

---

# **Early assessment of PK properties using ADMET predictor HTPK Simulation Technology: Deployment of a high-throughput mechanistic PBPK approach at Roche**

*Dr. Andrés Olivares-Morales*

*Roche Pharma Research and Early Development (pRED), Roche Innovation Center, Basel, Switzerland.*

*21.04.2021*

# Acknowledgements

## **DMPK and M&S**

- Neil Parrott
- Nenad Manevski
- Holger Fischer
- Matthias Wittwer
- Doha Naga
- Andrea Morger
- Kenichi Umehara

## **pRED Informatics**

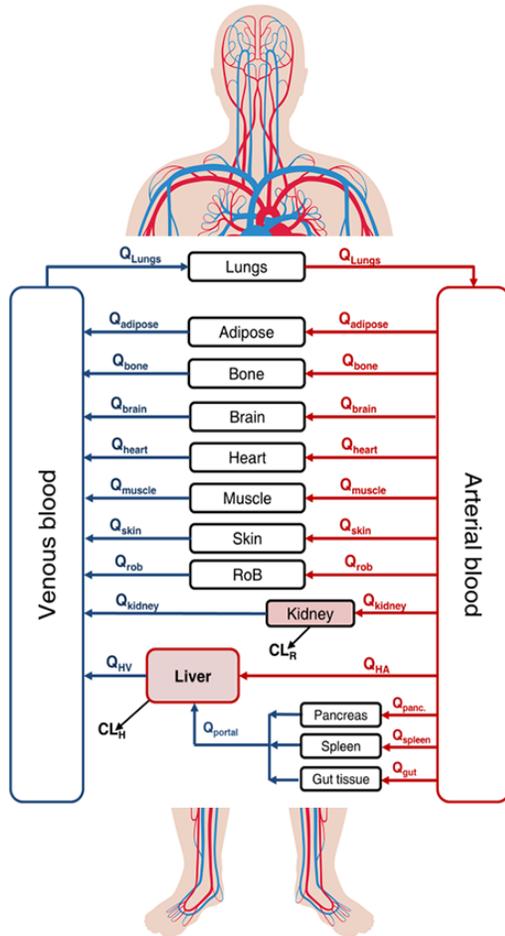
- Yaniv Cohen
- Peter Curle

## **Small Molecule Research**

- Michael Reutlinger
- Giuseppe Cecere

# INTRODUCTION

# Physiologically-based pharmacokinetic modeling (PBPK)



A mathematical modeling technique to predict pharmacokinetics

Combines physiological knowledge and compound properties

Input parameters can be in silico, in vitro or in vivo

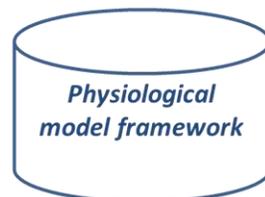
Well established in the industry with user friendly commercial software available

**In vitro**



Compound physicochemical & in vitro data

**Simulation**



**In vivo**

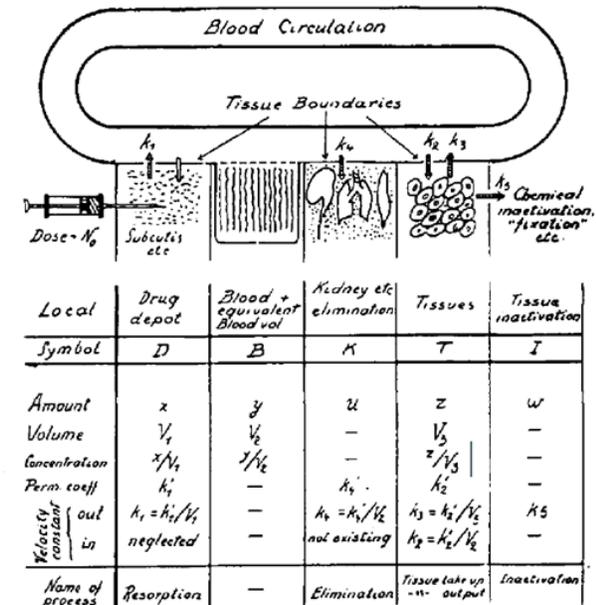
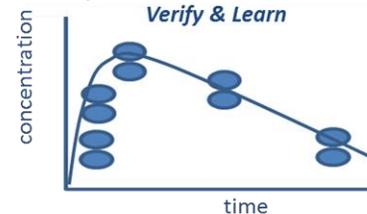


