

Flexibility in Clinical Trial Design using Software in combination with R Code: Incorporating Bayesian Treatment Resistance Assumptions

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Who we are

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Considerations in Clinical Trial Design



Simulation-Guided Design

A means to assess trial performance given <u>specific</u> assumptions

- Trial design software
 - Validated design workflows and analysis types
 - Turnkey operation
 - Industry-accepted tools
- Custom coding
 - Allows for flexibility in methods and analysis types
 - Requires coding skills and validation
 - Increased regulatory acceptability

What if assumptions are uncertain?

Trusted capabilities of **traditional software + flexible R** code can offer a more comprehensive assessment than either option alone



A Case Study

Basic Study Design

Parameter	Inputs
Endpoint Type	Binary
Follow-Up Time	12 months
Planned Sample Size	400
One-Sided Type-1 Error	0.025
Control Proportion	0.20
Treatment Proportion	0.45
Enrollment Rate	Poisson Arrival Assumption

Design Variations

Parameter	Inputs
Endpoint Type	Binary
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Enrollment Rate	Poisson Arrival Assumption

Parameter	Inputs
Treatment Resistance Assumptions	0% , 20%, 40%
Treatment Difference	0.1, 0.15, 0.2, 0.25 , 0.3
Planned Sample Size	400 :500:5

Methods Two-Step



Analyzing a frequentist go/no-go decision using a simplified limits of confidence interval design



Using posterior probabilities for a Bayesian simulation of a mixture distribution of treatment effect with varying treatment resistance assumptions



About <u>CyneRgy</u>

With the enablement of R connectivity in its Software, Cytel's Innovation Group has created a dedicated, continuously updating resource library with compatible code examples and templates for edit and use in Cytel Software. The resource is available on GitHub

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···· </>= Includes code templates and all relevant documentation

An open-source tool to allow variation and additions



Go/No-Go Decision Using Limit of Confidence Interval

Analyzing a frequentist go/no-go decision rule

In this example of upper and lower confidence boundary designs, if it is likely that the treatment difference is above the **Minimum Acceptable Value (MAV)** then a **Go decision is made**. This is the case if the Lower Limit of the CI, denoted by LL, is greater than the user specified dLowerLimit.

If a Go decision is not made, then if it is unlikely that the treatment difference is above the **Target Value (TV)** a **No-Go decision is made**. This is the case if the Upper Limit of the Cl, denoted by UL, is less than user-specified dUpperLimit.



Visualizing the Decision Framework



Go if : $PCT_{10} > MAV$ and $PCT_{90} > TV$

Consider if: PCT₁₀≤MAV & PCT₉₀> TV

Stop if : $PCT_{10} \le TV$

where PCT_x denotes the x-th percentile of P (Δ)

Go: Lower Confidence Limit (LCL) above MAV

Stop: Upper Confidence Limit (UCL) below TV

If both happen at final analysis, stop rule takes precedence

Mixture Distribution for Patient Simulation

For this study, the patient outcome is binary where a value of 0 represented a treatment failure/**non-response**, and a value of 1 represented **response**.

There is an unknown proportion of patients who are treatment-resistant and will not respond to treatment, and thus, have an outcome of 0. Using historical data, it is estimated that the proportion of non-responders is between 20% and 40%.

An R function is inserted to explore the proportion of patients that are treatment resistant and the impact on expected study power.

Analysis using a frequentist go/no-go decision rule, but sampling patient data using a mixture distribution with a fixed non-responder rate or assuming a prior distribution for the non-responder rate.



Procedure Details

A binomial distribution is utilized to simulate if the patient is treatment resistant. If the patient is not treatment resistant, then their outcome is simulated from a binomial distribution with the response in East Horizon and sent to R. In the East Horizon Inputs:

1. Prob(0) = 0, Assume that no patients are treatment resistant

2. Prob(0) = 0.2, assumes 20% of patients are treatment resistant

3. Prob(0) = 0.4, assumes 40% of patients are treatment resistant

4. Prob(0) ~ beta (a, b) – depending on what historical data suggests, could be treatment armspecific

Parameter	Inputs
Treatment Resistance Assumptions	0%, 20%, 40%
Treatment Difference	0.1, 0.15, 0.2, 0.25, 0.3
Planned Sample Size	400:500:5

Results – Original Study Design

No Treatment Resistance						
Treatment Effect	Null	0.1	0.15	0.2 (expected)	0.25	0.3
Power	0%	26%	62%	90%	99%	100%

20% Treatment Resistance						
Treatment Effect	Null	0.1	0.15	0.2 (expected)	0.25	0.3
Power	0%	19%	48%	80%	96%	100%

40% Treatment Resistance						
Treatment Effect	Null	0.1	0.15	0.2 (expected)	0.25	0.3
Power	0%	17%	36%	64%	85%	95%

Simulations of the original study design demonstrated that as the proportion of nonresponders increased, the observed treatment effects diminished, leading to reduced probability of success.

Designs with a larger sample size showed improved study power.

Heatmap Depicting Simulation Results (Score)



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Cost

Strategic

Goals

Study Duration

Power

Heatmap Depicting Simulation Results (Power)



Heatmap Depicting Power Threshold (90%)



Summary

- Simulation-guided design relies on confident assumptions
- Uncertainty can be mitigated via an iterative process of simulation
- Design software + custom code allow for reliability & flexibility
- Analysis can be extended with either Bayesian or Frequentist approaches

Examples:

Prior distributions for treatment response rate; treatment resistance rates; Bayesian assurance; etc.









Thank you!

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References

Cynergy Packages Used:

<u>AnalyzeUsingPropLimitsOfCI()</u>

Analyze using a simplified limits of confidence interval design.

<u>SimulatePatientOutcomePercentAtZero()</u>

Simulate patient outcomes from a normal distribution with a percent of patients having an outcome of 0.

- Developed by J. Kyle Wathen, Valeria A. G. Mazzanti.