

# **Sequential designs for Individualized dosing algorithms**

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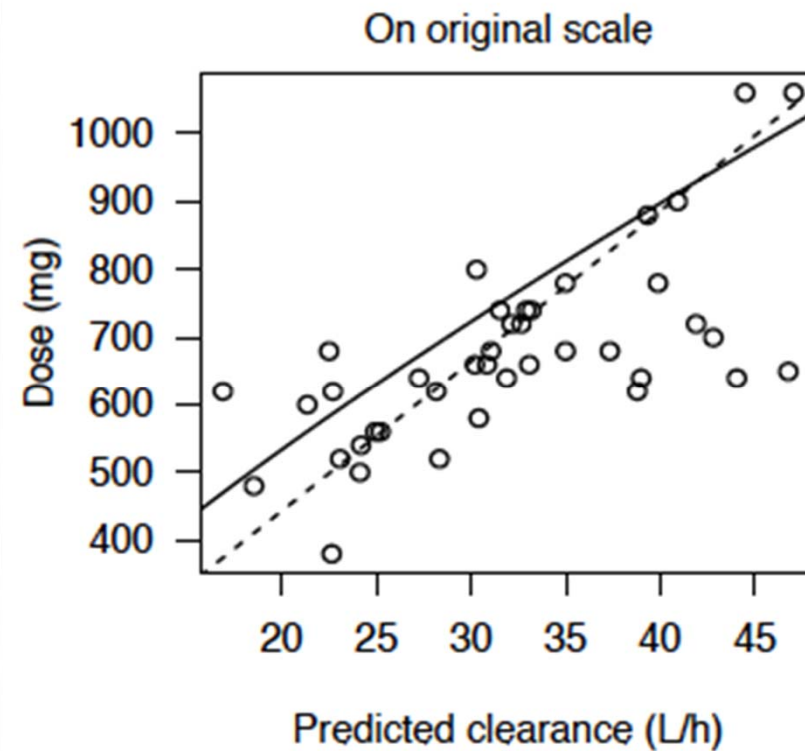
Mao, Cheung (2016+). Sequential designs for individualized dosing in phase I cancer clinical trials. Contemporary Clinical Trials. In press.

# Agenda

- Data, design objective & least squares recursion
- Eigenvalue condition (EVC)
- **Method: Least squares recursion with EVC**
- Simulation study
- Discussion

