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# IVIVC current status and future perspectives

*LAI 2019 conference*

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# IVIVC

## Definition

An In-vitro/In-vivo correlation (IVIVC) has been defined by the Food and Drug Administration (FDA) as “a predictive mathematical model describing the relationship between an in-vitro property of a dosage form and an in-vivo response

## Purpose

- Substitute for additional in vivo experiments (under certain conditions)
- Optimization of formulation
- Scale up post approval changes (Time and cost saving during the product development)
- Surrogate for in vivo bioequivalence

# Going beyond the traditional view: IVIVC as a tool for optimizing the clinical benefit of a treatment (CB)

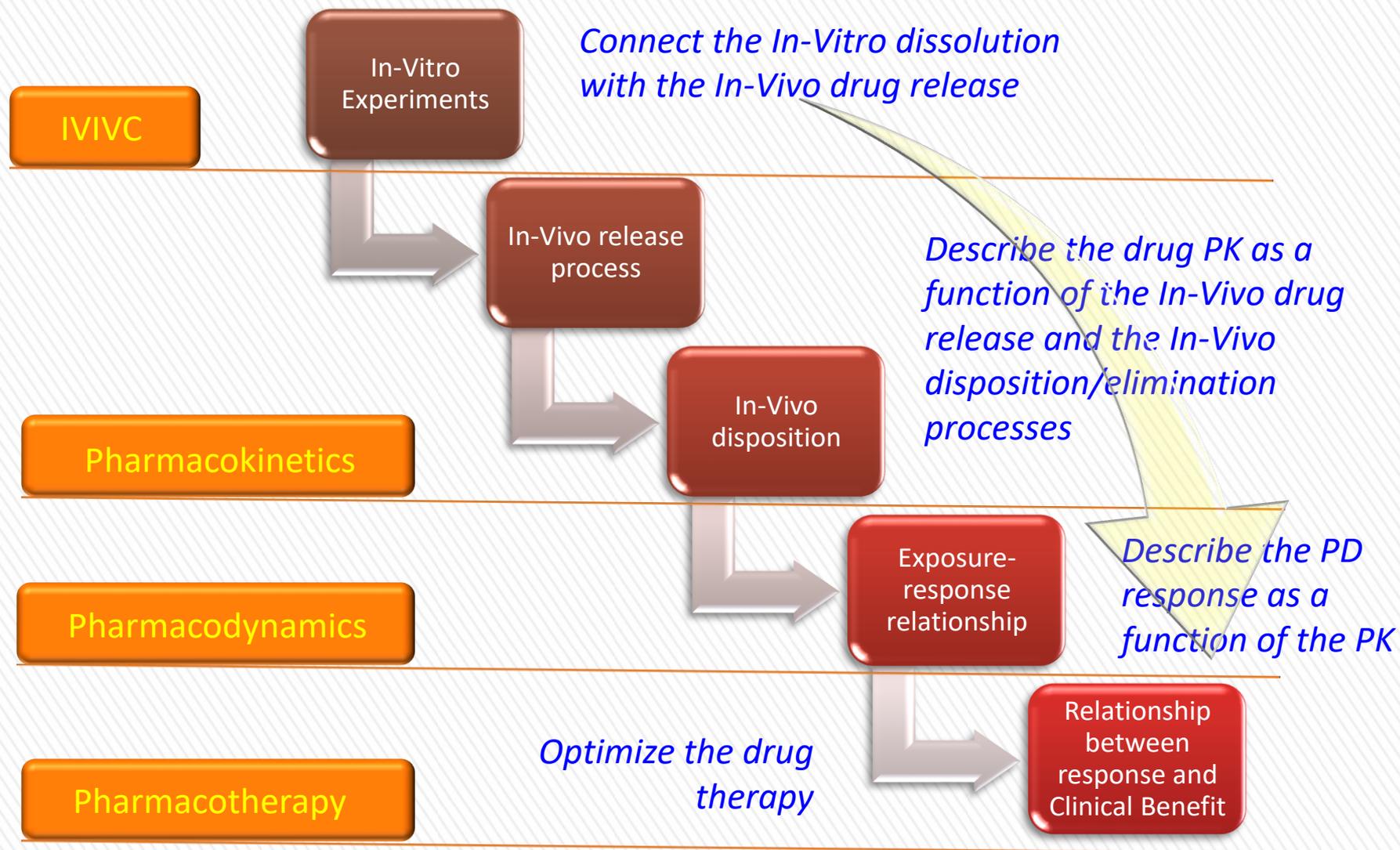
The CB optimization can be achieved by identifying the best performing dose, and dosage regimen jointly with the best performing *in-vivo* release properties of a drug.

The key components of this convolution-based modelling approach \* are:

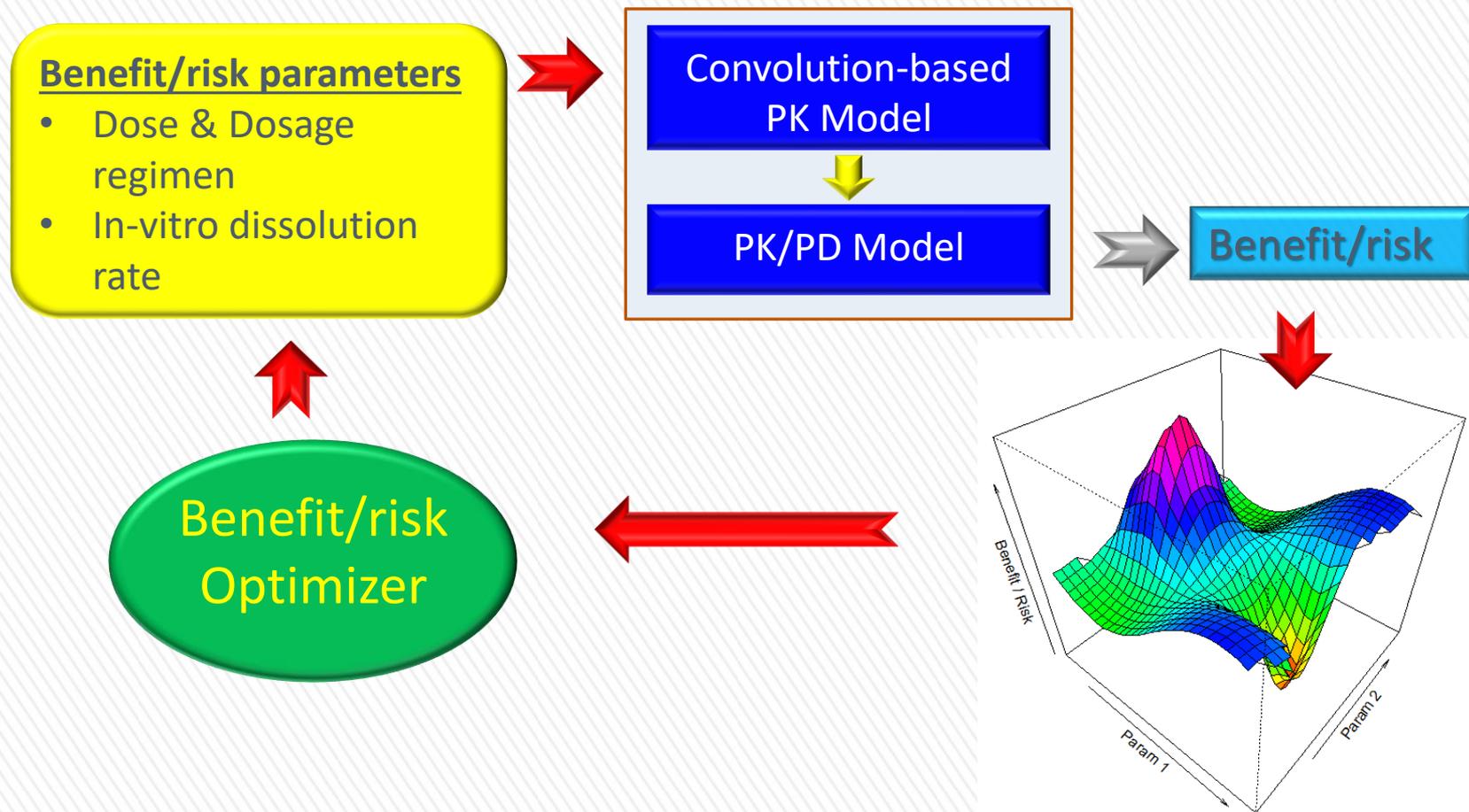
- Assessment of the *in-vivo/in-vitro* correlation (IVIVC),
- Characterization of the drug pharmacokinetics (PK),
- Linking drug exposure and pharmacological response accounting for the placebo effect (PK/PD),
- Identification of the optimal dose and the optimal *in-vivo* drug release properties appropriate for maximizing the CB.

\* Gomeni R, Fang LL, Bressolle-Gomeni F, Spencer TJ, Faraone SV, Babiskin A. A general framework for assessing IVIVC as a tool for maximizing the benefit-risk ratio of a treatment using a convolution-based modeling approach. *CPT Pharmacometrics Syst Pharmacol*. 2019 Jan 18. doi: 10.1002/psp4.12378.

