

## INTRODUCTION

**In vitro-in vivo correlation (IVIVC):** Defined by the **FDA** as “predictive mathematical model describing the relationship between an *in vitro* property of a dosage form and an *in vivo* response” → can act as a **surrogate for bioequivalence or bioavailability testing** in human subjects → support biowaivers → **reduce costs and duration** of optimization process.

**Problem:** Current IVIVC models often entail complex potentially unstable mathematical deconvolution operations, are assessed applying purely frequentist methods on averaged data.

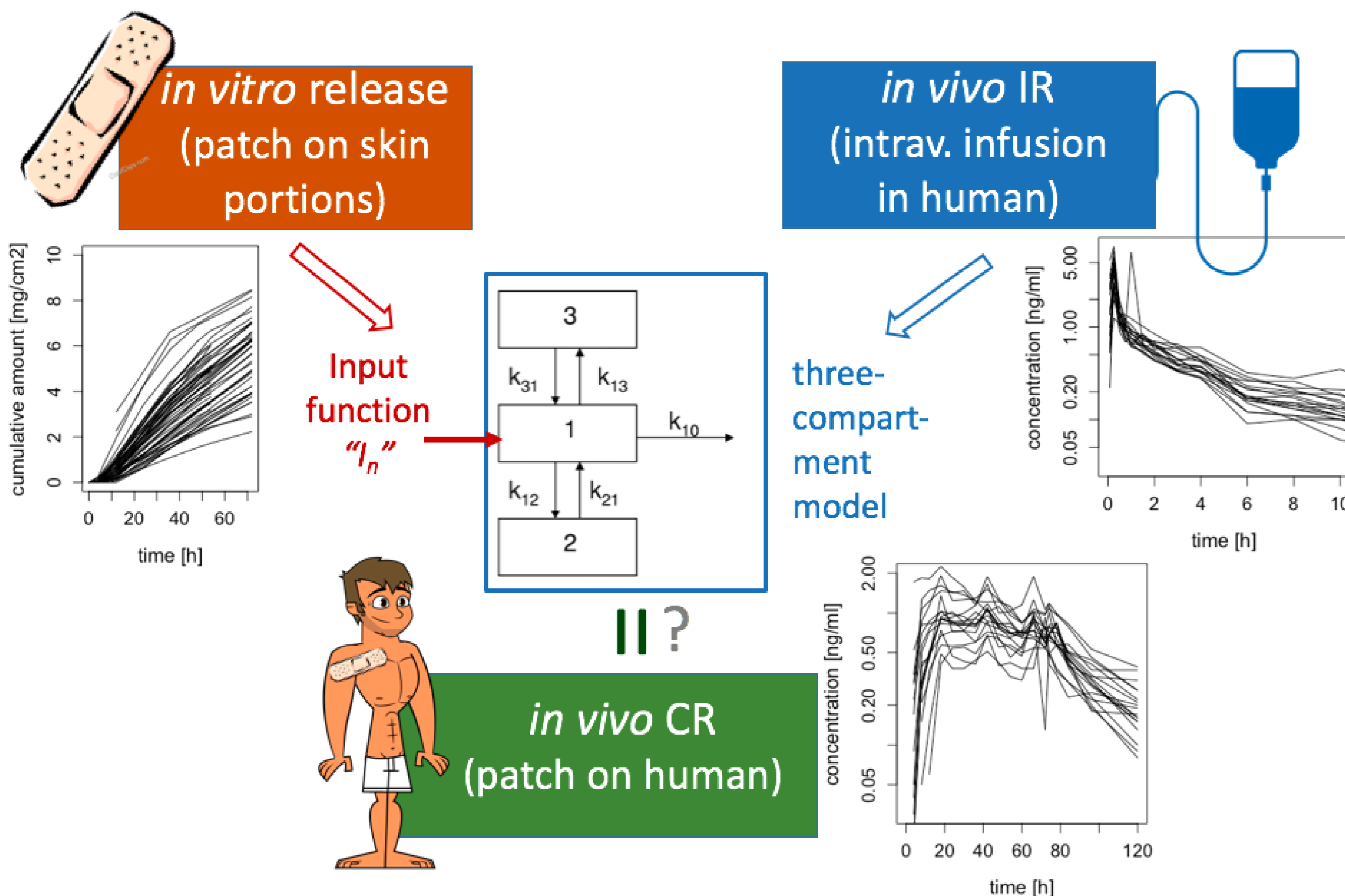
## METHODS I

We propose a **Bayesian convolution-based IVIVC approach** including:

- (1) a nonlinear mixed effects model for the *in vitro* **release/permeation** data;
- (2) a population pharmacokinetic (PK) compartment model for the *in vivo* **immediate release (IR)** data;
- (3) a system of ordinal differential equations (ODEs), containing the submodels (1) and (2), which approximates and predicts the *in vivo* **controlled release (CR)** data.

The innovation consists of splitting the parameter space between submodels (1) and (2) versus (3) and, subsequently, accounting for the uncertainty around the parameters via prior distributions in a Bayesian framework.

Case study example: transdermal patch, in (1) and (3), intravenous infusion, in (2).

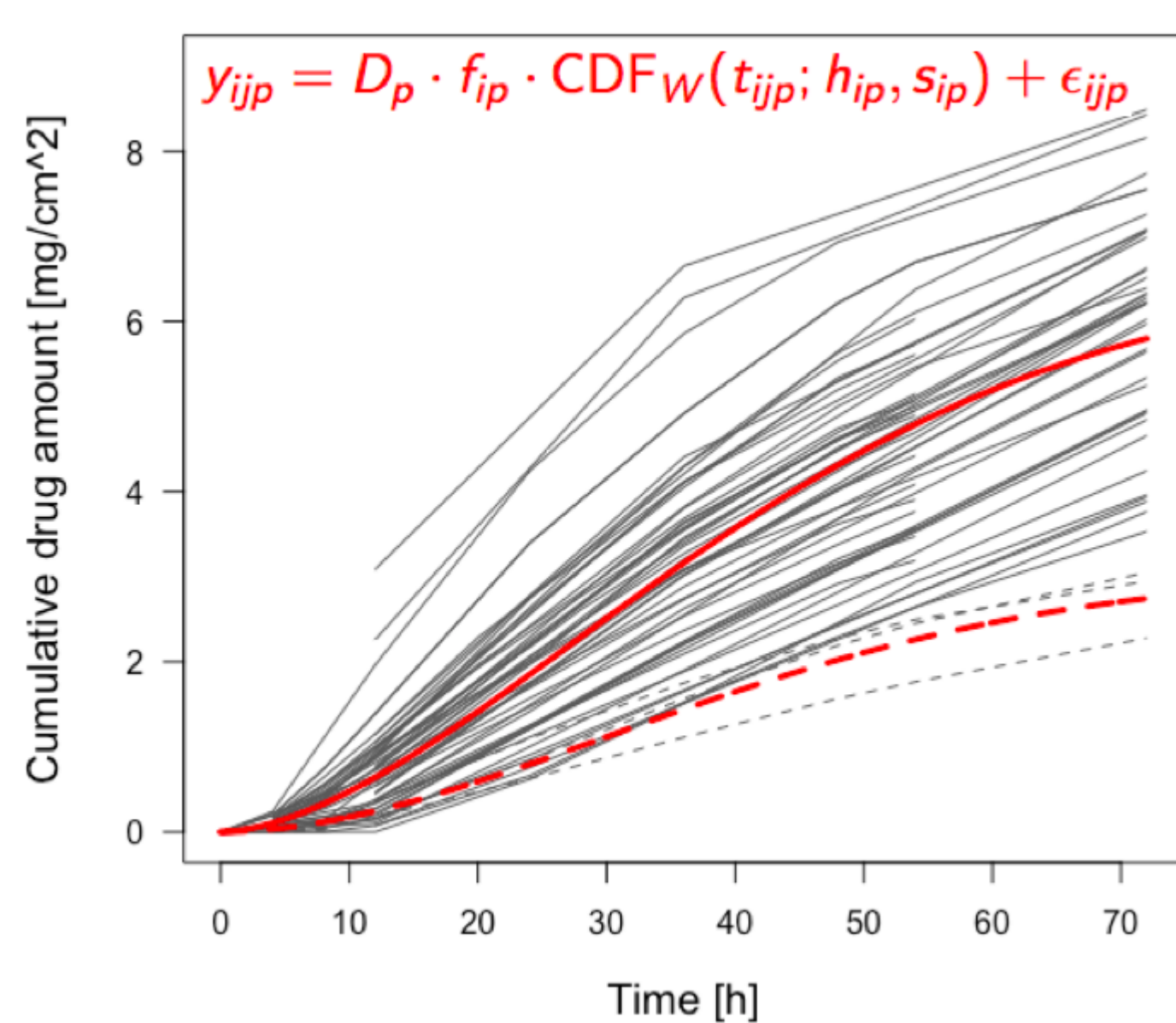


### Cumulative amount of drug permeated through skin portions

Dose  $D_p$  ( $p = 1, 2$ ); Weibull distribution CDF  $W$ .

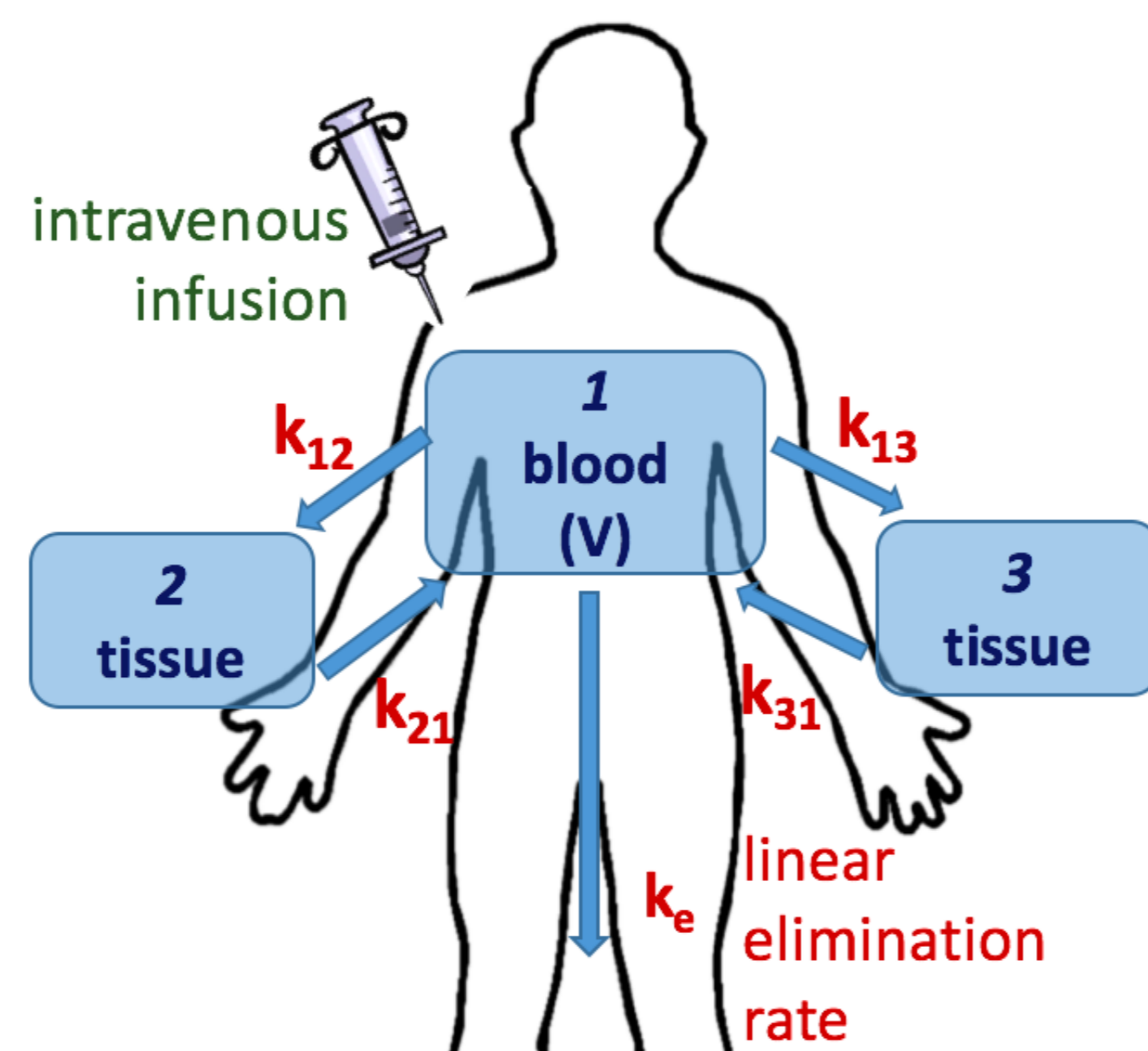
To estimate: shape  $h_{ip}$ , scale  $s_{ip}$ ,