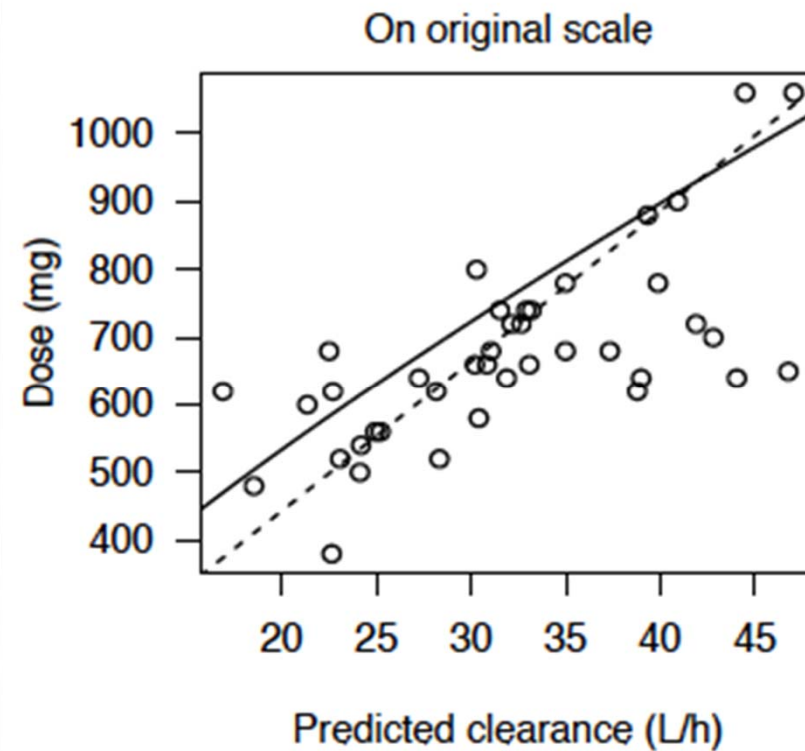
# Data

- *Irinotecan*
- *BSA formula (n = 20)*
  - $X = \log(350) + \log(\text{BSA})$
- *Dosing Equation (n = 20)*
  - Target AUC at 22.157 micrograms h/ml
  - Dotted line



# Objectives

- *Estimate a dosing algorithm (solid line)*
- *Treat study subjects close to their targets*



# Defining the problem

- $Y = \log(\text{AUC}); X = \log(\text{Dose}); Z = \log(\text{Biomarker})$

$$Y = \alpha + \beta X + \gamma Z + \epsilon, \quad \beta > 0, \gamma \leq 0,$$

The trial objective is, for each subject with  $z_i$ , to determine a dose  $x_i$  such that  $E(Y|X = x_i, Z = z_i) = t_0$ , i.e. to estimate the patient-specific dosing function:

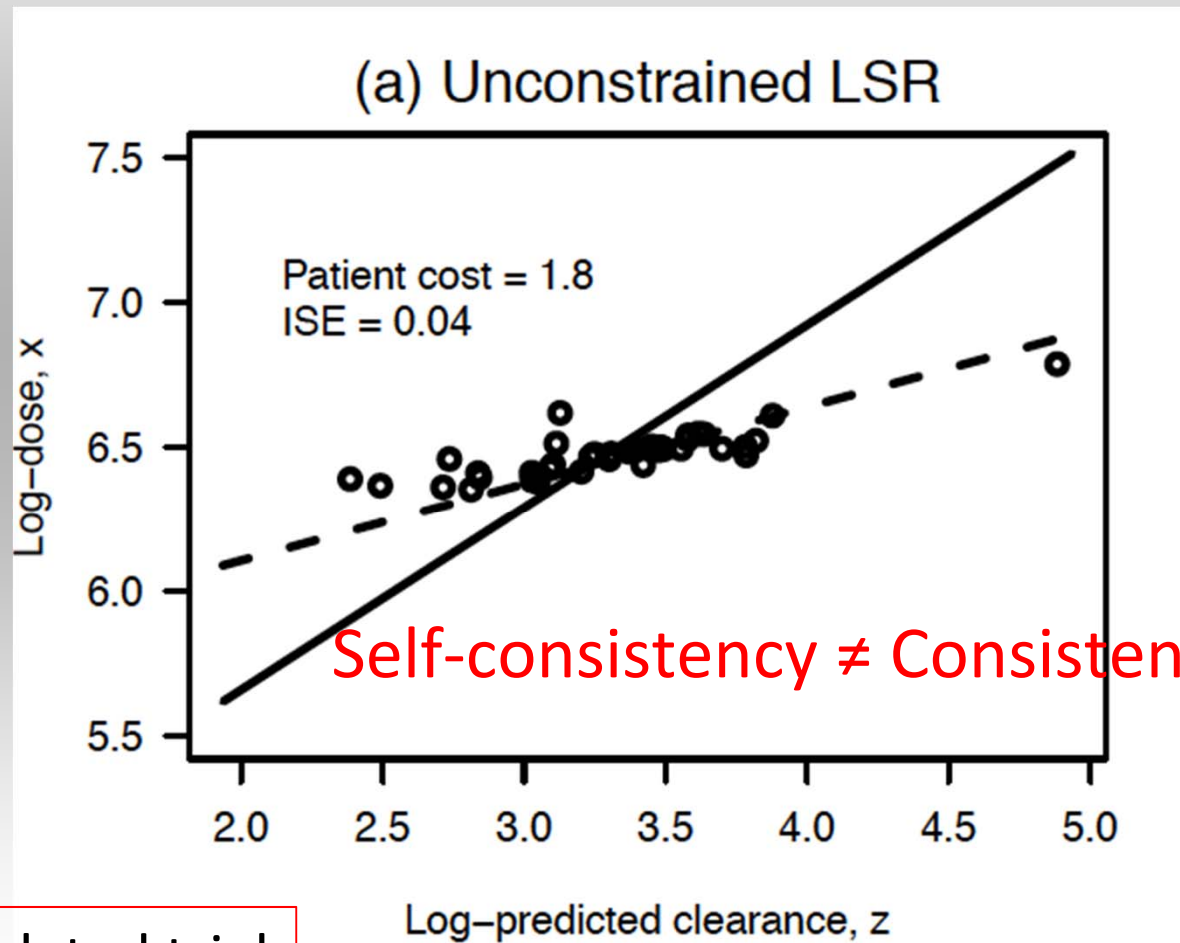
$$\theta(z) = \frac{t_0 - \alpha - \gamma z}{\beta}, \quad \text{for any given } z \in I_Z. \quad (3)$$

