

Safety-Driven Response Adaptive Randomisation

An Application in Non-inferiority Oncology Trials



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Statistical Considerations in
Oncology Study Design



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BACKGROUND

The Challenge in Modern Oncology



FDA Project Optimus

A **paradigm shift toward patient-centered dosing** — seeking the optimal balance between drug efficacy and safety to maximize patient benefit while minimizing toxicity. This initiative challenges traditional dose-selection approaches.



Modern Treatment Landscape

Targeted therapies, monoclonal antibodies, and immune checkpoint inhibitors typically span prolonged treatment cycles with chronic, low-grade adverse events (fatigue, GI disturbances, dermatologic reactions) that significantly impact adherence and quality of life.



Plateauing Efficacy

Novel agents often exhibit plateauing efficacy at doses well below MTD, underscoring the need for a revised perspective on the interplay between safety and efficacy outcomes.



Case Study: Sotorasib

Initial Selection

960 mg dose selected for pivotal trials in KRAS G12C inhibitor

Subsequent Analysis

240 mg dose offered **similar efficacy** with **better safety profile**

Regulatory Action

FDA mandated post-marketing dose optimization study

Singh et al., Journal of Clinical Oncology 2025



Key Insight

Traditional early-phase trials prioritize immediate, severe safety data, while later phases focus primarily on efficacy.

Safety information is typically not formally integrated into late-phase design, despite the massive amount of safety data that become rapidly available from the very early follow-up period.



Research Question & Motivation



Core Research Question

How can a **late-phase adaptive design** help identify **alternative dosing strategies** (lower or fractionated doses, different schedules) with **comparable or superior efficacy** and **fewer side effects**?



The Challenge with Traditional RAR



Delayed Efficacy Outcomes

Most RAR designs rely on efficacy data to guide allocation, but in oncology trials, primary efficacy outcomes (e.g., overall survival, PFS) are observed with random delay.



Limited Applicability

When efficacy outcomes are unavailable during enrollment, traditional RAR becomes challenging due to lack of timely, informative data for adaptation.



Surrogate Endpoint Limitations

While surrogate endpoints have been proposed, they require validation and may not always be available or appropriate.

✓ Our Solution



1 Leverage Early Safety Data

Use early-emerging safety data (e.g., time to dose-reduction/discontinuation) to inform treatment allocation decisions.



2 Non-inferiority Framework

Particularly relevant for non-inferiority trials to demonstrate experimental treatment is not inferior to standard of care while offering improved tolerability.



3 Address Dosing Decisions

Address the potential impact on Phase II/III studies from dosing decisions in early trials often based on immediate and severe safety data.



"Agents with delayed efficacy signals and cumulative toxicity profiles that influence long-term adherence and outcomes."



The Statistical Trade-off

🎯 Balanced Allocation: The Gold Standard

In non-inferiority trials, a **balanced 1:1 allocation ratio is typically optimal** due to the mathematical structure of the variance.

Mathematical Rationale:

- Under H_1 , treatment effects are clinically equivalent within a narrow margin
- Outcome variances in both arms are expected to be similar

Neyman Allocation Insight:

Strategies minimizing variance of estimated treatment effect (Neyman allocation) tend to **approximate or coincide with balanced allocation** in trials with Exponentially distributed outcomes (e.g., time to progression/death).

↔ The Unavoidable Trade-off



Statistical Efficiency

Preserve inferential efficiency for the primary non-inferiority outcome. Maintain adequate power to demonstrate that experimental treatment is not inferior to control.



Safety Considerations

Integrate safety considerations into the randomization process through RAR. Preferentially allocate patients to arms with superior safety profiles.

⚡ The Safety-driven RAR Challenge

Response-adaptive randomization driven by safety data can dynamically skew allocation favoring the SAFER arm, which may **deviate from the optimal variance-reducing strategy** for the efficacy endpoint test.

↓ Power Loss

Unequal allocation can reduce statistical power for detecting non-inferiority.

↑ Patient Benefit

More patients assigned to better-tolerated treatment arms.



Key Considerations

- 1 **Clinical Risk:** Assigning more patients to better-tolerated arms is not always optimal if that arm is less effective.
- 2 **Statistical Risk:** RAR designs may introduce challenges in preserving statistical power under certain conditions.
- 3 **Need for Balance:** A design that can dynamically adjust based on the observed association between endpoints.



