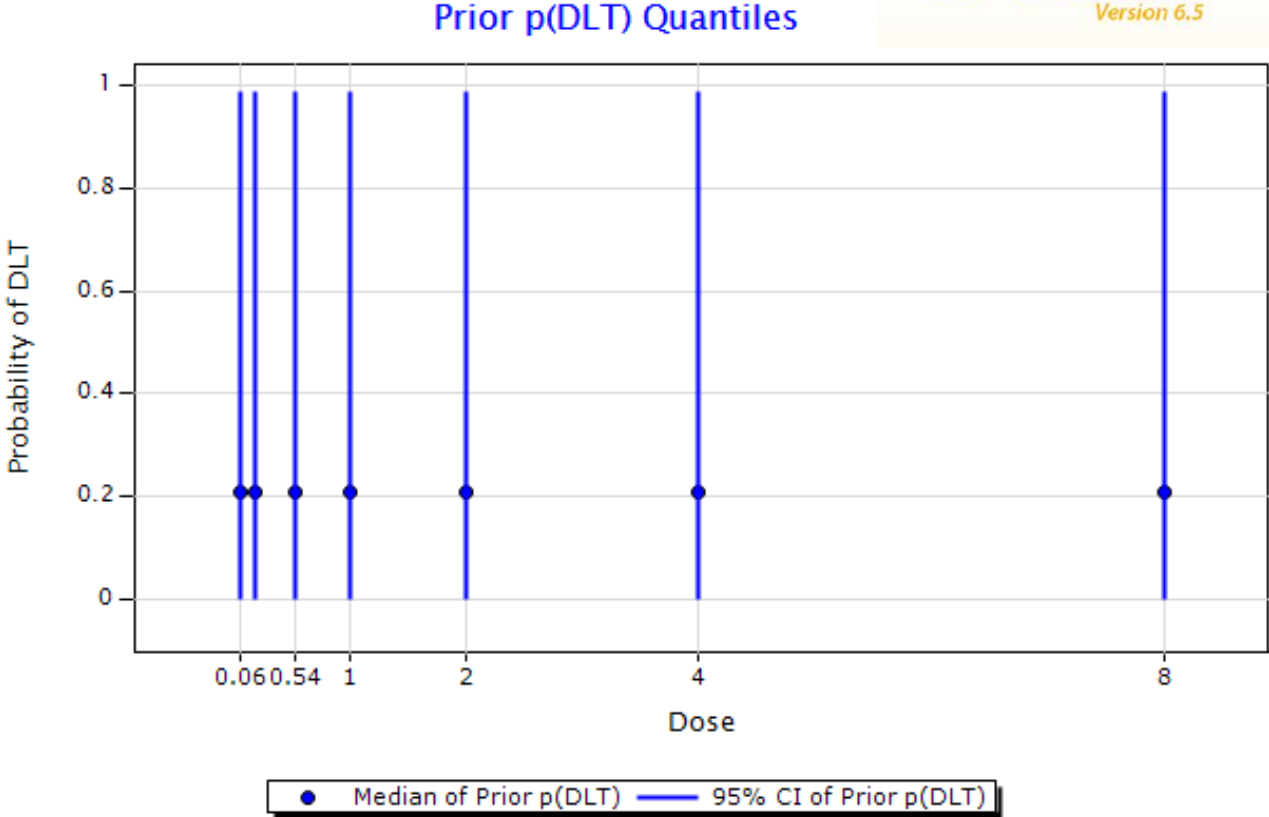
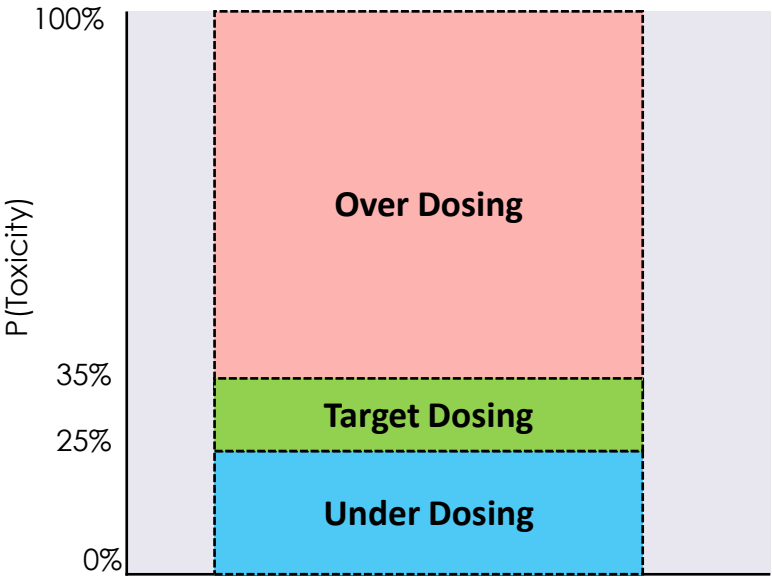


## Embracing model-based designs for dose-finding trials

Sharon B Love<sup>\*1</sup>, Sarah Brown<sup>2</sup>, Christopher J Weir<sup>3</sup>, Chris Harbron<sup>4</sup>, Christina Yap<sup>5</sup>, Birgit Gaschler-Markefski<sup>6</sup>, James Matcham<sup>7</sup>, Louise Caffrey<sup>8</sup>, Christopher McKevitt<sup>9</sup>, Sally Clive<sup>10</sup>, Charlie Craddock<sup>11</sup>, James Spicer<sup>12</sup> and Victoria Cornelius<sup>13</sup>



# Modified Target Probability Interval (mTPI)





# mTPI in EAST



Max. Number of Doses:

Design Parameters

Stopping Rules

Trial Monitoring Table

Response Generation

Simulation Controls

Max. Sample Size:

Cohort Size:

Start With

Switch to mTPI upon reaching MTD

Switch to mTPI upon observing first DLT

Target Probability of Toxicity ( $P_T$ ):

Toxicity Intervals	Lower Limit	Upper Limit
Under dosing	0.000	0.250
Proper dosing	0.250	0.350
Over dosing	0.350	1.000

Prior

$P_i \sim \text{Beta}(a, b)$



$P_i$ : True Toxicity Probability at Dose  $i$

a (Prior Toxicity):

b (Prior Non-Toxicity):

# mTPI Trial Monitoring Table

Edit Trial Monitoring Table: Click any cell to edit
  mTPI
  mTPI-2



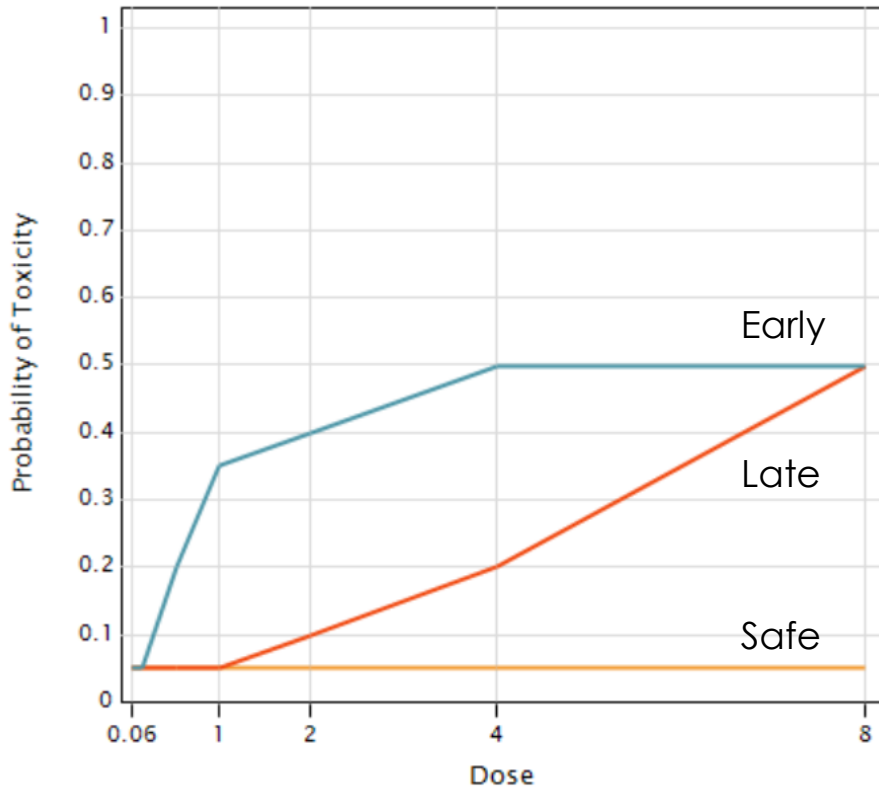
Number of patients treated at current dose

r\n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
0	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E
1	DU	DU	S	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E
2		DU	DU	DU	S	S	S	S	E	E	E	E	E	E	E	E	E	E	E	E
3			DU	DU	DU	DU	DU	S	S	S	S	S	S	E	E	E	E	E	E	E
4				DU	DU	DU	DU	DU	DU	DU	S	S	S	S	S	S	S	S	E	E
5					DU	DU	DU	DU	DU	DU	DU	DU	DU	S	S	S	S	S	S	S
6						DU	DU	DU	DU	DU	DU	DU	DU	DU	DU	DU	S	S	S	S
7							DU	DU	DU	DU	DU	DU	DU	DU	DU	DU	DU	DU	DU	S
8								DU	DU	DU	DU	DU	DU	DU	DU	DU	DU	DU	DU	DU
9									DU	DU	DU	DU	DU	DU	DU	DU	DU	DU	DU	DU
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16																DU	DU	DU	DU	DU
17																	DU	DU	DU	DU
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19																			DU	DU

- E = Escalate to the next higher dose
  - S = Stay at the current dose
  - D = De-escalate to the next lower dose
  - DU = The current dose is unacceptably toxic
- Target Toxicity (%) = 30%
- Sample Size = 30

# Example: Toxicity Profile Scenarios

Dose Toxicity Curve



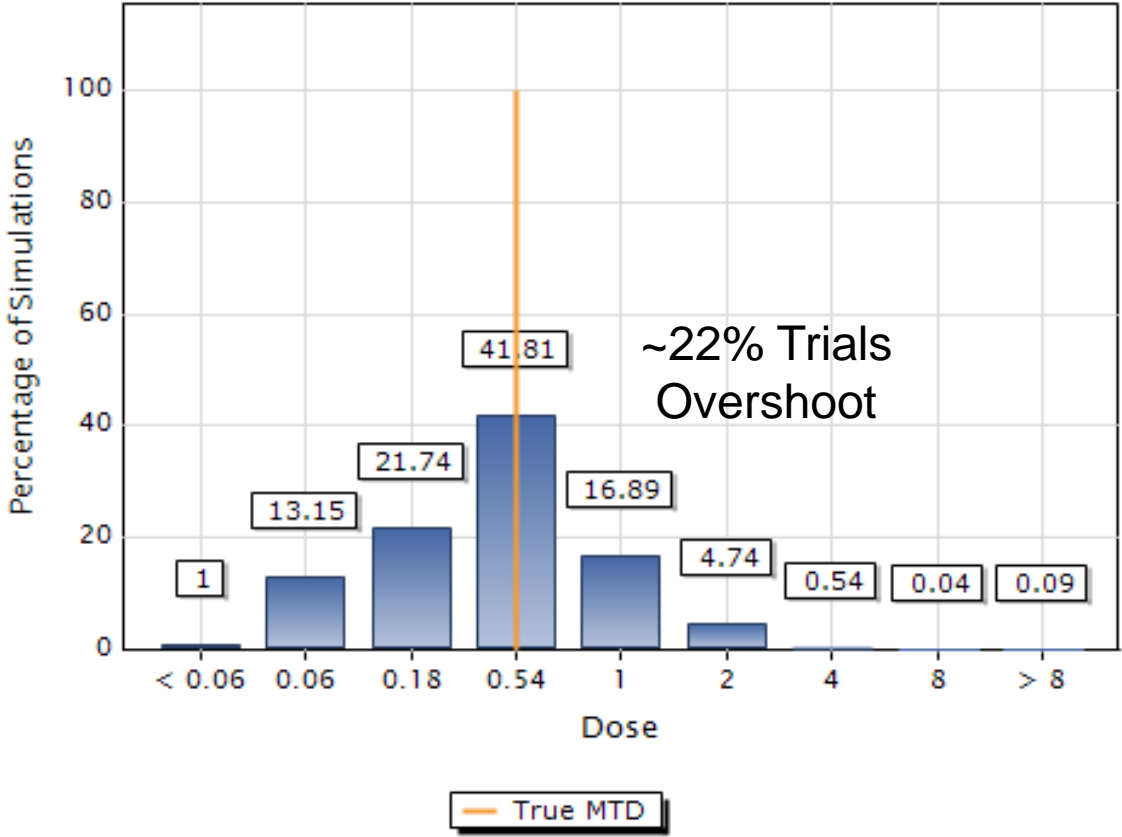
Probability of Toxicity

Toxicity Profile	Dose Level						
	0.06	0.18	0.54	1	2	4	8
Safe	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Late	0.05	0.05	0.05	0.05	0.1	0.2	0.5
Early	0.05	0.05	0.2	0.35	0.4	0.5	0.5