# Least Squares Recursion (LSR)

$$\hat{\theta}_i(z) = \frac{t_0 - \hat{\alpha}_i - \hat{\gamma}_i z}{\hat{\beta}_i},$$

$$x_{i+1} = \min \left\{ \max \left\{ \hat{\theta}_i(z_{i+1}), x_{min} \right\}, x_{max} \right\}, \quad (4)$$

# Least Squares Recursion (LSR)



A simulated trial

# Eigenvalue condition

- In dose finding, we are dealing with a stochastic design matrix  $M_n$ , which requires stronger conditions for consistency than a fixed  $M_n$ . Lai and Wei (1982):

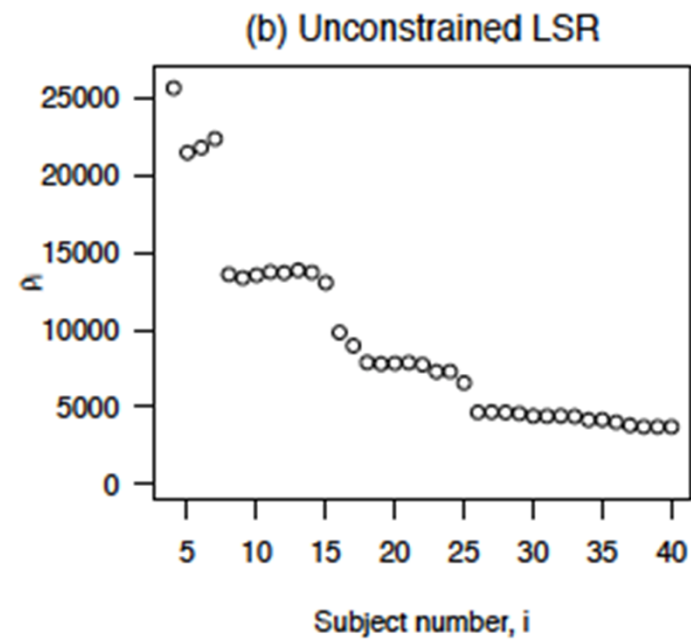
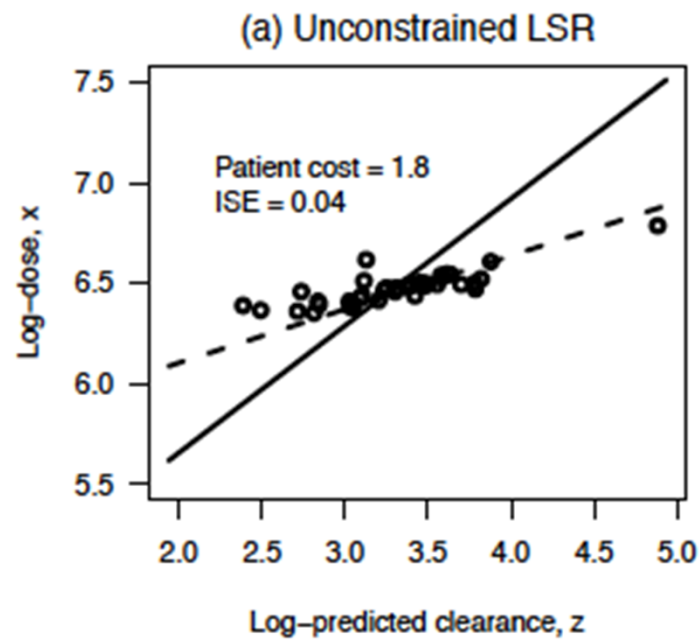
The eigenvalue condition (EVC):