# Modelling components

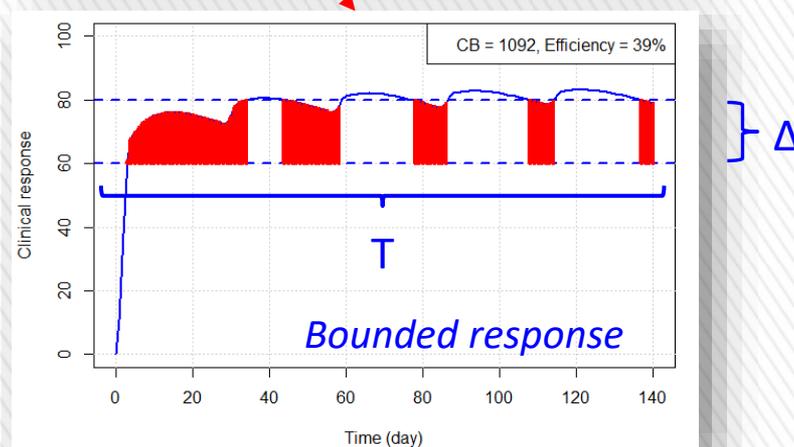
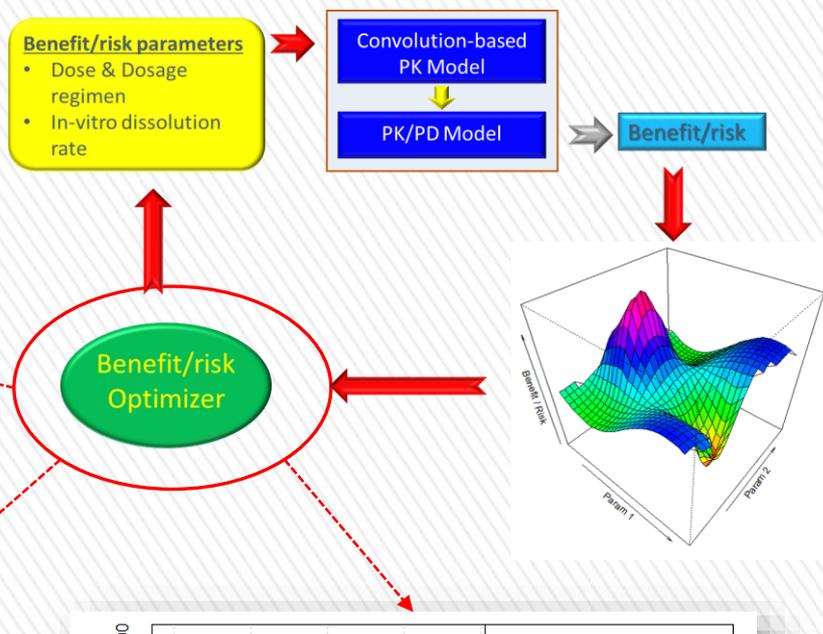
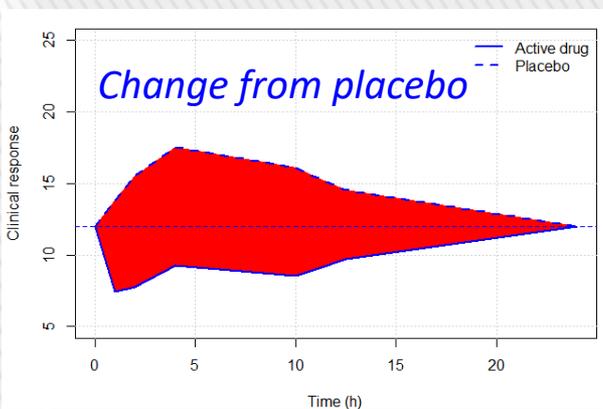
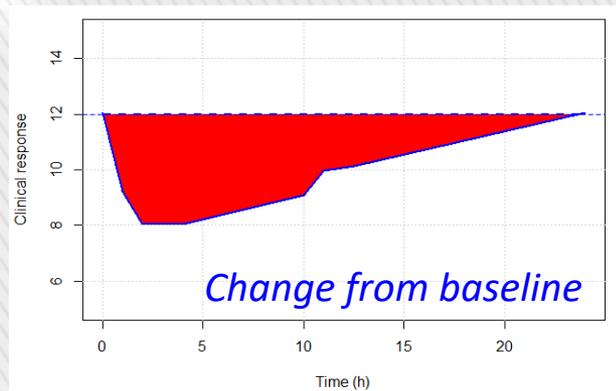


# Response Surface Analysis and Nonlinear Optimization Algorithm for Maximization of Clinical Benefit



The optimization process is conducted using the derivative-free non-linear optimization algorithm implemented in the R library NLOPT ( <http://ab-initio.mit.edu/nlopt> )

# Clinical Benefit



} Δ

# Convolution-based PK model

The integrated PK model linking in-vivo drug release with the disposition and elimination processes can be developed using a convolution-based approach. The drug concentration ( $C_p$ ), resulting from an arbitrary dose, can be described by convolution as:

$$C_p(t) = f(t) * d(t)$$

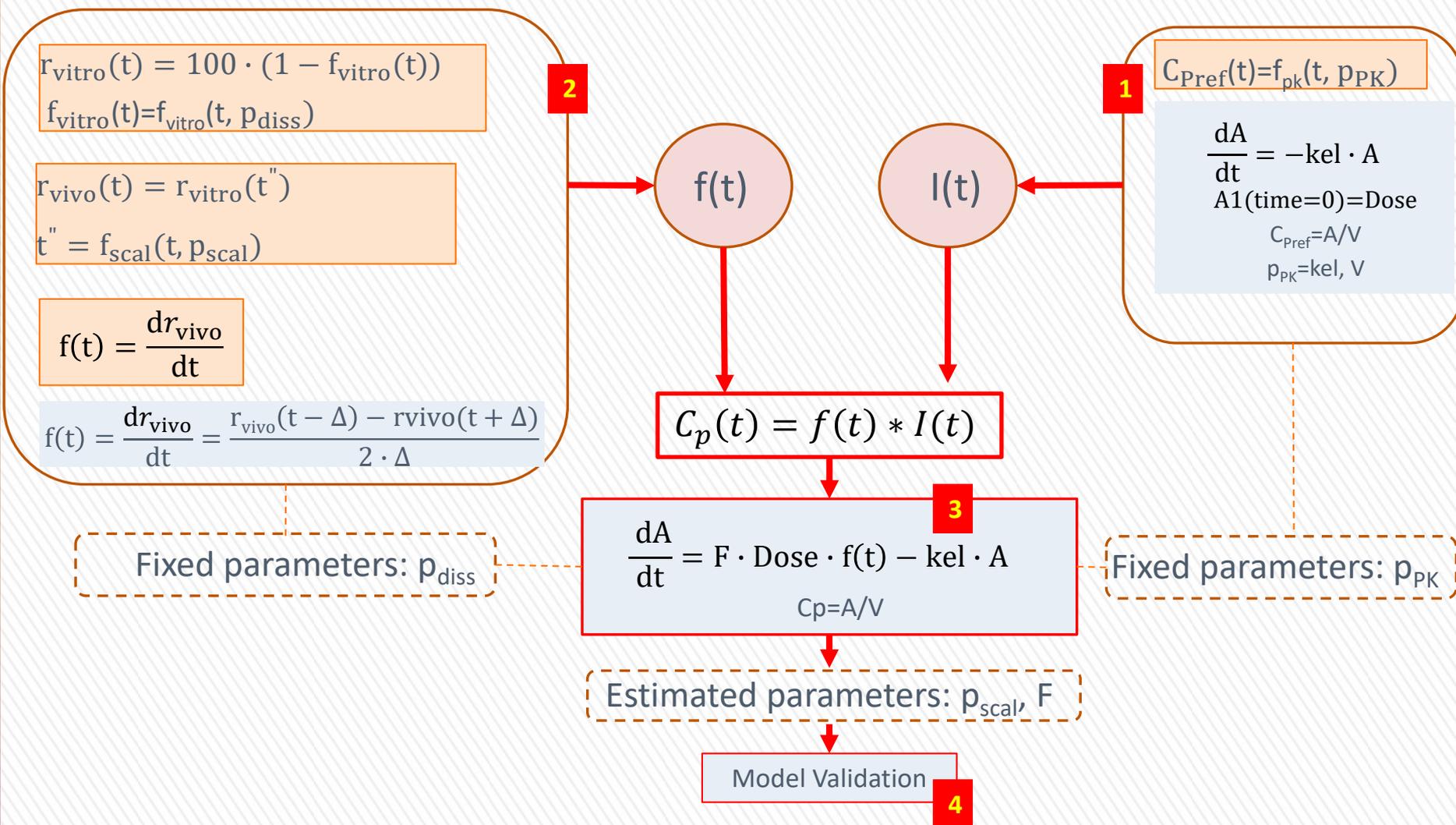
where  $f(t)$  is the rate of in-vivo drug delivery,  $d(t)$  is the unit impulse response and  $*$  is the symbol defining the convolution.

In case of a simple disposition process (say one compartment), the model equation describing  $C_p(t)$  can be written as

$$\frac{dC_p}{dt} = f(t) - K \cdot C \quad \text{where} \quad f(t) = \frac{dr}{dt}$$

Assuming that the time-varying fraction of the dose released can be described by the function  $r(t)$  (input function), we can solve the previous equation by estimating  $f(t)$  as the first derivative of  $r(t)$ . This can be computed analytically or can be approximated using the finite difference approach (see an example of implementation in NONMEM)

# Implementing IVIVC using a convolution-based modelling approach



# Assessing IVIVC using a convolution-based modelling approach

The IVIVC analysis was conducted using a 4-step approach :

1. Fit the mean PK time-course of the IR formulation (**Step 1**);
2. Individually fit the mean *in-vitro* dissolution data of the slow, medium, and fast formulations using the release function ( $r(t)$ ) (**Step 2**);
3. Evaluate IVIVC by jointly applying the convolution model to the *in-vivo* data of the slow, medium, and fast formulations (**Step 3**) and by:
  - Fixing the *in-vivo* drug release parameters for each formulation to the values estimated in Step (2)
  - Estimating the time scaling factors common to all formulations
4. Evaluate the internal predictability by comparing the predicted (estimated in Step 3)  $C_{max}$ ,  $AUC_{inf}$ ,  $pAUC_{0-3}$ ,  $pAUC_{3-7}$ , and  $pAUC_{7-12}$  with the observed values (**Step 4**).

# Example of Convolution-based model

in case of a simple *in-vitro* dissolution and *in-vivo* disposition (i.e., one compartment), the convolution-based model describing  $C_p(t)$  can be written as:

- *in-vitro* dissolution, constant dissolution rate:

$$r_{\text{vitro}} = \text{Dose} \cdot (1 - e^{-k_a \cdot t})$$

where  $k_a$  is the first order absorption rate constant

- PK disposition, one compartment with first order elimination rate:

$$\frac{dA}{dt} = -k_{el} \cdot A$$

with the assumption that  $r_{\text{vivo}} = r_{\text{vitro}}$ , the *in-vivo* drug delivery rate is computed (by numerical approximation or by analytical solution) as:

$$f(t) = \frac{dr_{\text{vivo}}}{dt} \cong \frac{r_{\text{vitro}}(t - \Delta) - r_{\text{vitro}}(t + \Delta)}{2 \cdot \Delta} = \text{Dose} \cdot k_a \cdot e^{-k_a \cdot t}$$

- Convolution model:

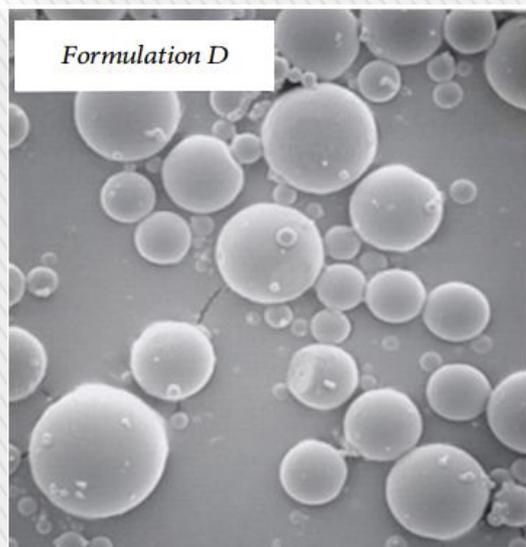
$$\frac{dA}{dt} = f(t) - k_{el} \cdot A = F \cdot \text{Dose} \cdot k_a \cdot e^{-k_a \cdot t} - k_{el} \cdot A; \quad C_p = \frac{A}{V}$$