Efficacy-Safety Association

🛡️ The Safeguard Mechanism

If the allocation is primarily driven by safety, there's an **inherent risk of preferentially assigning patients to a treatment that, although better tolerated, may be less effective.**

Solution:

The design should incorporate a **safeguard mechanism** that exploits the estimated relationship between efficacy and safety outcomes. It can detect situations where an apparent safety advantage is offset by insufficient efficacy.

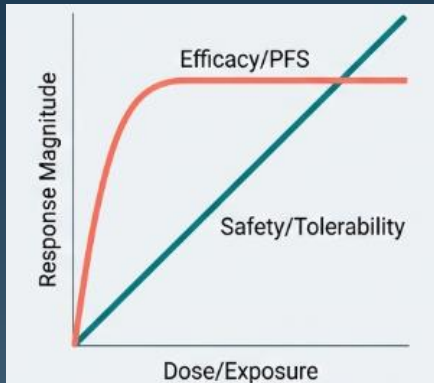
❌ Without Safeguard Mechanism

Risk of allocating to safer but potentially futile or inadequately active treatment arm.

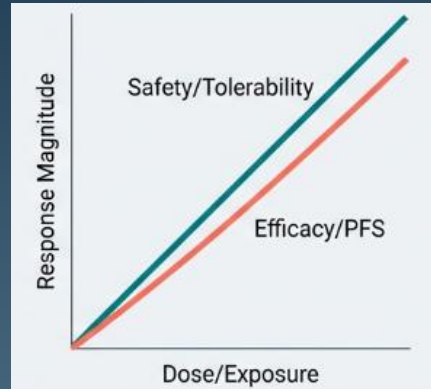
✅ With Safeguard Mechanism

Allocation reverts toward 1:1 if efficacy data fail to demonstrate benefit.

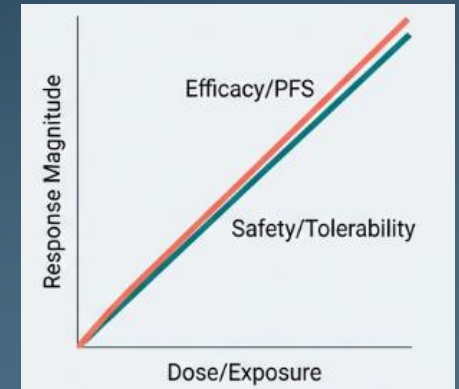
The plateau target



The trade-off risk



The cytotoxic paradigm





PROPOSED SOLUTION

Introducing SAFER: Design Overview



Safety-Aware Flexible Elastic Randomization

A Novel RAR Design

SAFER dynamically adjusts patient allocation proportions based on accumulating safety endpoint data, with the aim of **leveraging the association between efficacy and safety outcomes** to balance clinical benefit and statistical validity.

★ Key Innovations



Safety-Driven Adaptation

Uses **early-emerging safety data** (time to dose-reduction/discontinuation) rather than delayed efficacy outcomes to inform allocation decisions.



Endpoint Association

Explicitly evaluates and incorporates **the interplay between safety and efficacy** endpoints through the Φ **weight parameter**.



Flexible Elasticity

The η **parameter controls adaptation aggressiveness**, allowing customization based on clinical context and trial objectives.

SAFER Design Workflow



Burn-in Period

Equal 1:1 randomization for initial patients (e.g., first 3 months)



