



MRC
Biostatistics
Unit



UNIVERSITY OF
CAMBRIDGE

Short course on Response-Adaptive Methods for Clinical Trials

Lecture 4: Applications of RAR: Backfill in dose finding and RAR Repository

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Outline

1. Implementing and assessing Bayesian response-adaptive randomisation for backfilling in dose-finding trials

- Introduction

- Method

- Simulations

- Discussion

2. The RA-ClinicalTrials Repository

- Motivation

- The Repository

- Analysis

- Call to Action

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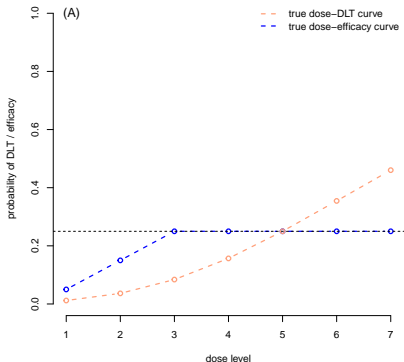
- The Repository

- Analysis

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Motivation

- Phase-II Dose-Finding Study
- Efficacy Plateau
 - ▶ in oncology with targeted agents or immunotherapy
- **Identify** the lowest dose level that maximises efficacy whilst remaining tolerable and **allocating** patients close to that dose level
 - ▶ Backfill + RAR



Previous Work

- Continual Reassessment Method (CRM) to identify *Maximum Tolerated Dose (MTD)* [O'Quigley et al (1990)]
- Backfill with Equal Randomization (ER) under MTD to identify *Recommended Phase 2 Dose (RP2D)* [Dehbi et al (2021)]
- Backfill with Response Adaptive Randomization (RAR) under MTD to identify RP2D and allocated patients better [Pin et al (2024)]

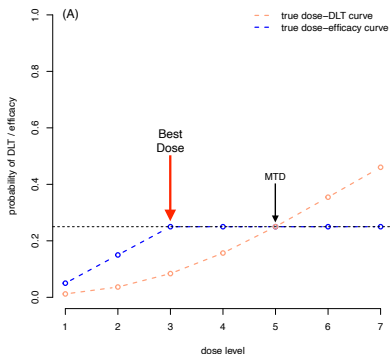


Figure: Dose 3 (RP2D) < Dose 5 (MTD)

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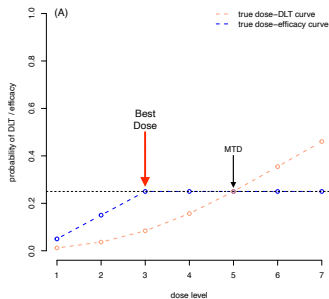
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Call to Action

- Multi-armed trial: $1, \dots, K$ different dose levels
- Fix number of patients in the trial: $n = \sum_{k=1}^K n_k$
 - ▶ n_k is the number of patients on dose level k
- Potential efficacy outcomes: $Y_{ki} \stackrel{\text{iid}}{\sim} \text{Bern}(p_k)$
 - ▶ p_k is success probability
- Binary indicator a_{ki} s.t. $\sum_{k=1}^K a_{ki} = 1 \ \forall i$
- Response-adaptive-randomization: $P(a_{ki} = 1 | a^{(i-1)}, Y^{(i-1)})$

How does Backfill work?

Algorithm backfill($n = 57, c = 3$)
 $MTD \leftarrow 1$
while $MTD = 1$ **do**
 allocate c patients to dose level 1
 $MTD \leftarrow$ update through CRM
end while
while Number of allocated patients $< n$
do
 allocate c patients to MTD
 randomise c backfill-patients with ER
 or RAR to dose levels 1, ..., $MTD - 1$
 $MTD \leftarrow$ update through CRM
end while
Choose Model with(out) Plateau
return RP2D



- **Equal randomisation (ER)** allocated backfill patients with equal probability ($1/(\text{size of backfill set})$) to one of the dose level in the backfill set
- **Bayesian RAR (BRAR)** adjusts probabilities based on efficacy data from dose-escalation and backfill patients
 - ▶ BRAR design: use a posterior probability of interest to determine assignment **probabilities** [Thompson (1933)].
 - ▶ BRAR allocation probability: $P(a_{k,i} = 1 | \mathbf{A}^{(i-1)}, \mathbf{Y}^{(i-1)}) = P(\max_{1 \leq h \leq MTD-1} p_h = p_k | \mathbf{A}^{(i-1)}, \mathbf{Y}^{(i-1)}) = q^{(i-1)}$

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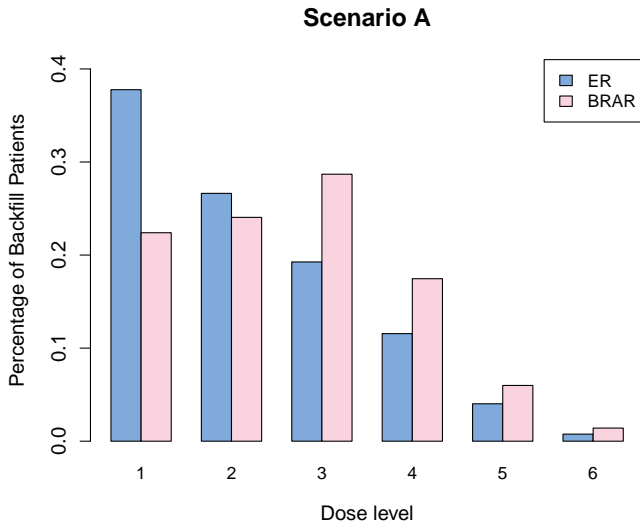
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Allocation of Backfill Patients



