



An Adaptive Sequential Bayesian Design for a COVID Vaccine Trial

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Ingrid Lönnstedt

PhD Mathematical Statistics

Work experience

Pharmaceutical industry

- Consulting in drug development and life science as biostatistician ~15 years
(last > 5 years with SDS Life Science/Cytel: **clinical trial designs and exploratory analyses, regulatory**)
- Management and biostatistics in global big pharma company 3 years (CSL)

Academia

- Bioinformatics research position 4 years



A Sequential Predictive Power Design for a COVID Vaccine Trial

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ABSTRACT

Medical investigations for therapeutics and vaccines for combating a pandemic such as COVID-19, call for flexible and adaptive trial designs that are capable of producing robust results amidst uncertainties. Here, we present a Bayesian sequential design to study the efficacy of Bacillus Calmette–Guérin (BCG) in providing protection against COVID-19 infections via its known “trained-immunity” mechanism. The main design consideration is to provide a framework to rapidly establish a proof-of-concept on the vaccine efficacy of BCG under a constantly evolving incidence rate and in the absence of prior efficacy data. The trial design is based on taking several interim looks and calculating the predictive power with the current cohort at each interim look. Decisions to stop the trial for futility or stopping enrollment for efficacy are made based on the current cohort predictive power computation. At any interim, if any of the above decisions cannot be taken then the study continues to enroll till the next interim look. Via extensive numerical studies, we show that the proposed design can achieve the desired frequentist operating characteristics, currently required by regulatory bodies while offering greater flexibility in terms of sample size and the ability to make robust interim decisions.

ARTICLE HISTORY

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KEYWORDS

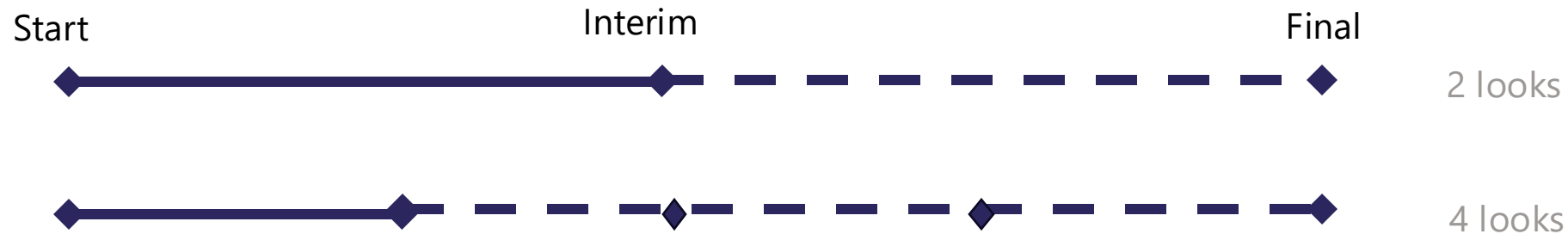
Bayesian adaptive designs;
COVID-19; Frequentist
operating characteristics;
Predictive power; Vaccine
trials



Background

Confirmatory trials - Hypothesis testing framework

Evaluate the study sequentially at **interim analyses**



Interim data will be used to make predictive judgement on the final study outcome.

Two approaches to predict and evaluate study outcomes

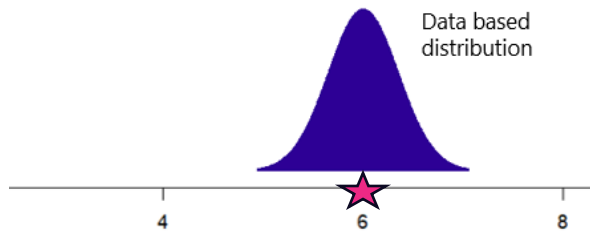
Frequentist (traditional)