Safety Data Collection

Accumulate safety data from enrolled patients



Estimate Target Allocation

Compute target allocation based on safety data to the Experimental a



Evaluate Efficacy Evidence

Calculate Φ weight from available efficacy data



Apply SAFER Function

Compute SAFER() incorporating both safety and efficacy information



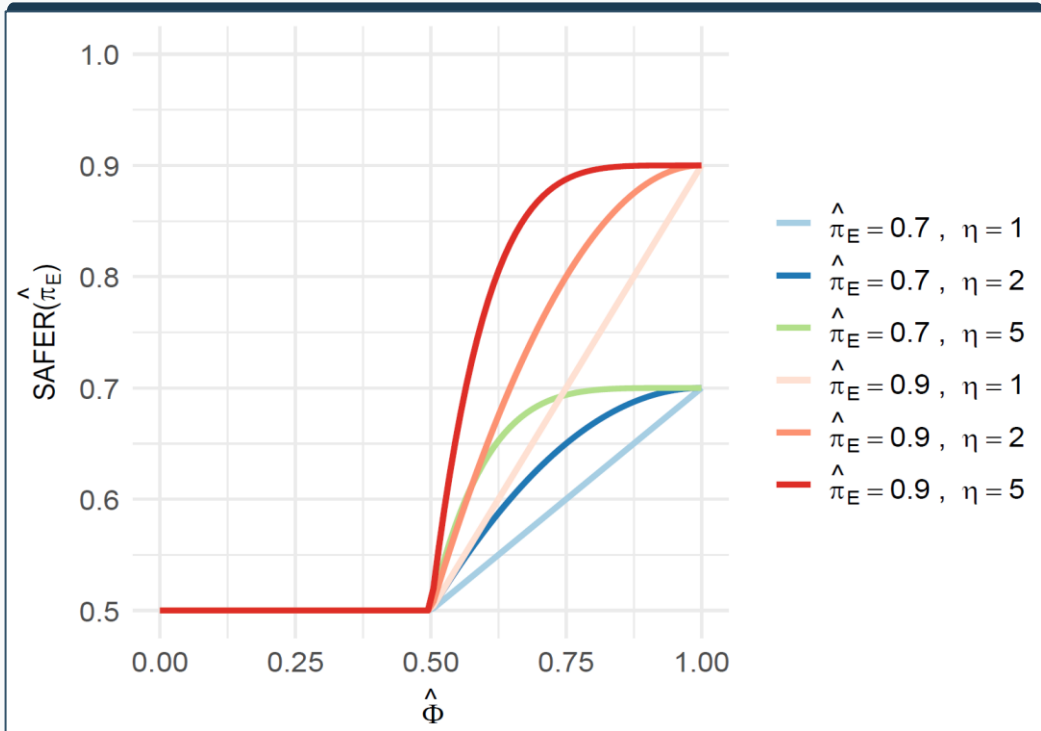
Update & Continue

Use updated allocation for next enrollment period, repeat process



The SAFER Function

SAFER Function Visualization



Key Insight

The SAFER function provides **regularization** that prevents premature and extreme imbalances in allocation. This is especially critical in non-inferiority settings where the experimental arm could ultimately prove inferior.

Mathematical definition

SAFER($\hat{\pi}_E$) =

if $\hat{\Phi}$ OR $\hat{\pi}_E \leq 0.5$: 0.5

if $0.5 < \hat{\Phi} < 1$: $0.5 + (\hat{\pi}_E - 0.5) * (1 - (1 - \frac{\hat{\Phi} - 0.5}{0.5})^\eta)$

if $\hat{\Phi} = 1$: $\hat{\pi}_E$

Weight Parameter (Φ):

Larger values = stronger efficacy evidence.

Elastic Parameter (η):

Controls adaptation aggressiveness. $\eta = 1$ (linear), $\eta > 1$ (concave, conservative early).

Function Behavior



$\hat{\Phi} \leq 0.5$ (Weak Efficacy)

Allocation reverts to **0.5** (equal randomization). Protects against assigning patients to **safer but potentially inferior arm**.



$0.5 < \hat{\Phi} < 1$ (Moderate Efficacy)

Gradual increase in allocation based on η . Higher η = more conservative early, aggressive late.



$\hat{\Phi} = 1$ (Strong Efficacy)

Allocation reaches $\hat{\pi}_E$ (full Neyman allocation). Maximum benefit from safety advantage.