# Case studies

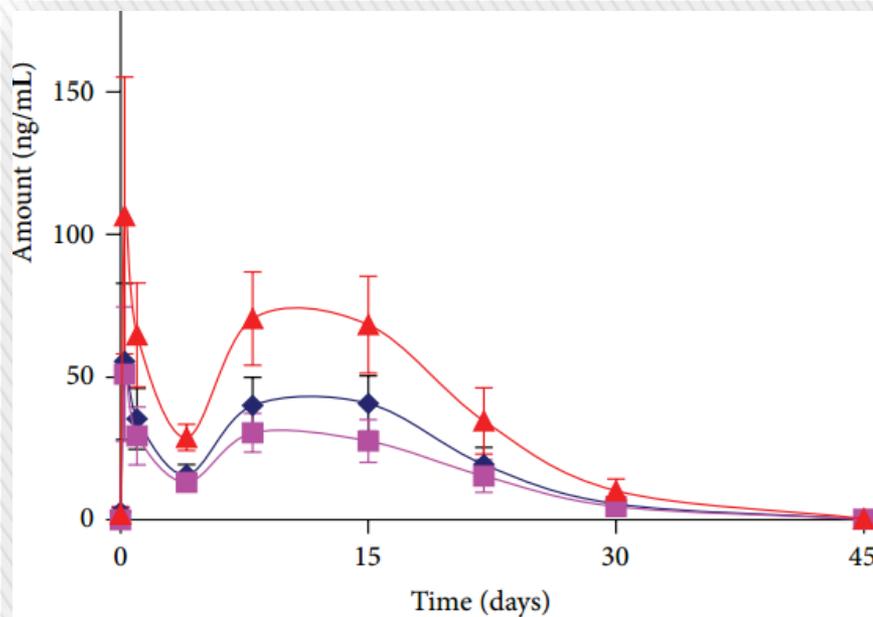
- Use convolution-base modelling for assessing IVIVC for Risperdal® Consta® LAI formulation of risperidone for the treatment of schizophrenia
- Optimize benefit-risk via IVIVC and convolution-based modeling for methylphenidate for the treatment of ADHD

# Risperdal® Consta® LAI formulation of risperidone

The objective of this study was to establish IVIVC using the dissolution data of 4 long-acting subcutaneous risperidone formulations and the in-vivo PK measurements. Two copolymers of PLGA (50:50 and 75:25) were used to prepare four microsphere formulations of risperidone, an atypical antipsychotic.



*Formulation D: Scanning electron microscopy of Risperidone PLGA microspheres*



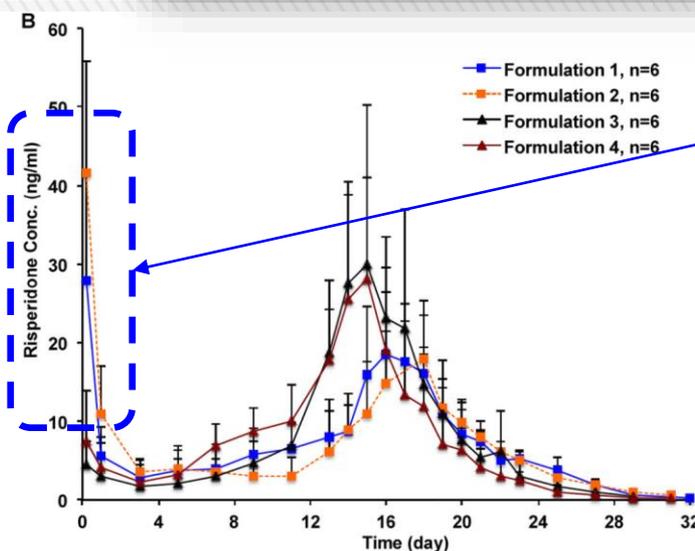
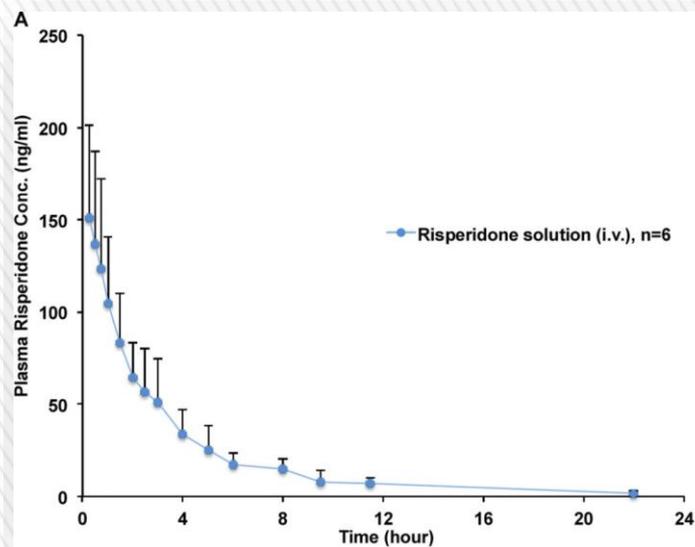
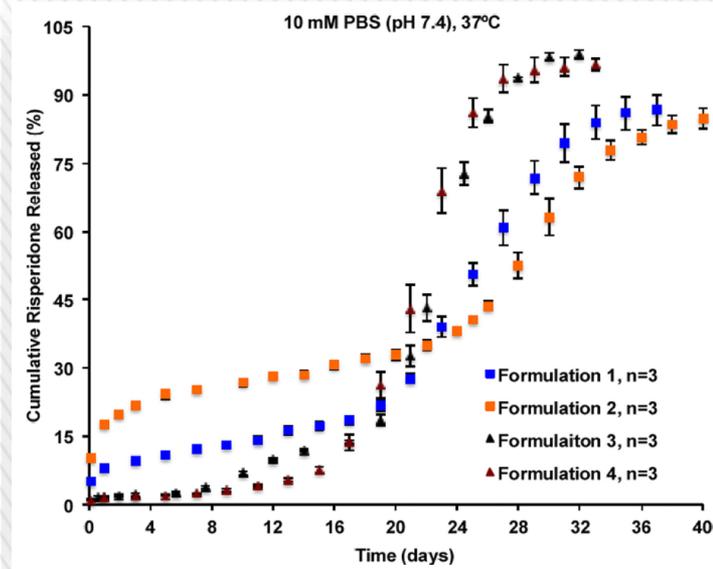
*Formulation D: In vivo PK time course*

*D'Souza S., Faraj J.A., Giovagnoli S., DeLuca P.P. Development of Risperidone PLGA Microspheres. Journal of Drug Delivery. 2014, 620464, 11*

# Risperdal Consta<sup>®</sup> - Study design

*In vitro* release of the risperidone PLGA microspheres was investigated using 4 release testing methods. *In vivo* PK profiles of the risperidone microsphere was evaluated using:

- IV dose of 0.2 mg/kg
- intramuscular administration of the prepared risperidone PLGA microspheres at a dose of 1.92 mg/kg



Shen J, Choi S, Qu W, Wang Y, Burgess DJ. *In vitro-in vivo* correlation of parenteral risperidone polymeric microspheres. *J Control Release*. 2015 Nov 28;218:2-12.

# Implementing a convolution based model for LAI products

$t_1 = \text{time} - \text{delt}$

$t_2 = \text{time} + \text{delt}$

$$abs1 = f \cdot e^{-\left(\frac{t_1}{td}\right)^{ss}} + (1-f) \cdot e^{-\left(\frac{t_1}{td1}\right)^{ss1}}$$

$$abs2 = f \cdot e^{-\left(\frac{t_2}{td}\right)^{ss}} + (1-f) \cdot e^{-\left(\frac{t_2}{td1}\right)^{ss1}}$$

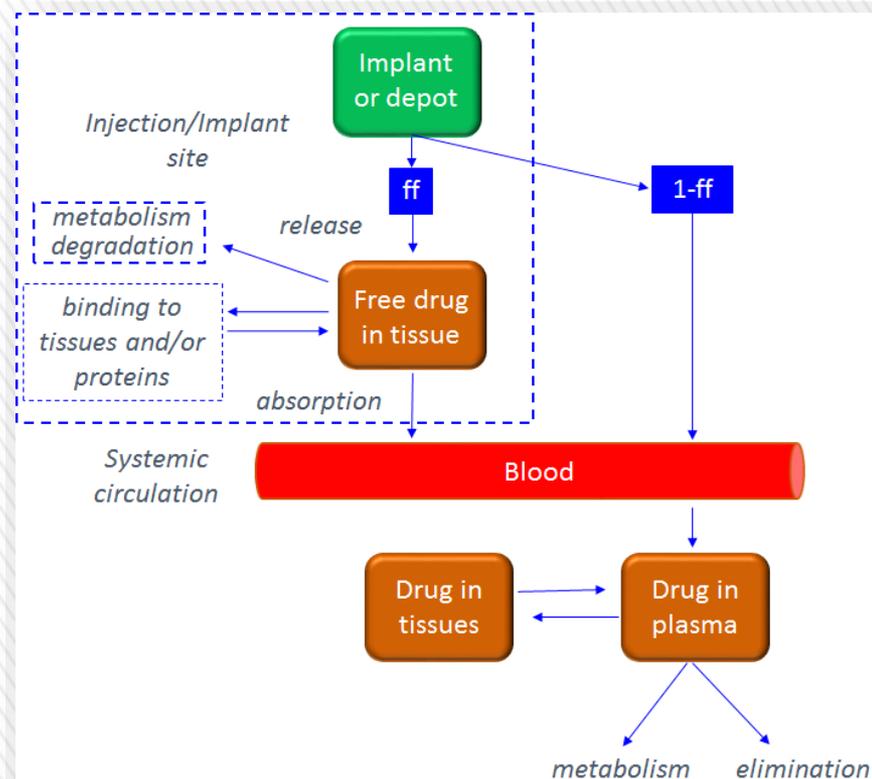
$$kab = \frac{(abs1 + abs2)}{(t_2 - t_1)}$$

$$\frac{dA_1}{dt} = Dose \cdot kab - (kel + k12) \cdot A_1 + k21 \cdot A_2$$

$$\frac{dA_2}{dt} = k12 \cdot A_1 - k21 \cdot A_2$$

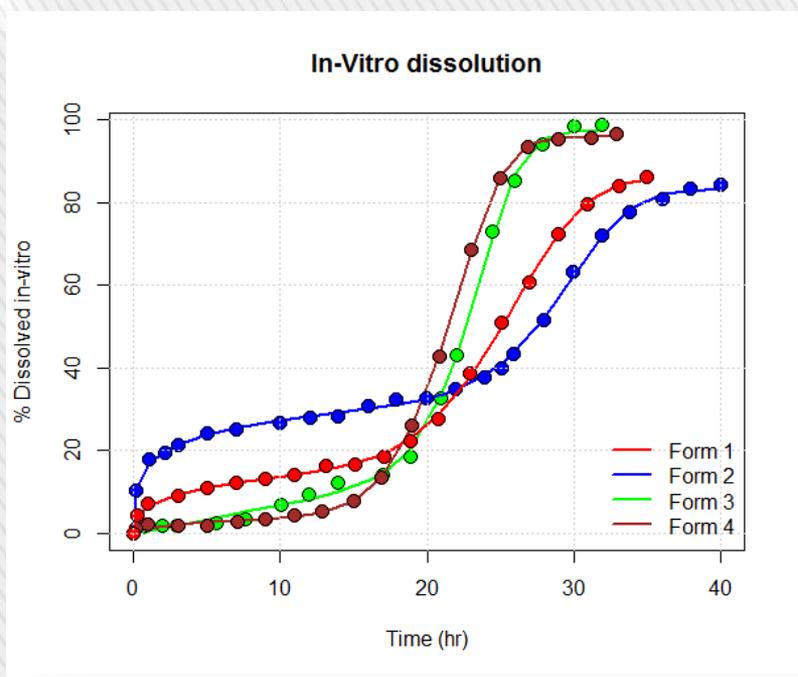
$$A_1(\text{time} = 0) = ff \cdot Dose \text{ [Depot]}$$