Bayesian

Interim analysis
e.g. for
Sample-Size Re-estimation

Conditional power

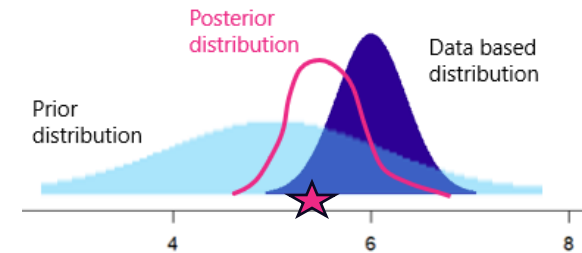
Probability of positive study
Given **interim effect estimates**



Intermediate:
Assurance

Predictive power

Probability of positive study
Given **posterior interim effect distribution**



Final analysis

P-value < 0.05 of treatment effect

Absence of any treatment effect is very unlikely, based on the **study data**

Posterior probability of treatment effect > 0.95

Posterior probability of treatment effect based on the **study data and prior distribution**

Prior/posterior = Learn/confirm = Adaptive
Flat prior or borrow information

Covid vaccine trial

Optimized for speed

Pfizer's RAM vaccine and I_SPY Covid 19 platform trials were both Bayesian designs.

Primary objective

Short term efficacy of BCG (Bacillus Calmette-Guérin), Proof of Concept

(BCG was developed against tuberculosis, there are other BCG studies on Covid, too.)

If successful, a long-term efficacy trial was planned.

Primary endpoint

Confirmed symptomatic Covid-19 (x = yes/no)

3 months follow-up after vaccination

π_B incidence proportion with BCG

π_C incidence proportion with control (placebo)

$H_0: \pi_B - \pi_C \geq 0$

$H_A: \pi_B - \pi_C < 0$

FDA prerequisites

π_B incidence proportion with BCG

π_C incidence proportion with control (placebo)

$H_0: \pi_B - \pi_C \geq 0$

$H_A: \pi_B - \pi_C < 0$

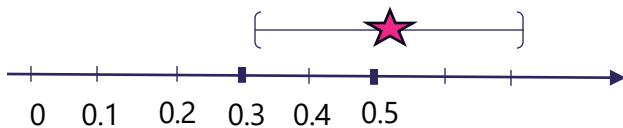
VE = vaccine efficacy = $1 - \frac{\pi_B}{\pi_C}$ (will be > 0 if treatment effect)

FDA requirements:

$\widehat{VE} \geq 0.5$ reducing incidence by at least 50%

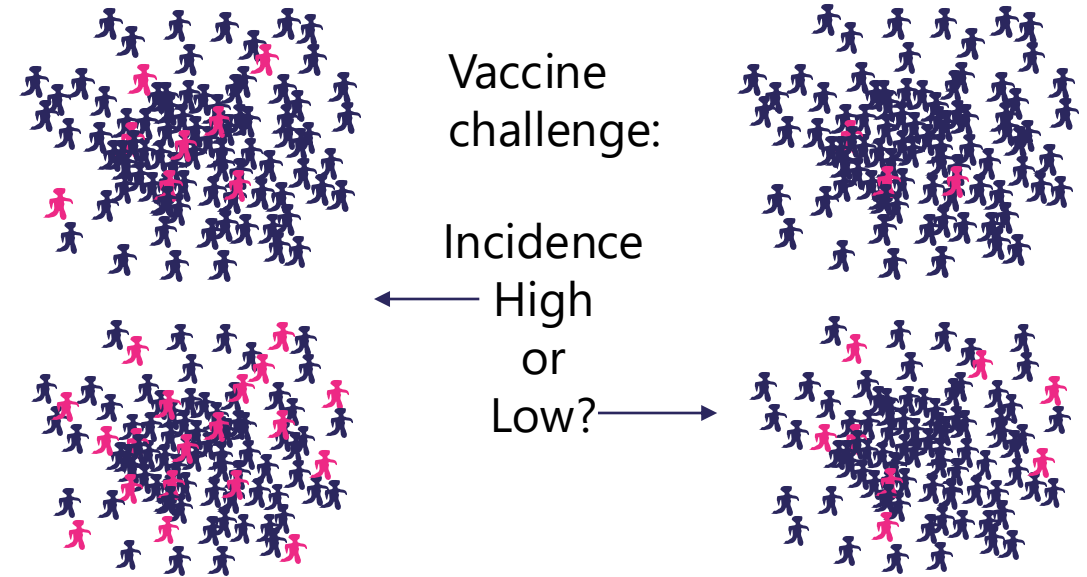
& $CI > 0.3$

(i.e. superiority margin of 0.3 -> large study)



One-sided $\alpha = 2.5\%$

90% power



Testing for difference in proportions with pooled variance, assuming $\pi_C = 20\%$, with **0 superiority margin**

->

645 patients needed, 8% dropout -> **700 patients** randomized 1:1 to detect 50% reduction.