MOTIVATING EXAMPLE

The CAPP-IT Study & Re-design framework

Original Study Design

Study Type

Multicentre, randomized, double-blind, placebo-controlled Phase III trial (10 UK sites)

Population

Patients with colorectal or breast cancer receiving a treatment with single-agent capecitabine

Intervention

Concomitant pyridoxine vs. matching placebo to reduce capecitabine dose modifications

Primary Objective

Assess whether pyridoxine could reduce need for capecitabine dose reduction

Original Study Results

Recruitment Challenge

Study closed prematurely after enrolling **106 patients** (target: 270)

Objective Response Rate

Pyridoxine did not demonstrate statistically significant effect (OR: 1.37; 95% CI: 0.475–3.96)

PFS Result (Concerning)

Median PFS: 7.4 months (pyridoxine) vs. 9.9 months (placebo)

HR: 1.62 (95% CI: 0.91–2.88)

SAFER Re-design Framework

Primary Endpoint

The design accommodates typical Phase II/III oncology trial endpoints—**time-to-event measures such as PFS**. Sample size and primary analysis are expressed in terms of this endpoint.

Non-inferiority Hypothesis

Control Arm PFS monthly rate

$\lambda_c = 0.069$

Median \approx 10 months

Non-inferiority Margin

$HR_0 = 1.25$

Median $>$ 8 months

Under regularity conditions, construct **Wald statistic** for hypothesis testing.

Safety Endpoint Definition

Time to dose-reduction or drug discontinuation due to low drug tolerability or adverse events (AEs).

Clinical Rationale

This endpoint captures treatment tolerability and directly impacts patient adherence and quality of life—critical in modern oncology with prolonged treatment cycles.



Target Allocation

Target Allocation

Goal: The larger is the mean in the experimental arm ($\hat{\theta}_{E(s)}$), the higher is the proportion assigned to the Experimental Arm

Estimated Target Allocation:

$\hat{\theta}_{E(s)}^2$: Variance of time to drug discontinuation in arm E (experimental)

$\hat{\theta}_{C(s)}^2$: Variance of time to drug discontinuation in arm C(control)

$$\text{Neyman proportion} = \hat{\pi}_E = \hat{\theta}_{E(s)}^2 / (\hat{\theta}_{E(s)}^2 + \hat{\theta}_{C(s)}^2)$$

Sequential Update Mechanism

- 0 **Burn-in Period (u = 0)**
 $\hat{\pi}_E = 0.5$ (equal allocation) for patients before first update
- 1 **First Update (u = 1)**
 $\hat{\pi}_E$ estimated using all available safety data up to first update time
- 2 **Subsequent Updates (u = 2, ..., U)**
Pattern continues with increasingly refined estimates

Implementation Details

U = 15 updates every 3 months (months 3-45), 48-month enrollment period. Updates independent of interim analyses.

Why Neyman Allocation?

1. Ethical Alignment (Exponential)

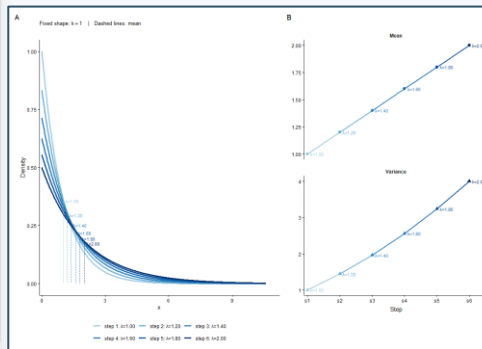
Under **exponential distribution**, Neyman allocation consistently assigns majority to treatment with longer expected time to dose reduction (better tolerated).

2 Statistical Efficiency

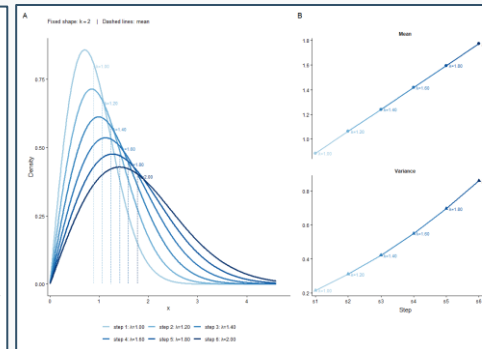
Maximizes power of Wald test to detect true difference between arms by minimizing variance of treatment effect estimator.

Note: This alignment is specific to exponential distribution and may not hold for binary endpoints. However, it is robust in many cases when the Weibull is assumed as underlying distribution, since variability and mean increase /decrease on the same direction!!!!