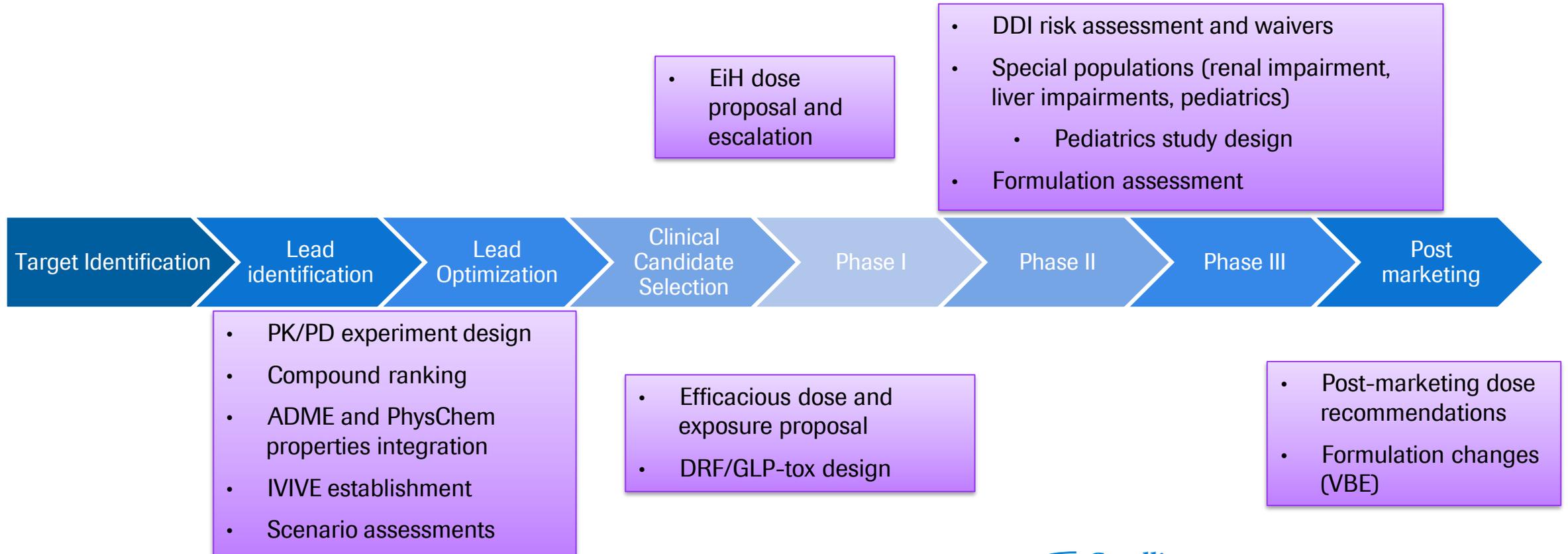
FIG. 1

Scheme of the Concept of Drug Distribution used in this paper. Instead of the injection pictured in the figure, the administration of the drug depot can be made per os, per rectum, by inhalation, etc.

