

Achieving Robust Evidence while Minimising Expected Control Group Size - A Bayesian Adaptive Trials Perspective

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Disclosure: Current Scientific Advisor to Phase V and Former Visiting Researcher at Google.

Outline

Adaptive Designs

Early Stopping + Allocation Ratio Update

Adaptive Use of Historical Control Data

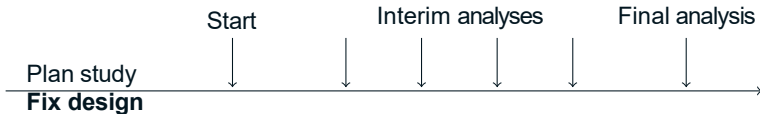
Final Thoughts

Fixed Sample Design



- **total** sample size known in advance
- no adjustment possible
- Requires strong assumptions in the planning stage

Adaptive Design



At each interim example of possible adaptations include:

- decide whether or not to stop
- change the target total sample size
- change the allocation ratio per treatment groups
- change the endpoint
- ... more

The additional flexibility results in higher variability of the resulting design and this can result in e.g.:

- lower **expected** sample size (advantage of the flexibility)
- larger **maximum** sample size (disadvantage to preserve integrity of analysis)

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The ARREST Trial - The Condition and Motivation

- More than **350,000 people** in the US **die** from out-of-hospital cardiac arrest (**OHCA**) each year.
- Patients with refractory ventricular fibrillation/pulseless ventricular tachycardia (VF/VT) OHCA have one of the worst prognosis (**85-90% mortality**), however the **underlying cause** of cardiac arrest is likely to be **reversible**.
- Adult patients (18-75 years old) with VF and VT who are transferred by emergency medical services (EMS) will receive one of the **2 standards of care practiced**.
 - Extracorporeal membrane oxygenation facilitated resuscitation (**ECMO**) (**Treatment 1**)
 - Standard advanced cardiac life support resuscitation (**ACLS**) (**Treatment 0**).
- The primary objective: **Survival to hospital discharge**.
- The primary endpoint is a **binary endpoint** observable in 30 days.

The ARREST Trial - Hypotheses

- Phase II, single center, partially blinded, intention to treat, safety and efficacy clinical trial where **primary study hypotheses** are

$$H_0 : p_1 = p_0 \text{ vs } H_A : p_1 \neq p_0.$$

- p_1 the **probability** of a **positive response** in the target population under ECMO.
- p_0 the **probability** of a **positive response** in the target population under ACLS.
- We are **interested in** $P(p_1 > p_0 | \text{Data}) = 1 - P(p_1 < p_0 | \text{Data})$.

The ARREST Trial - Priors and Posteriors

- $Beta(1, 1)$ **prior distributions** for p_1 and p_0 .
- $Beta(s_1 + 1, n_1 - s_1 + 1)$ **posterior distribution** for p_1 .
- $Beta(s_0 + 1, n_0 - s_0 + 1)$ **posterior distribution** for p_0 .
 - n_1, n_0 denotes the number of participants assigned to treatment 1 and 0.
 - s_1, s_0 denotes the number of positive responses (successes) observed in treatment 1 and 0.
- We then calculate

$$P(p_1 > p_0 | Data)$$

- In a Bayesian adaptive design, this probability will inform interim decisions.

The ARREST Trial - Early Stopping

- Interim analyses are **conducted after every 30 patients are randomised**.
- The trial will stop for **efficacy** if:

$$P(p_1 > p_0 | Data) \geq \xi.$$

- ξ is the level needed to reject the **null hypothesis**.
- The trial will stop for **inferiority** if:

$$P(p_1 < p_0 | Data) \geq \xi.$$

The ARREST Trial - Response Adaptive Randomisation

- The initial **burn-in is size 30** with equal allocation (15 patients in each treatment).
- If the trial does not stop, a form of Bayesian Response-adaptive randomisation is used. The next group of patients is randomized to ECMO with a target probability that is proportional to its posterior probability of superiority , i.e., $P(p_1 > p_0 | Data)$.
- An additional restriction is the **randomization probability may not exceed 75%** in either direction.