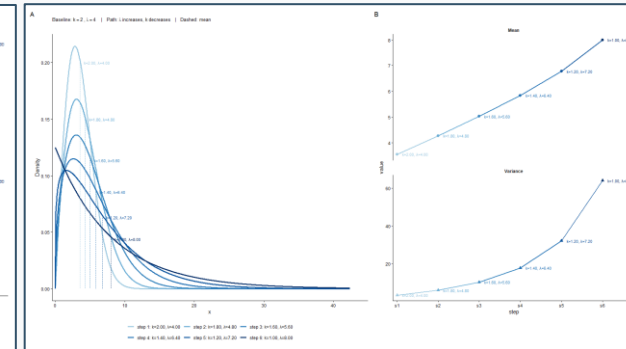
K=1, λ= from 1 to 2



K=2, λ= from 1 to 2

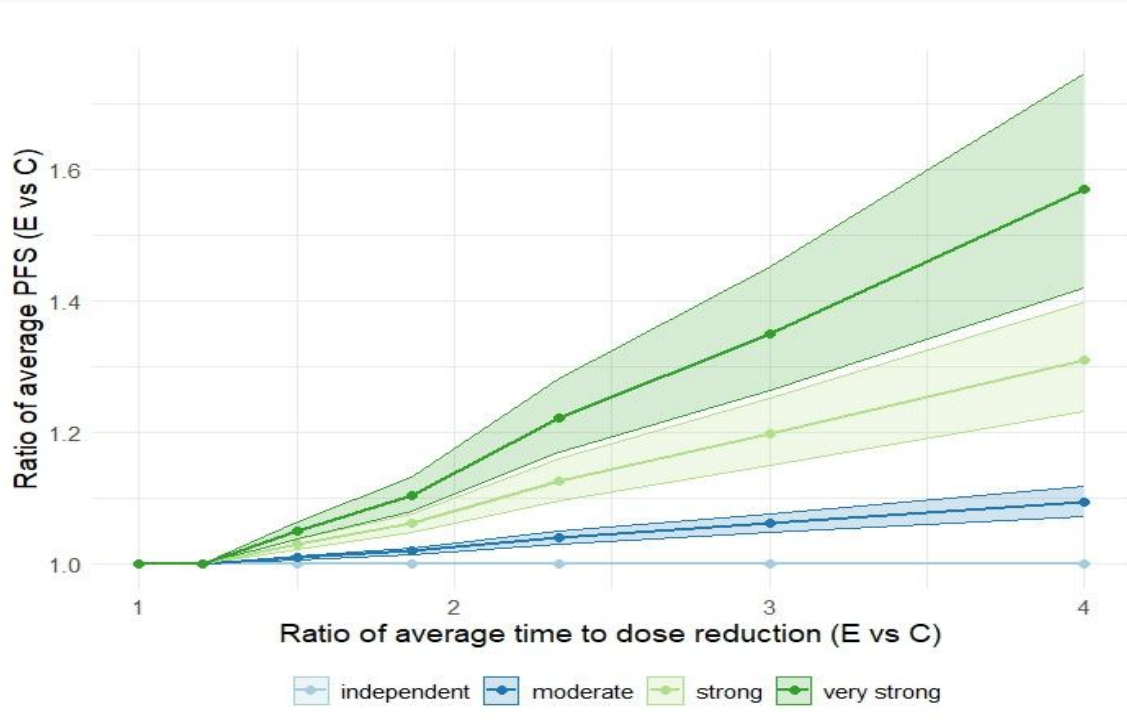


K=from 1 to 2, λ= from 4 to 8





Endpoints Linear Association



How The Φ Weight Parameter is Estimated?

Definition:

$\hat{\Phi}$ is calculated as the **cumulative distribution function (CDF)** of the Wald-statistic (Z-scale) from the efficacy analysis (Cox model).

Transformation:

For Cox model (negative coefficient = risk reduction), **invert z-value sign** so larger $\hat{\Phi}$ consistently corresponds to stronger efficacy evidence.

Range: $\hat{\Phi} \in [0, 1]$, with default threshold at 0.5 (z-statistic = 0)



Why Not Simple Correlation to detect their association?

A simple correlation metric between safety and efficacy is **not appropriate** in this context because it fails to account for the specific characteristics of survival endpoints.