$$A_2(\text{time} = 0) = (1 - ff) \cdot Dose \text{ [Plasma comp]}$$



# Risperdal Consta<sup>®</sup>: Modelling In-vitro dissolution and IV data

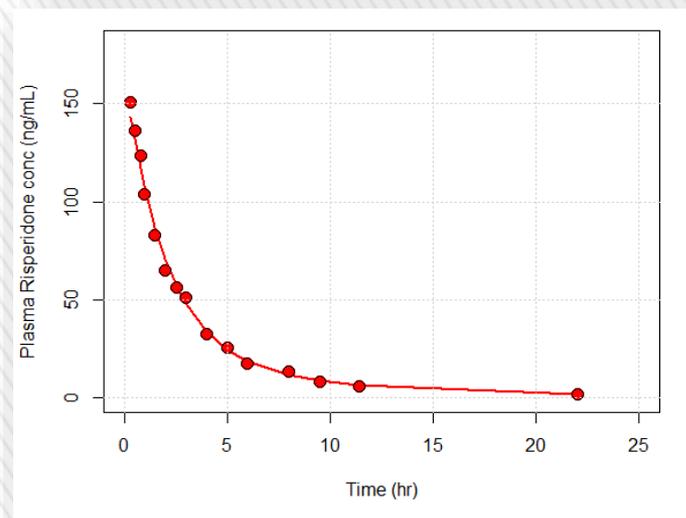
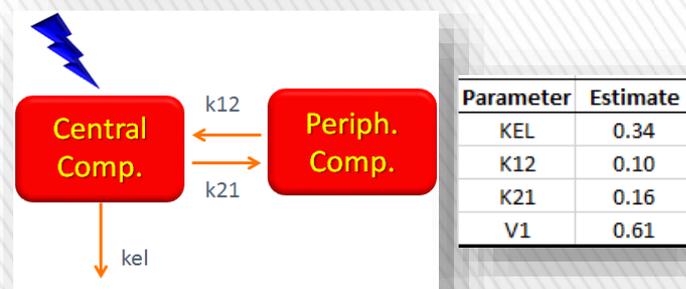
## In-Vitro: Double Weibull model



Formulation	TD	SS	TD1	SS1	FF
1	18.02	1.21	23.92	9.35	0.18
2	44.31	0.50	22.47	7.86	0.10
3	26.71	0.29	30.29	8.46	0.52
4	56.11	0.37	26.70	6.45	0.33

$$r_{\text{vitro}}(t) = 100 \cdot \left[ 1 - \left( ff \cdot e^{-\left( \frac{\text{time}}{\text{td}} \right)^{ss}} \right) + (1 - ff) \cdot e^{-\left( \frac{\text{time}}{\text{td1}} \right)^{ss1}} \right)$$

## In-Vivo: Two-compartment model



# Time scaling

In a linear correlation, the *in-vitro* dissolution and *in-vivo* input curves may be directly super-imposable or may be made to be super-imposable by the use of a “scaling factor”

A general model for time-scaling model for the IVIVC assessment was used (\*)

$$r_{vivo}(t) = a_1 + a_2 \cdot r_{vitro}(tt)$$

$$tt = b_1 + b_2 \cdot t^{b_3}$$

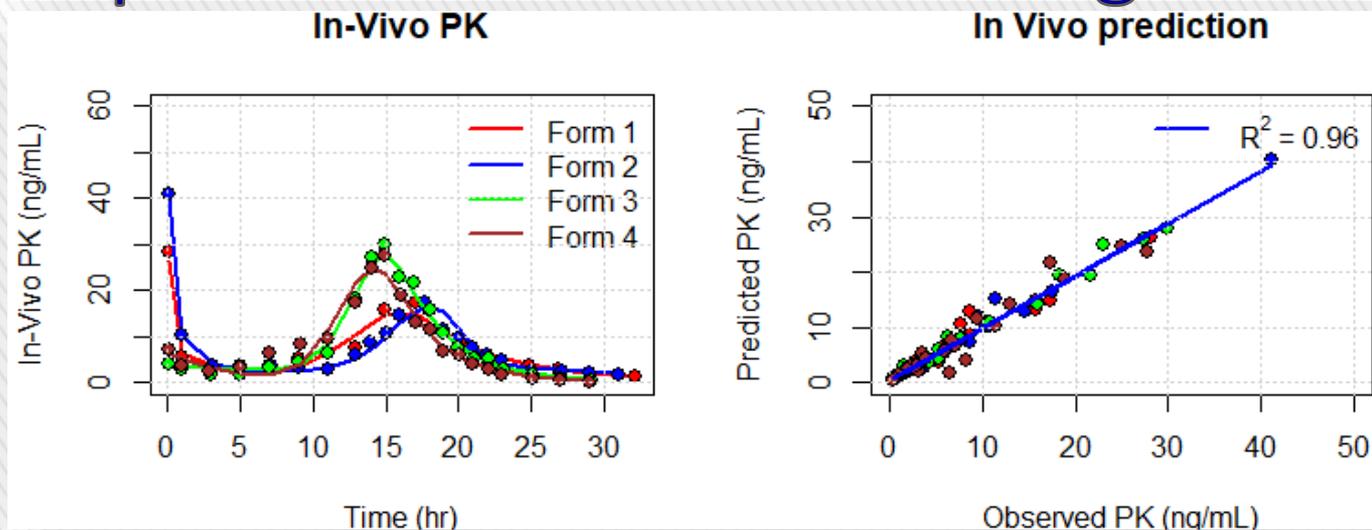
In case of absence of time scaling between  $r_{vivo}$  and  $r_{vitro}$ :

$$a_1 = 0, a_2 = 1, b_1 = 0, b_2 = 1, \text{ and } b_3 = 1.$$

Otherwise, the values of the parameters  $a_1$ ,  $a_2$ ,  $b_1$ ,  $b_2$ , and  $b_3$  time scaling can be estimated in the IVIVC modeling step the appropriate. The model includes a linear component (intercept of  $a_1$  and slope of  $a_2$ ), and a nonlinear component describing the time-shifting ( $b_1$ ), time-scaling ( $b_2$ ), and time-shaping factor ( $b_3$ ).

\* Gomeni R, Fang LL, Bressolle-Gomeni F, Spencer TJ, Faraone SV, Babiskin A. A general framework for assessing IVIVC as a tool for maximizing the benefit-risk ratio of a treatment using a convolution-based modeling approach. *CPT Pharmacometrics Syst Pharmacol.* 2019 Jan 18. doi: 10.1002/psp4.12378.

# Risperdal Consta<sup>®</sup>: Modelling IVIVC data



Parameter	Estimate
A1	0.00
B1	1.78
A2	0.14
B2	1.62
B3	1.00
Bioav	0.74
ff	0.99

$$PE = \frac{1}{n} \sum_{i=1}^n \frac{|\text{Obs. value} - \text{Pred. value}|}{\text{Obs. value}} \cdot 100$$

Formulation	Observed values		Predicted values		Prediction error	
	Cmax (ng/mL)	AUC (ng*hr/mL)	Cmax (ng/mL)	AUC (ng*hr/mL)	p_AUC (%)	p_Cmax (%)
1	28.21	207.92	26.28	211.02	1.49	6.84
2	41.11	200.61	40.34	200.46	0.08	1.89
3	29.94	225.91	27.96	232.16	2.77	6.62
4	27.79	215.91	24.81	209.34	3.04	10.73
<b>Average</b>					<b>1.84</b>	<b>6.52</b>