Lower exposure -> lower π_C , underpowered!

Assuming $\pi_C = 6 - 8\%$ and $VE = 70\%$

->

1200 patients needed

Head for a study design with flexible sample size!



An Adaptive Sequential Bayesian Design

Adaptive Sequential Bayesian

Interim analyses
throughout the study

Adjust to learnings
from data

Use predictive
power and posterior
distribution for
decisions

Adaptive Sequential Bayesian – at it's extreme

What?

Interim analyses after say 30%, 40%, 50%, ... have been enrolled.

Allow sequential possibility to adapt

- Stop accrual early for futility
- Stop accrual early for predicted efficacy
- Re-estimate sample size and continue

How?

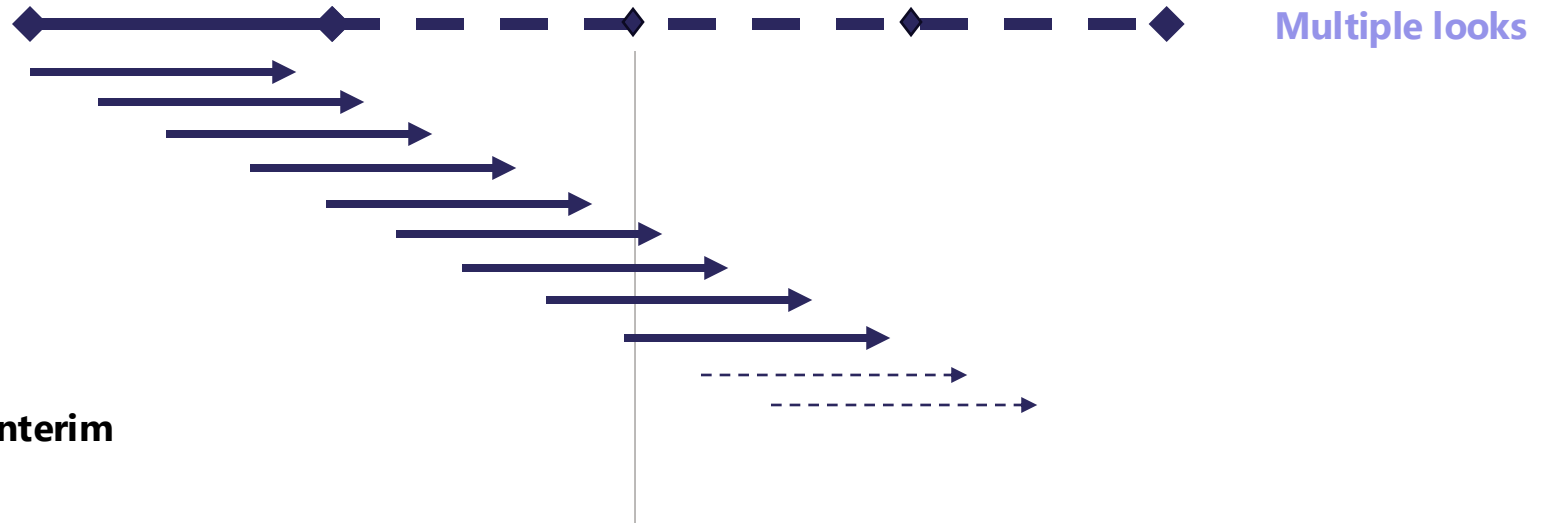
Predict treatment effect of enrolled patients at interim

Early stopping boundaries on predictive power

- S success threshold 80-99%
- F futility threshold 2.5-20%

Note!