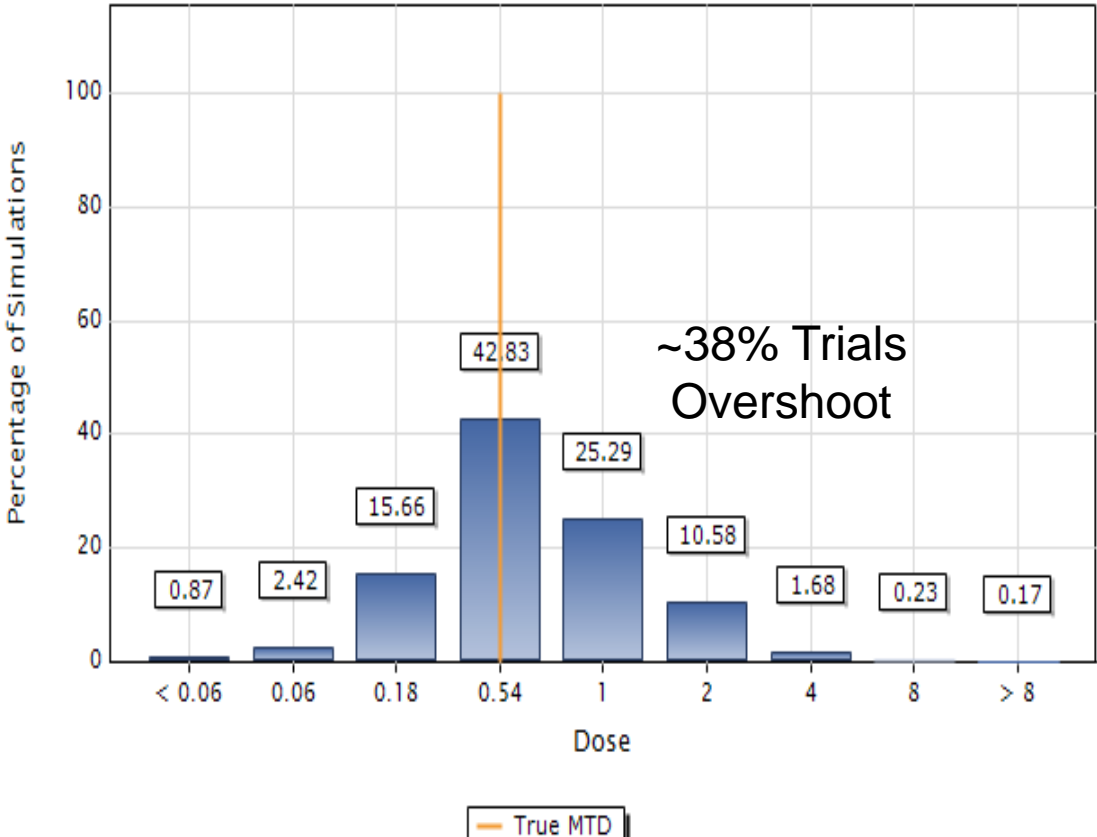
# mTPI vs 3+3: Early Scenario



MTD - mTPI Early



MTD - 3+3 Early



# mTPI Comments

- mTPI provides a 'statistician-free' DRC meeting
- Allows possibility of any number of patients at each dose
- Does not use any information from adjoining doses
- Each dose is treated separately
- Does not inform intermediate doses

# Bayesian Logistic Regression Model

We can model the toxicity response curve using a logistic model relating the  $P(\text{toxicity})$  to the dose

$$\text{logit}(p_i) = \ln(\alpha) + \beta \ln(x_i/x_{ref})$$

where  $p_i$  is the  $P(\text{toxicity})$  at dose  $x_i$  and  $x_{ref}$  is a reference dose.

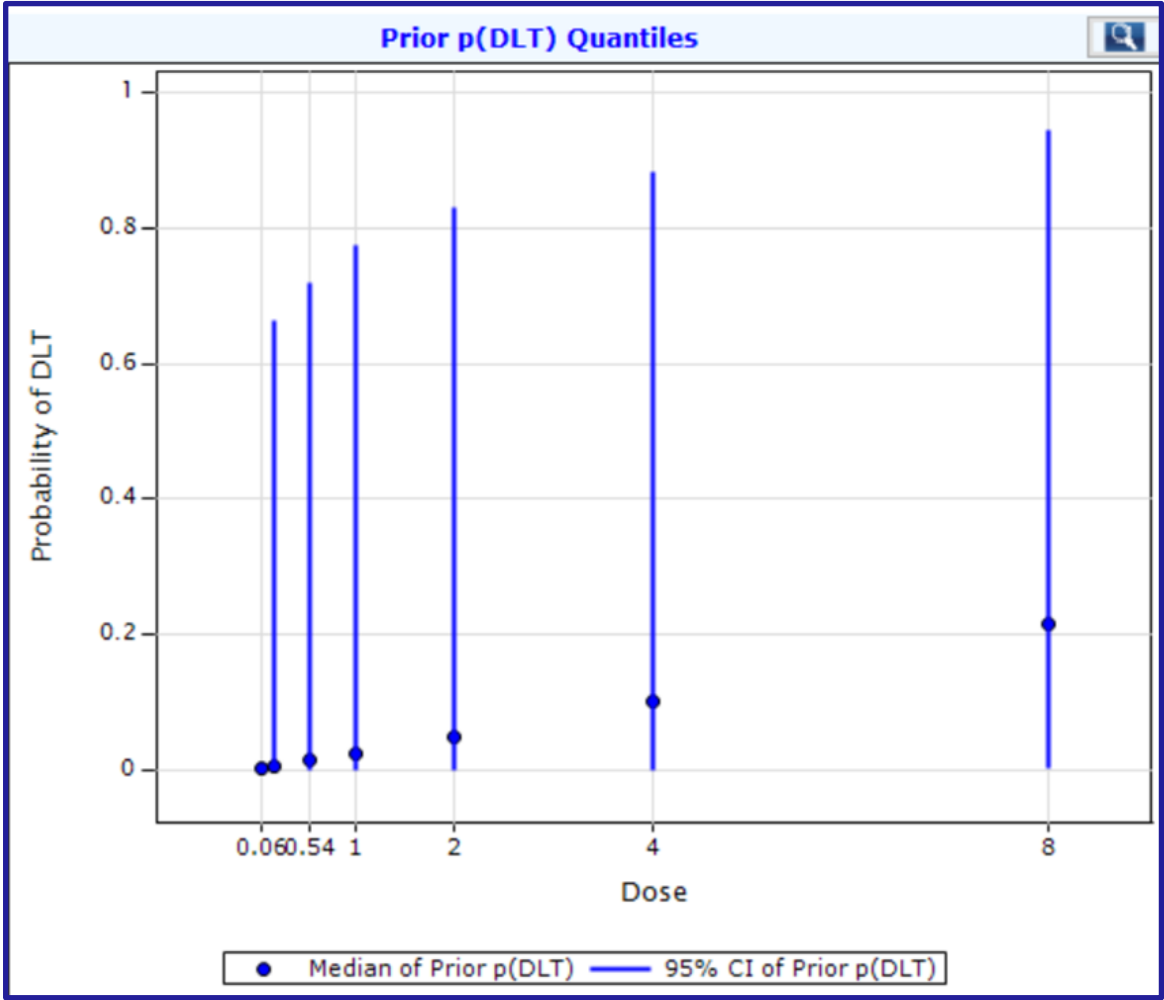
Using a Bayesian approach we can

- use informative priors for  $\alpha$  and  $\beta$
- predict the  $P(\text{toxicity})$  after each cohort
- use this to choose the next dose

# Priors for $\alpha$ and $\beta$

$\text{Ln}(\alpha) \sim N(-0.847, 2)$   
 $P(\text{tox})=42\%$  at dose=10

$\text{Ln}(\beta) \sim N(0,1)$   
Assumes monotonic increasing



# BLRM Specification in EAST



Max. Number of Doses:

Design Parameters

Stopping Rules

Response Generation

Simulation Controls

Max. Sample Size:

Cohort Size:

Start With

Switch to BLRM upon reaching MTD

Switch to BLRM upon observing first DLT

Target Probability of Toxicity ( $P_T$ ):

Dose Selection Method

Max Targeted Toxicity  Bayes Risk

Toxicity Intervals	Lower Limit	Upper Limit
Under dosing	0.000	0.250
Targeted toxicity	0.250	0.350
Excessive toxicity	0.350	1.000
Unacceptable toxicity		

EWOC: Prob. (Overdosing) <

Reference Dose ( $D^*$ ):

Distribution: Bivariate Normal

Prior Specification

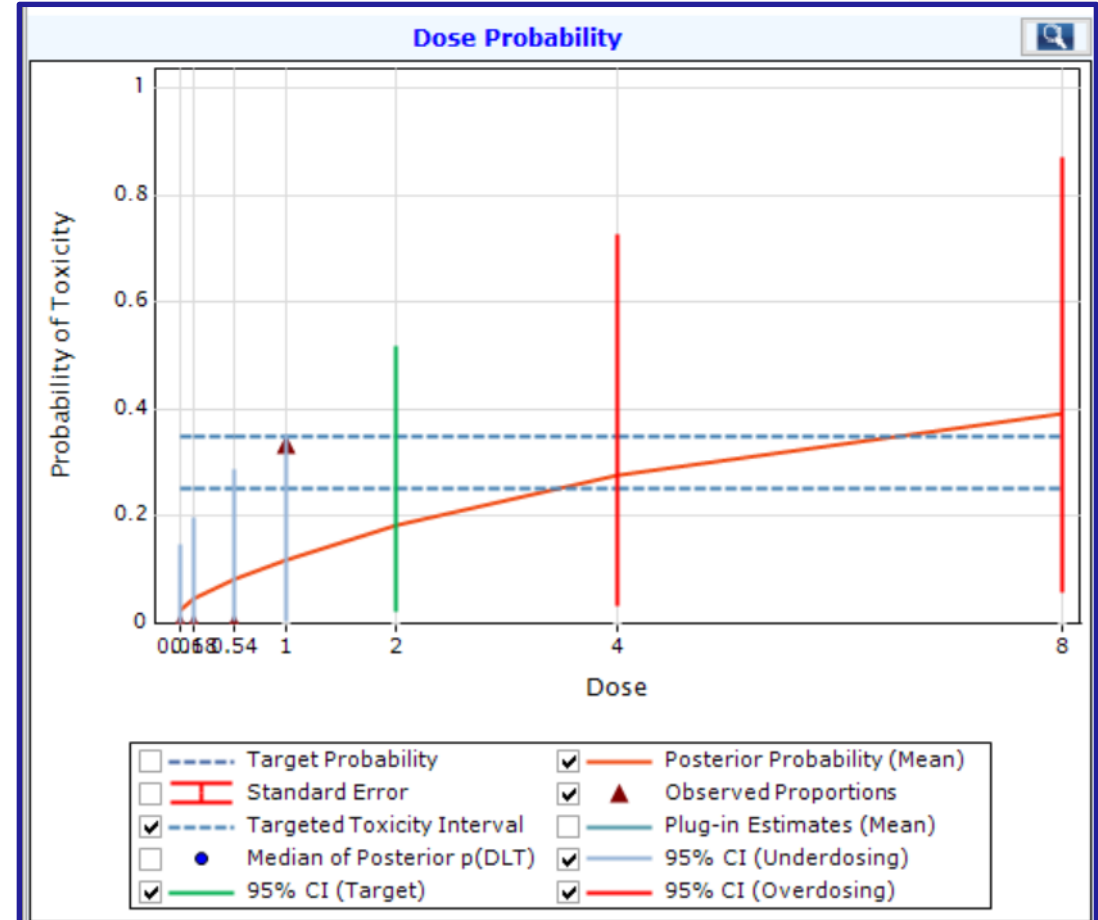
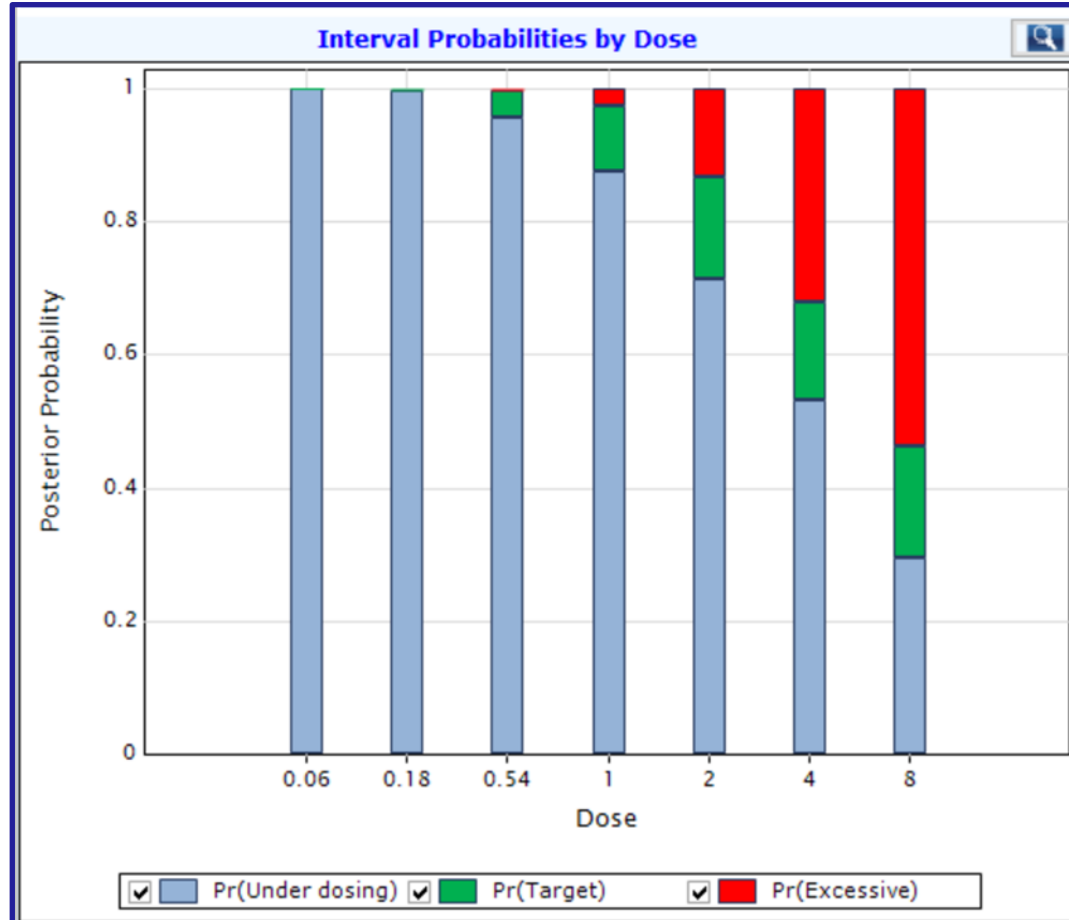
Mean:

SD:

Correlation:

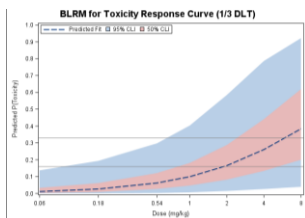


# Output



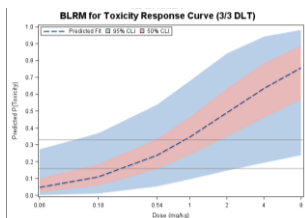
# Playbook Support

DLT=1/3



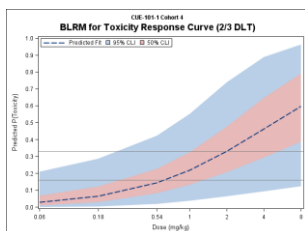
Dose (mg/kg)	0.06	0.18	0.54	1.0	2.0	4.0	8.0
Excess: P(Tox) $\geq$ 33%	0.1	0.2	1.5	5.7	19.2	38.8	56.6
Target: P(Tox) $\geq$ 16%, $<$ 33%	1.5	4.2	13.8	24.4	32.1	30.5	24.3
Under: P(Tox) $<$ 16%	98.5	95.6	84.7	69.9	48.7	30.6	19.1

DLT=2/3



Dose (mg/kg)	0.06	0.18	0.54	1.0	2.0	4.0	8.0
Excess: P(Tox) $\geq$ 33%	0.3	1.2	8.5	24.3	50.2	69.7	81.1
Target: P(Tox) $\geq$ 16%, $<$ 33%	5.3	14.1	36.0	42.6	33.8	22.2	14.3
Under: P(Tox) $<$ 16%	94.3	84.7	55.5	33.1	15.9	8.1	4.6

DLT=3/3



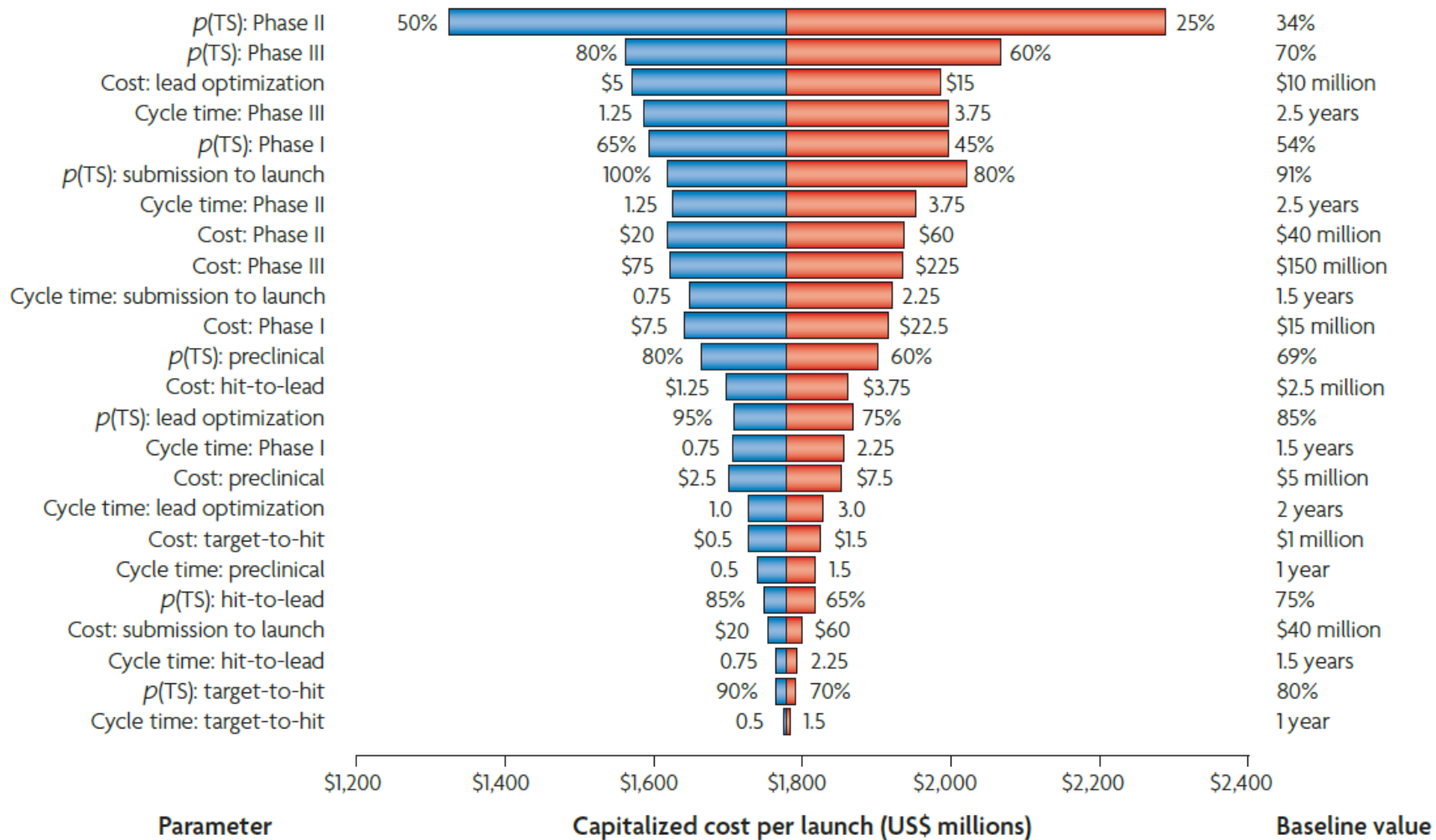
Dose (mg/kg)	0.06	0.18	0.54	1.0	2.0	4.0	8.0
Excess: P(Tox) $\geq$ 33%	1.0	4.3	25.9	53.9	78.0	89.0	93.8
Target: P(Tox) $\geq$ 16%, $<$ 33%	10.7	27.3	47.5	36.1	18.6	9.6	5.4
Under: P(Tox) $<$ 16%	88.3	68.4	26.5	9.9	3.3	1.4	0.7

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- **Decision Making**
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- Q&A



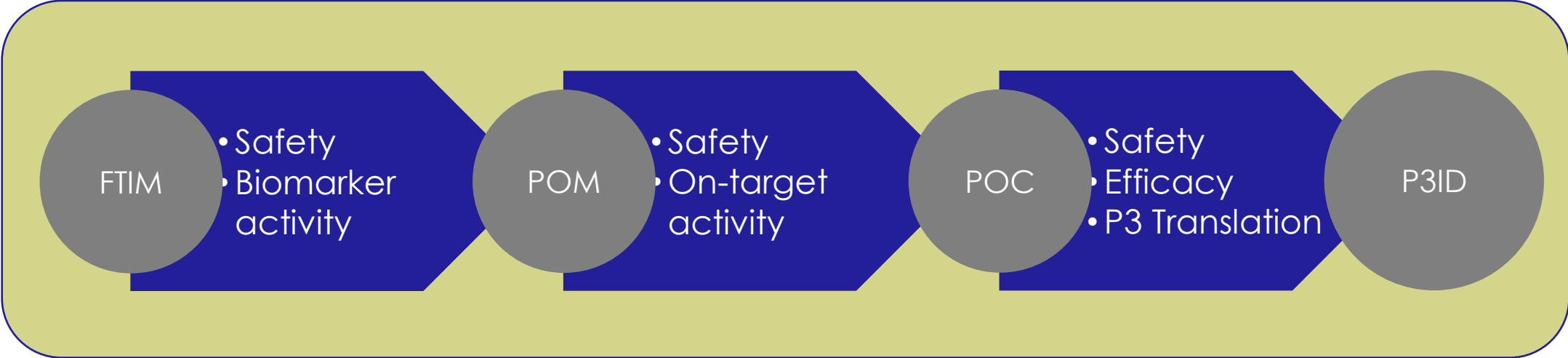
# Decision Making Today



Paul et al (2010)

# Early Phase Decision-Making

In a candidate-rich early phase portfolio, there is a focus on good decision-making at the point of investment decisions



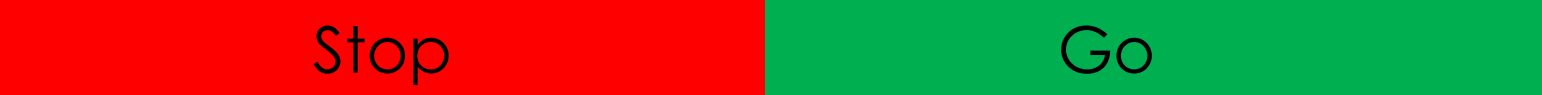
# Decision Making Approaches

- Decisions at interims are common
- Single indication
- Biomarker Endpoint
- Sized to exceed a minimum Target Response
- Simon's 2 Stage Design only gives futility decision
- Bayesian interim decisions are now more common
  - GO =  $P(\text{Response} > p_o) > 80\%$  , STOP if  $P(\text{Response} > p_o) < 10\%$
- Early phase studies can be expanded to pivotal for accelerated approval
- Determine baseline biomarker cut-off values
- Bayesian learning about biomarker cut-off points
  - SCUBA, SBATT methods



