

Group Sequential Designs and Sample Size Re-estimation – Modern Uses

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Group Sequential Designs and Sample Size Re-estimation – Modern Uses

Agenda:

Group Sequential Methods:

- Challenges of Traditional Designs and Benefits of Group Sequential Methods
- Method Theory
- Case Studies
- Design Options and Discussion

Sample Size Re-estimation

- Challenges of Traditional Designs and Benefits of Sample-Size Re-estimation Methods
- Method Theory
- Case Studies
- Discussion

Factors to Consider and Summary

Q&A

Conclusion

Group Sequential Design
Challenges of Traditional Design and
Benefits of Advanced Methods

Why Use Group Sequential Methods?

I shall focus on the design of
Phase 3 trials. These studies are

- A critical step on the way to drug approval
- Large and expensive

**A group sequential design can
reduce the length of a Phase 3 trial**

- Saving resources
- Reaching a conclusion sooner

Group Sequential

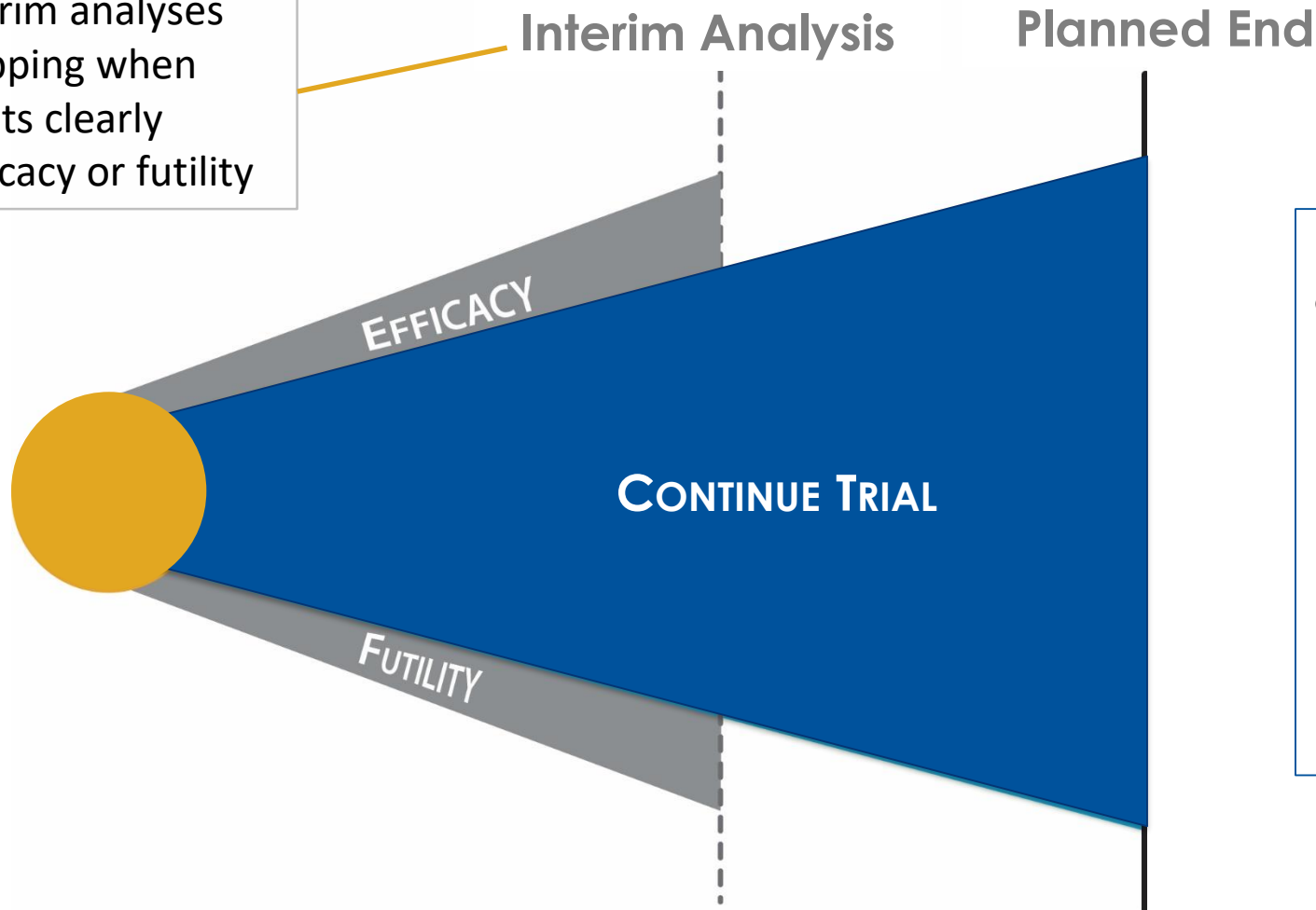


Fixed Sample



Group Sequential Design Can Reduce Sample Size And Duration, Conserving Resources & Accelerating Development

Pre-planned interim analyses enable early stopping when preliminary results clearly demonstrate efficacy or futility



Designs with 2 or 3 analyses and a maximum sample size 5% or 10% greater than the fixed sample test can **reduce expected sample size by around 30%** versus fixed designs.