The ARREST Trial - Type I Error and Power

- Aims: **Type 1 error** rate of 5% two sided, and **power** of 90%, assuming success rates of 12% vs. 37% in the 2 groups.
- This was achieved by a design with $\xi = 0.986$ and up to **5 analyses interim after 30 patients** in an **expected required sample size** is $N = 148$ (inflated to $N = 174$ for **15% expected drop out**). Only the **first 150 patients** are evaluated.

	Scenario	Prob reject null	$E(N)$	$E(N_1)$	$E(N_0)$	n- $E(N)$	n/2- $E(N_0)$
GS-RAR	Null	0.048	148.5	74.2	74.3	-12	-6
GS-RAR	Alternative	0.905	81.6	52.5	29.2	54	39
GS-ER	Null	0.050	148.8	74.4	74.4	-13	-6
GS-ER	Alternative	0.930	83.2	41.6	41.6	53	26
ER	Null	0.050	136	68	68	0	0
ER	Alternative	0.950	136	68	68	0	0

Table 1: Simulated operating characteristics of two adaptive designs against the non-adaptive RCT.

- $E(N)$ expected total sample size, $E(N_1)$ expected sample size for ECMO and $E(N_0)$

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Re-use of Historical Data in Clinical Trials

- There are lots of data available (particularly on control treatments). How can we use these to reduce the size / risk of failure a new trial by re-using that data?
- Historical controls are common in device and early oncology trials. Current interest lies in paediatric drug development (partial adult efficacy/safety extrapolation) and historical controls for late-phase/regulatory use.
- Most approaches for handling historical data downweight the historical information. When we maximise the downweight, no historical data are used in the current study, if we maximise the borrowing/learning from it then all the historical data are used in a pooled analysis with current data (no downweight at all of past data).
- How to determine this weight? Modified power prior, empirical power prior, or equivalence probability weight approach (by Maxine Ajimi, formally known as M. Bennett)

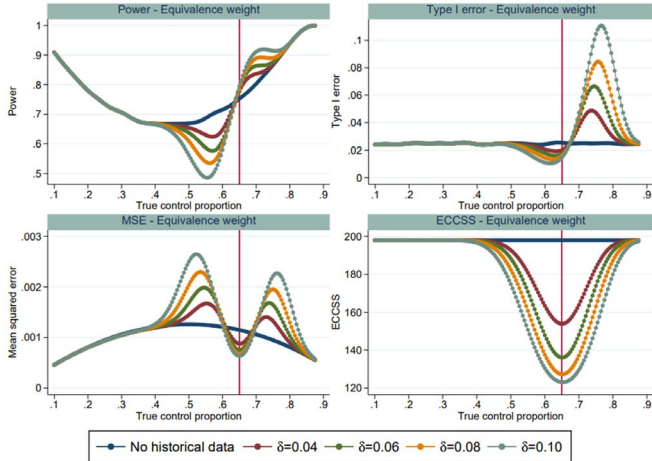
Adaptive partial replacement design

- Standard two arm RCT where 400 patients (randomised 1:1), 12% treatment effect (TE) to detect, 2.5% error rate and 76% power. Binary endpoint (success/failure)
- Historical data available on 100 (n_h) control patients with a response probability of 65%.
- Adaptive design (changing allocation ratio)
 - Stage 1: Randomise n_t^1 to treatment and n_c^1 to control (e.g. $n_t^1 = n_c^1 = 100$); Calculate the weight for historical data using the first stage controls and the historical data. The resulting weight determines $ESSh1$.
 - Stage 2: Randomise $(n_t - n_t^1)$ to treatment and $\max(n_c - n_c^1 - ESSh1; nmin)$ to control (e.g., $nmin = 20$). Recalculate the weight, at the end of the study using all current control data. Compute a posterior probability for the final decision rule $P(TE \geq 12\%|data) > \xi$

The equivalence approach is flexible and the equivalence bounds can be chosen to control the maximum inflation in type I error across all true current control proportions.

Operating Characteristics

When perfect alignment, with most/least conservative equivalence criteria the reduction in control group is of 40 (200-160)/ 75 (200-125).



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Adaptive Designs in Rare Diseases

In many settings, designing trials to meet conventional evidentiary standards may not be feasible → Balance is needed between what is necessary and what is possible.