# Decision Outcomes

Two Outcome Decisions



Three Outcome Decisions



# Example Decision Framework

Three outcome decision



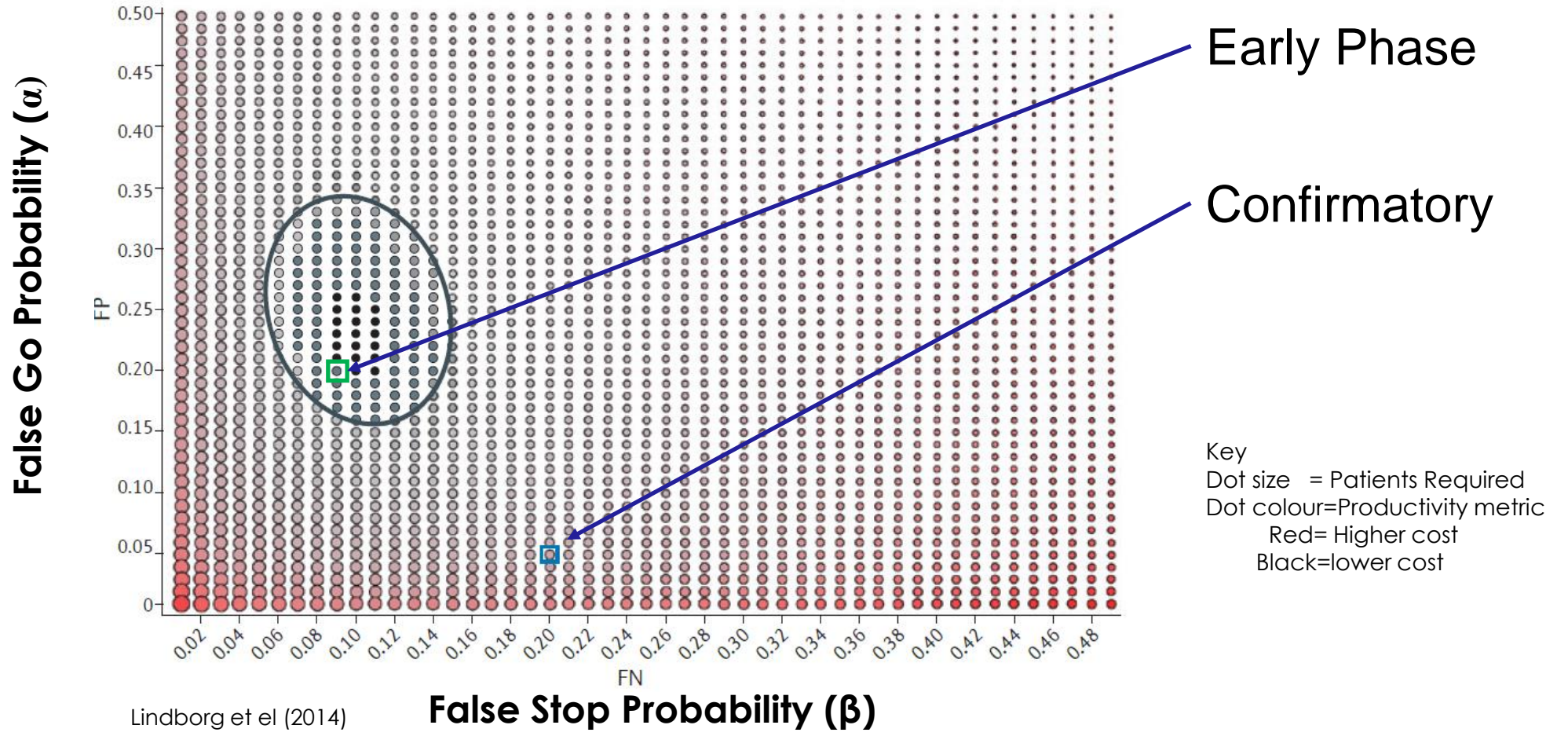
Decision parameters

Target Value (TV)	Desired level of performance
Lower Reference Value (LRV)	Minimal level of performance
False Stop Risk	Risk of a “Stop” decision if the truth is better than the TV
False Go Risk	Risk of “Go” decision if the truth is at worse than the LRV

Frewer et al (2016)

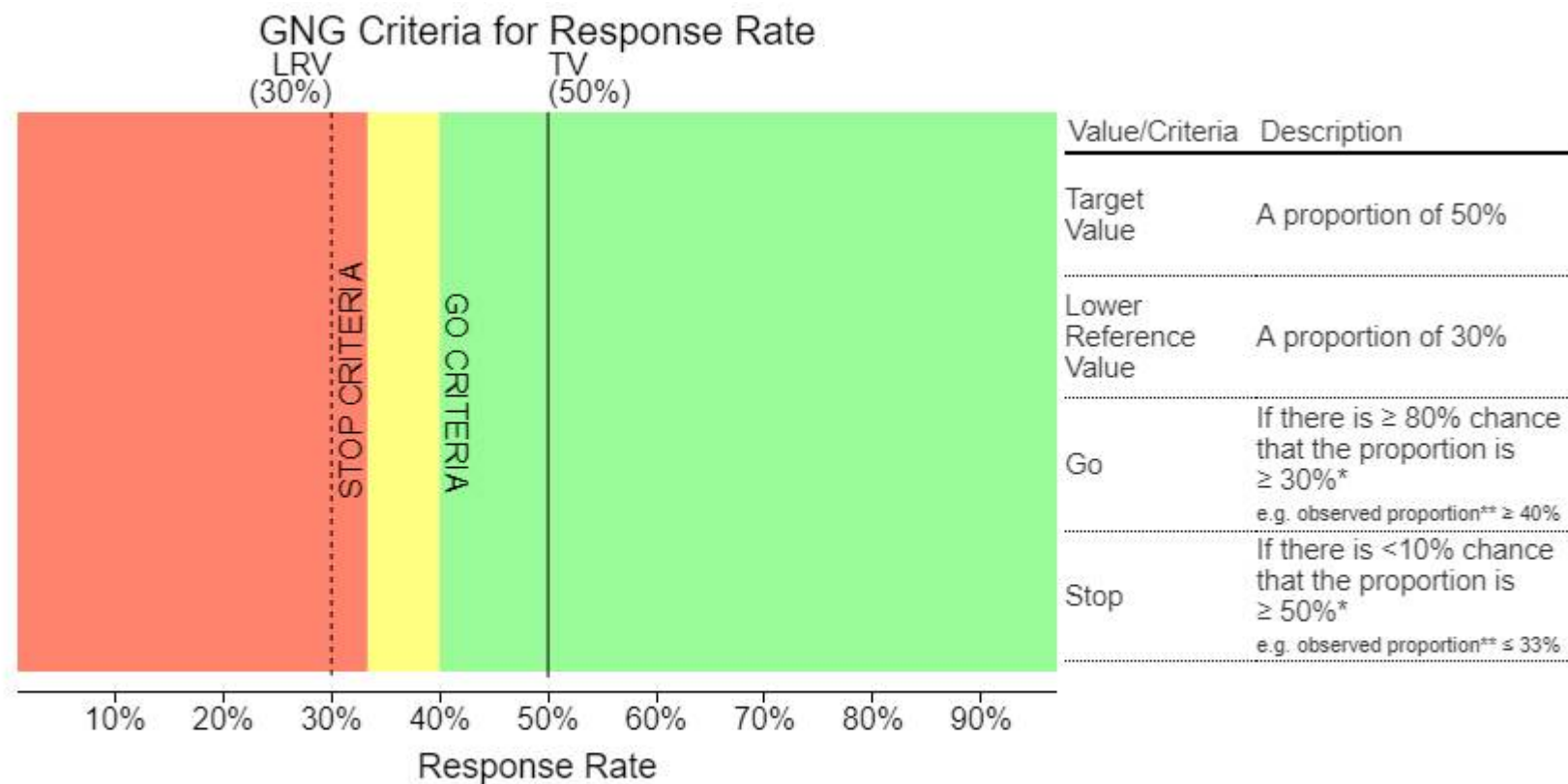


# Decision Error Probabilities



Lindborg et al (2014)

# Decision Making



\*\* Assuming 30 patients

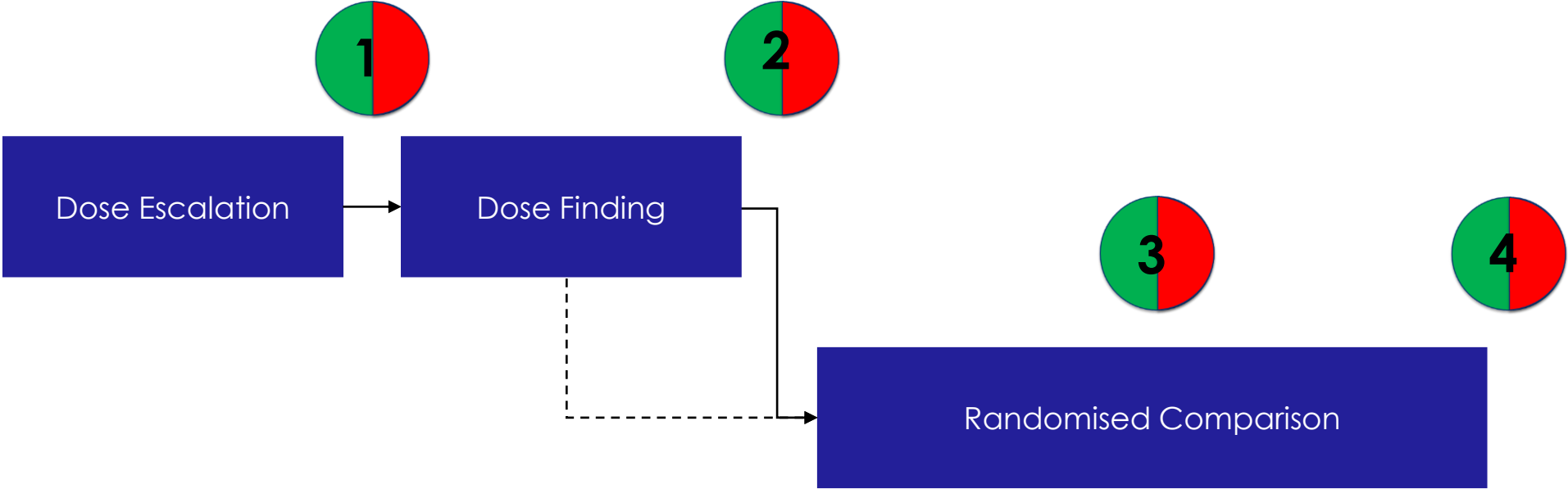
\* Stop and Go correspond to upper-limit of 1-sided 90% CI and lower-limit of 1-sided 80% CI

# Probability of Success

At the end of Phase 2, the following probabilities can be calculated to help in the decision to proceed to the Phase 3 stage

Probability	Definition
Technical Success	Probability of Phase3 study with a significant p-value
Technical and Regulatory Success	... and a clinically relevant treatment effect
Market Success	... that is better than the competitor product

# Clinical Development Decision Points



# Agenda

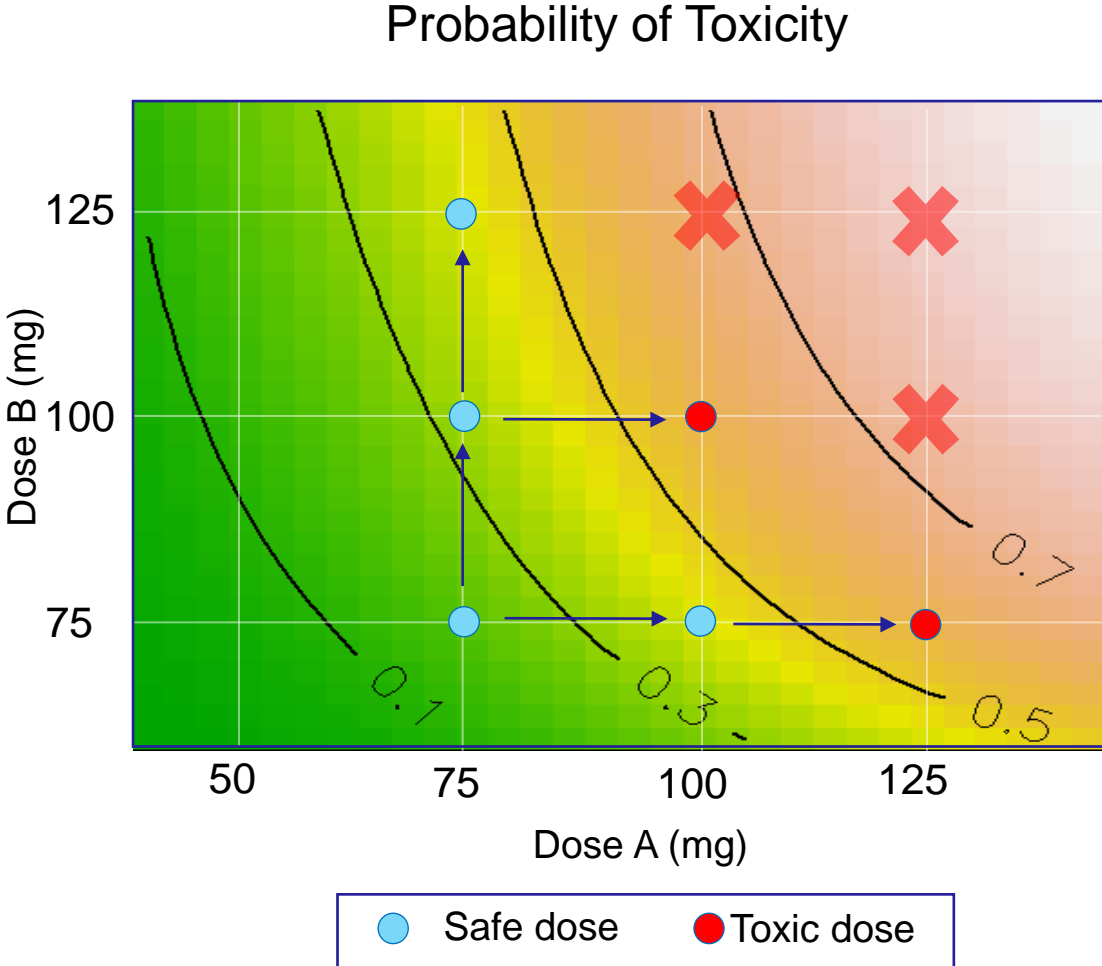
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# Combination Therapies