What Do Group Sequential Methods Offer?

Consider A Phase 3 Trial with

- Type I error rate $\alpha = 0.025$,
- Power 0.9 at treatment effect $\theta = 1$

Fixed Sample Size Design:

100 patients per treatment

Group Sequential Trial, 3 Analyses:

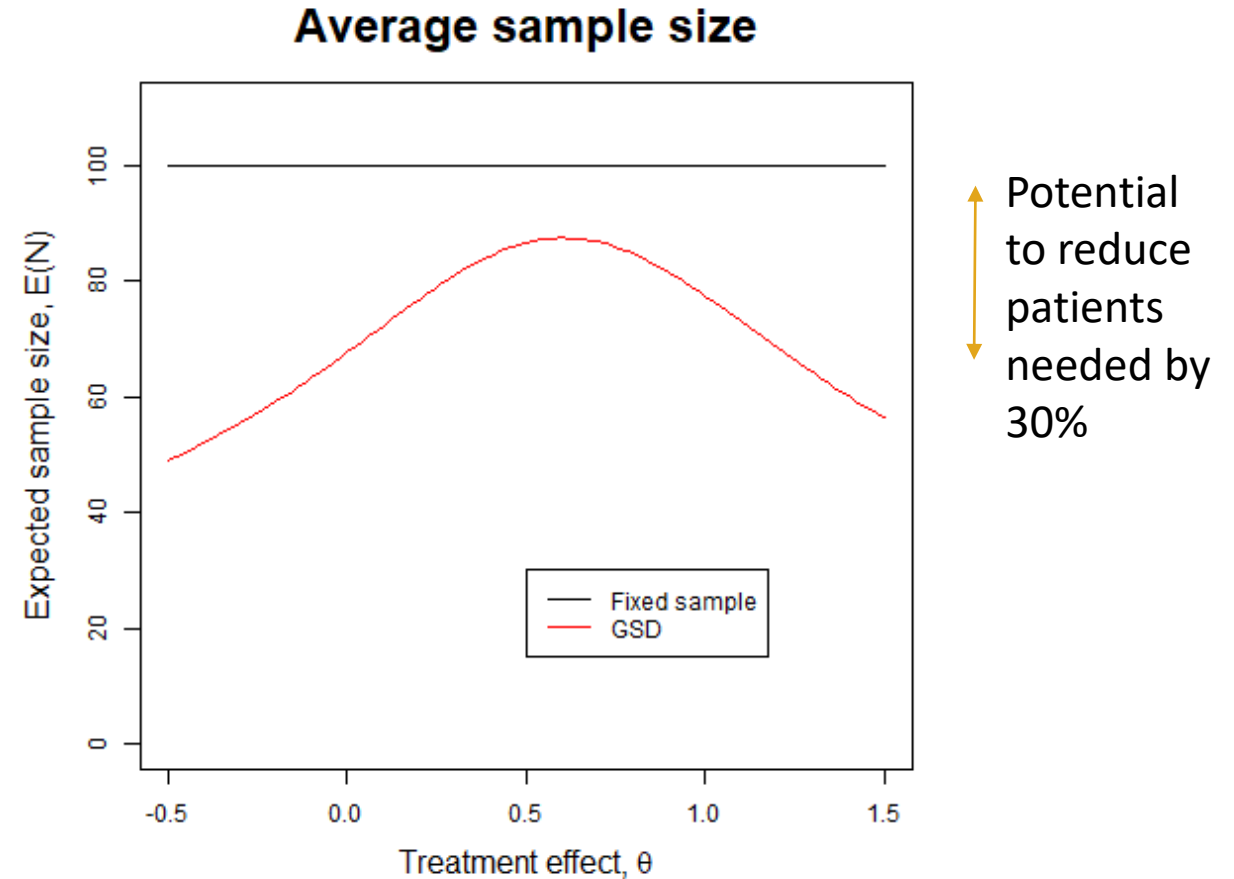
Up to 105 patients per treatment

Group Sequential Trial has expected sample size $E(N)$:

66 at treatment effect $\theta = 0$

87 at treatment effect $\theta = 0.5$

77 at treatment effect $\theta = 1$



Poll Question

Do you use Group Sequential designs?