**Teorell 1937**

# PBPK/PD in drug research and development

*The applications span from early discovery to late development*

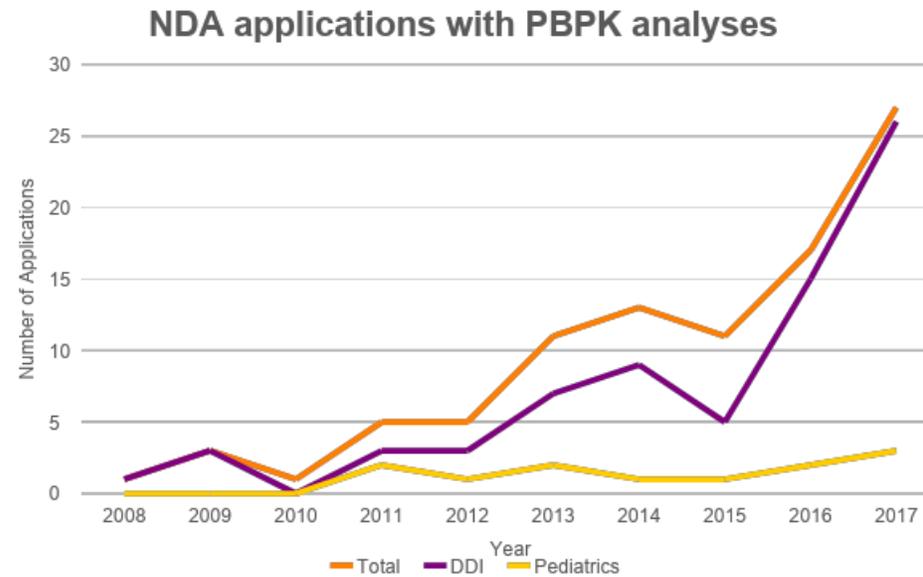
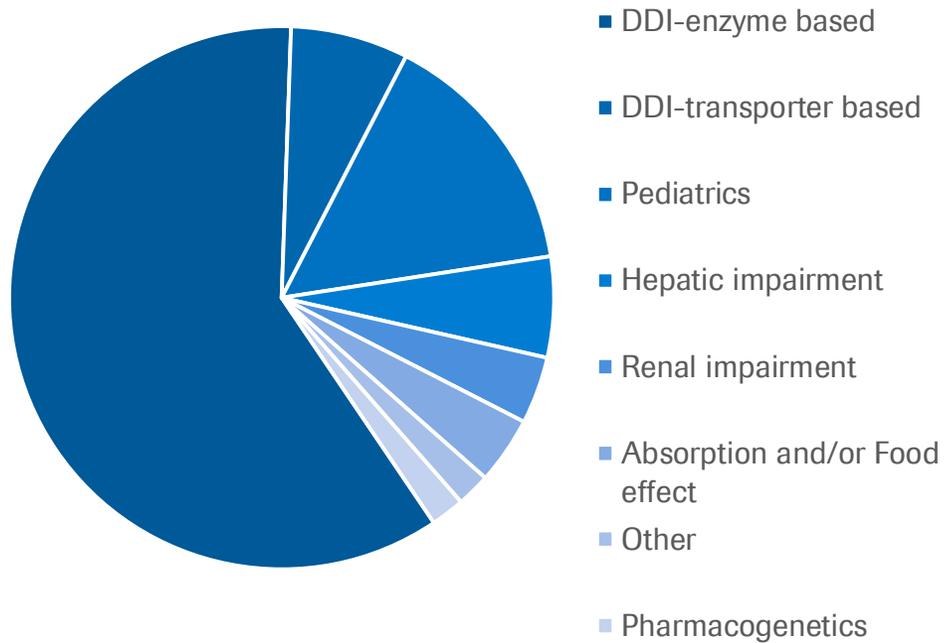


PBPK Informs Drug Labels e.g. }

- Cotellic
- Alecensa
- Rozlytrek

# PBPK model applications in drug development

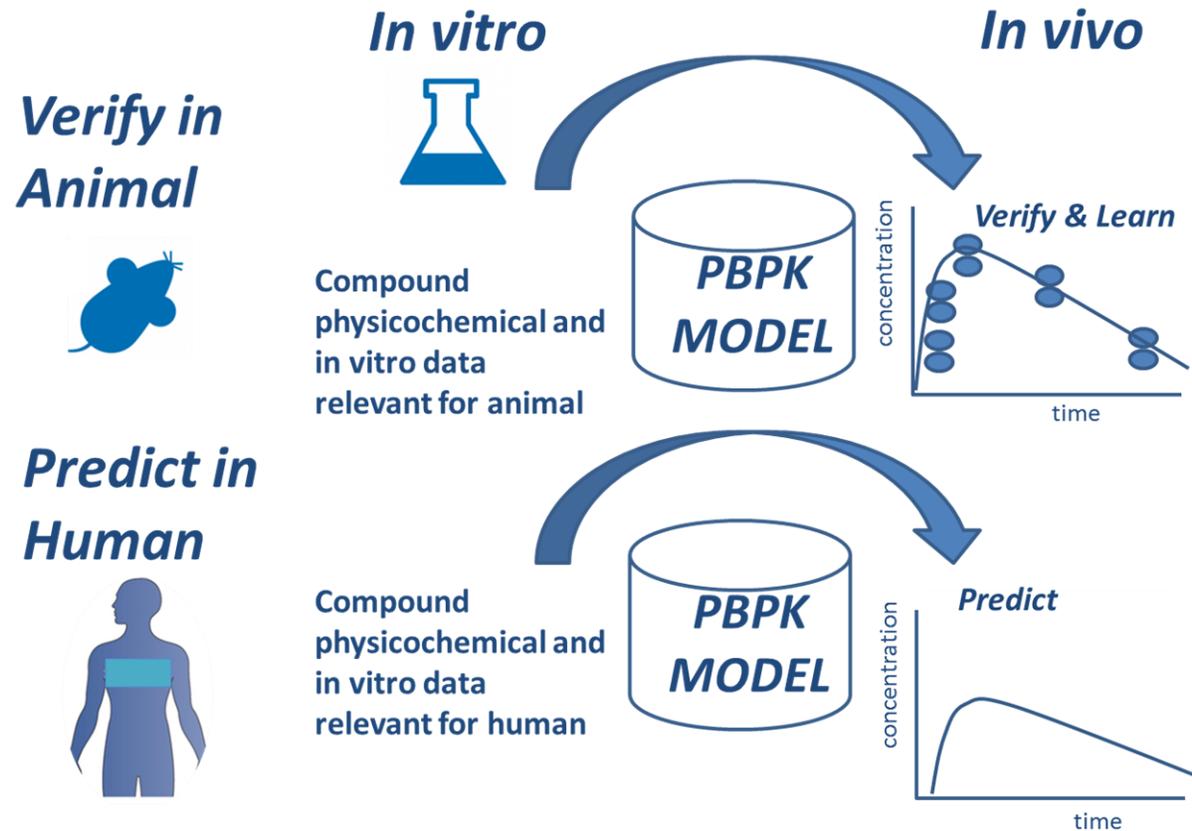
*Increased regulatory acceptance over the years*