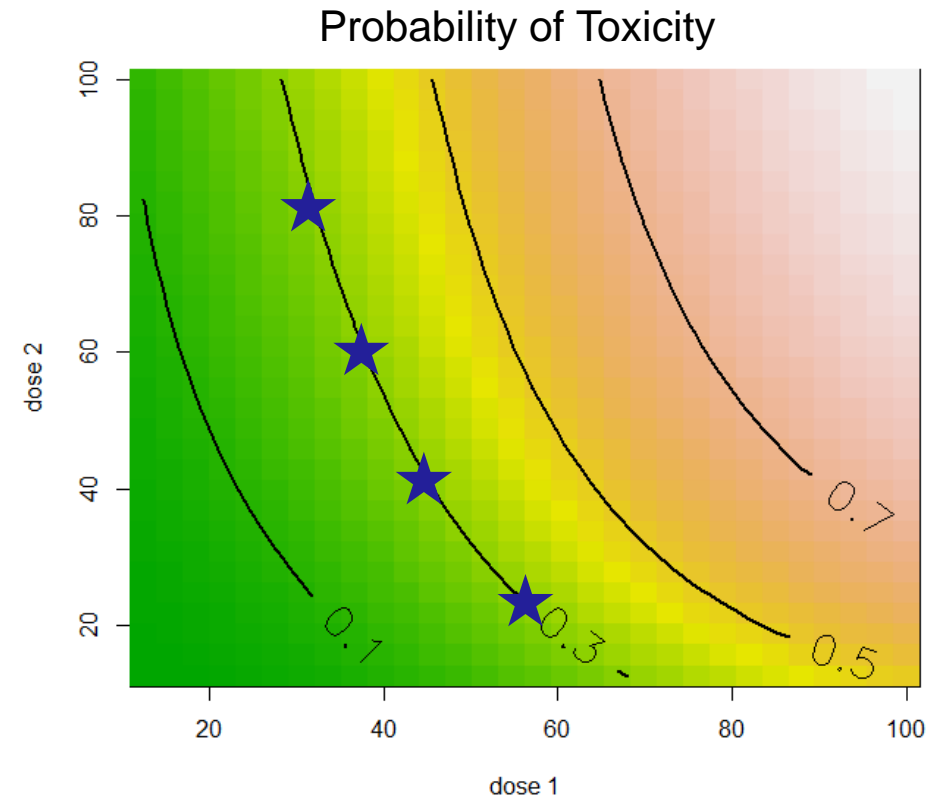
- Combination of two (or more) treatments to provide enhanced efficacy
  - Enhanced efficacy can also result in enhanced toxicity
  - Investigate overlapping toxicities
- One treatment is often new, and the other existing
  - Dose escalation with new treatment with fixed dose of standard
  - Dose escalation of both treatments
- Demonstration of correct doses and schedules are needed
- One treatment can influence the PKPD of the other treatment

# Escalation with Dual Agents



# Dose Escalation with Dual Agents

- Discover multiple dose combinations with similar safety for further exploration
- Then compare to get the best efficacy
- Use of historical data on the standard and all other data on new drug to improve escalation decisions





# Dose Escalation with Dual Agents

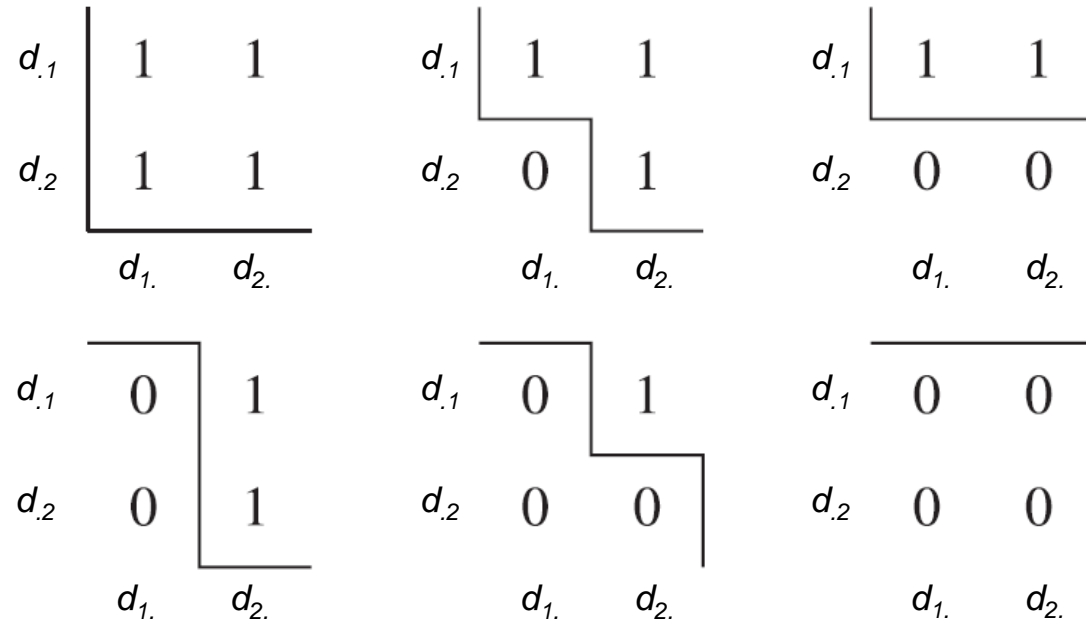
- One dimensional dose escalation
  - 3 parameter BLRM model:  $\text{logit}(p_i) = \ln(\alpha_i) + \beta \ln(x_j/x_{ref})$
- Fix each dose of A then escalate up doses of B (Yuan and Yin, 2008)
- Assume prior ordering, then do single dimension CRM (Kramar et al (1999))
- Logistic model with 6 parameters (Thall et al, 2003)
- Contour finding methods (Mander and Sweeting, 2015)
- Assumption of monotonicity is not unreasonable

# Product of Independent Probabilities (PIPE)

For dose combinations  $i, j$  assume

$$\pi_{ij} | a_{ij}, b_{ij} \sim \text{Beta}(a_{ij}, b_{ij}) \quad \forall i, j.$$

Assume monotonicity and then evaluate all possible contours  
(Mander and Sweeting 2015)



# Which Dual Agent Design?

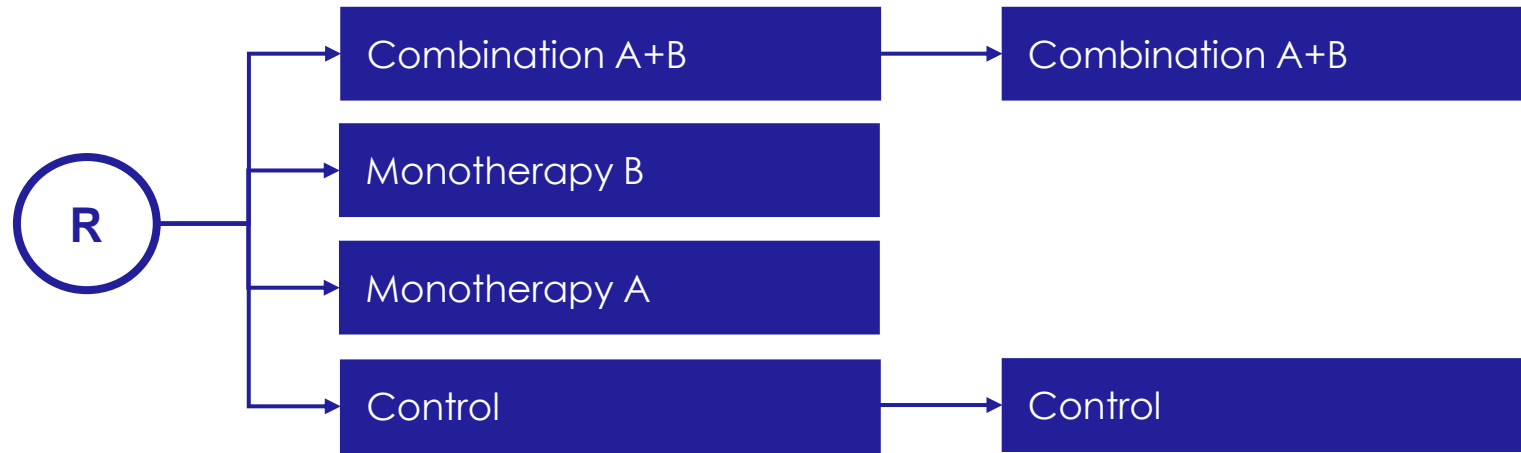
**Table 1** | Summary of features for various dual-agent dose escalation study designs

Study	Number of model parameters	Stages	Outcomes	Response values	Number of RP2D combinations
<i>Rule-based designs</i>					
Hamberg and Verweij (2009) <sup>57</sup>	–	1	Toxicity	Binary	1 or 2
Lee and Fan (2012) <sup>58</sup>	–	1	Toxicity	Binary	1 or 2
Huang et al. (2007) <sup>71</sup>	–	2	Toxicity and efficacy	Binary	0 or 1
Lee et al. (2008) <sup>59</sup>	–	2	Toxicity	Binary	1
<i>Model-based designs</i>					
Wang and Ivanova (2005) <sup>60</sup>	3	2	Toxicity	Binary	Minimum number of doses of drug A or drug B
Yin and Yuan (2009) <sup>62</sup>	3	2	Toxicity	Binary	1
Yin and Yuan (2009) <sup>63</sup>	3	2	Toxicity	Binary	1
Kramar et al. (1999) <sup>61</sup>	2	2	Toxicity	Binary	1
Su (2010) <sup>64</sup>	1	3	Toxicity	Binary	1
Thall et al. (2003) <sup>31</sup>	6	2	Toxicity	Binary	3
Mandrekar et al. (2007) <sup>73</sup>	6	1	Toxicity and efficacy	Binary (toxicity and efficacy)	1
Houede et al. (2010) <sup>77</sup>	21	1	Toxicity and efficacy	Ordinal (toxicity and efficacy)	1
Dragalin et al. (2008) <sup>79</sup>	8	2	Toxicity and efficacy	Binary, ordinal or continuous (toxicity and efficacy)	1
Whitehead et al. (2011) <sup>75</sup>	Between $K$ and $3K^*$	1	Toxicity and efficacy	Binary (toxicity and efficacy)	Trial dependent (0–9)
Conaway et al. (2004) <sup>68</sup>	$K$	2	Toxicity	Binary	1
Wages et al. (2011) <sup>70</sup>	$M^\dagger$	2	Toxicity	Binary	1
Wages et al. (2011) <sup>69</sup>	$M^\dagger$	1	Toxicity	Binary	1
Braun and Wang (2010) <sup>80</sup>	6	1	Toxicity	Binary	1
Bailey et al. (2009) <sup>67</sup>	$\geq 3^{\S}$	1	Toxicity	Binary	1

\*Number of parameters depends on the choice of discrete values for the dose-escalation model. <sup>†</sup>Two parameters required for  $M^\dagger$ . <sup>‡</sup>One parameter for  $K$ , number of combinations;  $M$ , number of simple orders;  $F$ , number of combinations. <sup>§</sup>One parameter for  $\geq 3^{\S}$ . Abbreviations:

Harrington et al (2013)

# Seamless Phase 2a/b Combination Design



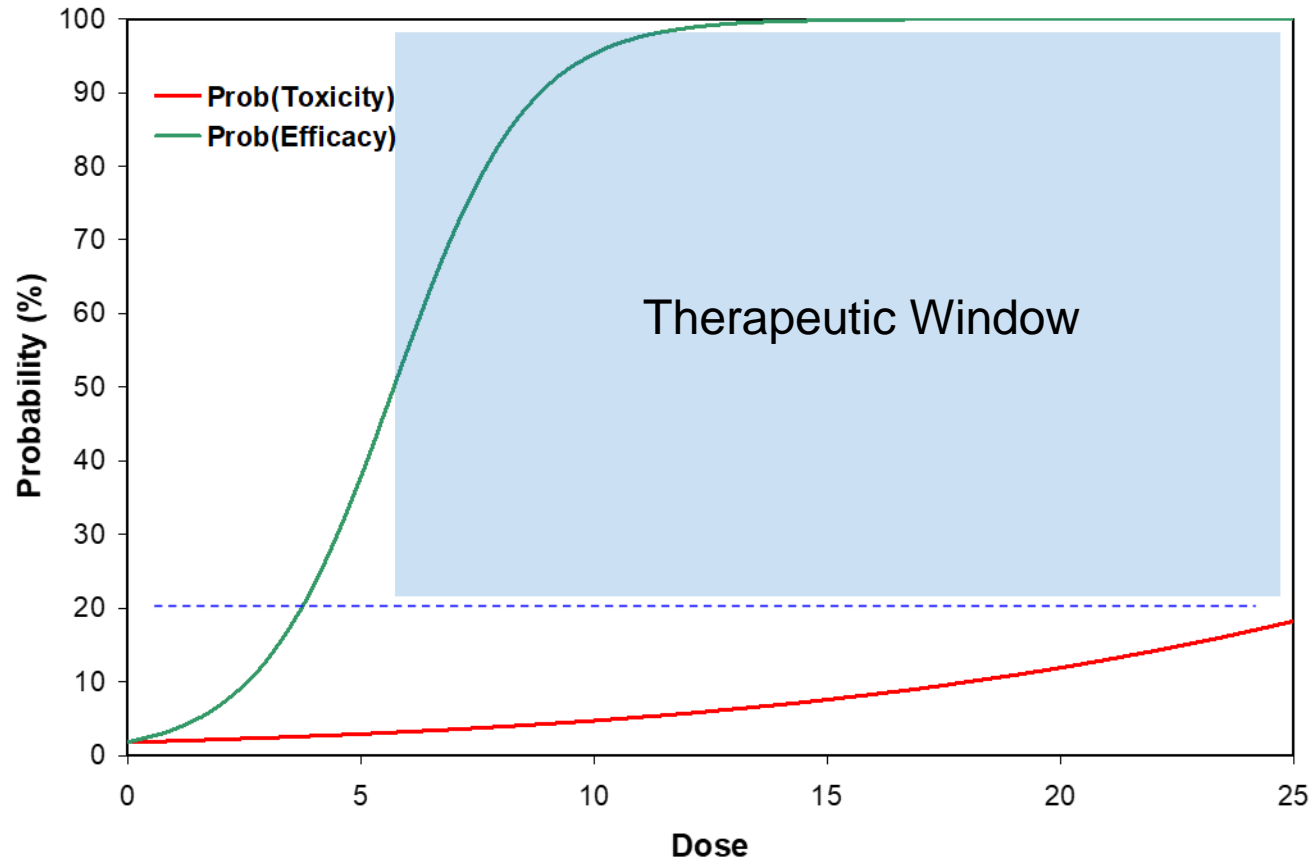
- Regulators require demonstration of contribution of components
- Minimise number of patients exposed to monotherapies
- Can use Historical Data for the established monotherapy
- Use unequal randomization ratios
- Adaptive dose dropping based on futility at interim

