

A comparative analysis of Phase I dose-finding designs incorporating pharmacokinetics information

Axel Vuorinen^{*1}, Emmanuelle Comets^{3,4}, and Moreno Ursino^{1,2}

¹INSERM-INRIA-University Paris Cité, UMRs 1138, Team 22 (HeKA), CRC ; ²Unit of Clinical Epidemiology, Assistance Publique-Hôpitaux de Paris, CHU Robert Debré, Inserm CIC-EC 1426, F-75019 Paris, France ³Univ Rennes, Inserm, EHESP, Irset (Institut de recherche en santé, environnement et travail) - UMR_S 1085, F-35000 Rennes, France ⁴Universit. Paris Cité and Université Sorbonne Paris Nord, Inserm, IAME, F-75018 Paris, France

Introduction

- “First-in-human” (FIH) studies for promising therapies aim at evaluating the safety of a candidate drug, along with pharmacokinetics (PK), in humans, and typically include a small sample of healthy volunteers or patients.
- Conventional randomized designs can be unsafe and inaccurate with low sample size. Adaptive approaches use Bayesian experimental designs to perform dose-finding trial, leveraging pre-existing data to make prior guesses on the parameters, thereby compensating for small population sizes.
- In most Phase I and Phase I/II studies in patients, dose-finding and pharmacokinetics/pharmacodynamics (PK/PD) are still analyzed separately [1]. Various dose-finding methods using PK data have been proposed in recent literature based on different approaches to integrate PK data in the toxicity estimation.

Scenarios

- 26 scenarios were implemented exploring different settings with deviation on the position of the MTD and/or misspecification of PK measures of exposure or PK model.
- In total, 6 sets of scenarios are created with the last one containing only one scenario, named respectively set A, B, C, D, E or F. In each set, each of the 5 scenarios corresponds to a location of the MTD among the four doses, except the last scenario, which models the case where all doses are too toxic.