- Useful when small to moderate delay between enrollment and observing primary outcome
- Extensive simulations needed



Study procedure

$N_{\text{plan}} = 700$ patients
 $N_{\text{max}} = 1200$ patients

Plan the 1st interim look when 75% of N_{plan} patients have been enrolled (not finished), and subsequent interim looks at 10% increments.

At k:th interim look, derive Predictive Power (PP):

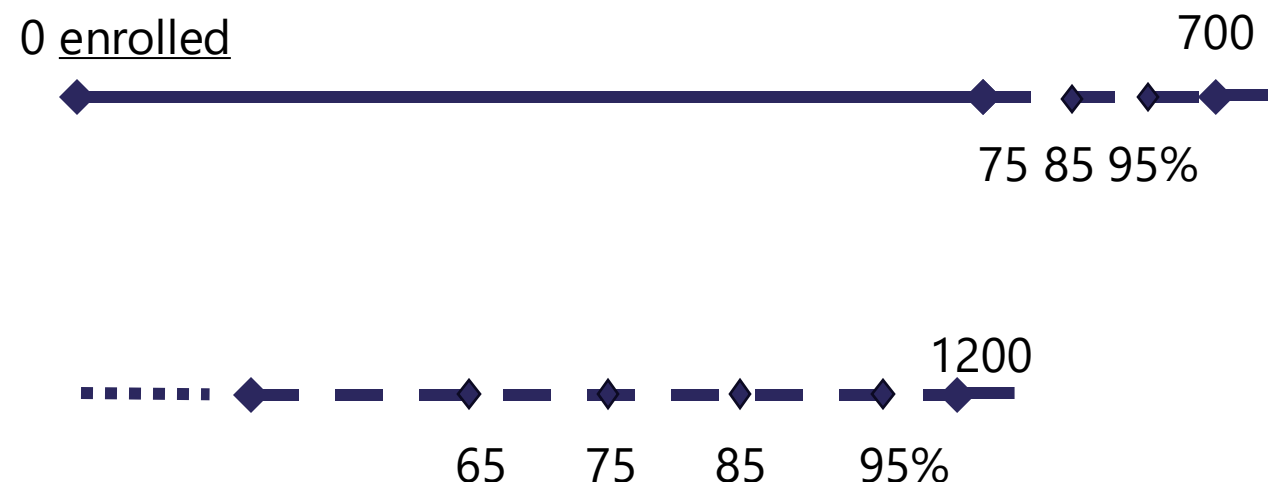
- If $PP \geq S = 90\%$ stop enrolling for efficacy
- If $PP < F = 20\%$ stop enrolling for futility

At last interim look before N_{plan} recruited:

- If $F < PP \leq 0.5$ carry out study as planned with $N_{\text{plan}} = 700$ patients.
- If $0.5 < PP < S$ increase sample size to $N_{\text{max}} = 1200$ patients and continue enrollment to next interim look at 65% of 1200.

➔ max 7 interim looks, at 75%, 85%, 95% of 700, then 65%, 75%, 85% and 95% of 1200.

Study is positive if posterior probability of $H_A > \gamma$.



Bayesian analysis

π_B incidence proportion with BCG

π_C incidence proportion with control (placebo)

$H_0: \pi_B - \pi_C \geq 0$

$H_A: \pi_B - \pi_C < 0$

Reject if the posterior probability $Pr(H_A|Data) > \gamma$,
where γ is set by simulation.