A: No

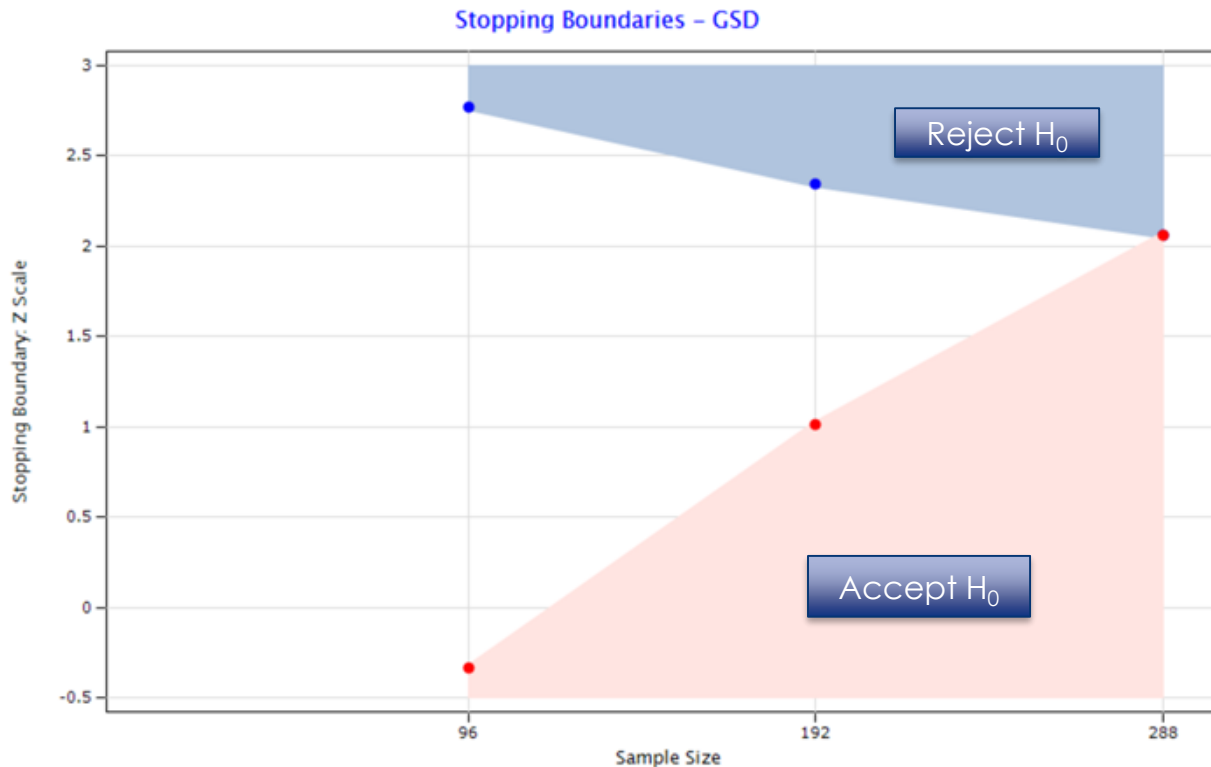
B: Yes, but only rarely

C: Yes



Group Sequential Design *Method Theory*

How Do Group Sequential Tests Work?



Note:

Z_k is a measure at analysis k of the evidence against the null hypothesis H_0 , which states that the new treatment is no better than the control.

The boundary is chosen so that

- Type I error rate is $\alpha = 0.025$
Note: Multiple testing can inflate Type 1 error, so the boundary is set to avoid this
- Power is 0.9 at treatment effect $\theta = \delta$

At each analysis, we calculate the Z -statistic for testing H_0 :
 $\theta \leq 0$ vs $\theta > 0$

We stop the trial when this statistic crosses a boundary

How Do Group Sequential Tests Work?

Underpinning Theory

The joint distribution of the sequence of Z -statistics has a standard form for many different response distributions, including survival data.

Computation

Type I error probability and power are computed by numerical integration – which is fast and accurate.

Software

is available to implement these methods

Error Spending Group Sequential Tests

Sample size or, more generally, observed information, is unpredictable.

In an *error spending* design, we define boundaries at each analysis so that the cumulative type I and type II error probabilities are equal to a certain function of the observed information.

Here, the information for the treatment effect, θ , at analysis k is defined as

$$I_k = \frac{1}{\text{Var}(\hat{\theta}_k)},$$

where $\hat{\theta}_k$ denotes the estimated treatment effect at this analysis.

Group Sequential Design

Case Studies

Example: A Trial For A Cholesterol Lowering Drug

To Compare
Experimental
treatment vs
placebo control

Endpoint
Reduction in serum
cholesterol (mg/dL)
after 4 weeks

Responses
Normally distributed
with standard
deviation $\sigma = 25$

Treatment Effect
 $\theta =$ Difference in
mean response
between treatments

Example: A trial for a cholesterol lowering drug

First, consider how you would design a fixed sample trial.

We wish to $H_0: \theta \leq 0$ vs $\theta > 0$ with type I error rate $\alpha = 0.025$

We observe responses from n patients on each treatment arm,
compute the Z -statistic,

and reject H_0 if this is significant at level 0.025.

(For simplicity we assume σ known: in practice, we would use a t -test.)

In order to achieve power 0.9 when $\theta = 10$, we find we need a sample size of

$$n_{fix} = 132$$

subjects on each treatment.

Example: A Trial For A Cholesterol Lowering Drug

In creating a group sequential design, we specify

- 3 analyses (2 interim analyses, 1 final analysis)
- An error spending design, spending error in proportion to Information²
- A non-binding futility boundary

This design has an “Inflation factor” of 1.093, so we shall need up to $1.093 \times 132 = 144$ patients per treatment arm.