fraction of dose delivered  $f_{ip}$ .



### 3-compartment-model for intravenous infusion

To estimate:  $V_{1,i}$ ,  $k_e$ ,  $k_{12}$ ,  $k_{21}$ ,  $k_{13}$ ,  $k_{31}$ .



### Combined ODE system to model the *in vivo* CR

$$I_n(t_{ijp}) = D_p \cdot F_{ip} \cdot B_{ip} \cdot \frac{h_{ip}}{s_{ip}} \cdot \left(\frac{t_{ijp}}{s_{ip}}\right)^{h_{ip}-1} \cdot \exp\left\{-\left(\frac{t_{ijp}}{s_{ip}}\right)^{h_{ip}}\right\}$$

$$\frac{da_1(t_{ijp})}{dt} = I_n(t_{ijp}) + k_{21}a_2(t_{ijp}) + k_{31}a_3(t_{ijp}) - [k_{12}a_1(t_{ijp}) + k_{13}a_1(t_{ijp}) + k_e a_1(t_{ijp})]$$

$$\frac{da_2(t_{ijp})}{dt} = k_{12}a_1(t_{ijp}) - [k_{21}a_2(t_{ijp})]$$

$$\frac{da_3(t_{ijp})}{dt} = k_{13}a_1(t_{ijp}) - [k_{31}a_3(t_{ijp})]$$

$$C_1(t_{ijp}) = \frac{a_1(t_{ijp})}{V_{1,i}}$$

## METHODS II

$I_n(t_{ijp})$ : input function,  $a_c$ : amount of drug in compartment  $c$ , ( $c = 1, 2, 3$ ). At time  $t = 0$ :  $a_1(0) = a_2(0) = a_3(0) = 0$ .

$F$ : fraction of dose delivered;  $B$ : fraction of dose delivered which is actually absorbed into the systemic circulation.

Each dataset consists of  $j$  repeated measurements originating from different subjects/skins  $i \Rightarrow$  **Nonlinear mixed effects modelling**

$$y_{ijp} = f(t_{ijp}; \theta_{ijp}) + \epsilon_{ijp}, \quad \epsilon_{ijp} \sim \mathcal{N}(0, \sigma^2), \quad i = 1, \dots, N, \quad j = 1, \dots, T_i$$

Parameters are varying between subjects/skins  $i$ , thus, are the sums of population (fixed) effects  $\mu$  and individual (random) effects  $\eta_i$ :

$$\theta_i = \mu + \eta_i \quad \text{with} \quad \eta_i \sim \mathcal{N}(0, \Omega^2)$$

### Bayesian hierarchical 2-stage model

**Likelihood:** Observed conc.  $y(t_{ijp}) \sim \mathcal{G}((C_1(t_{ijp})/\sigma)^2, C_1(t_{ijp})/\sigma^2)$

**Joint prior:** Normally distributed population parameters

$$\theta_i = (B, \ell h_{ip}, \ell s_{ip}, \ell V_i, \ell k_{12}, \ell k_{21}, k_{13}, \ell k_{31}, \sigma^2) \sim \mathcal{N}(\cdot, \cdot)$$

PK and Weibull parameters are assumed to be log-normally distributed → priors of  $\ell k_e := \log(k_e)$  etc. are normal distributions, each with specific mean and variance - obtained via frequentist estimation in (1) and (2).

## RESULTS

Figure 1: Serum concentrations (dots) with posterior median (black lines) and 90% credible bands of predicted individual observations in study subjects.