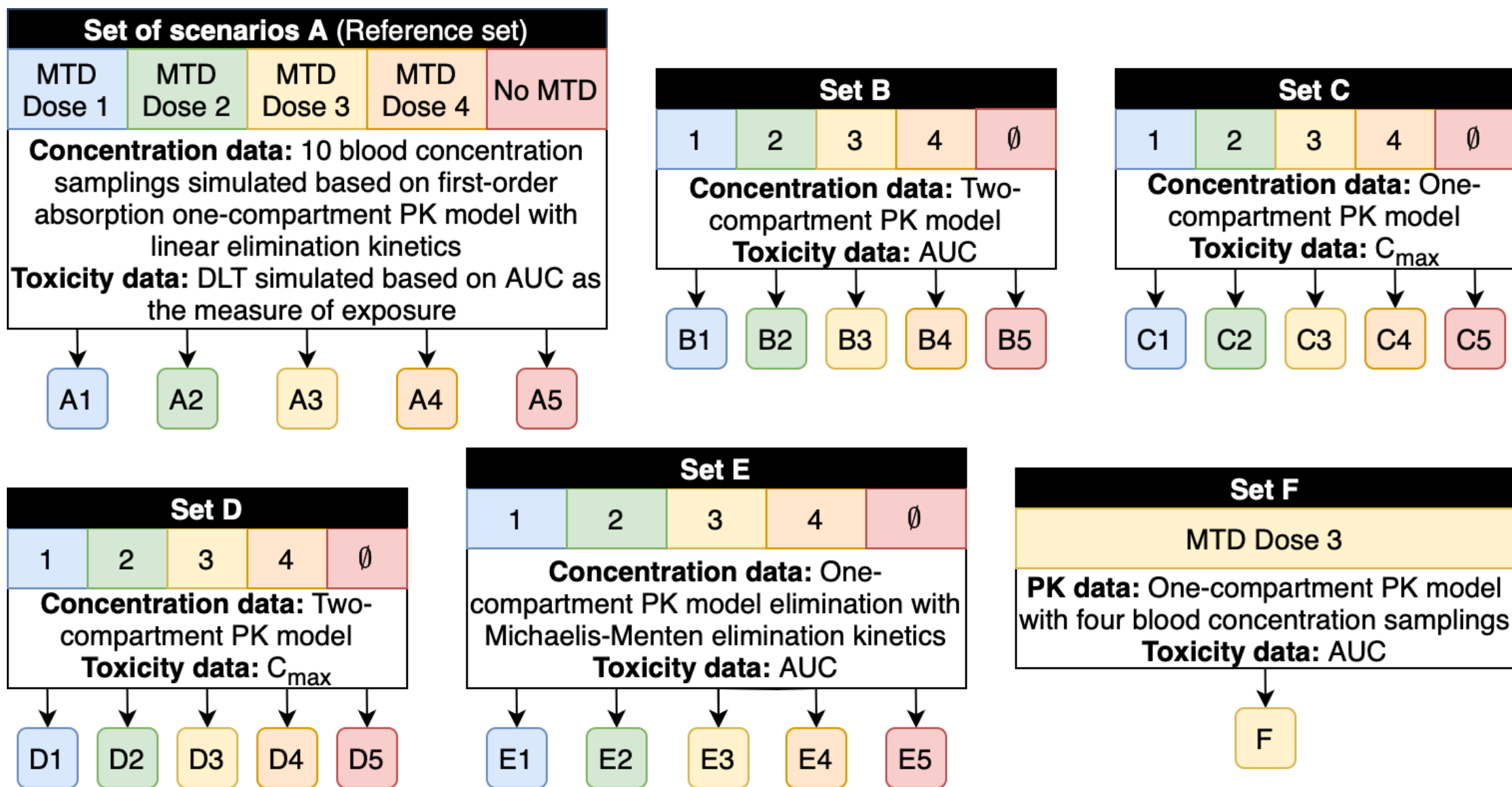


Figure 1: Construction of the sets of scenarios with their respective simulation framework to obtain drug concentration and toxicity data.

Objective

Explore how PK information is used in existing prospective Bayesian dose-finding designs and assess via extensive simulations the performance and the robustness to model misspecification/deviation of these methods for accurate toxicity estimation and MTD identification.

Methods

We conducted an extensive narrative review to identify dose-finding designs using PK data and classified separately the different selected approaches for PK integration: PK logistic (PKLOGIT) model [2]; Exposure Driven Escalation with Overdose Control (ED-EWOC) method [3]; Time-To-Event PK (TITE-PK) design [4]. We also implemented an alternative design to ED-EWOC, called Exposure Driven (ED), without the EWOC dose allocation rule. Finally, the Bayesian Logistic Regression Method (BLRM), that does not use PK data, was chosen as a benchmark for the simulation study.

Notation: p_T represents the probability of toxicity. Let d_k be the dose—level k and λ the target probability of toxicity. Drug concentrations in patients are sampled at times $t = (t_1, \dots, t_j, \dots, t_J)$, with $C_i(t_j)$ and c_{ij} respectively the actual concentration and the measured concentration of the drug in the i -th patient at time t_j . Let z_i be the logarithm of the AUC of the i -th patient, $z_i = \log(\text{AUC}_i)$, and z^* be the reference $\log(\text{AUC})$ computed on the reference dose d^* .

Name	Model
BLRM	Logistic regression $\text{logit}(p_T(d_k, \beta)) = \log(\beta_1) + \beta_2(\log(d_k) - \log(d^*))$
PKLOGIT	Normal approximation of AUC $z_i \beta, v \sim \mathcal{N}(\beta_0 + \beta_1 \log(d_i), v^2)$ Logistic regression $\text{logit}(p_T(z, \beta')) = \beta_2 + \beta_3(z - z^*)$
ED-EWOC/ED	PopPK model $C(t_j d_i, \beta_{1i}) = c(d_i, t_j, \beta_{1i}) \times (1 + \epsilon_{ij}), \quad \epsilon_{ij} \sim \mathcal{N}(0, \sigma_{\epsilon}^2)$ Logistic regression $\text{logit}(p_T(z_i \beta_2, \beta_3)) = \beta_2 + \beta_3(z_i - z^*)$
Informed and naive TITE-PK	K-PD: One-compartment model with IV bolus $\begin{cases} \frac{dC(t)}{dt} = -k_e C(t) \\ \frac{dC_{\text{eff}}(t)}{dt} = k_{\text{eff}}(C(t) - C_{\text{eff}}(t)) \end{cases}$ Complementary log-log regression $\text{cloglog}(P(T \leq t^* C_{\text{eff}}(t^* d))) = \log(\beta) + \log(\text{AUC}_E(t^* C_{\text{eff}}(t^* d)))$

Table 1: Bayesian inference – Modelling of dose-finding designs using PK data for toxicity assessment.

Simulation settings

All methods were evaluated for a Phase I dose-finding trial based on the development of the TGF- β inhibitor LY2157299 [5], in a simulation study consisting of...

- 1000 clinical trials,
- 30 patients per trial,
- 4 doses (30.6 mg, 50.69 mg, 93.69 mg, and 150.37 mg) with dose-level 3 as the reference,
- cohorts of size 2,
- and a targeted probability of toxicity $\lambda = 25\%$.