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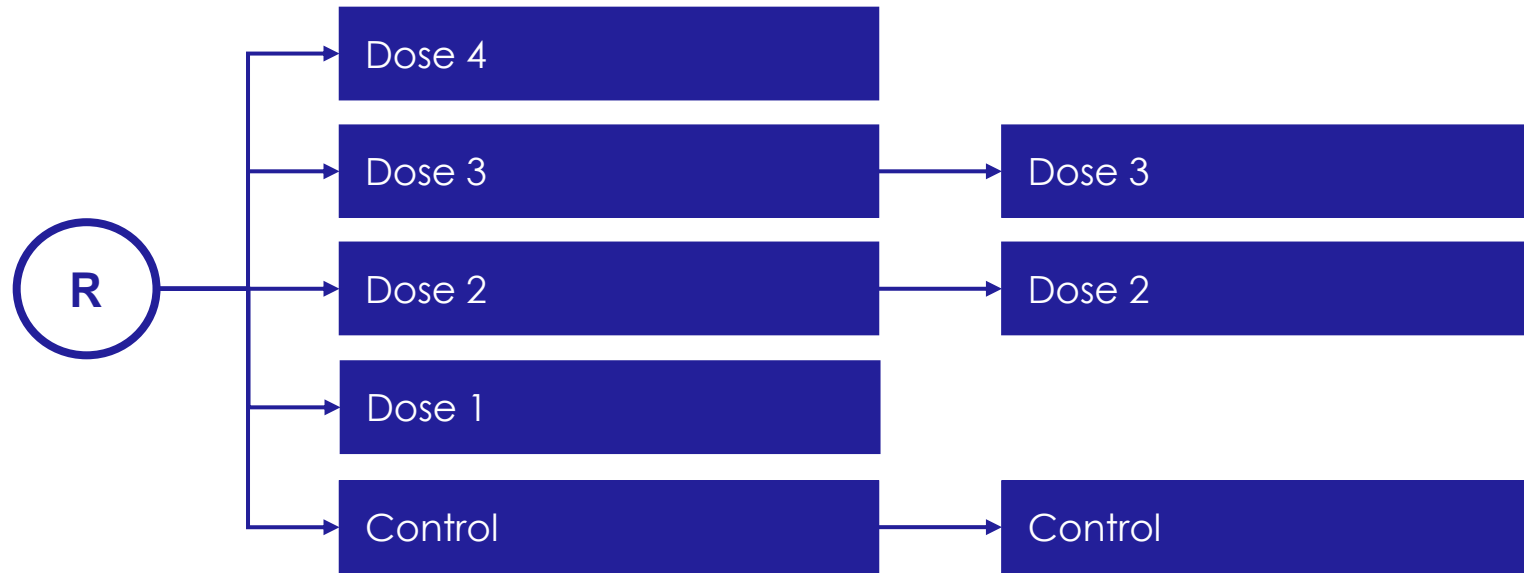


# Dose Finding



Questions: What is the minimum effective dose?  
What is the dose that gives the desired efficacy?

# Seamless P2a/b Dose Response Design



- Model-based dose response is now preferred and should now be our standard approach to proposing doses for phase 3
- Uses fewer resources to get to dose decisions
- In most cases the form of the dose response model is known
- Current thinking is that Phase 2A should begin with 4-8 doses groups, covering an 80-fold range of doses. In phase 2b the number of dose groups should reduce to 2-4.

# Dose-Response Studies

## Establish Proof-of-Concept (PoC)

- Change in dose  desirable change in endpoint of interest

## Dose finding step

- Select one (or more) “good” dose levels for confirmatory Phase III once PoC has been established



# Traditional Approach

**Proof-of-Concept: Conducted using (multiple) active arms and control**

**Selection of Target Dose:**

1. statistically significant at the proof-of-concept stage
2. smallest of statistically significant doses but also clinically relevant

**Dose-Response Modeling:**

1. use data from PoC and earlier trials
2. find a statistical model capturing the effects of target dose on dose-response

# Modern Approaches to Dose Finding

## Traditional ANOVA

### Design Focused

- Adaptive Bayesian Modelling
- D-Optimality

### Analysis Focussed

- Multiple Testing Procedures
- MCP-Mod
- Bayesian Model Averaging

# Multiple Testing Approaches

- Pairwise comparison of each dose to control
- Aim to control Type 1 Error

Parametric	P-Value
Dunnett's single step	Bonferroni
Dunnett's step-down	Sidak
Dunnett's step-up	Holm step down
	Weighted Bonferroni
	Hochberg's step up
	Hommel's step up



# Bayesian Adaptive Model

Phase 2A: Doses = 0, 1, 3, 10, 30, 100, 300, 600

5 pts/dose group

Sigmoidal Emax Model

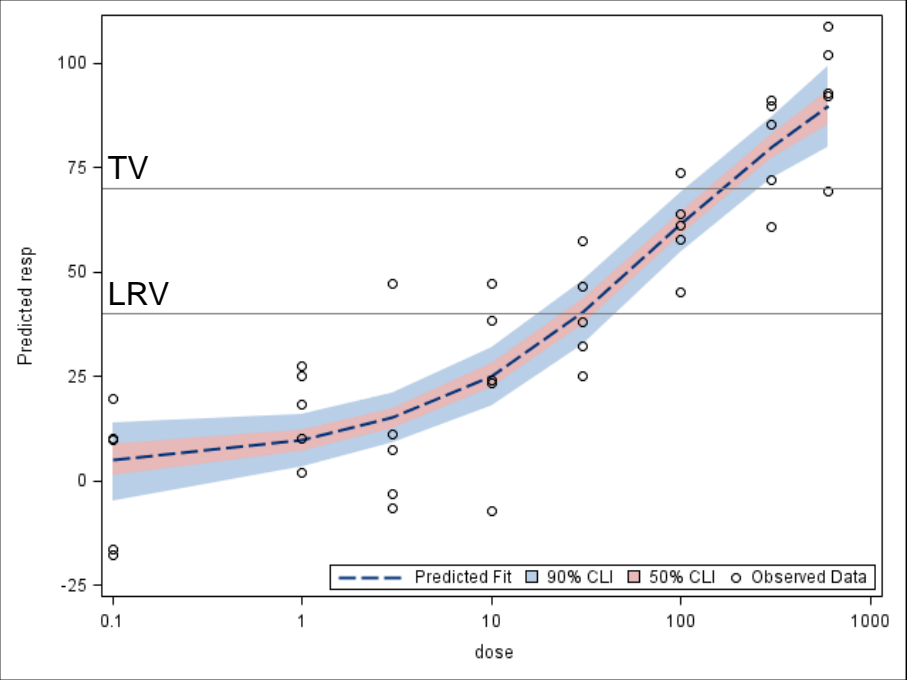
$$y = e_0 + e_{\max} \frac{dose^h}{dose^h + ED50^h}$$

Prior information available

Parameter	Prior	
hill	$Ln(h) \sim N(0,0.53^2)$	Median=1.0 90%CL(0.1,10)
ED50	$Ln(ED50) \sim N(1.3,0.53^2)$	Median=50 90%CL(1,500)
Placebo	$e_0 \sim N(0,100^2)$	Uninformative
Max Effect	$e_{\max} \sim N(0,100^2)$	Uninformative

# Bayesian Adaptive Model: Example

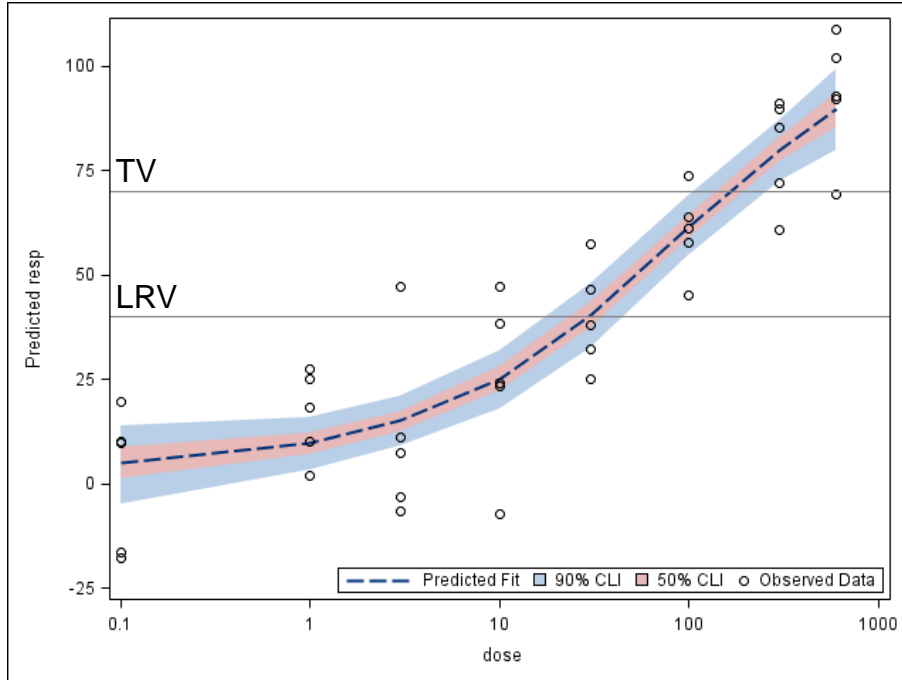
## Interim



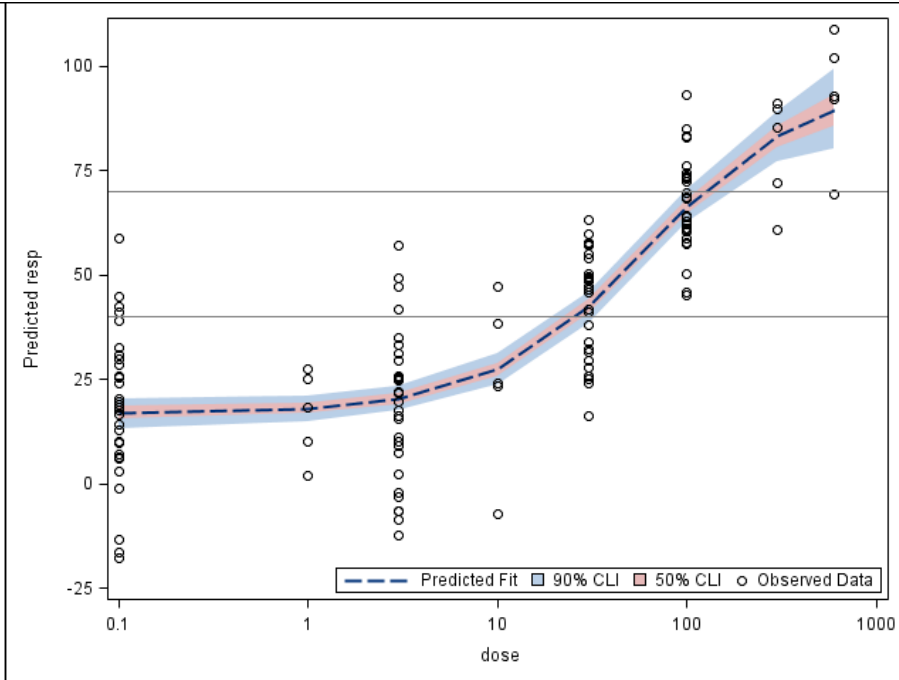
- Optimisation**
- D-Optimality
- C-Optimality
- ED50
- MED
- Target Response