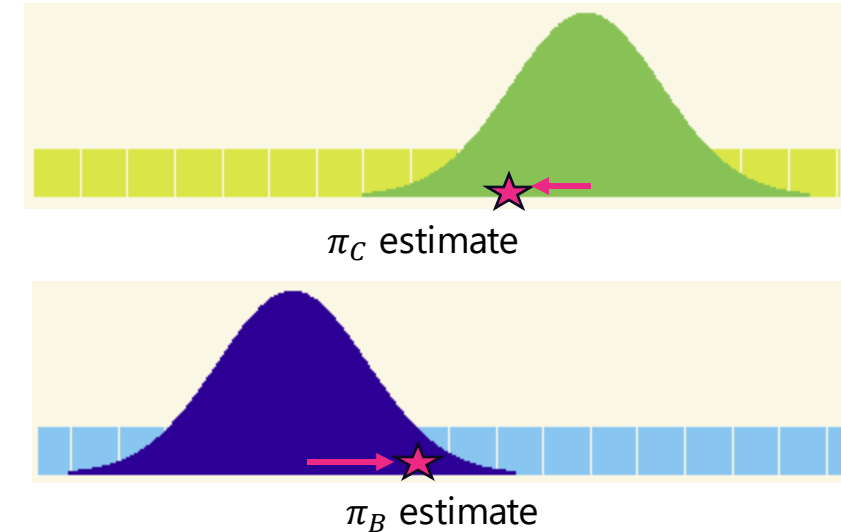
Beta Binomial conjugate prior-posterior derivation:

Each $\pi \sim \beta(\alpha = 1, \beta = 1)$ (uniform prior)

Each $x \sim \text{Bin}(n, \pi)$

->

Posterior distribution $(\pi|x) \sim \beta(\alpha + x, \beta + n - x)$



More advanced versions: include observations
taken so far on started patients (dichotomous or
survival analysis)

Posterior distributions are pulled
closer to each other - conservative!

Multiple testing/type I error control

No study evaluation at interim:

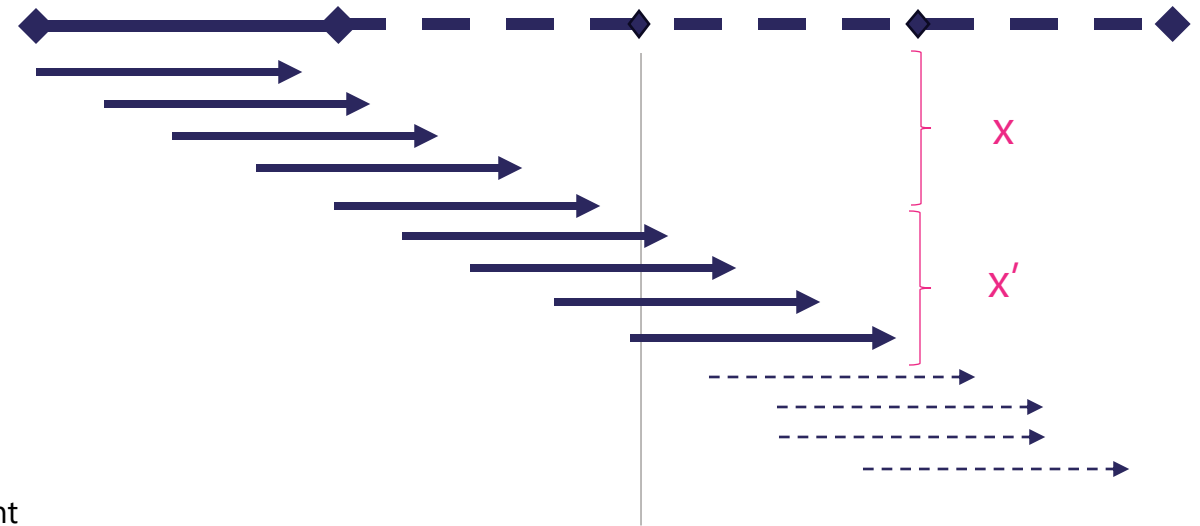
- we look at PP of those enrolled, not at the posterior distribution of all patients.
- Outcome of x' is predicted, not known.

Derive Predictive Power PP:

$$PP = E_{p(x'|x)} \{Pr(H_A | \underline{x}, \underline{x}') > \gamma\}$$

Posterior predictive distribution

Data so far
 \underline{x} finished patient
 \underline{x}' started but unfinished patient



Upon enrollment stop, the last enrolled patients will be finished before final study evaluation.

→ Multiple testing issue less pronounced, we earn some alpha

← Type I error risk, false positive risk

Use simulations to set γ that preserves Type I error risk < 2.5% one-sided.