Demonstration of East Software

Cholesterol Study:

- A fixed sample size design
- Group sequential design
- Interim analyses: Data entry and boundary calculation
- Simulating the group sequential design

	Ex:GSD	Ex:Fixed Sample
Mnemonic	MN-2S-DI	MN-2S-DI
Test Parameters		
Design Type	Superiority	Superiority
No. of Looks	3	1
Test Type	1-Sided	1-Sided
Specified α	0.025	0.025
Attained α	0.024	
Power	0.901	0.9
Model Parameters		
Allocation Ratio (n_t/n_c)	1	1
Input Method	Individual Means	Individual Means
Diff. in Means ($\delta = \mu_t - \mu_c$)	10	10
Mean Control (μ_c)	0	0
Mean Treatment (μ_t)	10	10
Std. Deviation (σ)	25	25
Test Statistic	Z	Z
Boundary Parameters		
Spacing of Looks	Equal	
Efficacy Boundary	Rho (2)	
Futility Boundary	Rho (2) (NB)	
Sample Size		
Maximum	288	263
Expected Under H0	169.642	
Expected Under H1	198.33	

Design Type: Superiority Number of Looks: 1

Test Parameters

Test Type: 1-Sided Input Method: Individual Means Test Statistic: Z

Type I Error (α): 0.025

Power: 0.9

Sample Size (n): 263

Allocation Ratio (n_t/n_c): 1

Specify Mean Responses

Mean Control (μ_c): 0

Mean Treatment (μ_t): 10

Std. Deviation (σ): 25

Design Type: Superiority Number of Looks: 3

Test Parameters Boundary

Test Type: 1-Sided Input Method: Individual Means Test Statistic: Z

Type I Error (α): 0.025

Power: 0.9

Sample Size (n): 288

Allocation Ratio (n_t/n_c): 1

Specify Mean Responses

Mean Control (μ_c): 0

Mean Treatment (μ_t): 10

Std. Deviation (σ): 25

Design Type: Superiority Number of Looks: 3

Test Parameters Boundary

Efficacy

Boundary Family: Spending Functions

Spending Function: Rho Family

Parameter (ρ): 2

Type I Error (α): 0.025

Futility

Boundary Family: Spending Functions

Spending Function: Rho Family

Parameter (ρ): 2

Type II Error (β): 0.1

Non-Binding

Binding

Spacing of Looks: Equal Unequal

Boundary Scale: Z Scale

Look #	Info. Fraction	Stop for Efficacy	Stop for Futility	Cum. α Spent	Efficacy Boundary	Cum. β Spent	Futility Boundary
1	0.333	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	0.003	2.773	0.011	-0.330
2	0.667	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	0.011	2.347	0.044	1.010
3	1.000	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	0.025	2.062	0.100	2.062

Group Sequential Design *Design Options and Discussion*

How Rapidly Should We “Spend” Alpha?

The ρ -Family Of Error Spending Functions

We fix the parameter ρ and maximum number of analyses K .

Then, at analysis k , with observed information I_k , boundaries are set so that

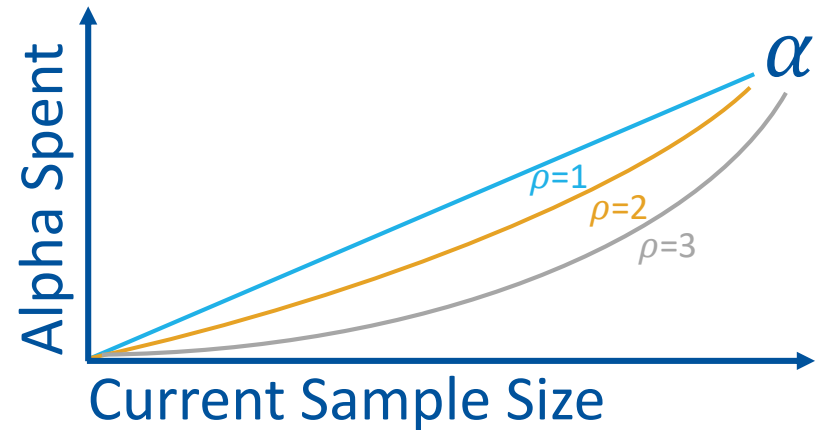
$$\text{Cumulative type I error probability} = (I_k/I_{max})^\rho \alpha \quad (\text{under } \theta = 0),$$

$$\text{Cumulative type II error probability} = (I_k/I_{max})^\rho \beta \quad (\text{under } \theta = \delta).$$

We set $I_{max} = RI_{fix}$, so boundaries meet at analysis K if we observe

$$I_1 = \frac{1}{K} I_{max}, \dots, I_{K-1} = \frac{K-1}{K} I_{max}, I_K = I_{max}.$$

Here, I_{fix} is the information for a fixed sample test and the “Inflation factor” R depends on α , β , ρ and K .



Note: The more aggressively you spend alpha early on in the study, the greater potential reduction in expected sample size for the study.

Choosing ρ & K

Properties of ρ -family designs with non-binding futility boundaries, type I error rate $\alpha = 0.025$, and power 0.9 when $\theta = \delta$.

For $\rho=2$:

Number of analyses, K	Inflation factor, R	Expected Sample Size, $E(N)$		
		When $\theta = 0$ as % of n_{fix}	When $\theta = \delta/2$ as % of n_{fix}	When $\theta = \delta$ as % of n_{fix}
2	1.06	70.7	89.2	80.8
3	1.09	64.4	84.8	75.3
4	1.12	61.1	82.4	72.4
5	1.13	59.2	80.9	70.6

Choosing ρ & K

Properties of ρ -family designs with non-binding futility boundaries, type I error rate $\alpha = 0.025$, and power 0.9 when $\theta = \delta$.