Results

- Set A:** The designs performed well in terms of correct MTD selection for scenario A1, except both TITE-PK methods, displaying a tendency to overdose for the lowest doses. PKLOGIT performed on average marginally worse than the most effective PK methods. When comparing the two PK dose-finding methods using a popPK model, ED-EWOC outperformed substantially ED, demonstrating effective overdose control for lower-dose MTD. However, in scenarios A3 and A4, the results were reversed.
- Set B:** Similar results to set A.
- For scenarios C1, C5, D1, and D5, ED-EWOC and ED were outperformed by informed and naive TITE-PK methods respectively.
- Set E:** Compared with set A, all dose-finding methods displayed on average better performance in terms of correct MTD selection.
- BLRM struggled to recommend the appropriate dose as MTD in scenarios with intermediate-dose MTDs.
- PK dose-finding methods were better than BLRM in estimating the probabilities of toxicity for all doses, especially in the case of low-dose MTD, as in scenario A1 for example.

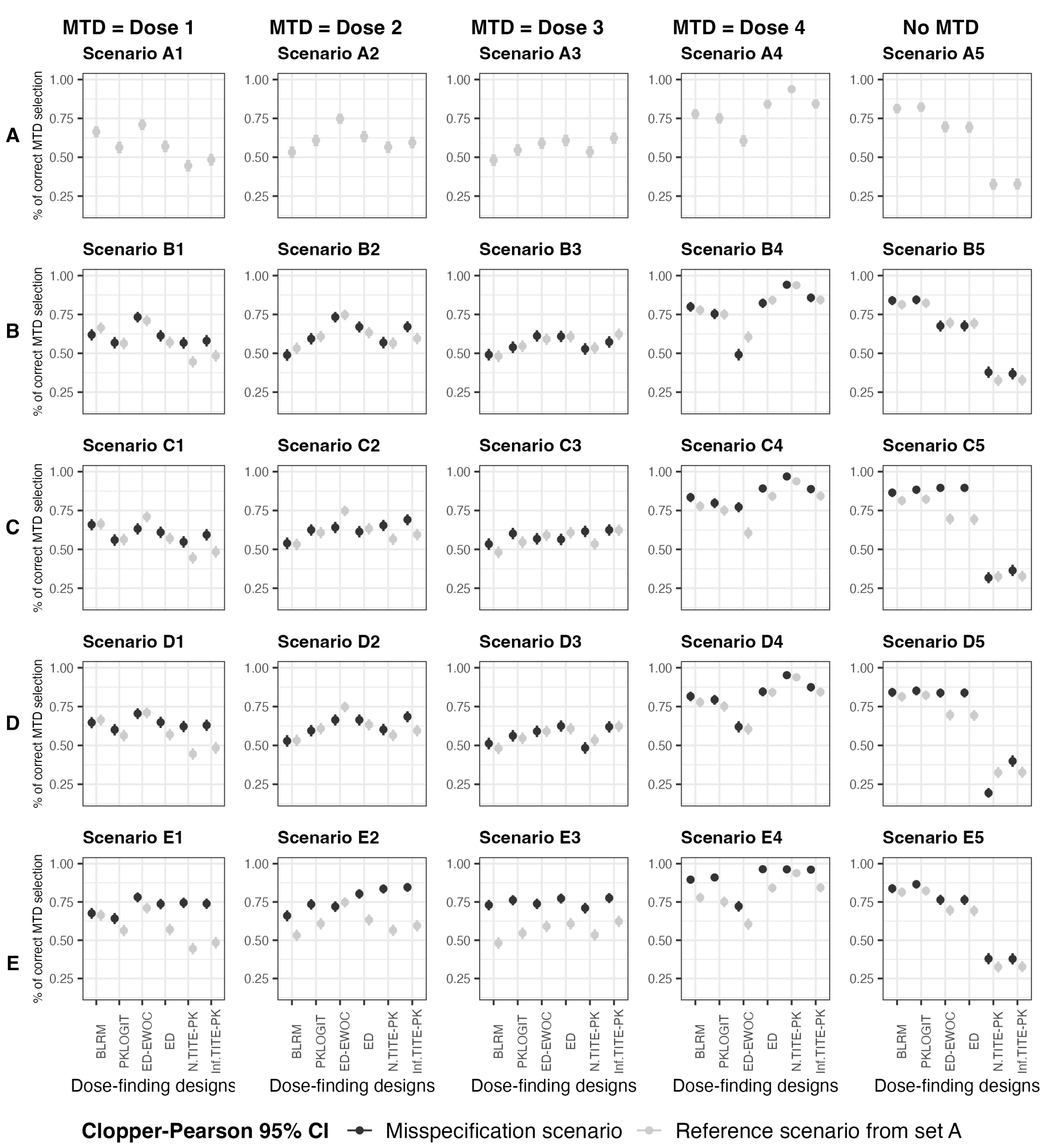


Figure 2: Percentage of correct MTD selection with Clopper-Pearson 95% confidence intervals for reference set of scenarios A (A1-A5) and for deviation/misspecification scenarios (B1-E5) compared with MTD-associated scenarios from set A.