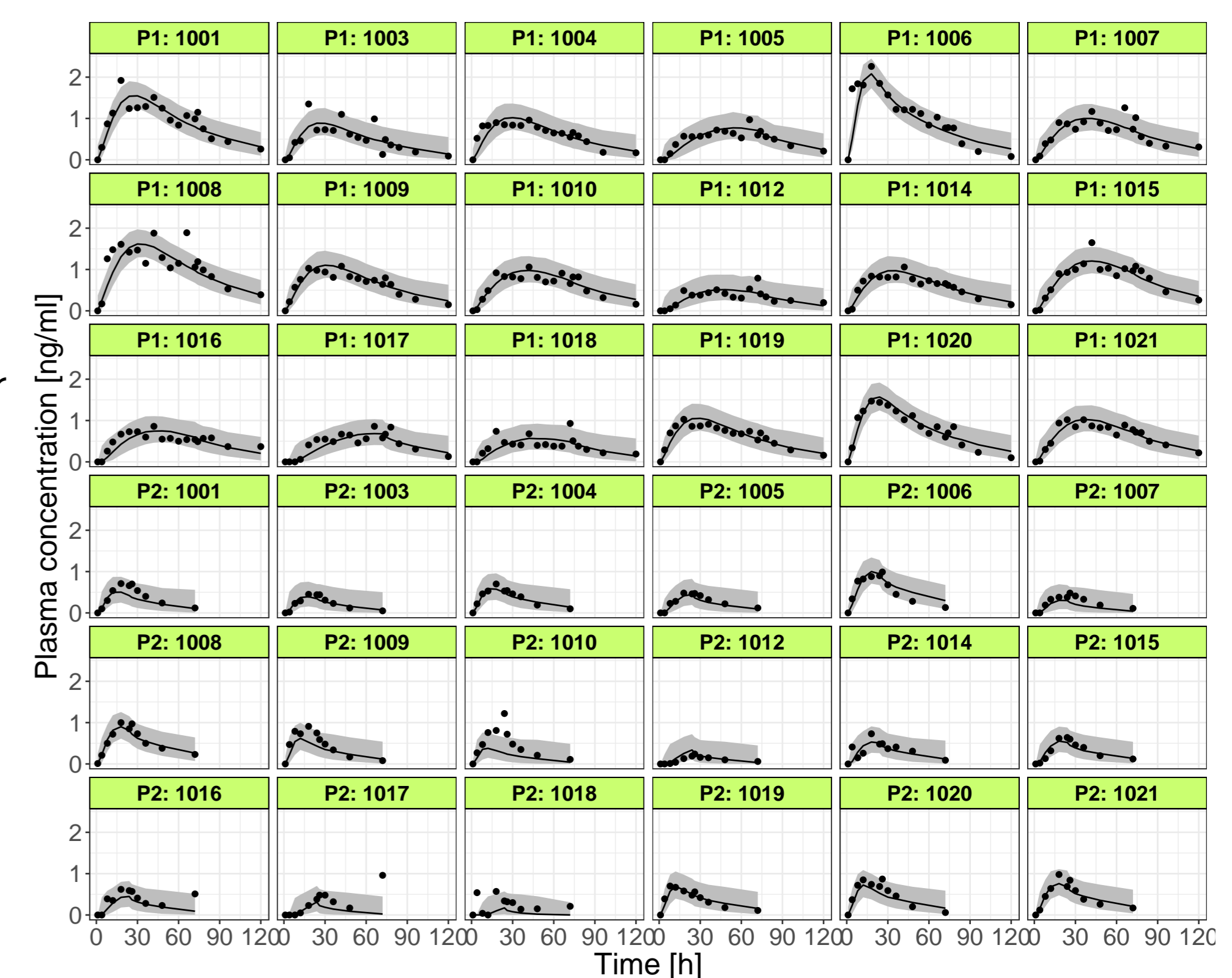
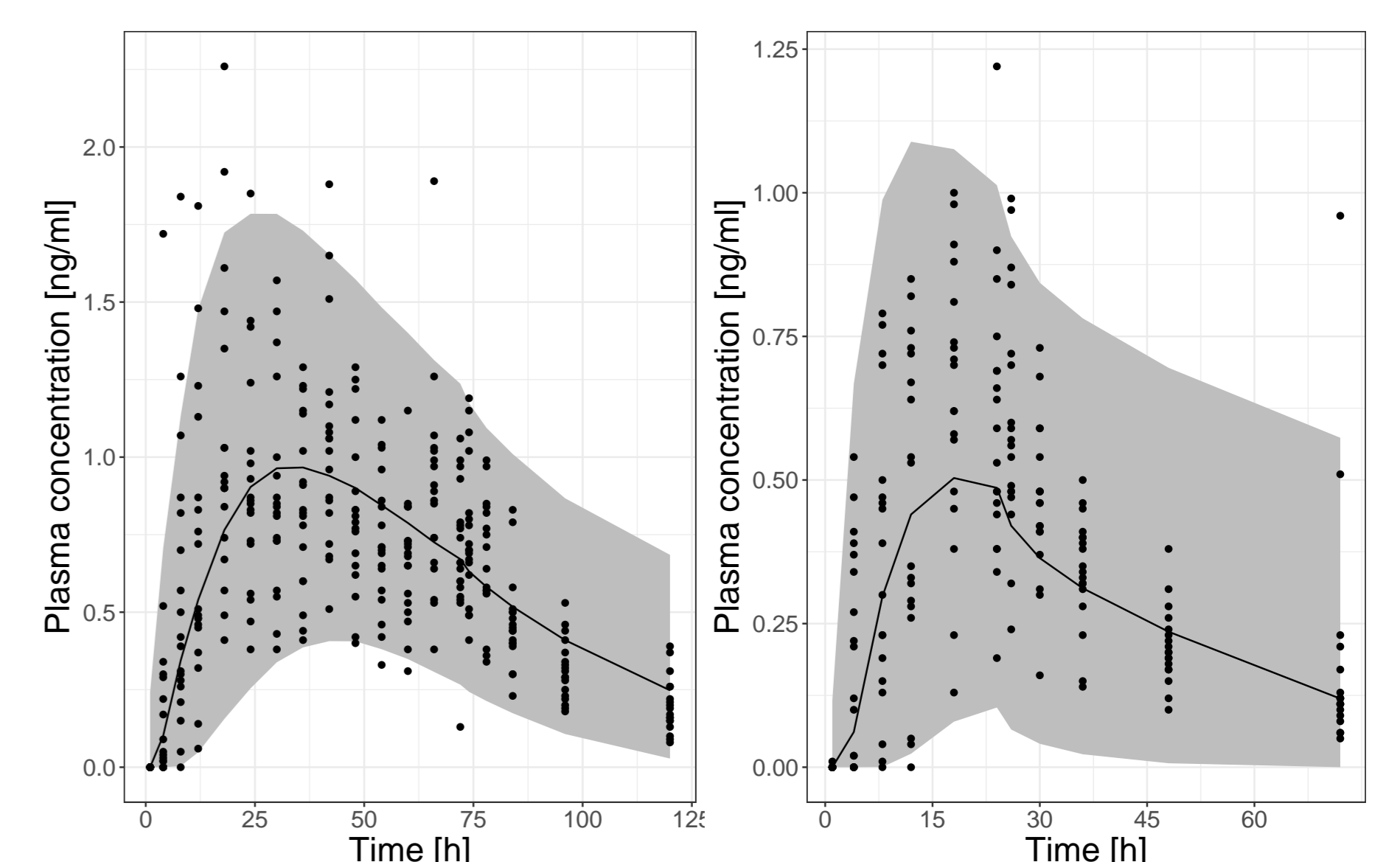


Figure 2: Serum concentrations (dots) with posterior median (black lines) and 90% credible bands of predicted population observations in new subjects. Left: 72 h formulation; right 24 h formulation of patch.



## DISCUSSION

The developed IVIVC model provides a **satisfactory estimation** of the PK population data of a transdermal patch. The Bayesian framework allows a natural **integration** of knowledge from one source of information into another (*in vitro* to *in vivo*), while accounting for the parameters uncertainties. This work is an **extension** of the current IVIVC methodology where biased deconvolution techniques and averaged data are common.

## REFERENCES

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