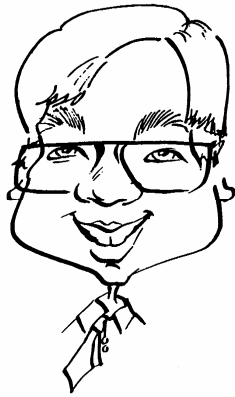


# Adaptive Design Methods in Clinical Trials

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# Outline

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- What and why?
- Type of adaptive designs
- Regulatory/statistical perspectives
- Moving target population
- Statistical inference
- Concluding remarks



# What Is Adaptive Design?

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- There is no universal definition
  - Adaptive randomization, group sequential, and sample size re-estimation, etc.
  - Chow, Chang, and Pong (2005)
  - PhRMA (2006)
- Adaptive design is also known as
  - Flexible design (EMA, 2002, 2006)
  - Attractive design (Uchida, 2006)



## PhRMA's Definition

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*PhRMA (2006), J. Biopharm. Stati., 16 (3), 275-283.*

An adaptive design is referred to as a clinical trial design that uses *accumulating data* to decide on how to *modify* aspects of the study as it *continues*, without undermining the *validity* and integrity of the trial.



# PhRMA's Definition

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- Characteristics

- Adaptation is a design feature.
- Changes are made “by design” not on an “ad hoc” basis.

- Comments

- It does not reflect real practice.
- It may not be flexible as it means to be.



# Type of Adaptation

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- Prospective adaptation
  - Adaptive randomization
  - Interim analysis
  - Stop trial early due to safety, futility/efficacy
  - Sample size re-estimation  
etc.
- Concurrent adaptation
  - Trial procedures
- Retrospective adaptation
  - Statistical procedures



# Nature of Adaptation

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- Prospective adaptation
  - By design
- Concurrent adaptation
  - Ad hoc
- Retrospective adaptation
  - Prior to database lock and/or unblinding



# Adaptive Designs

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- Adaptive randomization design
- Adaptive group sequential design
- N-adjustable design
- Drop-the-loser design
- Adaptive dose-escalation design
- Biomarker-adaptive design
- Adaptive treatment-switching design
- Adaptive-hypotheses design
- Adaptive seamless phase II/III trial design
- Any combinations of the above (multiple adaptive design)





# Regulatory/Statistical Perspectives

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- May introduce **operational bias**.
- May not be able to preserve **type I error rate**.
- **P-values** may not be correct.
- **Confidence intervals** may not be reliable.
- May result in **a totally different trial** that is unable to address the medical questions the original study intended to answer.



# Implementation of Adaptation

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- Prospective adaptation
  - By design
  - Study protocol
- Concurrent adaptation
  - Ad hoc
  - Protocol amendments
- Retrospective adaptation
  - Prior to database lock and/or unblinding
  - Statistical analysis plan



## Practical Issues in Clinical Trials

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- On average, for a given clinical trial, we may have 2-3 protocol amendments during the conduct of the trial.
- It is not uncommon to have 5-10 protocol amendments regardless the size of the trial.



# Protocol Amendments

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- Rationale for changes
  - Clinical
  - Statistical
- Review process
  - Internal protocol review
  - IRB
  - Regulatory agencies



# Target Patient Population

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- Has the disease under study
- Inclusion criteria to describe the target patient population
- Exclusion criteria to remove heterogeneity
- Subpopulations may be defined based on some baseline demographics and/or patient characteristics



## Target Patient Population

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- Denote **target** patient population by  $(\mu, \sigma)$ , where  $\mu$  and  $\sigma$  are population mean and standard deviation, respectively.
- After a modification made to the trial procedures, the target patient population lead to the **actual** patient population of

$$(\mu_{Actual}, \sigma_{Actual}) = (\mu + \varepsilon, C\sigma)$$



## Target Patient Population

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$$\left| \frac{\mu_{Actual}}{\sigma_{Actual}} \right| = \left| \frac{\mu + \varepsilon}{C\sigma} \right| = \left| \frac{\Delta\mu}{\sigma} \right| = |\Delta| \left| \frac{\mu}{\sigma} \right|,$$

where  $\Delta = \frac{1 + \varepsilon / \mu}{C}$



## Target Patient Population

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- $\left| \frac{\mu}{\sigma} \right|$  is usually referred to as the effect size
- The effect size after the modification made is inflated or reduced by the factor of  $\Delta$ .
- “Clinically meaningful difference” may have been changed after the modification (adaptation) is made.