Assessment of PK methods

- PKLOGIT, like BLRM, struggles with lower-dose MTD selection, stopping more often for safety reasons than other PK dose-finding methods.
- ED-EWOC and ED show potential, especially under misspecification, but are generally inferior to TITE-PK for MTD selection.
- TITE-PK performs consistently well, barring low-dose MTDs and misspecification scenarios, but unlike ED-EWOC and ED, fails to estimate properly the probabilities of toxicity.

Scenario A1 - Estimated probabilities of toxicity from simulated trials for each dose-finding design

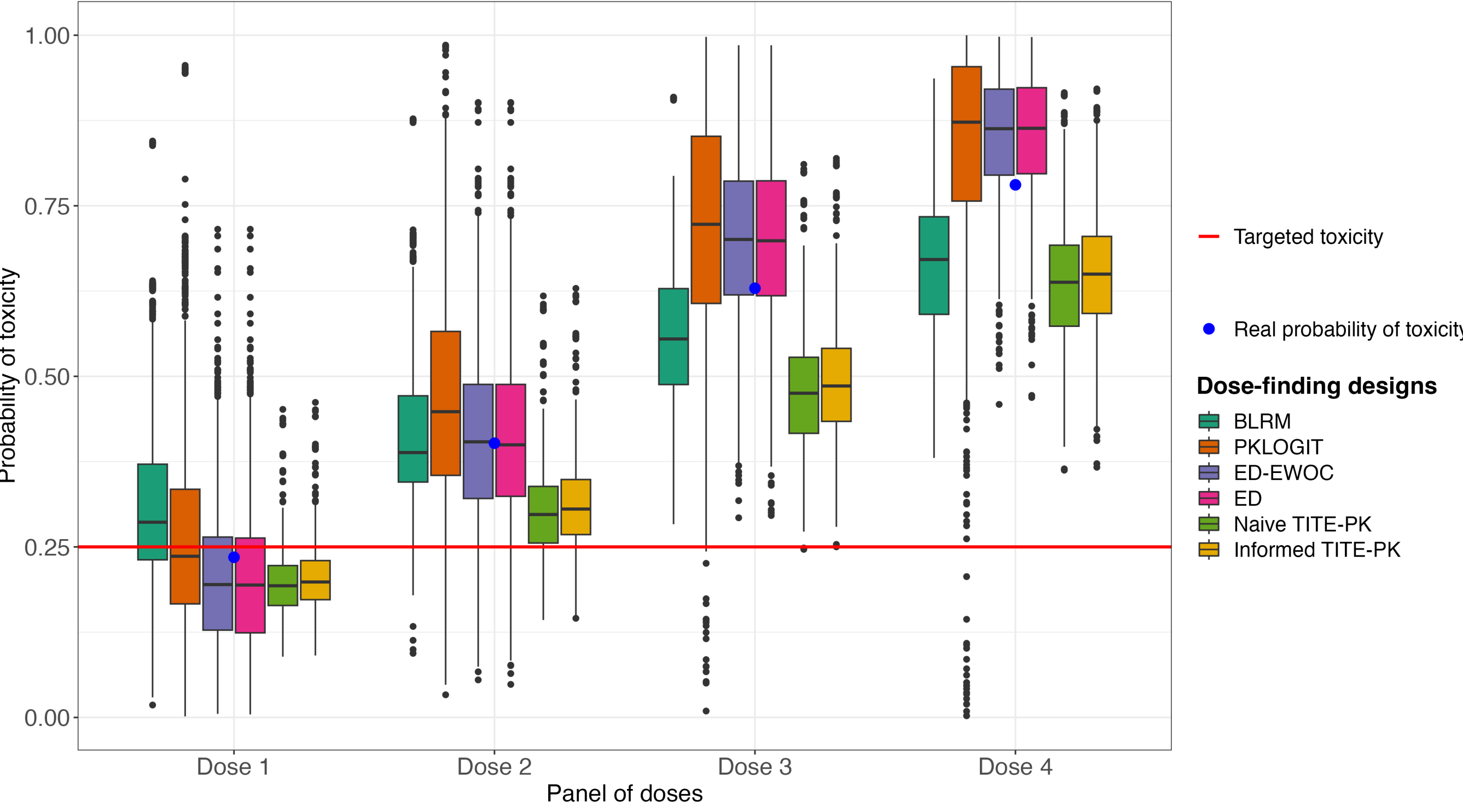


Figure 3: Scenario A1 - Estimated probabilities of toxicity at all doses for all dose-finding methods where the MTD is on dose-level 1.

Discussion

- Incorporating PK information into model-based approaches as a covariate or using a PK latent model for Phase I dose-finding trial is likely to achieve safer dose-escalation and to recommend, at least as much as the BLRM, the accurate MTD for further investigation.
- Additionally, PK dose-finding methods can evaluate the full dose-toxicity curve for the drug and provide plausible estimates of the probability of toxicity for each dose with limited sample size.