For $\rho=2$:

Cholesterol
study example

Number of analyses, K	Inflation factor, R	Expected Sample Size, E(N)		
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Choosing ρ & K

Properties of ρ -family designs with non-binding futility boundaries, type I error rate $\alpha = 0.025$, and power 0.9 when $\theta = \delta$.

For $\rho=3$:

Number of analyses, K	Inflation factor, R	Expected Sample Size, $E(N)$		
		When $\theta = 0$ as % of n_{fix}	When $\theta = \delta/2$ as % of n_{fix}	When $\theta = \delta$ as % of n_{fix}
2	1.02	74.8	92.0	84.1
3	1.04	68.8	87.2	78.2
4	1.06	65.4	84.7	75.1
5	1.07	63.3	83.2	73.3

Discussion: Group Sequential Tests

Designs from the ρ -family of error spending tests are highly efficient:
Values of $E(N)$ are close to the minimum possible for a given number of analyses K and inflation factor R .*

A lower value of ρ gives greater reductions in expected sample size and time to a conclusion, but at the cost of a higher maximum sample size.

Tables of operating characteristics, as in the previous slides, can aid the choice of a suitable design.

*Barber & Jennison, *Biometrika*, 2002.

Sample Size Re-Estimation *Benefits of Advanced Methods*

Sample Size Re-estimation (SSR)

Another way to seek the same benefits of

- Reduced sample size
- An earlier conclusion

In a group sequential test, we set a large sample size and hope to stop early.

Some prefer the philosophy of “Start small, then ask for more”.

In a two-stage design with Sample Size Re-estimation, we:

Set an initial sample size

Conduct an interim analysis

Possibly increase the sample size

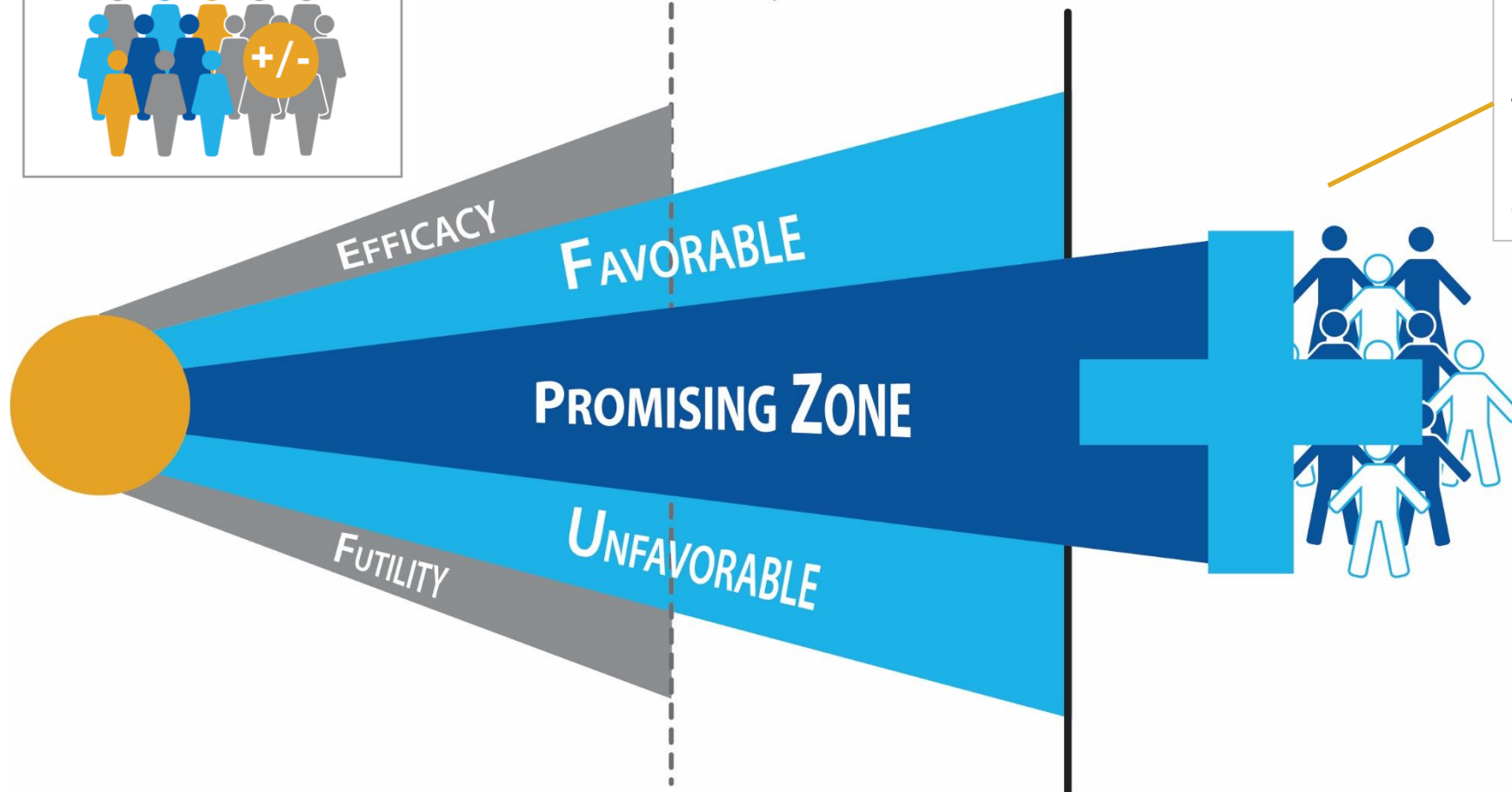
Analyse the final set of data

Adaptive Sample Size Re-estimation Can Increase Probability of Success

SAMPLE SIZE RE-ESTIMATION



Interim Analysis Planned End



Pre-planned criteria for increasing enrollment when expected trial end may not reach a meaningful conclusion