# Roche's pRED PBPK strategy

## *A continuous learn and confirm approach*

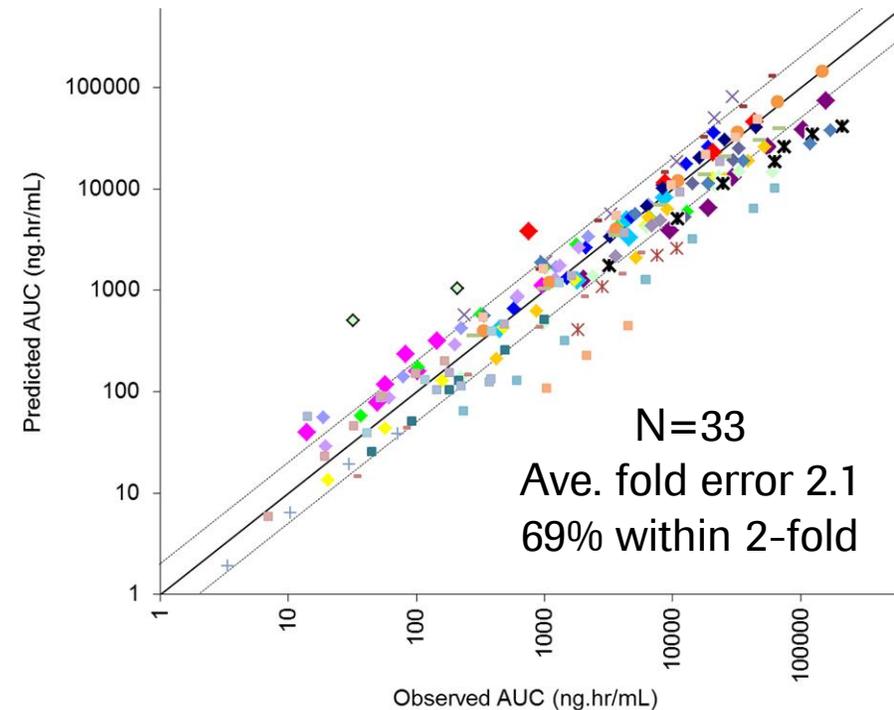
- *Overarching goal is to predict therapeutic window in humans as a function of dose using a PBPK/PD approach*



# Roche has a long history of applying PBPK modeling

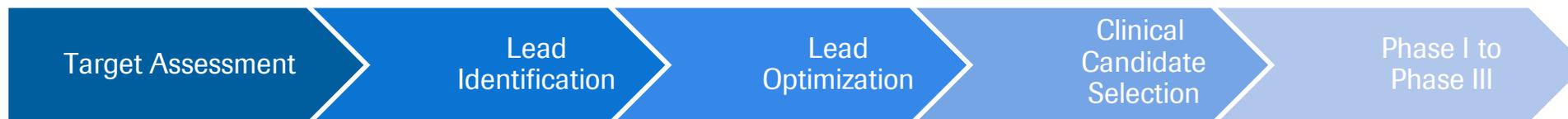
## *Successful prediction of EiH doses and exposures*

- First applied at Roche in 2003
- Key validation efforts & strategy published 2006
- Systematic use since 2010
- Retrospective analysis in 2017 showed 69% success rate