## Target Patient Population

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- $\Delta$  is referred to as a sensitivity index.
- When  $\varepsilon = 0$  and  $C = 1$  (i.e., there are no impact on the target patient population after the modifications made). In this case, we have  $\Delta = 1$  (i.e., the sensitivity index is 1).



# Sensitivity Index

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- A shift in mean of the target patient population may be offset by the inflation (or reduction) of the variability, e.g.,
  - A shift of 10% (-10%) in mean could be offset by a 10% inflation (reduction) of variability
- $\Delta$  may not be sensitive due to the **masking effect** between  $\mathcal{E}$  and  $\mathcal{C}$ .



# Moving Target Patient Population

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- Under the moving target patient population, the effect size is the original effect size times the sensitivity index,

that is

$$\left| \frac{\mu_{Actual}}{\sigma_{Actual}} \right| = |\Delta| \left| \frac{\mu}{\sigma} \right|$$

- How will this impact statistical inference?



# Inference with Protocol Amendments

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*Chow SC and Shao J. (2005). J. Biopharm. Stat., 15, 659-666.*

Model the population deviations due to protocol amendments using some covariates and develop a valid statistical inference procedure.



# Inference with Protocol Amendments

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- The idea is to relate the means before and after protocol amendments by means of some covariates. In other words,

$$\mu_k = f(x_k), k = 1, \dots, m,$$

where  $\mu_k$  and  $x_k$  are the mean and the corresponding covariate after the *k*th protocol amendment,  $f$  is a given function (linear or non-linear), and  $m$  is the number of protocol amendments.



# Statistical Inference

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- Notations

$P_o$  : Target patient population

$P_k$  : Patient population after the *k*th  
protocol amendment,  $k = 1, \dots, m$

$\mu_o$  : Target patient population mean

$\mu_k$  : Patient population mean after the  
*k*th protocol amendment



# Statistical Inference

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- Assumption

$$\mu_k = \beta_0 + \beta' \mathbf{x}_k \quad k = 1, \dots, m$$

where  $\beta_0$  is an unknown parameter,  $\beta$  is an unknown parameter vector whose dimension is the same as  $\mathbf{x}$ ,  $\beta'$  denotes the transpose of  $\beta$ , and  $\mathbf{x}_k$  is the value of  $\mathbf{x}$  under the *k*th amendment

- Note that although  $\mu_1, \dots, \mu_m$  are different from  $\mu_0$ , the above assumption relates them with the covariate.



## Conditional Inference

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- First 
$$\begin{pmatrix} \hat{\beta}_0 \\ \hat{\beta} \end{pmatrix} = (X'WX)^{-1} X'W\bar{y}$$

where  $\bar{y} = (\bar{y}_0, \bar{y}_1, \dots, \bar{y}_m)'$ ,  $X$  is a matrix

whose  $k$ th row is  $(1, x'_K)$ ,  $K=0, \dots, m$ , and  $W$  is a diagonal matrix whose diagonal elements are  $n_0, n_1, \dots, n_m$ .

- An unbiased estimate of  $\mu_0$  can then be obtained as

$$\hat{\mu}_0 = \hat{\beta}_0 + \hat{\beta}'x_0$$





# Conditional Inference

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- Assumptions

- Conditional on the given protocol amendments, data from  $P_k$  are normally distributed with a common standard deviation  $\sigma$ .