Sample Size Re-Estimation *Method Theory*

SSR: Controlling The Type I Error Probability

A two-stage combination test (Bauer and Köhne, *Biometrics*, 1994)

In Stage 1: Calculate $Z_{(1)}$ based on Stage 1 data

In Stage 2: Calculate $Z_{(2)}$ based on new data from Stage 2

Define

$$Z = \frac{1}{\sqrt{2}} Z_{(1)} + \frac{1}{\sqrt{2}} Z_{(2)}$$

For a level $\alpha = 0.025$ test, reject the null hypothesis if $Z > 1.96$.

Note: Z is a measure of evidence against the null hypothesis, which states the new treatment is no better than the control.

Type I error is protected even if the Stage 2 sample size depends on Stage 1 data.

SSR: Controlling The Type I Error Probability

Multi-stage tests (Cui, Hung & Wang, *Biometrics*, 1999; Lehmacher & Wassmer, *Biometrics*, 1999)

Define a K -stage group sequential test.

Express the cumulative Z -statistic at analysis k as

$$Z_k = \frac{1}{\sqrt{k}} Z_{(1)} + \cdots + \frac{1}{\sqrt{k}} Z_{(k)} \quad (*)$$

where $Z_{(1)}, \dots, Z_{(k)}$ are the Z -statistics based on new data in each Stage $1, \dots, k$.

If “adaptation” has occurred at an analysis $j < k$, replace $Z_{(j+1)}, \dots, Z_{(k)}$ in (*) by the new $\tilde{Z}_{(j+1)}, \dots, \tilde{Z}_{(k)}$ and apply the original group sequential testing boundary.

Poll Question

Do you use Sample Size Re-estimation designs?

A: No

B: Yes, but only rarely

C: Yes



Sample Size Re-estimation *Case Studies*

SSR: An Example

Cholesterol Study:

Has $\alpha = 0.025$, power 0.9 when $\theta = 10$, $K = 3$ analyses, error spending test with $\rho = 2$, non-binding futility boundary.

Three groups are planned with 48 patients per treatment in each.

Suppose we observe

Analysis 1: $\hat{\theta}_1 = 4.2$, $Z_1 = 0.832$

Analysis 2: $\hat{\theta}_2 = 5.0$, $Z_2 = 1.386$ (based on cumulative data)

SSR: An Example

Cholesterol study

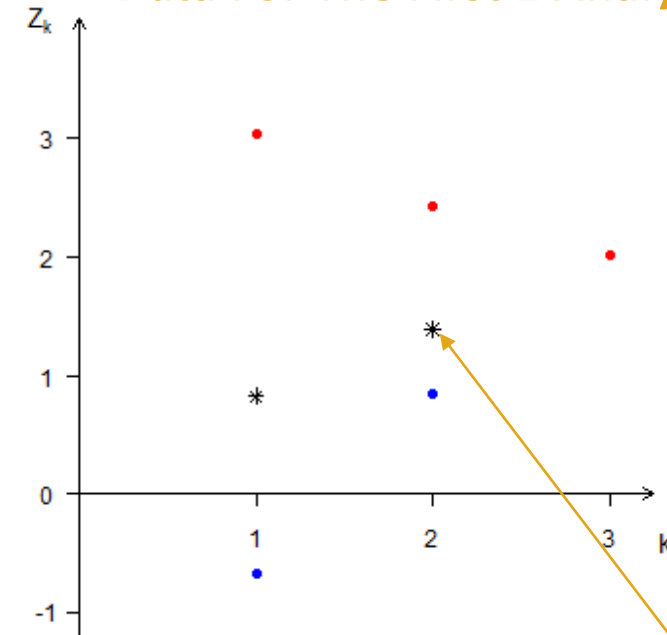
We Observe

Analysis 1: $\hat{\theta}_1 = 4.2$, $Z_1 = 0.823$

Analysis 2: $\hat{\theta}_2 = 5.0$, $Z_2 = 1.386$
(based on cumulative data)

Can we increase the final sample size?