### Predictability criteria:

- PE <15% for each formulation
- PE <10% for mean values

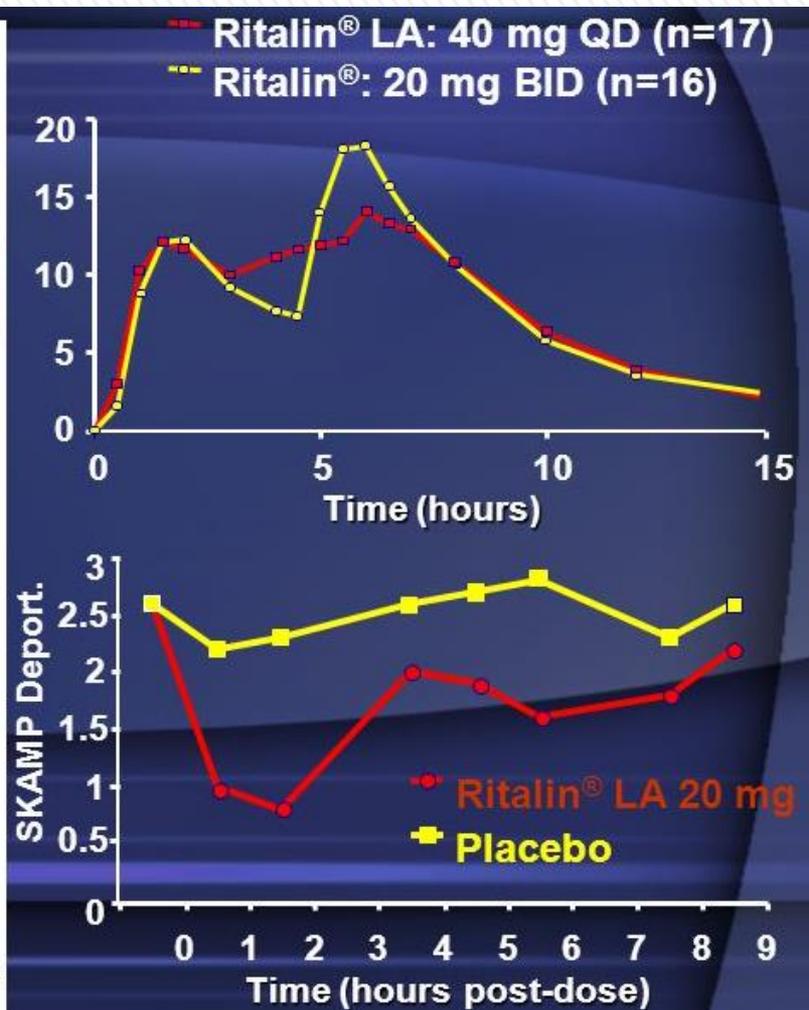
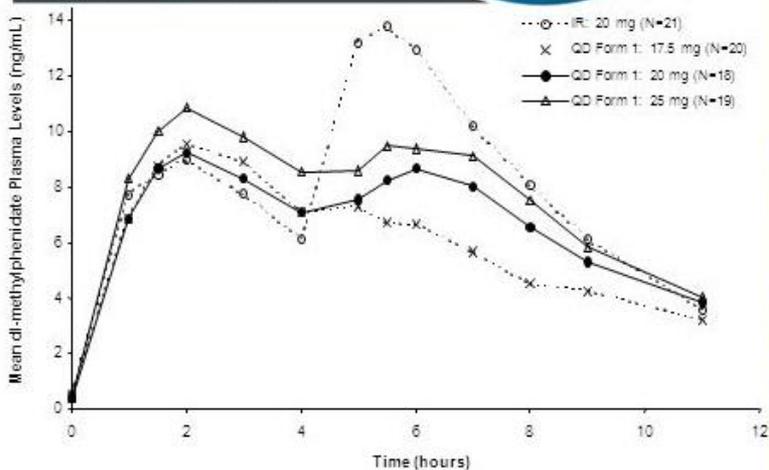
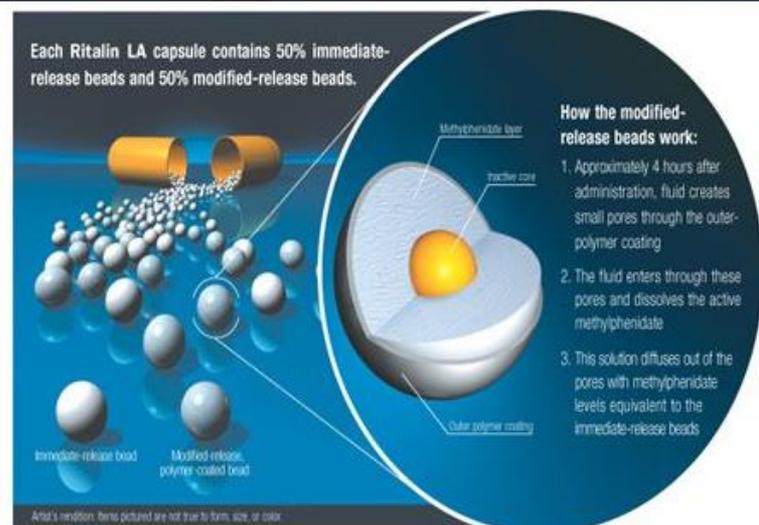
*The highest mean prediction errors is less than 15% for the individual formulations and the highest mean absolute prediction error for the 3 formulations is **6.52%** for Cmax. This value is less than the maximum allowable prediction errors 10% for mean absolute prediction error.*

# What is ADHD?

- Psychological disorder characterized by three main traits
  - *Inattention*
  - *Hyperactivity*
  - *Impulsivity*
- These symptoms can make it difficult for a child with ADHD to succeed in school, get along with other children or adults, or finish tasks at home
- ADHD is the most common psychological disorder of childhood, estimated to affect 3% to 9% of school-age children
- 1.29 million children with ADHD are being treated with stimulant medication
- Methylphenidate (MPH) is a stimulant medication used to treat children over 6 years old, adolescents, and adults with attention-deficit hyperactivity disorder (ADHD)

# Ritalin LA<sup>®</sup> bimodal MPH release for the treatment of ADHD

Ritalin LA<sup>®</sup> uses the proprietary SODAS<sup>®</sup> (Spheroidal Oral Drug Absorption System) technology



# Ritalin LA<sup>®</sup> IVIVC study

The objective of this study was to evaluate the in vitro dissolution and in vivo absorption of d,l-threo-methylphenidate (MPH) from a novel bimodal release formulation (Ritalin1 LA capsule) compared with an immediate-release formulation (Ritalin IR tablet) in healthy volunteers.

This was a four-treatment, four-period, single dose, randomized crossover study. 16 subjects were retained for the final PK analysis. The subjects received four treatments, after at least a ten h fast, three Ritalin LA capsule formulations (40 mg) and Ritalin IR tablets (two 20 mg given 4h apart) as the reference. The three Ritalin LA formulations were selected to provide slow-, medium- and fast-release in vitro dissolution rates, respectively.

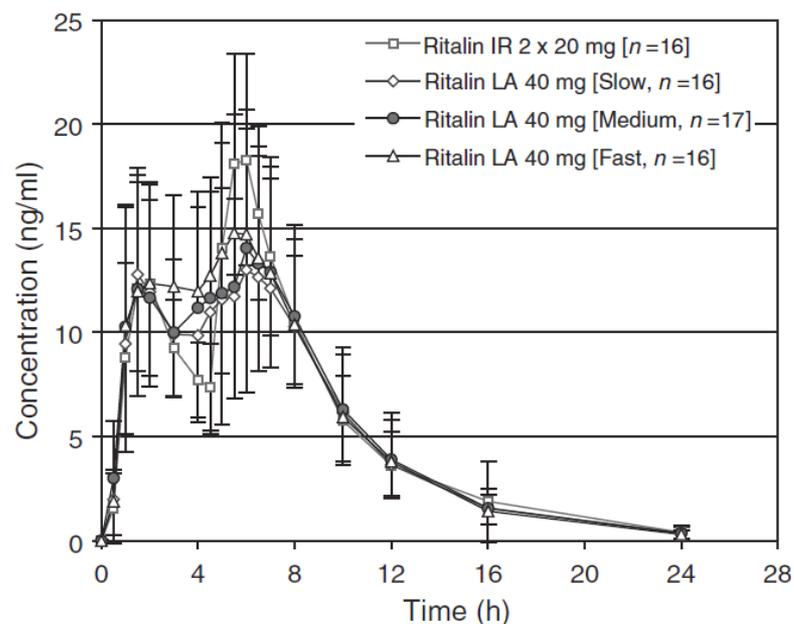


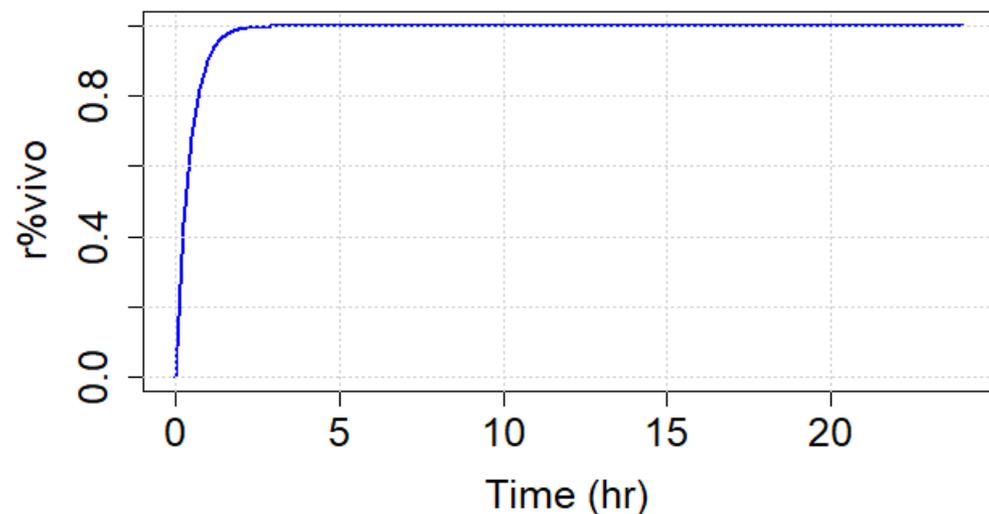
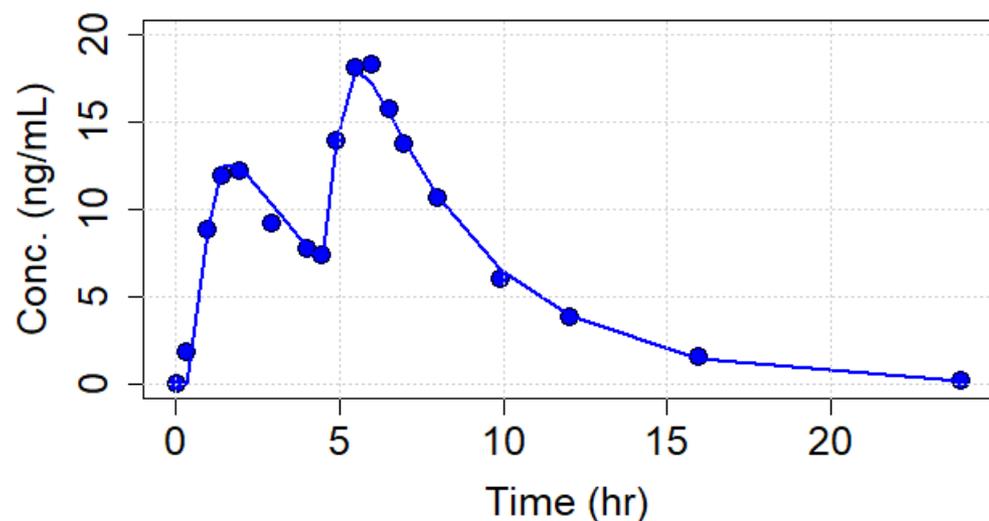
Figure 1. Plasma concentration (mean  $\pm$  SD)-time profile of MPH after a single dose of Ritalin LA slow-, medium- or fast-release formulation and Ritalin tablets (immediate release formulation) given 4 h apart

# Step 1: Estimate the disposition and the elimination of Ritalin IR

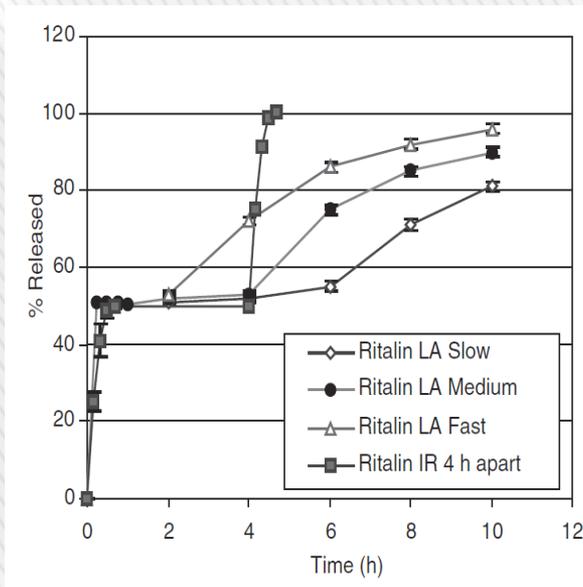
The PK data of Ritalin IR tablets (two 20 mg given four h apart) were considered as the reference and used to estimate the disposition ( $V$ ) and elimination parameters ( $k_{el}$ ) of Ritalin