# Bayesian Adaptive Model: Example

Interim

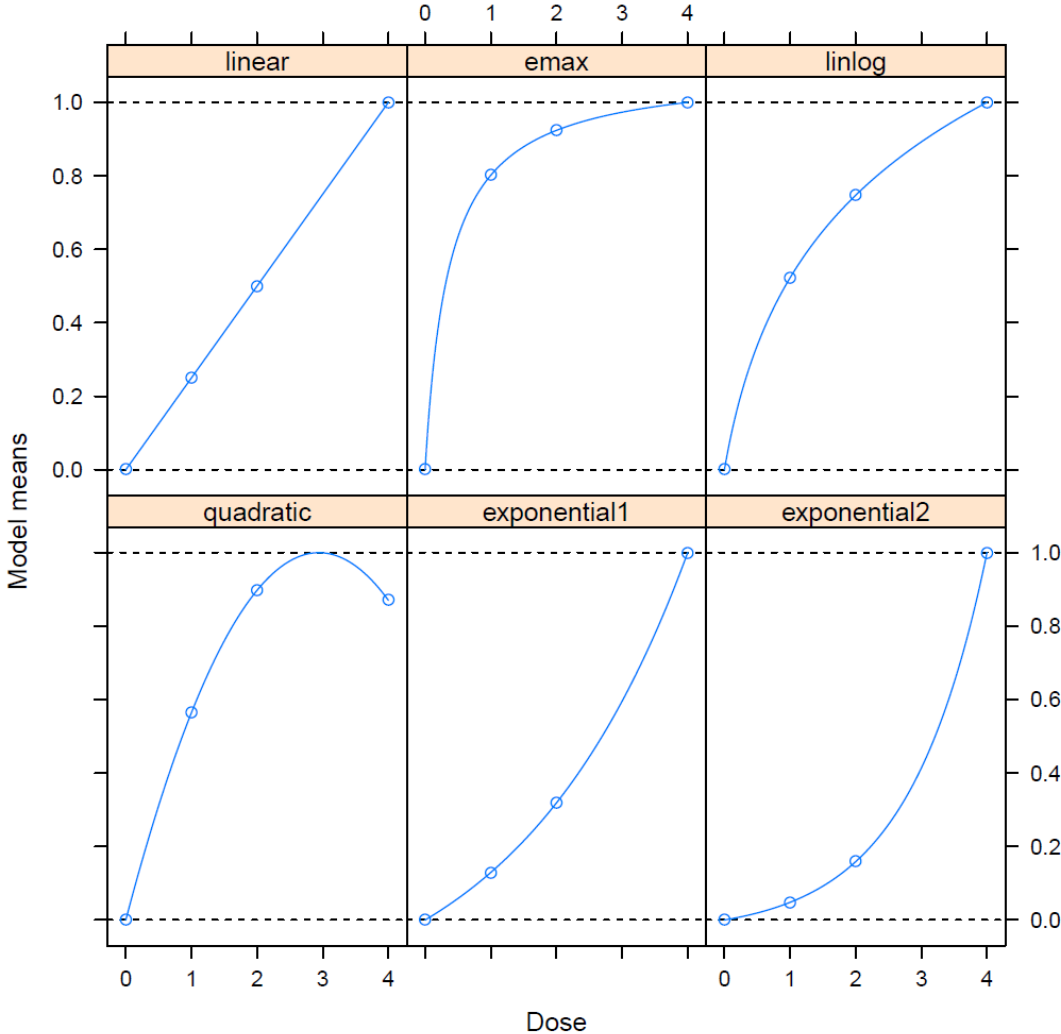


Final



**Optimisation**  
D-Optimality  
C-Optimality  
ED50  
MED  
Target Response

# Candidate Dose Response Models



# MCP + Mod = MCPMod

## Design Stage

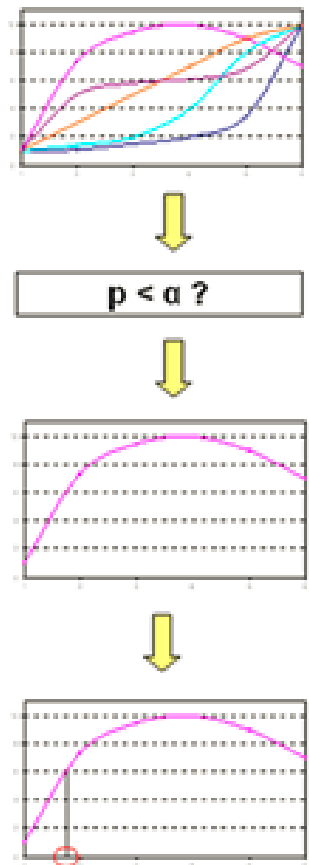
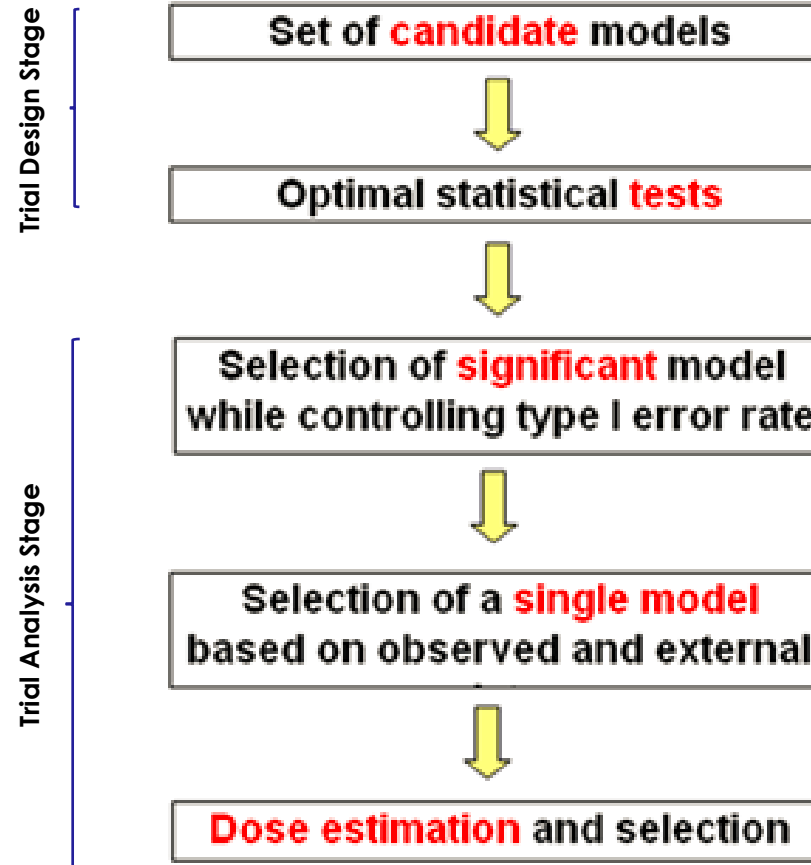
- Pre-specification of candidate dose-response models

## Analysis Stage (MCP-step)

- Statistical test for dose-response signal. Model selection based on significant dose response models

## Analysis Stage (Mod-step)

- Dose response and target dose estimation based on dose-response modeling





# MCP-Mod Regulatory Opinion

CHMP: First opinion issued in 2010, since then 12 qualification opinions (biomarkers, technologies/devices, simulation models)

MCP-Mod first statistical methodology qualified

FDA: Issued its Fit-for-Purpose (FFP) designation for guiding dose selection for Phase III testing.

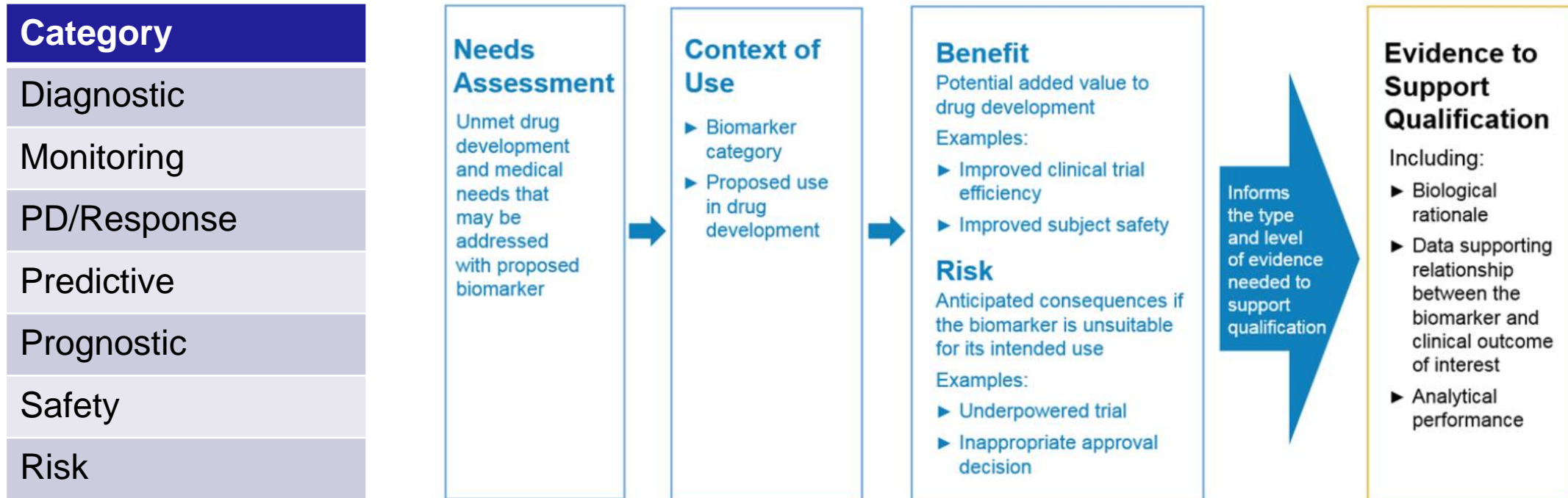
<https://www.fda.gov/downloads/Drugs/DevelopmentApprovalProcess/UCM508700.pdf>

# Agenda

- Background
- Dose Escalation
- Decision Making
- Combination Studies
- Dose Finding
- **Enrichment**
- Q&A



# Biomarker Development



# Biomarker Development

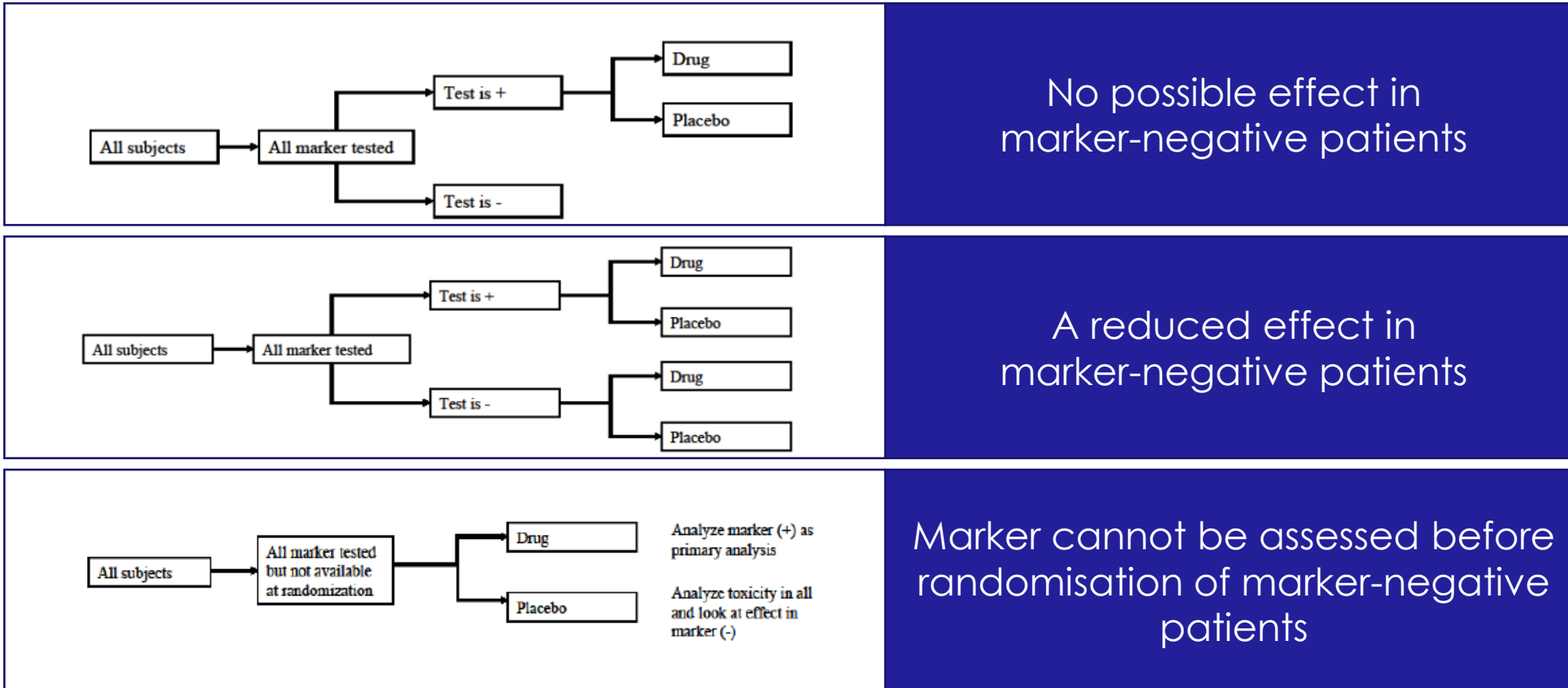
Regulatory guidance exists on the validation of biomarkers