No "special" rules by authorities for Bayesian studies, they need to adhere to the same risk limits as traditional studies.



Evaluations

Simulation results (1/3)

Table 1. Simulation results under the null scenario with 0% vaccine efficacy (BCG vs. Control), varying recruitment rate (Rec.) and success criteria γ . Up to 7 interim looks, $\eta = 0.9$, $\eta_1 = 0.5$, and $\eta_f = 0.2$.

	Success criteria (γ)	No. of interim looks mean (SD)	Sample size min, mean(SD), med, max	Prob. early efficacy stop enroll.	Prob. early futility stop	Prob. sample size inc. (N = 1200)	Type I error rate
Rec.: 50	0.975	1.22(0.76)	525, 705.79(68.34), 700, 1200	0.0236	0.9471	0.0217	0.02777
	0.977	1.21(0.74)	525, 705.50(66.37), 700, 1200	0.0220	0.9501	0.0204	0.02568
	0.978	1.20(0.74)	525, 705.40(65.49), 700, 1200	0.0211	0.9518	0.0200	0.02438
	0.980	1.19(0.72)	525, 705.16(63.63), 700, 1200	0.0195	0.9550	0.0188	0.02221
Rec.: 100	0.975	1.47(1.12)	525, 716.68(98.87), 700, 1200	0.0239	0.9019	0.0451	0.02688
	0.977	1.45(1.11)	525, 716.14(97.00), 700, 1200	0.0224	0.9060	0.0433	0.02494
	0.978	1.45(1.10)	525, 715.87(96.03), 700, 1200	0.0216	0.9081	0.0424	0.02393
	0.980	1.43(1.07)	525, 715.05(93.50), 700, 1200	0.0203	0.9126	0.0401	0.02197
Rec.: 150	0.975	1.86(1.41)	525, 730.13(129.96), 700, 1200	0.0350	0.8271	0.0760	0.02679
	0.977	1.84(1.39)	525, 729.22(128.01), 700, 1200	0.0335	0.8321	0.0734	0.02468
	0.978	1.83(1.38)	525, 728.77(127.02), 700, 1200	0.0327	0.8348	0.0721	0.02365
	0.980	1.81(1.36)	525, 727.90(125.01), 700, 1200	0.0311	0.8406	0.0697	0.02178

NOTE: Results are summarized over 200,000 simulated trials.

Type I error rate must be < 2.5%

Simulation results (2/3)

Table 2. Simulation results under the null scenario with 0% vaccine efficacy (BCG vs. Control), varying maximum number of interim looks (Max IAs) and recruitment rate (Rec.) per month.

	Rec.	No. of interim looks mean (SD)	Sample size min, mean(SD), med, max	Prob. early efficacy stop enroll.	Prob. early futility stop	Prob. sample size inc. ($N = 1200$)	Type I error rate
<i>Max IAs: 2</i>							
	50	1.04(0.19)	525, 716.52(95.82), 700, 1200	0.0124	0.9139	0.0391	0.02266
	100	1.07(0.26)	525, 733.34(129.46), 700, 1200	0.0129	0.8262	0.0733	0.02235
	150	1.15(0.36)	525, 770.26(179.58), 700, 1200	0.0204	0.6882	0.1500	0.02270
<i>Max IAs: 4</i>							
	50	1.13(0.45)	525, 707.84(72.15), 700, 1200	0.0190	0.9476	0.0227	0.02331
	100	1.27(0.63)	525, 718.68(101.55), 700, 1200	0.0194	0.8989	0.0452	0.02292
	150	1.51(0.77)	525, 733.00(132.74), 700, 1200	0.0285	0.8174	0.0771	0.02271

NOTE: Success criteria $\gamma = 0.978$, $\eta = 0.9$, $\eta_1 = 0.5$, and $\eta_f = 0.2$. Results are summarized over 200,000 simulated trials.