$$\frac{\log \lambda_{max}(n)}{\lambda_{min}(n)} \rightarrow 0 \text{ a.s., as } n \rightarrow \infty,$$

where  $\lambda_{max}(n)$  and  $\lambda_{min}(n)$  are respectively the maximum and minimum eigenvalues of  $M_n' M_n$ .



# Eigenvalue condition



# LSR with EVC

$$\tilde{\theta}_n(z_{n+1}) = \arg \min_x |x - \hat{\theta}_n(z_{n+1})| \text{ subject to } \rho_{n+1}(x, z_{n+1}) \leq r_{n+1}$$

$$\text{where } \rho_n(x, z) = \frac{\log \lambda_{\max}(n)}{\lambda_{\min}(n)}, \quad r_n \rightarrow 0$$

$$x_{n+1} = \max[\min\{\tilde{\theta}_n(z_{n+1}), x_{\max}\}, x_{\min}]$$

# LSR with EVC

## Practical Considerations

- Initial design
- Coherence
- $r_n$  : Calibration

# LSR with EVC

## Practical Considerations

- Initial design
- Coherence
- $r_n$  : Calibration

- Use conventional rule to start: e.g., BSA
- Transition to model based as long as LSE is “stable”

$$|M'_{n_0} M_{n_0}| \geq 0.01$$

# LSR with EVC

## Practical Considerations

- Initial design
- **Coherence**
- $r_n$  : Calibration
- Ethical consideration (Cheung, 2005, Biometrika)
- If the current patient has AUC lower than  $t_0$  and the next patient has a higher clearance, do not de-escalate

$$x_{n+1} = \begin{cases} \max[\min\{\tilde{\theta}_n(z_{n+1}), x_n\}, x_{\min}] & \text{if } y_n > t_0 \text{ and } z_{n+1} \leq z_n, \\ \min[\max\{\tilde{\theta}_n(z_{n+1}), x_n\}, x_{\max}] & \text{if } y_n < t_0 \text{ and } z_{n+1} \geq z_n, \\ \max[\min\{\tilde{\theta}_n(z_{n+1}), x_{\max}\}, x_{\min}] & \text{otherwise.} \end{cases}$$

# LSR with EVC

## Practical Considerations

- Initial design
- Coherence
- $r_n$  : Calibration

$$r_n = \frac{C \log n}{n^{\delta_1} (\log n)^{\delta_2}}$$

1. Iterate  $\delta_1$  and  $\delta_2$  on a relevant grid
2. Run simulation by drawing 10000 scenarios from the posterior distribution
3. Record average loss

Choose  $\delta_1$  and  $\delta_2$  with the minimum average loss

# LSR with EVC

## Practical Considerations

- Initial design
- Coherence
- $r_n$  : Calibration

Integrated error in estimation of theta(z)

$$C_{\kappa}(\delta_1, \delta_2) = \frac{1}{10000} \sum_{j=1}^{10000} \{D_n^{(j)} + \kappa n \overline{SE}_j\} := \bar{D}_n + \kappa n \overline{SE}$$