# PBPK application in the early small molecule portfolio

*Early space is dominated by ranking equations, PBPK is seldom applied*



## Simple equations

**LipE, eD2Man, Efficacy Index (EI), LipMET**

**Use:** Ranking and design, early doses

**Throughput:** high (hundreds to thousands of compounds per project)

**Implementation:** Easy (spreadsheet based, easy to implement in current project tools)

**Speed:** Instant

**Scope:** Limited (single properties or two properties combined at the most, simplified and assumption heavy)



## PBPK modeling

**GastroPlus, SimCYP (commercial), in-house (R, Matlab)**

**Use:** Human dose prediction, sensitivity analysis, biopharm, DDI, etc.

**Throughput:** low-to medium (handful of compounds per project, usually around CLS)

**Implementation: Complex** (manual data transfer and model set up. Learn and confirm cycle needed to gain confidence, data rich)

**Speed:** Moderate (minutes to hours)

**Scope:** All ADME and PK/PD properties as well as secondary parameters (half-life, Cmax, Bioavailability, Cmax)

# The limits of PBPK in early drug discovery?

*Several barriers identified*



## Current barriers to use in early discovery

- Multiple compounds & limited time
- Multiple software needed (e.g., GastroPlus, SimCYP, Phoenix, etc.)
- Lengthy set up & complex data transfers

## This results in

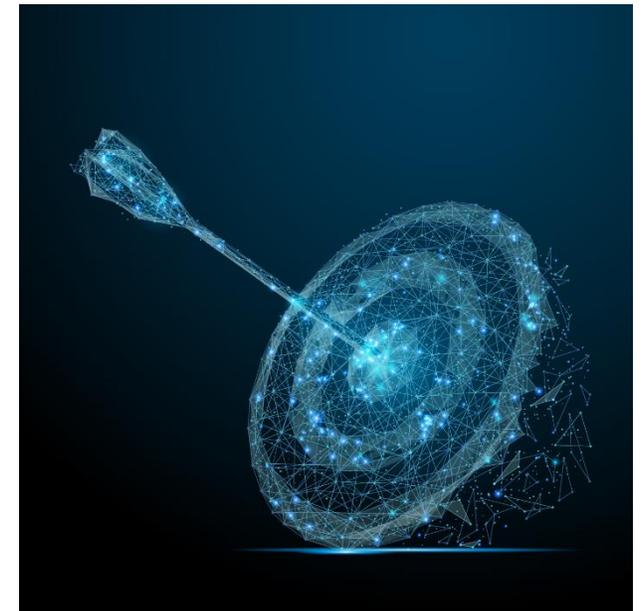
- Limited usage by “non-experts”
- Reliance on simplistic equation-based tools which are easier to implement



# Project overview

## Aims:

Faster, simpler, easier and accurate physiologically-based pharmacokinetic (PBPK) simulations in small molecule teams