OK

Type I error rate must be < 2.5%

Simulation results (3/3)

Table 3. Simulation results under design alternatives with 50% vaccine efficacy (VE, BCG vs. Control), varying maximum number of interim looks (Max IAs) and recruitment rate (Rec.) per month. Success criteria $\gamma = 0.978$, $\eta = 0.9$, $\eta_1 = 0.5$, and $\eta_f = 0.2$.

	Rec.	No. of interim looks mean (SD)	Sample size min, mean(SD), med, max	Prob. early efficacy stop enroll.	Prob. early futility stop	Prob. sample size inc. (N = 1200)	Power
<i>Max IAs: 7</i>							
	50	1.64(1.17)	525, 596.48(114.03), 525, 1200	0.7695	0.1149	0.0889	0.91360
	100	2.00(1.48)	525, 622.49(143.46), 525, 1200	0.7274	0.0723	0.1613	0.92110
	150	2.25(1.62)	525, 643.32(160.60), 595, 1200	0.6999	0.0522	0.2009	0.92040
<i>Max IAs: 4</i>							
	50	1.42(0.73)	525, 614.88(139.53), 525, 1200	0.7593	0.1068	0.1015	0.91760
	100	1.64(0.88)	525, 648.17(172.23), 525, 1200	0.7161	0.0640	0.1746	0.92580
	150	1.80(0.95)	525, 675.99(189.87), 665, 1200	0.6805	0.0463	0.2215	0.92630
<i>Max IAs: 2</i>							
	50	1.21(0.40)	525, 660.06(196.84), 525, 1200	0.6063	0.0928	0.2065	0.92220
	100	1.31(0.46)	525, 707.40(225.74), 525, 1200	0.5364	0.0518	0.3078	0.93040
	150	1.39(0.49)	525, 747.86(237.79), 700, 1200	0.4626	0.0355	0.3871	0.93160

NOTE: Results are summarized over 10,000 simulated trials.

Power must be > 90%

Compare to Group Sequential design

(Lan-DeMets alpha spending with O'Brien-Flemming boundaries)

GSD-OB

ASB

Up to 8 looks including the final
Max 1200 patients
Overall alpha 2.5% one-sided.
1st interim look at 30% of 1200 completed/enrolled
Subsequent looks every 10%

$\gamma = 0.978, \eta = 0.9, \eta_1 = 0.5, \text{ and } \eta_f = 0.2.$
strictly non-binding

VE = 50%
 $\pi_C = 20\%$
100 patients/month

97% power
SS average 1005
P(early stopping) = 98%

More
effective

92% power
SS average 622
P(early stopping) = 72%

VE = 70%
 $\pi_C = 6\%$
100 patients/month

85% power
SS average 1199

90% power
SS average 666

More
effective

Adaptive Sequential
Bayesian stops
earlier when
motivated!



Wrap up

An Adaptive Sequential Bayesian Design for a COVID Vaccine Trial

A Goldilocks approach to sample size selection
– not too big, not too small



1. Sample size will be tailored to vaccine incidence, to be adequate even with low spreading of the disease.
2. A "temporary high" in efficacy has a chance to be corrected in the final analysis including also the last enrolled patients.
3. Only recruitment rates of 50 – 150 patients per month. Check from case to case!
4. Infinite variations possible: add new arms, historical data in informative priors, ...
5. Wild and crazy design powered to prove Proof of Concept, i.e. not pivotal.
 1. Does not show $VE > 0.3$, and 3 months is too little safety.
 2. If $\widehat{VE} > 0.5$ a confirmatory trial will follow!
6. This trial could inform a confirmatory trial as informative priors.
7. Multiple looks -> heavy operational burden. Keep interim results blinded to investigators, investors, sponsors -> preserve the integrity of trial results.
8. Bayesian analysis – beware, in clinical trials we strive to be objective!

Some adaptive sequential designs successfully implemented with FDA

- Julian, T. B., Blumencranz, P., Deck, K., Whitworth, P., Berry, D. A., Berry, S. M., Rosenberg, A., et al. (2008). Novel intraoperative molecular test for sentinel lymph node metastases in patients with early-stage breast cancer. *Journal of Clinical Oncology: Official Journal of the American Society of Clinical Oncology* 26(20):3338–3345.
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