- 1 Administrative Censoring:** Both endpoints subject to truncation from study end.
- 2 Structural Truncation:** Safety endpoint truncated by PFS events (follow-up ends at progression).
- 3 Misleading Estimates:** Conventional correlation coefficients may yield misleading association estimates.



Simulation Study Design

Seven Simulation Scenarios

Scenario 0: Independence Baseline

Safety-driven RAR without SAFER under independence between endpoints (Type I Error evaluation under the null hypothesis)

Scenario 1: Complete Randomization

1:1 allocation with varying association levels (baseline for comparison)

Scenario 2: Safety-driven RAR

Pure safety-driven RAR without SAFER under varying association

Scenario 3a/b: SAFER Design

SAFER with $\eta = 1$ (3a) and $\eta = 5$ (3b) under varying association

Scenario 4: Endpoint Timing

Impact of differential timing in endpoint observation (PFS: 3-24 months)

Scenario 5: Informative Drop-out

Impact of informative drop-out (5% to 25%) with composite strategy

Scenario 6: Under-reporting

Impact of under-reported safety events on operating characteristics

Endpoint Association Levels

Independent

No relationship between safety and efficacy

$$E[\gamma_i] = 0.001$$

Weak

Minimal positive association

$$E[\gamma_i] = 0.005$$

Moderate

Meaningful positive association

$$E[\gamma_i] = 0.01$$

Strong

Substantial positive association

$$E[\gamma_i] = 0.03$$

Very Strong

Strong positive association

$$E[\gamma_i] = 0.05$$

Target Allocations

$$\pi_E = 0.5$$

Equal allocation

$$\pi_E = 0.6$$

Mild preference

$$\pi_E = 0.7$$

Moderate preference

$$\pi_E = 0.8$$

Strong preference

Performance Metrics

⚡ Statistical Power

Overall power (interim + final) and power at interim (power_i) under H₁

⚠️ Type-I Error Rate

Proportion of trials rejecting H₀ under null hypothesis (target: 0.05)

👤 Allocation Proportion

Average proportion of patients assigned to experimental arm (N_E/N)

❤️ Adverse Event Rate

Total AEs divided by total person-years (rate per patient-year)

⚙️ Simulation Setup

Iterations: 10,000 per scenario

Monte Carlo Error: < 0.5% for power and type-I error

Software: R with survival package

Validation: Theoretical power calculations vs. empirical results



Scenario 0: Independence Between Endpoints



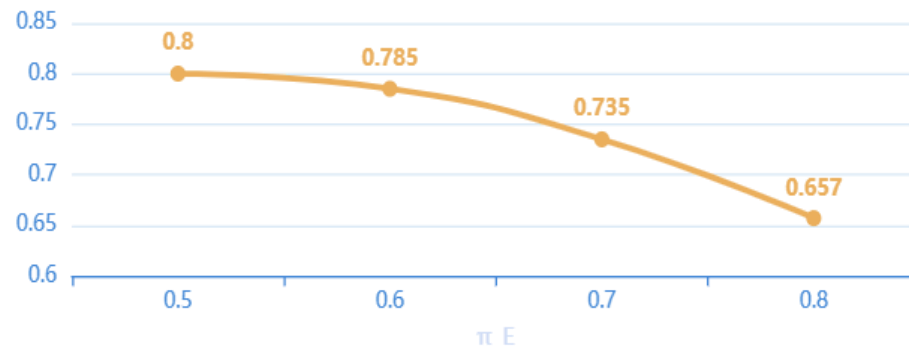
Allocation Proportion & Power Summary

πE	NE/N	Metric	IF=0.2	IF=0.3	IF=0.4	IF=0.5
0.5	0.50	Power	0.80	0.80	0.80	0.80
		Type-I Error	0.048	0.050	0.048	0.053
0.6	0.59	Power	0.78	0.79	0.78	0.78
		Type-I Error	0.047	0.050	0.055	0.053
0.7	0.69	Power	0.74	0.74	0.73	0.73
		Type-I Error	0.049	0.051	0.051	0.053
0.8	0.78	Power	0.66	0.66	0.65	0.66
		Type-I Error	0.050	0.055	0.056	0.051