Within trial dosing cost in a trial

# LSR with EVC

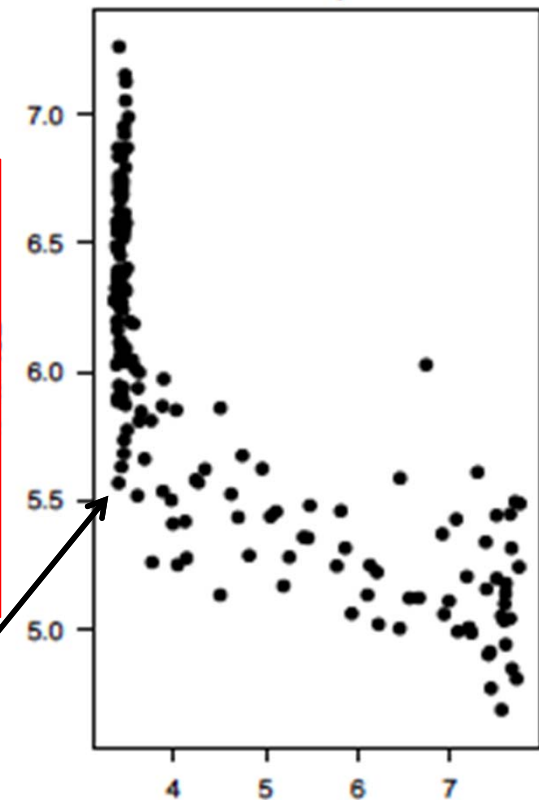
## Practical Considerations

- Initial design
- Coherence
- $r_n$  : Calibration

$$r_n = \frac{C \log n}{n^{\delta_1} (\log n)^{\delta_2}}$$

$$\delta_1 = 0.5 \text{ and } \delta_2 = 2$$

Estimation vs patient cost

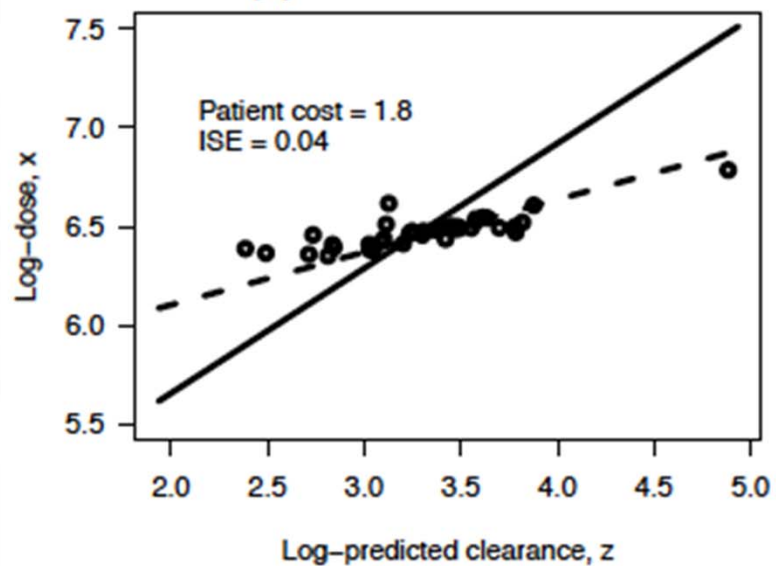


MSE for estimation

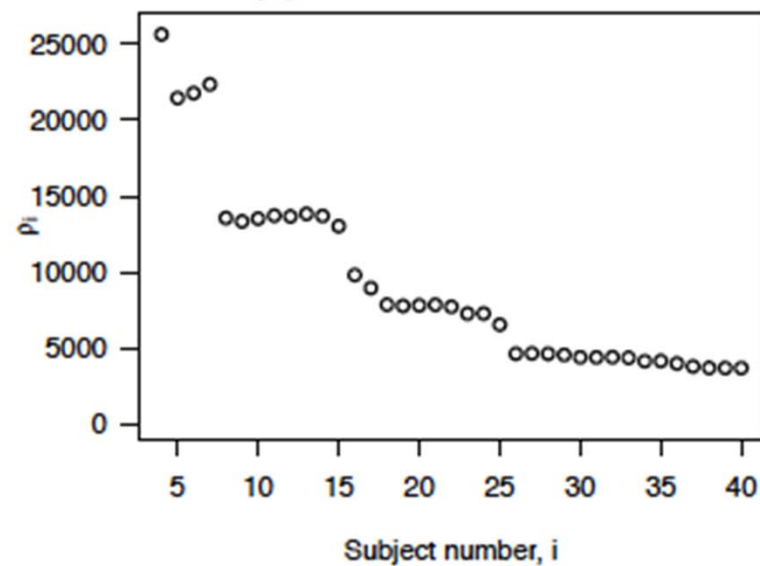
Within trial dosing cost



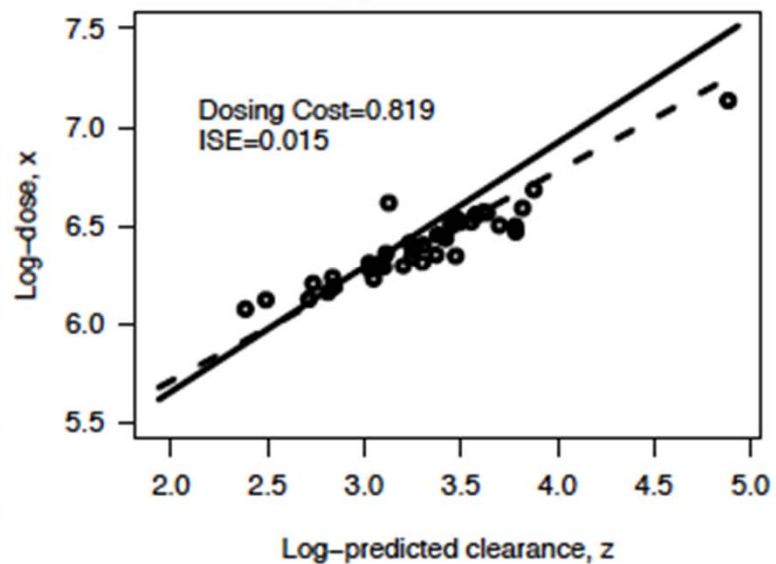
(a) Unconstrained LSR



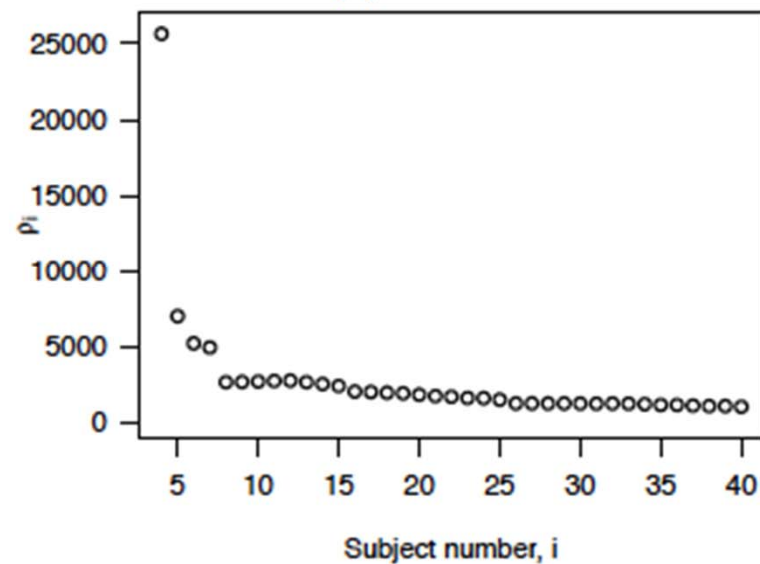
(b) Unconstrained LSR



(c) LSR-EVC



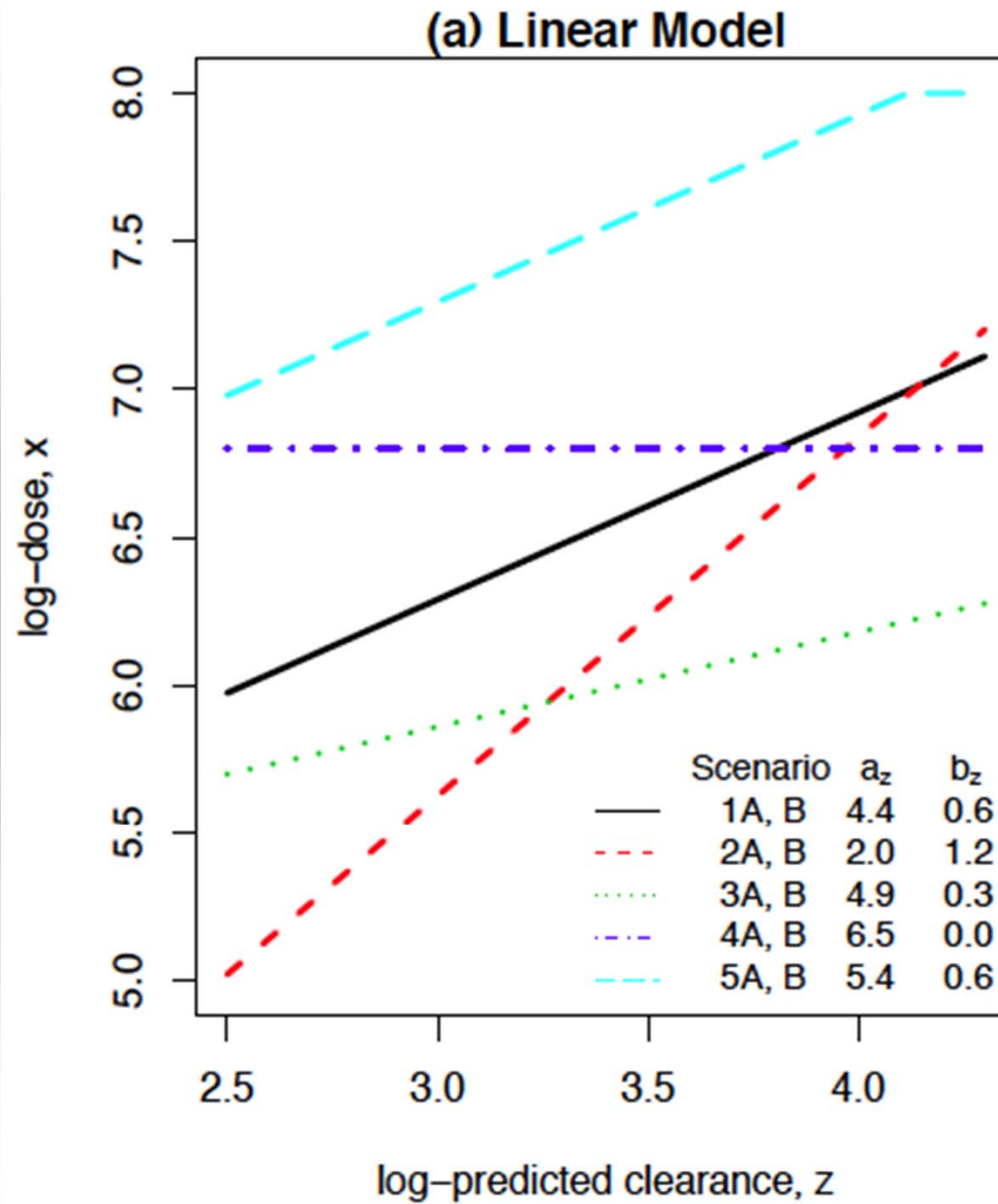
(d) LSR-EVC



# Simulation study

- Outcome generation:
  - $Y = g(a + bx + cz) + N(0, 0.26^2)$