# Project overview

## **This will change the way we discover medicines by:**

Bringing PBPK simulations and expertise to early discovery and design

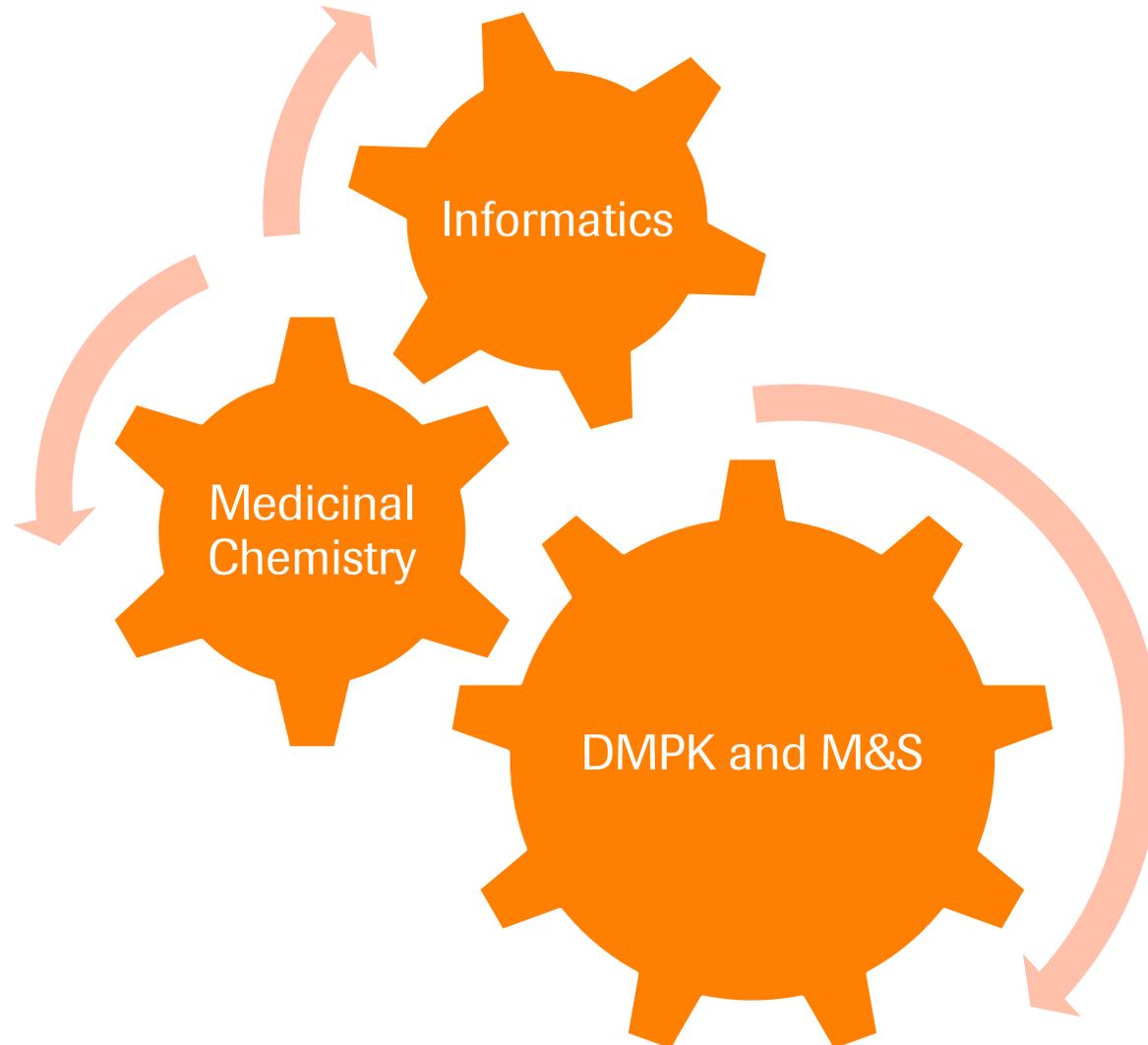
Eliminating manual data transfers and reporting

Providing model-based ADME and PK/PD insights that can lead to better compound design and selection

Reducing animal experimentation

Enabling predictions with **sparse or no data** (e.g. Machine Learning)