Key Validation Results

- Allocation Accuracy**
NE/N closely aligns with πE across all information fractions
- Power Target Achievement**
0.80 maintained at $\pi E=0.5$; expected decline at higher allocations
- Type-I Error Control**
Remains close to nominal 0.05; no consistent inflation pattern

Power vs. Allocation Trade-off

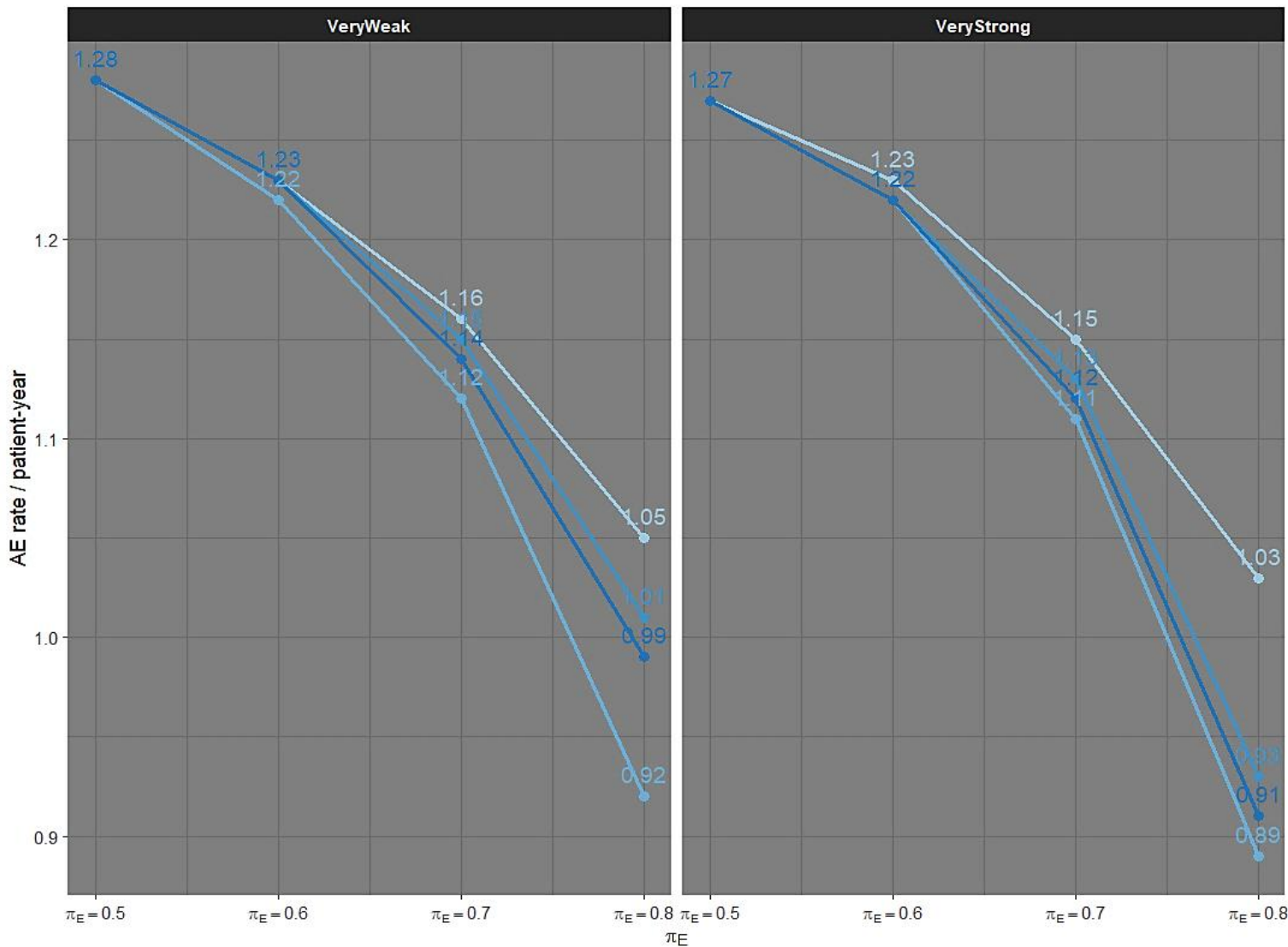


πE = True target allocation; NE/N = Estimated allocation; IF: information fraction at interim.