Data For The First 2 Analyses



Conditional power is less than desirable and study would benefit from increased sample size

Demonstration of East software

Cholesterol Study:

- Error Spending Group Sequential Design
- Conditional Power
- A “CHW” Design

Takeaways

Look #	Incremental Sample Size	Cumulative Sample Size	Incremental Statistic	Prespecified Weights	Weighted Statistic	δ	Standard Error	Efficacy	Futility	95% RCI for δ		Repeated p-value
										Upper	Lower	
1	96	96	0.823	0.333	0.823	4.2	5.103	2.773	-0.331	18.351	-9.951	1
2	96	192	1.137	0.333	1.386	5.8	5.103	2.347	1.01	13.47	-3.47	0.204
3	144	336	1.68	0.333	2.101	7	4.167	2.062	2.062	11.411	0.108	0.023

Click the "Edit Interim Data" button to

East 6

Since the value of weighted statistic is $>$ the critical point for efficacy, H_0 is rejected.

OK

Stopping Boundaries

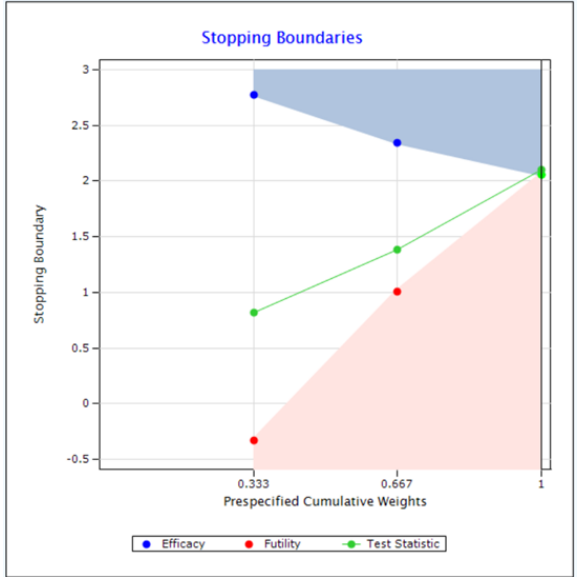
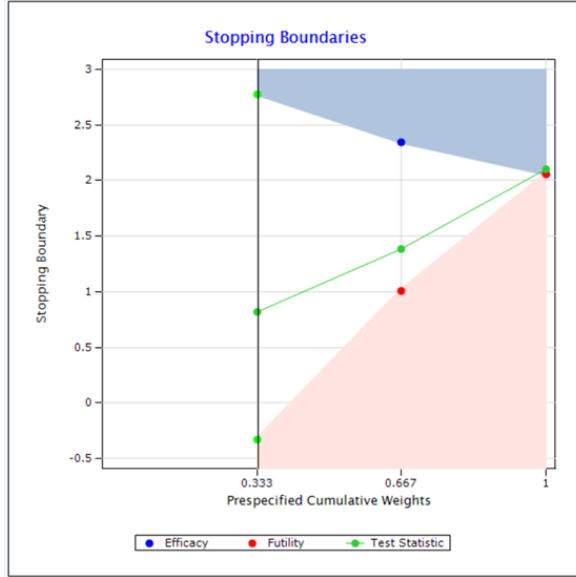
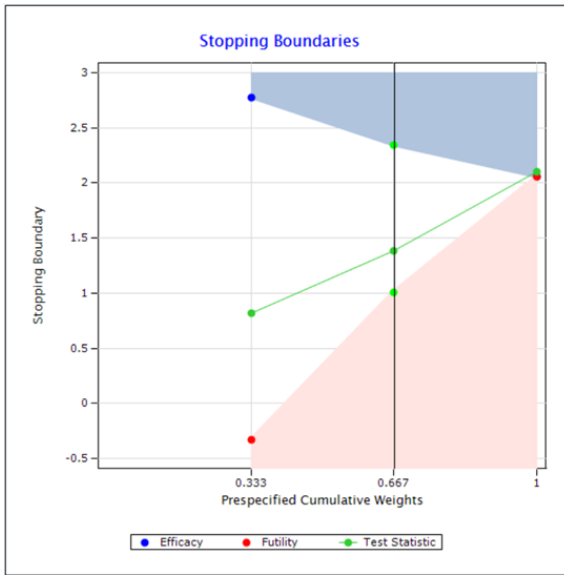
Cumul. Weight	Efficacy	Futility	Test Statistic
0.333	2.773	-0.331	0.823
0.667	2.347	1.01	1.386
1	2.062	2.062	2.101

Error Spending

Cumul. Weights	α	β
0.333	0.003	0.011
0.667	0.011	0.044
1	0.025	0.099

Repeated Confidence

Cumul. Weights	RCI Upper	RCI Lower
0.333	18.351	-9.951
0.667	13.47	-3.47



Sample Size Re-estimation *Discussion*

SSR: Discussion

The role of sample size re-estimation

- Rescuing an under-powered trial
- In a prospectively designed trial (FDA require *pre-specified* adaptive designs)

Assessing the performance of SSR designs

- The role of the sample size rule
- Compare a group sequential design with the same maximum sample size

Staging of investment

- Is this different in an SSR design?

SSR: Handling “Pipeline” Data

In a group sequential trial, data may still arrive after deciding to “stop”

- The primary endpoint has not yet been observed for recently treated patients
- Observations are recorded after data are “locked” for the interim analysis.

Hampson and Jennison (*J. Royal Statist. Soc., B*, 2013) proposed “**Delayed response group sequential designs**” to deal with this issue.

In a 2-stage design with a large number of pipeline patients, a design based on sample size re-estimation can be an attractive proposition.