  - Scenarios 1-5:  $g(s) = s$  for Scenarios 1-5
  - Scenarios 6-7: Nonlinear  $g(s)$
  - $b = 0.68, 0.32$
- Methods:  $n = 40$ 
  - LSR (with coherence constraint)
  - LSR-EVC
  - BSA
  - Equation formula

# Simulation Scenarios



# Simulation Results

Method	Scenario	$E(D_n)$	$E(\text{ISE}) \times 100$	Efficiency	Scenario	$E(D_n)$	$E(\text{ISE}) \times 100$	Efficiency
LSR	1A	2.20	1.17	1.00	1B	4.04	5.40	1.00
LSR-EVC		2.01	0.90	1.30		4.22	3.90	1.38
BSA		3.13	17.6	0.07		3.13	31.9	0.17
Equation		1.36	—	—		1.36	—	—
LSR	2A	4.36	0.88	1.00	2B	8.32	5.31	1.00
LSR-EVC		3.88	0.84	1.05		7.12	3.89	1.37
BSA		15.7	30.1	0.03		15.7	68.7	0.08
Equation		5.85	—	—		5.85	—	—

# Simulation Results

LSR	3A	3.45	0.95	1.00	3B	6.81	5.40	1.00
LSR-EVC		3.12	0.89	1.07		6.06	3.85	1.10
BSA		10.4	33.4	0.03		10.4	64.6	0.08
Equation		15.9	—	—		15.9	—	—
LSR	4A	2.41	1.04	1.00	4B	4.81	5.41	1.00
LSR-EVC		2.40	0.88	1.18		4.85	3.81	1.42
BSA		4.42	24.9	0.04		4.42	42.1	0.13
Equation		12.6	—	—		12.6	—	—
LSR	5A	8.40	0.72	1.00	5B	13.3	3.18	1.00
LSR-EVC		7.88	0.72	1.00		12.1	3.13	1.02
BSA		48.2	48.7	0.01		48.2	140	0.02
Equation		43.9	—	—		43.9	—	—

# Simulation Results (Non-linear Model)

Scenarios 6: E-max

Scenarios 7: Power

LSR	6A	6.25	1.59	1.00	6B	5.25	0.88	1.00
LSR-EVC		5.41	1.54	1.09		4.74	0.86	1.07
BSA		13.8	42.84	0.07		18.75	36.69	0.05
Equation		1.41	—	—		8.99	—	—
LSR	7A	5.05	1.99	1.00	7B	7.15	1.00	1.00
LSR-EVC		4.49	1.73	1.14		6.42	0.98	1.08
BSA		12.53	38.19	0.08		27.59	63.98	0.04
Equation		0.8	—	—		15.11	—	—

# Discussion 1

- EVC is easy to calculate: Free of model parameters
- EV condition for consistency holds for
  - GLM (for different endpoints; Chen et al., 1999)
  - Bayes estimation (for different estimation methods)
- EVC can be applied to other dose finding problems:
  - Drug combinations  $Y \sim X_1 + X_2$
  - Non-monotone dose response  $Y \sim f(X)$  as long as  $f$  is specified

# Discussion 2

- Design parameter: Convergence rate  $r_n$  is key
- Model robustness
  - Simulation
  - Extension from PK model



# Reference

- Mao, Cheung (2016+). Sequential designs for individualized dosing in phase I cancer clinical trials. Contemporary Clinical Trials. In press.