Adverse Event Rate Reduction

Design ○ Complete randomization ○ Safety-driven RAR ○ SAFER ($\eta=1$) ○ SAFER ($\eta=5$)



Key Findings

Complete Randomization **1.03**

SAFER ($\eta=1$) **0.93**

10% reduction vs. complete RAR

SAFER ($\eta=5$) **0.91**

12% reduction vs. complete RAR

Clinical Significance

SAFER designs achieve **AE rates below 1.0** for high allocation proportion values with both weak and strong endpoint associations. This represents substantial patient benefit through preferential assignment to better-tolerated arms while maintaining statistical power.



Comparative Design Performance

Performance Summary by Design Approach

πE	Association	Complete RAR			Safety-driven RAR			SAFER $\eta=1$			SAFER $\eta=5$		
		NE/N	p_1	Power	NE/N	p_1	Power	NE/N	p_1	Power	NE/N	p_1	Power
0.8	Very Weak	0.50	0.23	0.81	0.78	0.16	0.66	0.57	0.22	0.81	0.62	0.20	0.81
	Weak	0.50	0.28	0.87	0.78	0.19	0.73	0.59	0.27	0.87	0.64	0.25	0.86
	Moderate	0.50	0.34	0.92	0.78	0.24	0.79	0.60	0.33	0.92	0.66	0.31	0.91
	Strong	0.50	0.62	0.99	0.79	0.46	0.95	0.66	0.59	0.99	0.71	0.56	0.99
	Very Strong	0.50	0.82	1.00	0.79	0.66	0.99	0.70	0.80	1.00	0.74	0.76	1.00

p_1 = Power at interim; Power = Overall power; Bold gold = SAFER optimal performance

Red = Power loss >10% from target

Complete RAR

Power gains from endpoint association. power reaches 0.82 at $\pi E=0.8$ with very strong association

Safety RAR

Power decreases at weak associations, gains at strong. Risk of substantial power loss without SAFER

SAFER $\eta=1$

Shrinks allocation toward 0.5 at weak associations. Restores power while favoring better-tolerated arm

SAFER $\eta=5$

More aggressive approach reaching target allocation. Slight power reduction vs. $\eta=1$ but greater patient benefit

Key Takeaways & Future Directions

Safety-Driven Response Adaptive Randomisation in Non-inferiority Oncology Trials

Main Contributions

- 1 Power Preservation:** SAFER preserves statistical power while reducing adverse event rates through intelligent allocation adjustment.
- 2 Flexible Adaptation:** The design offers flexible adaptation speed based on temporal alignment of endpoints—faster when safety and efficacy are temporally aligned.
- 3 Safeguard Mechanism:** The Φ weight parameter protects against allocating to safer but potentially inferior arms when efficacy evidence is insufficient.
- 4 Practical Customization:** Comprehensive 9-step guidance enables adaptation across different trial settings, endpoint types, and monitoring schemes.

Clinical Impact

Patient-Centered Design

Enhances patient treatment experience by preferentially allocating to better-tolerated arms while maintaining statistical rigor.

Regulatory Alignment

Supports FDA Project Optimus objectives for dose optimization and benefit-risk balance in oncology drug development.

Late-Phase Applicability

Particularly suitable for Phase IIb/III trials where event accumulation is predictable and treatment effect estimates stabilize.

Future Directions

- How to manage informative drop-outs**
Using a composite strategy may inflate type-I error when safety & efficacy diverge; interpret as combined measure only
- Multi-arm Extensions**
Extend SAFER framework to trials with multiple experimental arms or dose levels.
- Digital Endpoints**
Leverage digital health technologies for more frequent adaptation and real-time monitoring.
- Non-monotonic Relationships**
Explore impact of non-monotonic safety-efficacy relationships
- Alternative Distributions**
Evaluate performance under Weibull, log-normal, and other survival distributions.
- Empirical Validation**
Validate design performance using real-world oncology trial data and case studies.

“SAFER offers a significant contribution in terms of practical tools to deliver patient-centred trials by adaptive learning from quickly observable safety data to proactively mitigate the assignment to poorly tolerated treatments without negatively affecting the power of the primary trial's objective.”