To achieve this with an adaptive design in the PBC setting it is essential to consider:

- The validation of a quickly observable endpoint (could be continuous).
- The use of a model that combines data from short and longer term endpoints to make interim decisions.
- The possibility of a platform trial with a shared placebo arm can also imply a reduction in the placebo arm without impacting power.
- Analysis methods crucially determined to give type I error guarantees.

Acknowledgments

Thank you for listening! :)



Ethics and Innovative Clinical Trial Designs: A Multi-Stakeholder Perspective on Adaptive Designs



24 April 2025, Newnham College, Cambridge



Speakers and Supporters:

Frank Bretz (Novartis), Laura Flight (NICE), Rieke van der Graaf (University of Utrecht), Thomas Jaki (MRC Biostatistics Unit), Jonathan Kimmelman (McGill University), Alex John London (Carnegie Mellon University), Richard Milne (University of Cambridge), Philip Pallmann (University of Cardiff), Mark Sheehan (Oxford Population Health), Jerome Singh (University of KwaZulu-Natal), Sofía S. Villar (MRC Biostatistics Unit), Sue-Jane Wang (Food and Drug Administration), Haiyan Zheng (University of Bath)



More info: www.cmu.edu/ethics-ai/events/adaptive-trials-2025.html

Registration: Scan QR code

A complimentary short course will be delivered on 23 April in Cambridge - details to follow



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References

Adaptive Designs Burnett, T., Mozgunov, P., Pallmann, P. et al. Adding flexibility to clinical trial designs: an example-based guide to the practical use of adaptive designs. BMC Med 18, 352 (2020). <https://doi.org/10.1186/s12916-020-01808-2>

ARREST trial

Yannopoulos, D and others (2020) Advanced REperfusion STRategies for Refractory Cardiac Arrest (The ARREST Trial) Protocol version 1.4 (2020a)

Yannopoulos, D and others (2020b) Rationale and methods of the Advanced R2Eperfusion STRategies for refractory cardiac arrest (ARREST) trial. *American Heart Journal*. 229 29–39.

Yannopoulos, D and others (2020c) Advanced reperfusion strategies for patients with out-of-hospital cardiac arrest and refractory ventricular fibrillation (ARREST): a phase 2, single centre, open-label, randomised controlled trial. *The lancet*. 396 1807–1816.

Equivalence Weighted Use of Historical Data

Bennett, M. and White, S. and Best, N. and Mander, A. (2021) A novel equivalence probability weighted power prior for using historical control data in an adaptive clinical trial design: A comparison to standard methods *Pharmaceutical statistics* 20(3)462–484 *Wiley Online Library*

Ensuring integrity robustly

Regulators do not trade-off type I and type II errors

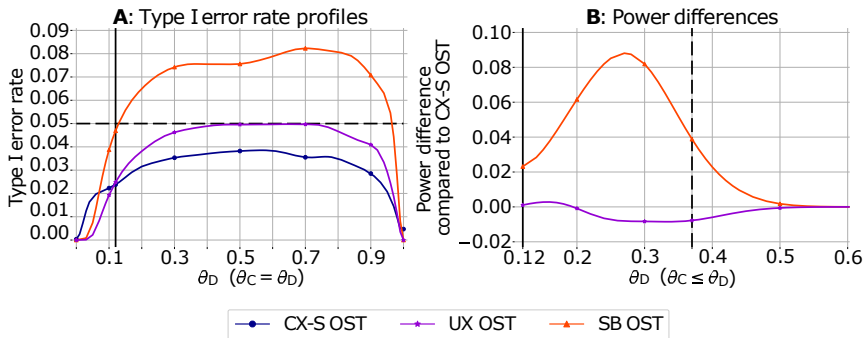


Figure 2: ARREST trial. Type I error under the SB (simulation based approach), CX-S (Conditional exact), and UX OST (Unconditional exact) for $p_0 = p_1$ (left), vertical line at $p_0 = p_1 = 0.12$. Power difference (right) for two tests compared to the CX-S OST vertical line denotes $p_1 = 0.37$.

<https://arxiv.org/abs/2407.01055v2>