# A cross functional collaboration



## External Collaborators



# **CASE STUDY**

# Example of an a early PoC

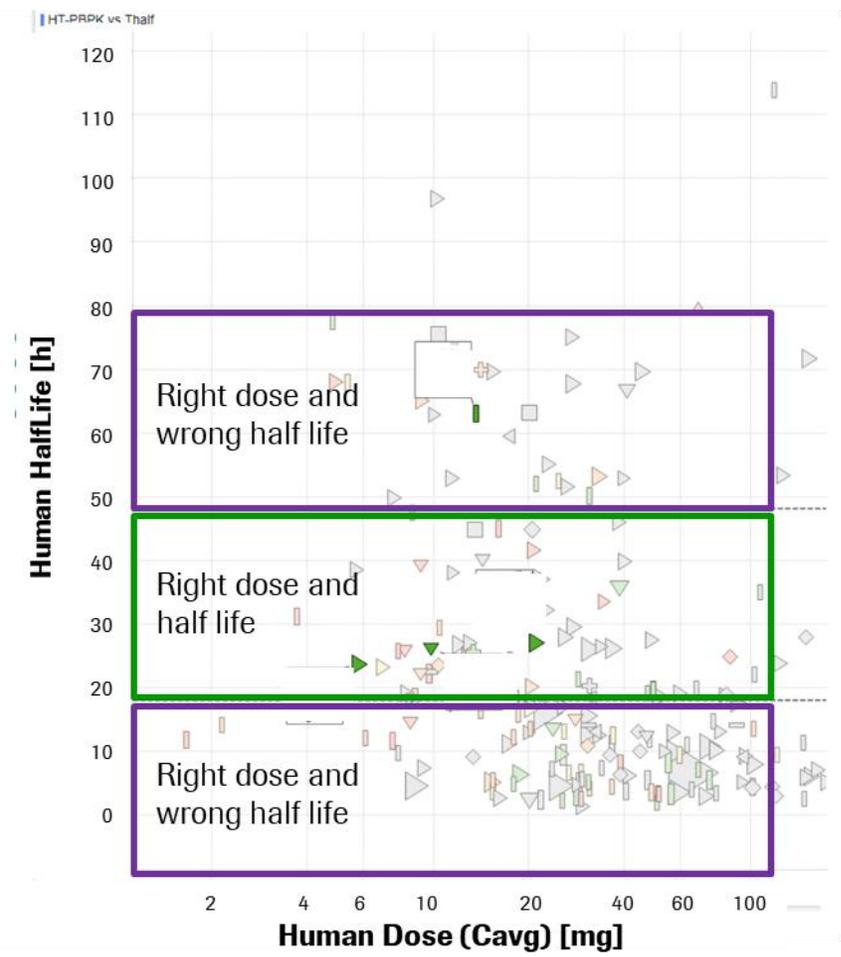
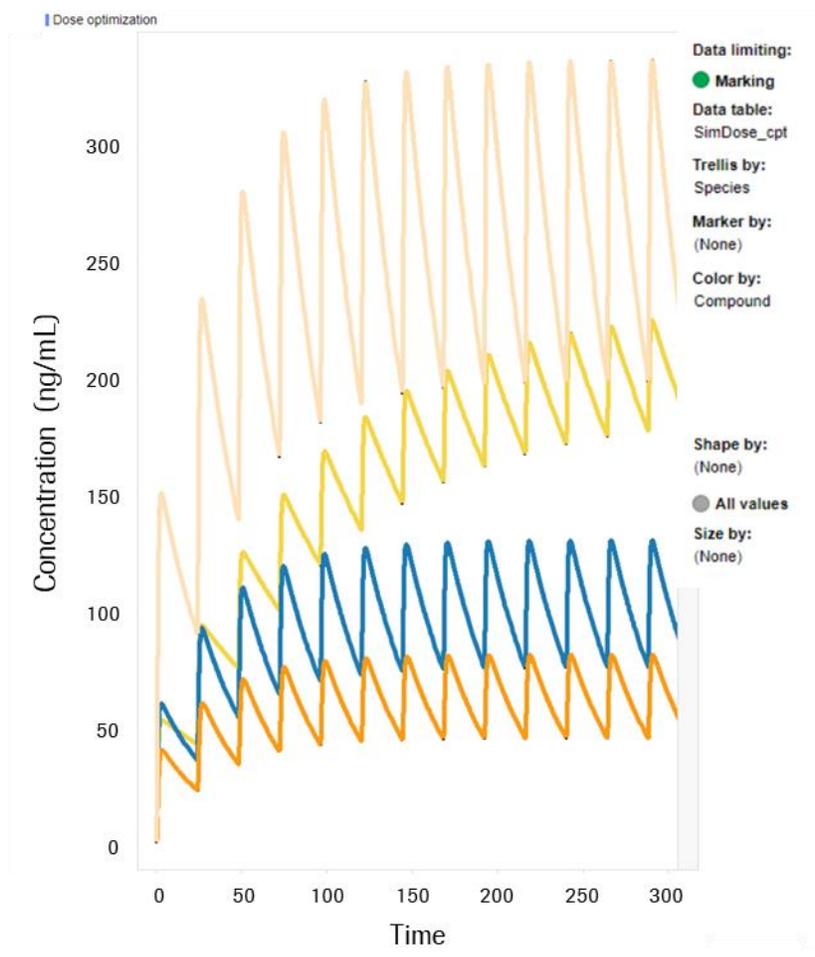
## Small molecule program

- Aim to find suitable molecules that can meet the following criteria
  - Projected early human dose target <200 mg
  - Predicted human **half-life of 12 – 48 h**
- **HT-PBPK** used by the team to generate design insights and find the right candidates