- Data from different  $P_{k_s}$  are independent

- $\hat{\mu}_0$  is distributed as,  $N(\mu_0, \sigma^2 C_0)$  where

$$C_0 = (1, \mathbf{x}_0)(X'WX)^{-1}(1, \mathbf{x}_0)'$$



## Conditional Inference

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Thus, confidence interval for  $\mu_0$  can be obtained based on the t-statistic

$$t = \frac{\hat{\mu}_0 - \mu_0}{\sqrt{C_0 s^2}} ,$$

where

$$s^2 = \sum_{k=0}^m \frac{(n_{k-1}) s_k^2}{N - m}$$

$$N = \sum_{k=0}^m n_k$$



## Conditional Inference

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When  $P_{k s}$  have different standard deviations and/or data from  $P_k$  are not normally distributed, we may consider the following approximation for large sample

$$\hat{\mu}_0 \underset{\text{approx}}{\sim} N(\mu_0, r^2) \quad ,$$

where

$$r^2 = (1, x_0) (X'WX)^{-1} X'W \Sigma X (X'WX)^{-1} (1, x_0)'$$

when  $\Sigma$  is the diagonal matrix whose  $k$ th diagonal element is the population variance of

$$P_k \quad , \quad k = 1, \dots, m$$



# Unconditional Inference

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- Notations

- $C_K$  = a particular set of  $K$  protocol amendments

- $C$  = the collection of all possible protocol amendments indexed by  $1, 2, \dots, M$

- Thus  $C_K = \{i_1, \dots, i_K\} \in C = \{1, \dots, M\}$

- $C_K$  is chosen based on a (random) decision rule  $\xi$  (adaptation rule)



## Unconditional Inference

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- For a particular  $C_K$ , let  $Z_{C_K}$  be the z-statistic. Also, let  $L(Z_{C_K} | \xi = C_K)$  be the conditional distribution of  $Z_\xi$  given  $\xi = C_K$ .

- Suppose that  $L(Z_{C_K} | \xi = C_K)$  is approximately standard normal. We have

$$L(Z_\xi) = E \left[ \sum_{C_K \in \mathcal{C}} L(Z_{C_K} | \xi = C_K) I_{\xi = C_K} \right]$$

where  $I_{\xi = C_K}$  is the indicator function of the set  $\{\xi = C_K\}$



# Unconditional Inference

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$$P\left(Z_{C_K} \leq t \mid \xi = C_K\right) \rightarrow \Phi(t) \quad \text{a.s.}$$

$$\Rightarrow P\left(Z_{C_K} \leq t \mid \xi = C_K\right) I_{\xi=C_K} \rightarrow \Phi(t) I_{\xi=C_K} \quad \text{a.s.}$$

$$\begin{aligned} \Rightarrow E\left[P\left(Z_{C_K} \leq t \mid \xi = C_K\right) I_{\xi=C_K}\right] &\rightarrow E\left(\Phi(t) I_{\xi=C_K}\right) \\ &= \Phi(t) E\left(I_{\xi=C_K}\right) \\ &= \Phi(t) P(C_K) \end{aligned}$$

$$\begin{aligned} \Rightarrow P\left(Z_{C_K} \leq t\right) &= \sum_{C_K \in \mathcal{C}} E\left[P\left(Z_{C_K} \leq t \mid \xi = C_K\right) I_{\xi=C_K}\right] \\ &\rightarrow \sum_{C_K \in \mathcal{C}} \Phi(t) P(C_K) = \Phi(t) \end{aligned}$$



## Practical Issues

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- In practice, covariates that will link the population means before and after protocol amendments may not exist or not observed.
- The impact of protocol amendments may be examined through the assessment of sensitivity index.



# Concluding Remarks

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- Clinical

- Adaptive design reflects real clinical practice in clinical development.
- Adaptive design is very attractive due to its flexibility and efficiency.
- Potential use in early clinical development.

- Statistical

- The use of adaptive methods in clinical development will make current good statistics practice even more complicated.
- The validity of adaptive methods is not well established.





# Concluding Remarks

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- Regulatory
  - Regulatory agencies may not realize but the adaptive methods for review/approval of regulatory submissions have been employed for years - no scientific basis.
  - Guidelines regarding the use of adaptive methods are necessary developed.
- IDMC (Independent Data Monitoring Committee)
  - Independent data monitoring, administrative looks, and/or interim analyses.
  - Integrity and validity of the trial