Parameter	Value
$k_a(\text{hr}^{-1})$	2.390
$k_{el}(\text{hr}^{-1})$	0.254
$V(\text{L})$	1.200
Lag(hr)	0.633

The value of volume ( $=1.20$  L) and elimination rate  $k_{el}$  ( $=0.254$   $\text{hr}^{-1}$ ) were fixed in the assessment of the IVIVC



# Step 2: Modelling the in-vitro dissolution data



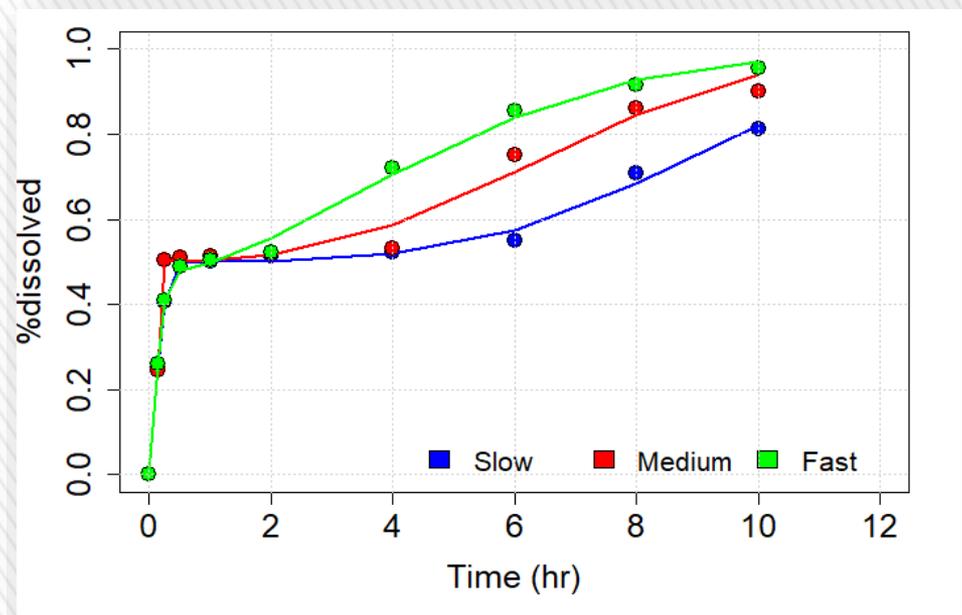
$$\%Dissolved = \left[ 1 - \left( ff \cdot e^{-\left( \frac{\text{time}}{td} \right)^{ss}} \right) + (1 - ff) \cdot e^{-\left( \frac{\text{time}}{td1} \right)^{ss1}} \right]$$

$ff, 1-ff$  = fraction of the drug in the rapid and slow dissolution phases

$ss, ss1$  = shaping factors

$td1, td2$  = time to absorb about 63% in the two dissolution phases

Parameter	Slow	Medium	Fast
td(hr)	0.19	0.16	0.17
ss	1.70	6.55	1.79
td1(hr)	9.91	7.55	5.42
ss1	3.59	2.63	1.75
ff(%)	0.50	0.50	0.47



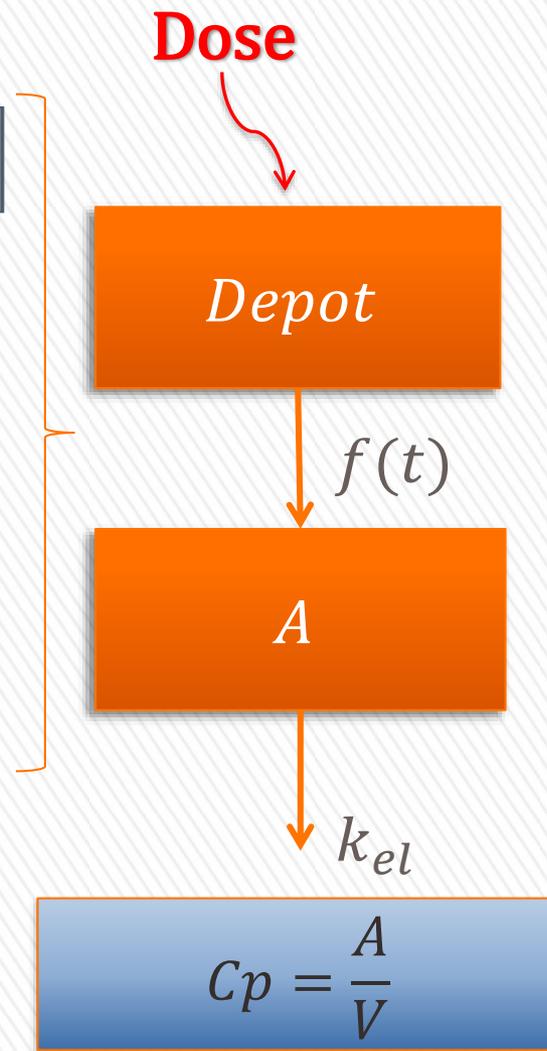
# Modeling IVIVC

$$r_{\text{vivo}}(t) = \text{Dose} \cdot \left[ 1 - \left( \text{ff} \cdot e^{-\left(\frac{\text{time}}{\text{td}}\right)^{\text{ss}}} + (1 - \text{ff}) \cdot e^{-\left(\frac{\text{time}}{\text{td1}}\right)^{\text{ss1}}} \right) \right]$$

$$f(t) = \frac{dr_{\text{vivo}}}{dt}$$

$$\frac{dA}{dt} = F_i \cdot \text{Dose} \cdot f(t) - k_{el} \cdot A$$

$F_i$  = Fraction of the dose available to reach the systemic circulation for the  $i^{\text{th}}$  formulation



# Implementing IVIVC in NONMEM

```

$PROBLEM Ritalin IVIVC fit
$INPUT ID TIME DV DOSE
$DATA ritapk.csv IGNORE=@
$SUBS ADVAN13 TOL=8
$MODEL COMP(A)
$PK

```

```

IF (ID.EQ.1) THEN      IF (ID.EQ.2) THEN      IF (ID.EQ.3) THEN
  TD=0.186              TD=0.159              TD=0.17
  SS=1.7                SS=6.55              SS=1.79
  TD1=9.91             TD1=7.55             TD1=5.42
  SS1=3.59             SS1=2.63             SS1=1.75
  FF=0.5               FF=0.502            FF=0.471
  BI=THETA (6)         BI=THETA (7)         BI=THETA (8)
ENDIF                  ENDIF                  ENDIF

```

```

A1=THETA (1)
A2=THETA (2)
B1=THETA (3)
B2=THETA (4)
B3=THETA (5)

```

```

DELT=0.01
KEL=0.254*EXP(ETA(1))
S1=1.2

```

```

ABS0=1-(FF*EXP(-(TIME/TD)**SS)+(1-FF)*EXP(-(TIME/TD1)**SS1))
TX=(B1+B2*TIME**B3)
TX1=(FF*EXP(-(TX/TD)**SS)+(1-FF)*EXP(-(TX/TD1)**SS1))
VABS0=1-(A1+A2*TX1)

```

```
$DES
```

```

TT1=T-DELT
TT2=T+DELT
IF (TT1.LE.0) TT1=0
IF (TT2.LE.0) TT2=0

```

```

TIM=(B1+B2*TT1**B3)
IF (TIM.LE.0)      TIM=0
VV=(FF*EXP(-(TIM/TD)**SS)+(1-FF)*EXP(-(TIM/TD1)**SS1))
FA=A1+A2*VV
IF (FA.LE.0)      FA=0
IF (FA.GT.1)      FA=1
ABS1=FA

```

```

TIM=(B1+B2*TT2**B3)
IF (TIM.LE.0)      TIM=0
VV=(FF*EXP(-(TIM/TD)**SS)+(1-FF)*EXP(-(TIM/TD1)**SS1))
FA=A1+A2*VV
IF (FA.LE.0)      FA=0
IF (FA.GT.1)      FA=1
ABS2=FA

```

```

KAB=(ABS1-ABS2)/(TT2-TT1)
DADT(1)=BI*DOSE*KAB-KEL*A(1)

```

$$r_{vivo}(t) = a_1 + a_2 \cdot r_{vitro}(tt)$$

$$tt = b_1 + b_2 \cdot t^{b_3}$$

# Step 3: Modelling the IVIVC

Two analysis scenarios were considered: in the first one 3 distinct  $F_{\text{}}$  parameters were estimated and in the second one the same  $F_{\text{}}$  value was assumed for the 3 formulations.

*Scenario 1: Parameter values estimated assuming a  $F_{\text{}}$  value different for each formulation*

Parameter	Value	FIX	SE	RSE
A1	0	FIX	0	0%
A2	1	FIX	0	0%
B1	0	FIX	0	0%
B2	0.20	-	0.003	1.40%
B3	2.24	-	0.051	2.30%
$F_{\text{Slow}}$	0.96	-	0.023	2.40%
$F_{\text{Medium}}$	0.92	-	0.023	2.50%
$F_{\text{Fast}}$	0.95	-	0.016	1.70%
err_add	1.12	-	0.096	8.60%
<i>OFV=60.974</i>				