Recommendation of Dose Level

Scenario A: % of recommendations per dose			
Dose Level	CRM	Backfill & ER	Backfill & BRAR
1	0%	0%	0%
2	0%	0.3%	0.1%
3	0.2%	27.3%	30.8%
4	15.7%	43.7%	44.7%
5	62.0%	19.4%	16.9%
6	20.7%	7.3%	5.9%
7	1.4%	2.0%	1.6%
RP2D	0.2%	27.3%	30.8%
[RP2D, MTD)	15.9%	70.9%	75.5%
[RP2D, MTD]	78.0%	90.4%	92.4%
(MTD, 7]	22.1%	9.3%	7.5%

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1. Whether backfill is beneficial depends on true DLT and Efficacy curves (7 other scenarios in [Pin et al (2024)]).
2. If Backfill is beneficial, using BRAR leads to *allocating more patients close to RP2D* and an *increased probability of recommending the correct dose level* at the end of the trial.
3. Future Research
 - 3.1 Impact of different cohort sizes on the design
 - 3.2 Other dose-escalation methods: 2-parameter CRM, BOIN
 - 3.3 Continuous endpoints → nonparametric RAR

References I

-  O'Quigley, John and Pepe, Marcello and Fisher, Lloyd (1990)
Continual Reassessment Method: A Practical Design for Phase 1 Clinical Trials in Cancer.
Biometrics, 46(1): 33–43. ISSN 0006341X. doi: 10.2307/2531628.
-  Dehbi, Hakim M. and O'Quigley, John and Iasonos, Alexia (2021)
Controlled backfill in oncology dose-finding trials.
Contemporary Clinical Trials, 111. ISSN 15592030. doi: 10.1016/j.cct.2021.106605.
-  Pin, Lukas and Villar, Sofia S. and Dehbi, Hakim M. (2024)
Implementing and assessing Bayesian response-adaptive randomisation for backfilling in dose-finding trials.
Contemporary Clinical Trials. doi: 10.1016/j.cct.2024.107567.
-  Thompson, William R. (1933)
On the likelihood that one unknown probability exceeds another in view of the evidence of two samples.
Biometrika, 25(3-4): 285–294. ISSN 0006-3444. doi: 10.1093/biomet/25.3-4.285. URL .

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The Current Perception:

- RAR is often dismissed as a "methodological curiosity."
- "Great theory, but nobody uses it."
- **Reality Check:** Is it truly absent, or just hard to find?

The Problem

"The uptake of RAR in clinical trial practice remains disproportionately low..." —

Robertson et al. (2023)

Our Solution: A living, crowd-sourced evidence base.

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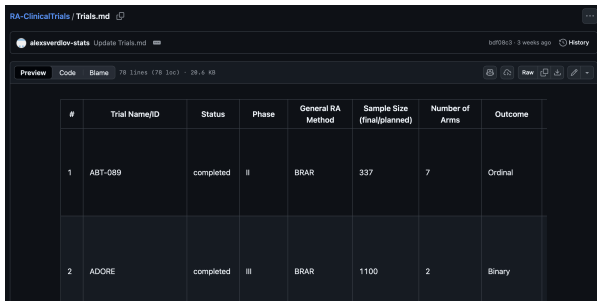
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RA-ClinicalTrials: A Living Database



The screenshot shows the GitHub interface for the RA-ClinicalTrials repository. The file 'Trials.md' is open, showing a table with 8 columns: #, Trial Name/ID, Status, Phase, General RA Method, Sample Size (final/planned), Number of Arms, and Outcome. The table contains two rows of data.

#	Trial Name/ID	Status	Phase	General RA Method	Sample Size (final/planned)	Number of Arms	Outcome
1	ABT-089	completed	II	BRAR	337	7	Ordinal
2	ADORE	completed	III	BRAR	1100	2	Binary

- **Open Source:** Hosted on GitHub.
- **Community Driven:** Additions via Pull Requests.
- **Quality Control:** Curated by MRC BSU.
- **Permanent:** Archived on Zenodo.

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Analysis: Breaking Down the 74 Trials

Trial Landscape (Nov 2025)

Category	Sub-Category	%
Method	BRAR	83.8%
	RPTW	2.7%
Phase	Phase II (Exploratory)	44.6%
	Phase III (Confirmatory)	20.3%
	Phase I/II or Seamless	6.8%

Key Insights:

- **Dominance:** BRAR is the standard.
- **Scale:** Used in massive platform trials (e.g., REMAP-CAP).
- **Scope:** Not limited to early phase oncology.

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Support this Project

Help us grow the evidence base

Have we missed a trial?



`github.com/lukaspinpin/
RA-ClinicalTrials`

How to Contribute

1. Fork the repository.
2. Add the trial to `trials.md`.
3. Open a **Pull Request**.

Official Citation (Zenodo)

Please use the DOI, not the GitHub link:

Pin, L., Neubauer, M., Voller, C., Wilson, I., Deliu, N., Baas, S., Dimairo, M., Robertson, D., & Villar, S. (2025).

Clinical Trials Using Response Adaptive Randomization (Version 1.1.1)
[Computer software].

Zenodo. **<https://doi.org/10.5281/zenodo.17493900>**

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Thank you for your attention!

Any questions?

Please reach out:

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