SSR: Handling “Pipeline” Data

Example: Schizophrenia Study

(Mehta and Pocock, *Statistics in Medicine*, 2010)

Endpoint: Improvement in NSA at 26 weeks

Initial sample size = 442

At The Interim Analysis

416 patients enrolled

208 observed responses,

208 “pipeline” patients

Sample Size Decision

Continue to the original target of 442 patients or increase the final sample size

SSR: Mehta and Pocock's “Promising zone” design

See Mehta & Pocock (2010) for more on their “**Promising zone**” design.

Jennison & Turnbull (*Statistics in Medicine*, 2015) discuss this design and **propose a cost-benefit approach, in which gains in conditional power are set against increased patient numbers.**

Hsiao, Liu & Mehta (*Biometrical Journal*, 2018) propose a **sample size rule that combines Jennison & Turnbull's approach with a requirement of a minimum conditional power for sample size to increase.**

Factors to Consider & Summary

Factors To Consider

The stopping boundary and sample size rule must be pre-specified

The Data Monitoring Committee should discuss the rationale for study design with the sponsor before the trial is under way and a “firewall” is in place.

We need to increase maximum sample size slightly to account for interim looks

Summary

Group sequential designs help reduce patient numbers and reach early conclusions.

Designs with 2 or 3 analyses and a maximum sample size 5% or 10% greater than the fixed sample test can make savings of around 30%.

Sample size re-estimation offers an alternative approach, and can be an attractive option when there is a large amount of “pipeline” data.

Error spending tests are efficient and flexible. Current software makes these methods straightforward to apply.



East

Easy Access to the Adaptive Designs That Matter



Delivered by the
Thought Leaders
Behind the Methods



Software that is
Faster & Easier
to Use



Popular Fixed and
Adaptive Designs
at your Fingertips

Global Products and Services



Statistical Software

Industry standard for trial design, including CID adaptive (East, EOD)

Leader in exact statistical solutions (Xact: StatXact, LogXact, Procs)

Operations software (e.g. ACES, EnForeSys, FlexRandomizer)

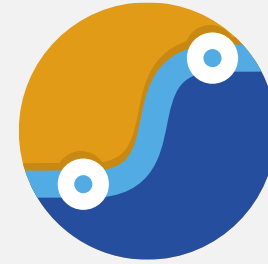
All 25 top biopharma companies, the FDA, EMA & PMDA use our software



Strategic Consulting

PhD statisticians expert in innovative design & complex statistical questions

Experts in Data Science, PK/PD, Enrolment & Event Forecasting, Portfolio/Program Optimization (NPV)



Project-Based Services

Reliable Biometrics service provider delivering high quality, on time

Lead staff with over 15 years industry experience on average

Including biostatistics & programming, ISC, data management, PK/PD analysis, medical writing



Functional Services Provision (FSP)

Creation of dedicated teams operating within/as an extension of the client's own biostatistics & programming, data management and PK/PD teams

Leader in offshoring of Biometrics competencies

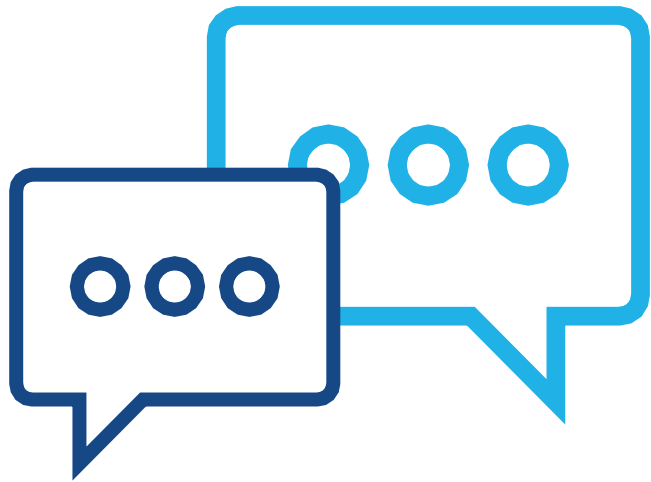
Conclusion

Upcoming Webinars

Topic	Date	Time	Speaker	
Complex Innovative Trial Designs at a Glance – The Concepts, the Promise, and the Factors to Consider	Wednesday, May 20, 2020	11:00AM EDT 16:00 GMT	Zoran Antonijevic	✓
Group Sequential Designs and Sample Size Re-estimation – Modern Uses	Wednesday, June 3, 2020	11:00AM EDT 16:00 GMT	Christopher Jennison	
Practical Model-based Approaches for Phase I Oncology Trials	Wednesday, June 17, 2020	11:00AM EDT 16:00 GMT	Satrajit Roychoudhury	
Introduction to Population Enrichment	Wednesday, July 15, 2020	11:00AM EDT 16:00 GMT	Thomas Burnett	

Other Topics Planned for Series: Introduction to Adaptive Dose Finding, Seamless Phase 2/3 Trial Designs, Basket Trial Designs, Umbrella Trial Design, Multi-arm Multi-stage Trial Design, and Program/Portfolio Designs

Recordings will be posted to www.cytel.com.



Thank you

Professor Chris Jennison

University of Bath, UK

Thank you

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