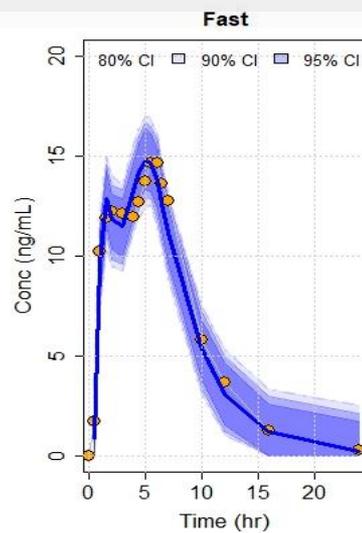
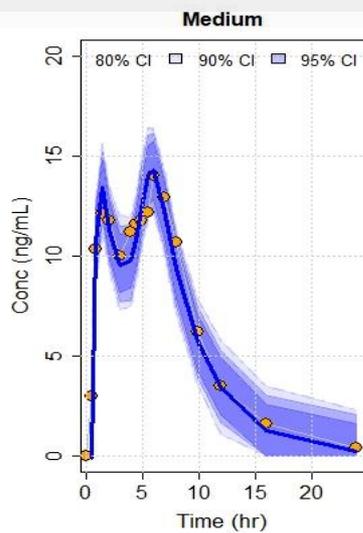
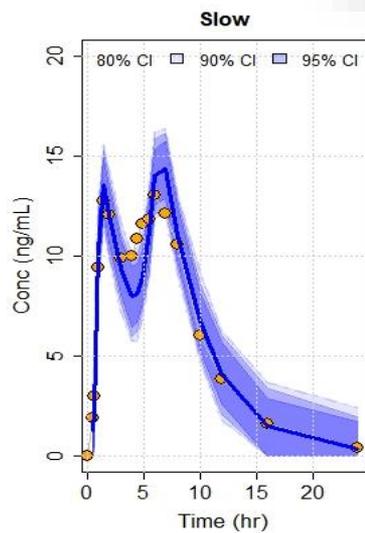
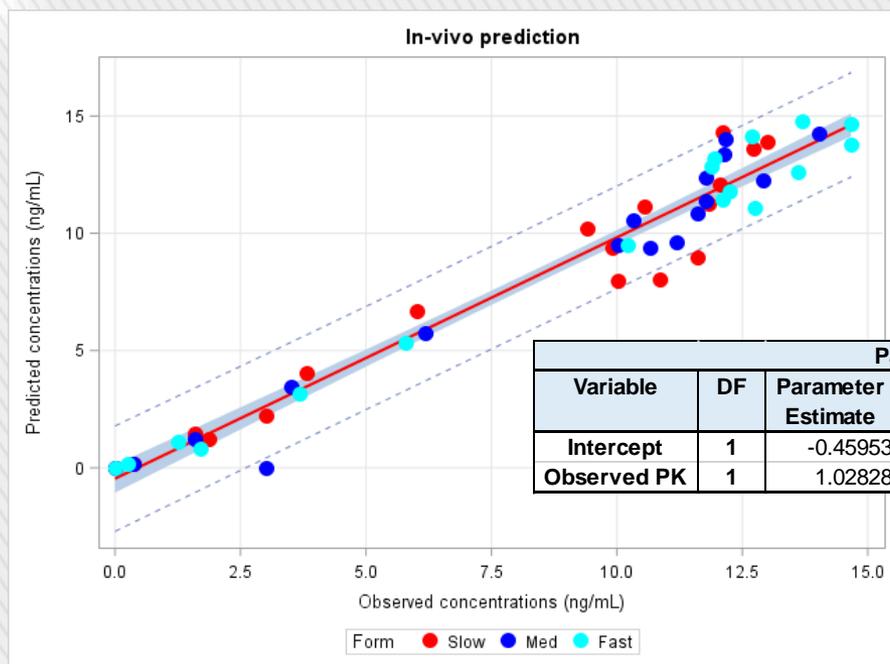
*Scenario 2: Parameter values estimated assuming the same  $F_{\text{}}$  value for each formulation*

Parameter	Value	FIX	SE	RSE
A1	0	FIX	0	0%
A2	1	FIX	0	0%
B1	0	FIX	0	0%
B2	0.19	-	0.002	1.20%
B3	2.24	-	0.053	2.40%
$F_{\text{}}$	0.94	-	0.018	1.90%
err_add	1.13	-	0.099	8.80%
<i>OFV=61.402</i>				

*OFV is the NONMEM estimated objective function value*

*The comparison of the change in the OFV value using the log-likelihood ratio test in the two modeling scenarios indicated that the assumption of a common  $F_{\text{}}$  value for the different formulation was the preferred option.*

# Step 3: Evaluating the IVIVC



Mean PK observed concentrations (orange dots) with the predicted values by the convolution model (blue solid lines) by formulation. The shaded areas represent the 80%, 90%, and 95% prediction intervals.

# Additional criteria for assessing predictability (%PE)

$$\%PE = \frac{1}{n} \sum_1^n \frac{|\text{Observed value} - \text{Predicted value}|}{\text{Observed value}} \cdot 100$$

In addition to AUCinf and Cmax, additional metrics based on the concept of partial AUC were considered for the assessment of %PE.

These criteria were based on the recent recommendations of the FDA for using partial AUC (pAUC) metrics for studies conducted in fasting conditions, to assess the bioequivalence of generic ER formulations of MPH\*.

The following pAUC were considered:

- *pAUC0-3, AUC from 0 to 3 hours,*
- *pAUC3-7, AUC from 3 to 7 hours,*
- *pAUC7-12, AUC from 7 to 12 hours*

\* Food and Drug Administration. Draft Guidance on Methylphenidate Hydrochloride 2015.

<https://www.fda.gov/downloads/drugs/guidancecomplianceregulatoryinformation/guidances/ucm281454.pdf>

# Refined Predictability

0 - 24 hr						
Formulation	cmax_o	auc_o	cmax_p	auc_p	pe_cmax	pe_auc
Slow	13.01	127.46	14.40	127.80	10.68	0.27
Medium	14.02	130.86	14.31	123.38	2.03	5.72
Fast	14.67	133.44	14.69	125.90	0.16	5.65
<b>Average</b>					<b>4.29</b>	<b>3.88</b>

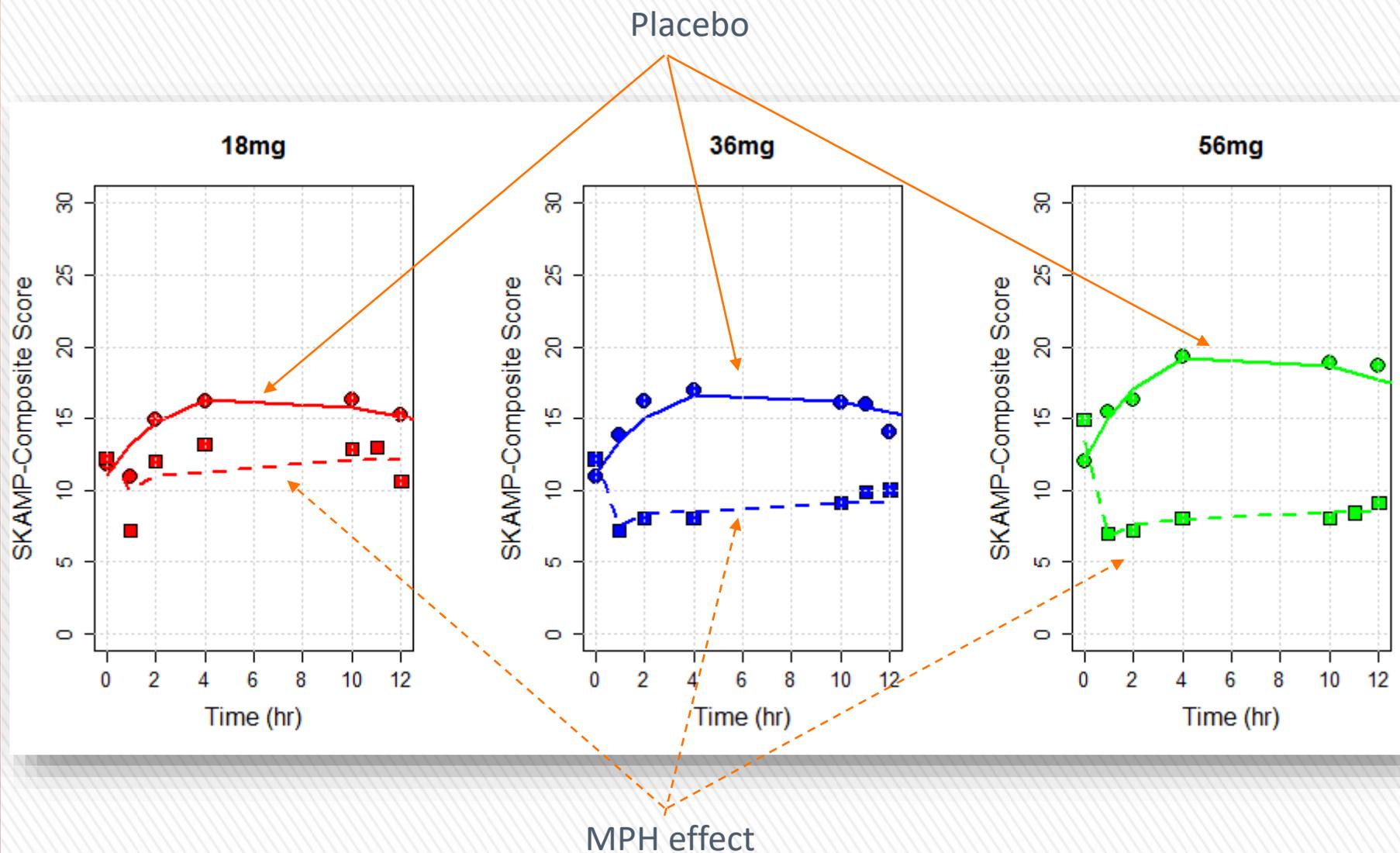
## Predictability criteria:

- PE <15% for each formulation,
- PE <10% for mean values

0 - 3 hr				3 - 7 hr				7 - 12 hr			
Formulation	auc_o	auc_p	pe_auc	Formulation	auc_o	auc_p	pe_auc	Formulation	auc_o	auc_p	pe_auc
Slow	14.70	15.14	2.95	Slow	44.70	41.84	6.40	Slow	26.25	28.55	8.76
Medium	16.99	16.35	3.77	Medium	46.70	46.32	0.83	Medium	25.96	23.89	7.98
Fast	15.18	14.68	3.30	Fast	45.96	46.83	1.91	Fast	36.63	32.38	11.61
<b>Average</b>			<b>3.34</b>	<b>Average</b>			<b>3.04</b>	<b>Average</b>			<b>9.45</b>

The highest mean prediction errors is **11.61%** for the individual formulations (**<15% max acceptable value**) and the highest mean absolute prediction error for the 3 formulations is **9.45 %** for pAUC7-12 (**<10% max acceptable value**)

# The PK/PD model – Effect of MPH on the SKAMP clinical scores



# Exposure-response model

$$SKAMP(effect)^* = P(t) + Delta - \frac{Emax \cdot C_p}{EC_{50} + C_p}$$

Where:  $P(t)$  is the placebo response defined by the model

$$\frac{dP}{dt} = k_{in} \cdot \left(1 + AA \cdot (e^{-t \cdot P1} - e^{-t \cdot P2})\right) - k_{out}P$$

$k_{in}$  = zero-order rate constant for production of response (P),

$k_{out}$  = first-order rate constant for the loss of response;

$AA$  = amplitude of the placebo effect,

$P1$  and  $P2$  = rate of onset and offset of placebo effect

$Delta$  = score difference at baseline depending on the treatment between assessment days