Diagnostic Biomarker

- Adaptive biomarker threshold setting

Population enrichment assessed using Adaptive Enrichment Design

# Diagnostic Biomarker Designs



# Studying Marker-Negative Patients

When the treatment represents an important advance for the marker-positive group, delaying approval because of limited data in the marker-negative group would generally be unreasonable

Determining the need for marker-negative data will be based on:

- the nature of the efficacy shown in the marker-positive population
- the risks of the drug
- whether the effect of treatment would be apparent to an individual patient
- the relative sizes of the marker-positive and -negative populations
- the desire to use the drug in the marker-negative

# Population Enrichment

*Prospective use of any patient characteristic to obtain a study population in which detection of effect is more likely than in unselected population*

## Types of PE

- Prognostic: identify high risk patients based on biomarkers
- Predictive: identify patients more likely to respond

## Importance

- Help identify highly responsive group, detect treatment effect with smaller sample size
- Failed molecules from one study, may succeed in a different group

## Example

- BMS immunotherapy Opdivo failed in lung cancer study whereas Merck competitor Keytruda succeeded: In later case study population was enriched by including only subjects with high level of PD-L1

# Method and Assumptions

Study population: divided in two groups based on a predefined biomarker

Study will materialize into two independent cohorts

- First cohort recruits from full population
- Second cohort recruitment depends on an interim analysis based on the first cohort data only

At interim:

- Continue with full population
- Continue with sub-population
- Stop the trial for futility

Subpopulation prevalence will be user-specified



# Case study: The TAPPAS trial

Angiosarcoma is an orphan disease

Poorly addressed by current treatments

- Pazopanib a VEGF inhibitor shows modest benefit
- TRC105 can compliment Pazopanib by inhibiting endoglin, a different angiogenic target

Adaptive trial considered optimal due to:

- Small population (1800 cases/year in US)
- Limited prior data
- Greater benefit possible with TRC105 for cutaneous vs visceral tumors

# The TAPPAS trial

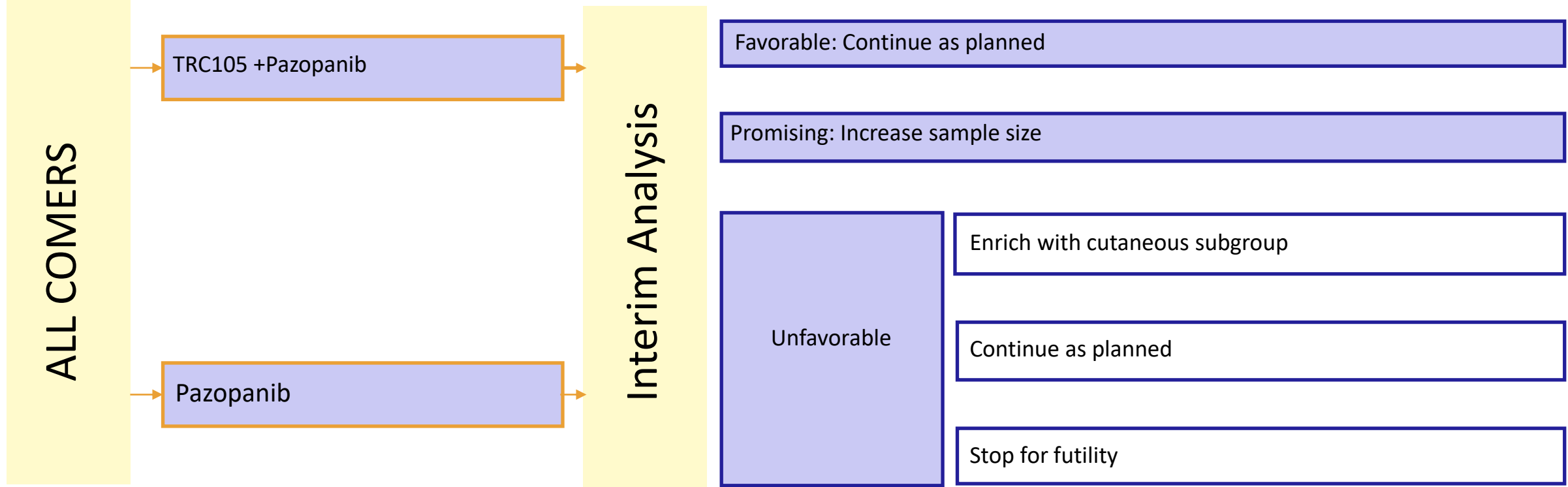
## Objective

Demonstrate superior PFS of TRC105 + pazopanib vs pazopanib alone

## Population

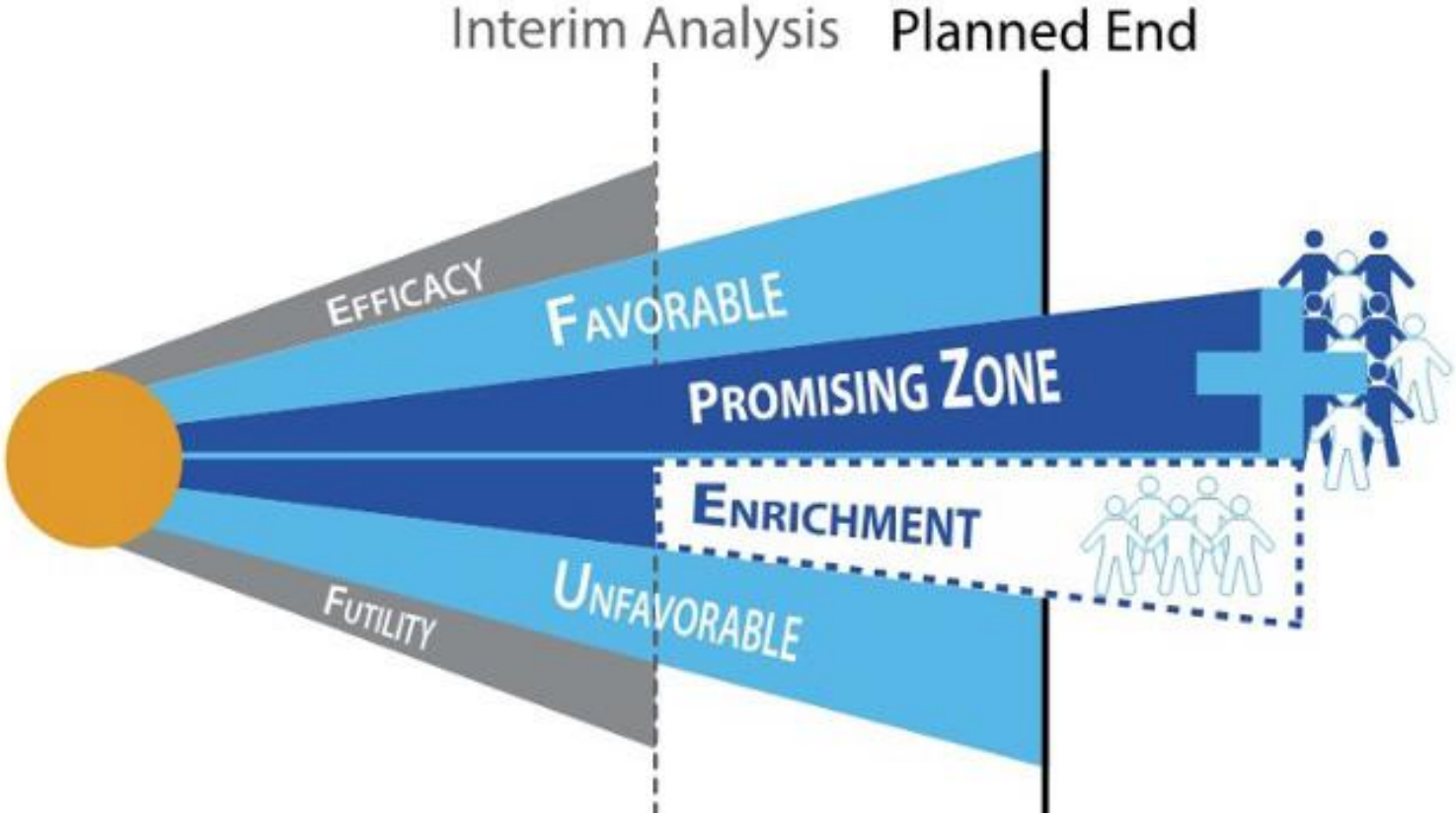
Overall, or in the cutaneous subgroup

# Two-Stage Design with SSR and Enrichment



$p_1$ : p-value for data from cohort 1  
 $p_2$ : p-value for data from cohort 2

# Adaptive Population Enrichment



# Analytical Approach

## Interim Analysis

$p_{int} < p\text{-stop}$

$C_p < C_p(\text{fut})$

$C_p < C_p(\text{min})$

$C_p(\text{min}) \leq C_p < C_p(\text{max})$

$C_p \geq C_p(\text{Max})$

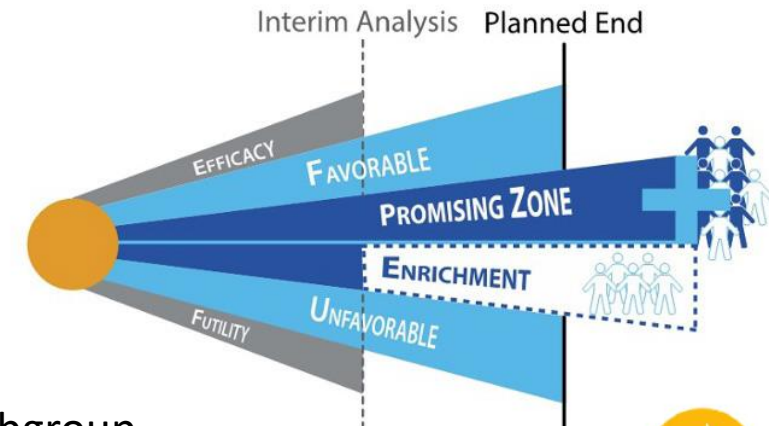
**Efficacy Zone.** Recommend stopping for efficacy

**Futility Zone.** Recommend stopping for futility

**Unfavourable Zone.** If  $C_p^s > C_p(\text{enrich})$  Enrich for subgroup

**Promising Zone.** The results are currently in the 'promising zone'. Increase sample size to achieve a conditional power of  $C_p(\text{max})$ .

**Favourable Zone.** Continue to the planned sample size as the results are currently 'favourable'



## Final Analysis

Based on combination of p-values

$p_1^F$ : p-value for full data from cohort 1

$p_2^F$ : p-value for full data from cohort 2

$p_1^S$ : p-value for full data from cohort 1

$p_2^S$ : p-value for full data from cohort 2

# Preserving Type I Error

Let  $H_0^F$  and  $H_0^S$  denote the null hypotheses for the full population and the subgroup respectively

Let  $H_0^{FS} = H_0^F \cap H_0^S$  denote the global null hypothesis

Closed testing principle states that type I error is strongly controlled as long as

- Each of the hypotheses in the closed family is tested at local level- $\alpha$
- $H_0^F$  significant only if both tests for  $H_0^F$  and  $H_0^{FS}$  are significant at local level- $\alpha$
- $H_0^S$  significant only if both tests for  $H_0^S$  and  $H_0^{FS}$  are significant at local level- $\alpha$

# TAPPAS Design

Adaptive design was smaller than the fixed design option (N=125 vs 200)

Adaptive design provides

- Greater power
- Smaller sample size
- Shorter duration

# Enrichment Summary

- Population Enrichment should be considered if there is a strong chance of an enhanced treatment effect in an easy to define subgroup at baseline
- It potentially enriches for the subgroup after the interim analysis
- The adaptation needs to be pre-defined in the protocol
- The timing of the interim analysis requires careful planning
- Thorough simulation of the design is necessary to understand the operating characteristics



# Conclusions

## Adaptive design in early phases

- accelerates clinical development
- reduces costs
- reduces sample size
- reduces time
- better dose selection
- enhances subgroup detection
- introduces decision points
- involves evidence-based decision making
- need careful planning

# Questions?

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