$Emax$  = maximal MPH related effect

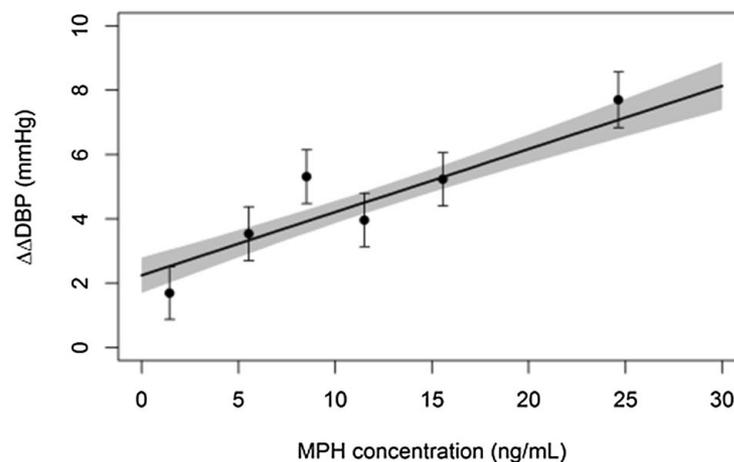
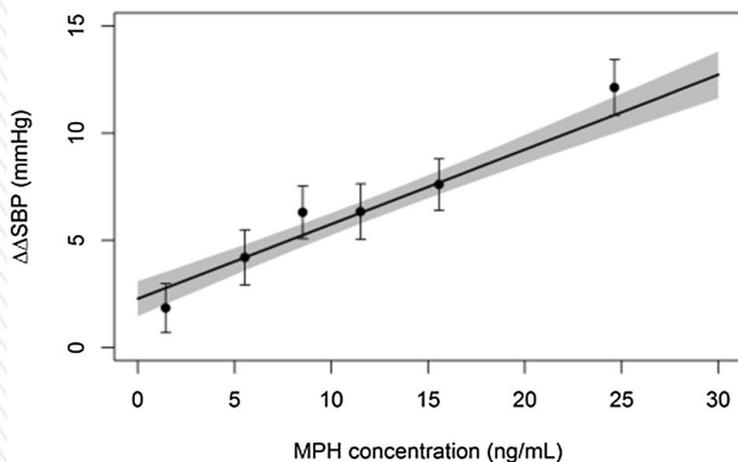
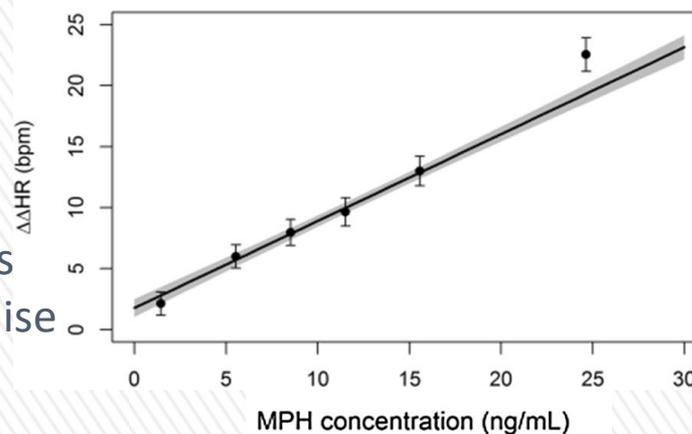
$EC_{50}$  = MPH concentration associated with 50% of the maximal effect

$C_p$  = MPH drug concentration

\*Gomeni R, Bressolle-Gomeni F, Spencer TJ, Faraone SV, Fang L, Babiskin A. Model-Based Approach for Optimizing Study Design and Clinical Drug Performances of Extended-Release Formulations of Methylphenidate for the Treatment of ADHD. *Clin Pharmacol Ther.* 2017 Dec;102(6):951-960. doi: 10.1002/cpt.684. Epub 2017 Sep 19.

# Exposure–response analyses of blood pressure and heart rate changes for methylphenidate in healthy adults

The exposure-response of blood pressure (BP) and heart rate (HR) for MPH in healthy adults indicated that the BP and HR changes were directly related and highly dependent on the MPH plasma concentration. These safety issues associated with MPH treatment may compromise the treatment course of ADHD in children and also raise parents' concerns over them.



Li L, Wang Y, Upoor RS, Mehta MU, Farchione T, Mathis MV, Zhu H. Exposure-response analyses of blood pressure and heart rate changes for methylphenidate in healthy adults. *J Pharmacokinet Pharmacodyn.* 2017 Jun;44(3):245-262. doi: 10.1007/s10928-017-9513-5.

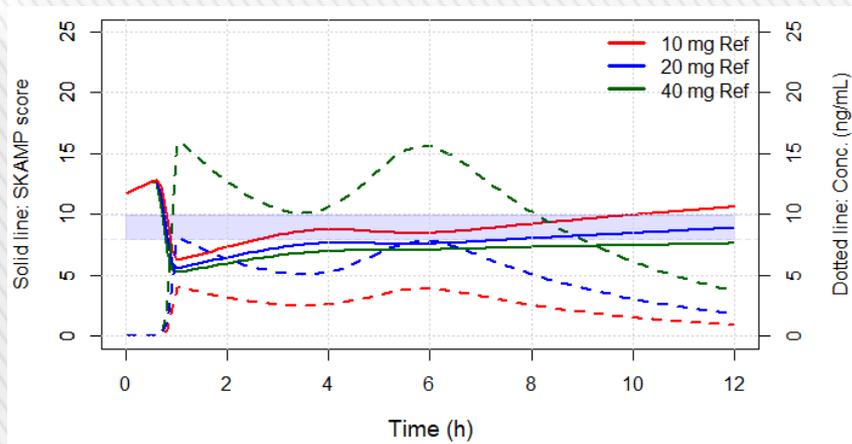
# Clinical benefit

$$SKAMP(effect) = P(t) + Delta - \frac{Emax \cdot C_p}{EC_{50} + C_p}$$

$$r_{vivo}(t) = Dose \cdot \left[ 1 - \left( ff \cdot e^{-\left( \frac{time}{td} \right)^{ss}} + (1 - ff) \cdot e^{-\left( \frac{time}{td1} \right)^{ss1}} \right) \right]$$

$$f(t) = \frac{dr_{vivo}}{dt}$$

$$\frac{dA}{dt} = F_i * Dose * f(t) - k_{el} \cdot A \quad \rightarrow \quad Cp = \frac{A}{V}$$

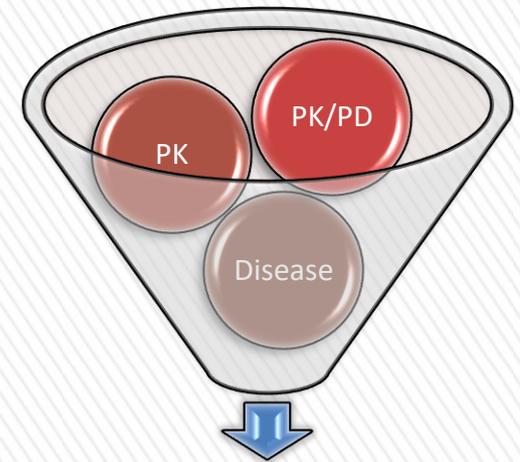


**CB: maintenance of SKAMP scores from 8 to 10 during 12 hours was considered as the target clinical response**

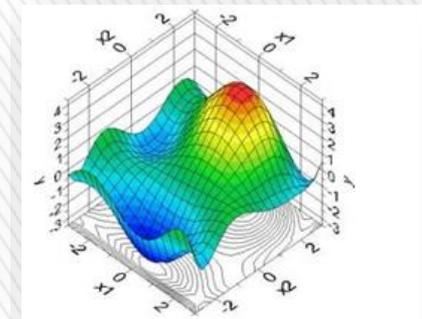
$$CB = f(SKAMP)$$

$$SKAMP = f(C_p)$$

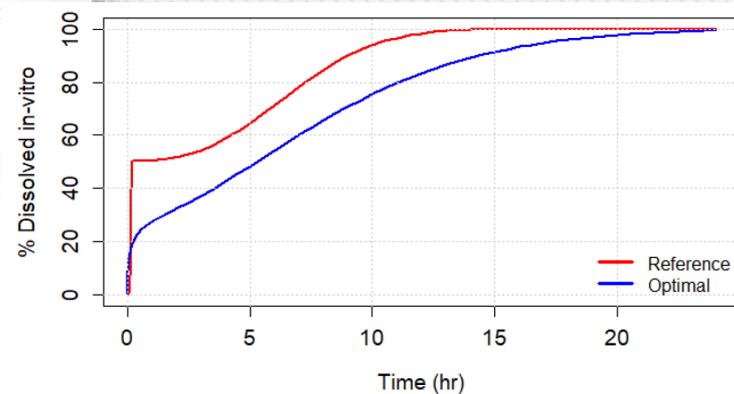
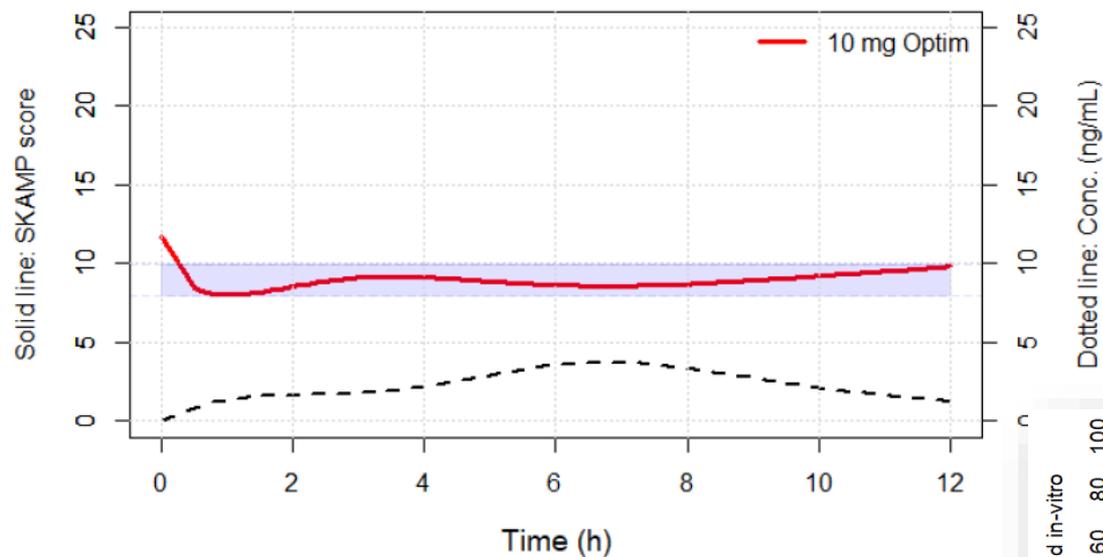
$$C_p(ff, ss, ss1, td, td1, Dose)$$



**Response variable = Clinical benefit**



# Optimized response



	TD (hr)	SS (unitles)	SS1 (unitles)	TD1 (hr)	FF (%)	DOSE (mg)	Cmax (ng/mL)
Reference	0.16	6.55	2.63	7.55	0.50	40	15.85
Optimized	0.17	0.53	1.68	9.58	0.28	10	3.73

# Conclusion

- A model-informed approach can be used for identifying the best performing *in-vivo* delivery rate appropriate for maximizing the benefit-risk ratio and for facilitating the development of a formulation with the required characteristics using *in-vitro/in-vivo* correlation.
- The surface-response analysis can be prospectively applied for optimizing the drug development process by identifying the drug properties associated with an optimized benefit-risk.
- The proposed model-informed approach provides the pharmaceutical companies with a methodological framework for developing drugs with drug delivery and a dose selection suitable to produce a clinical benefit prospectively defined by the clinicians and not just a clinical response better than the placebo response.

# Thank you

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