# HT-PBPK insights

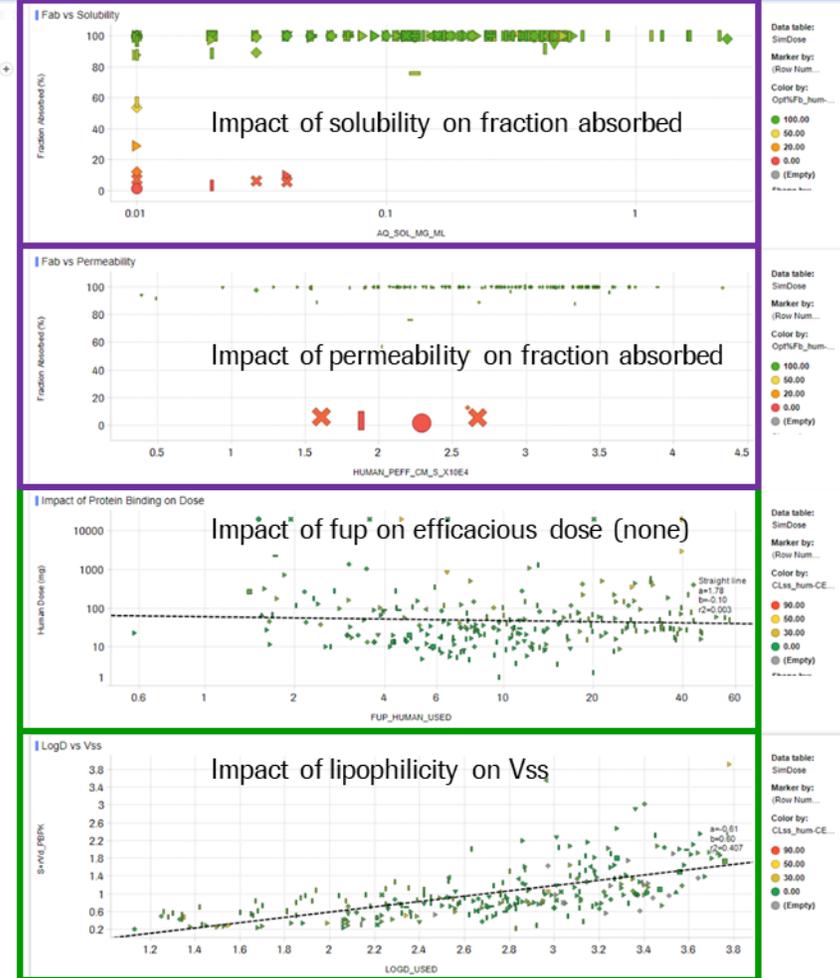
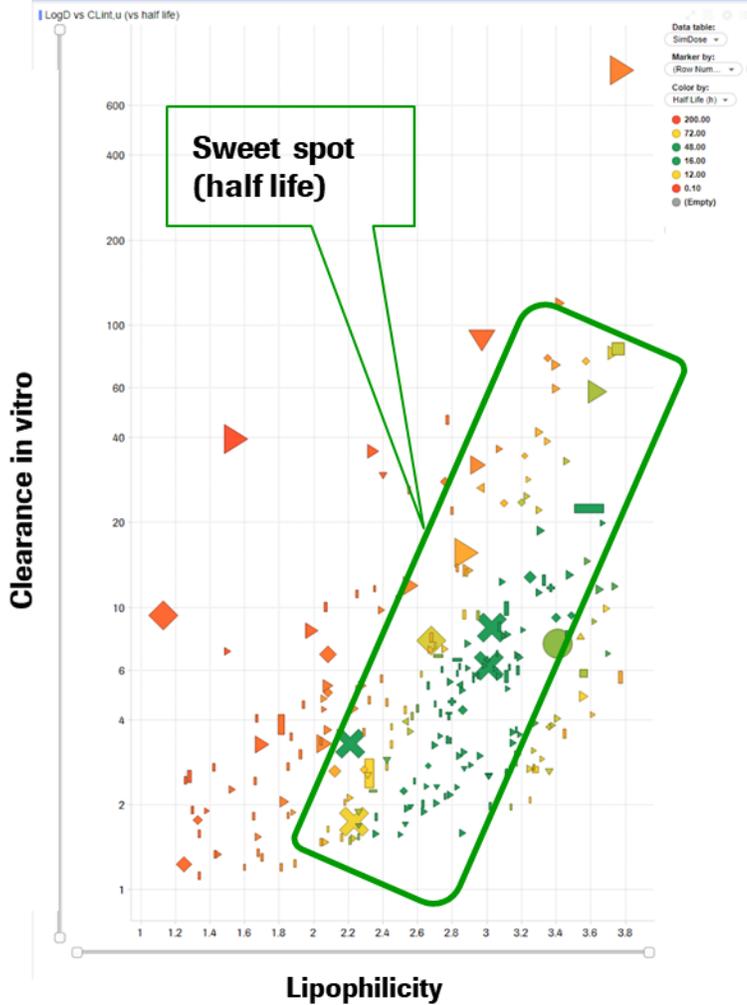
## *Dose and half life predictions in humans*

Total conc.  
needed to  
reach target



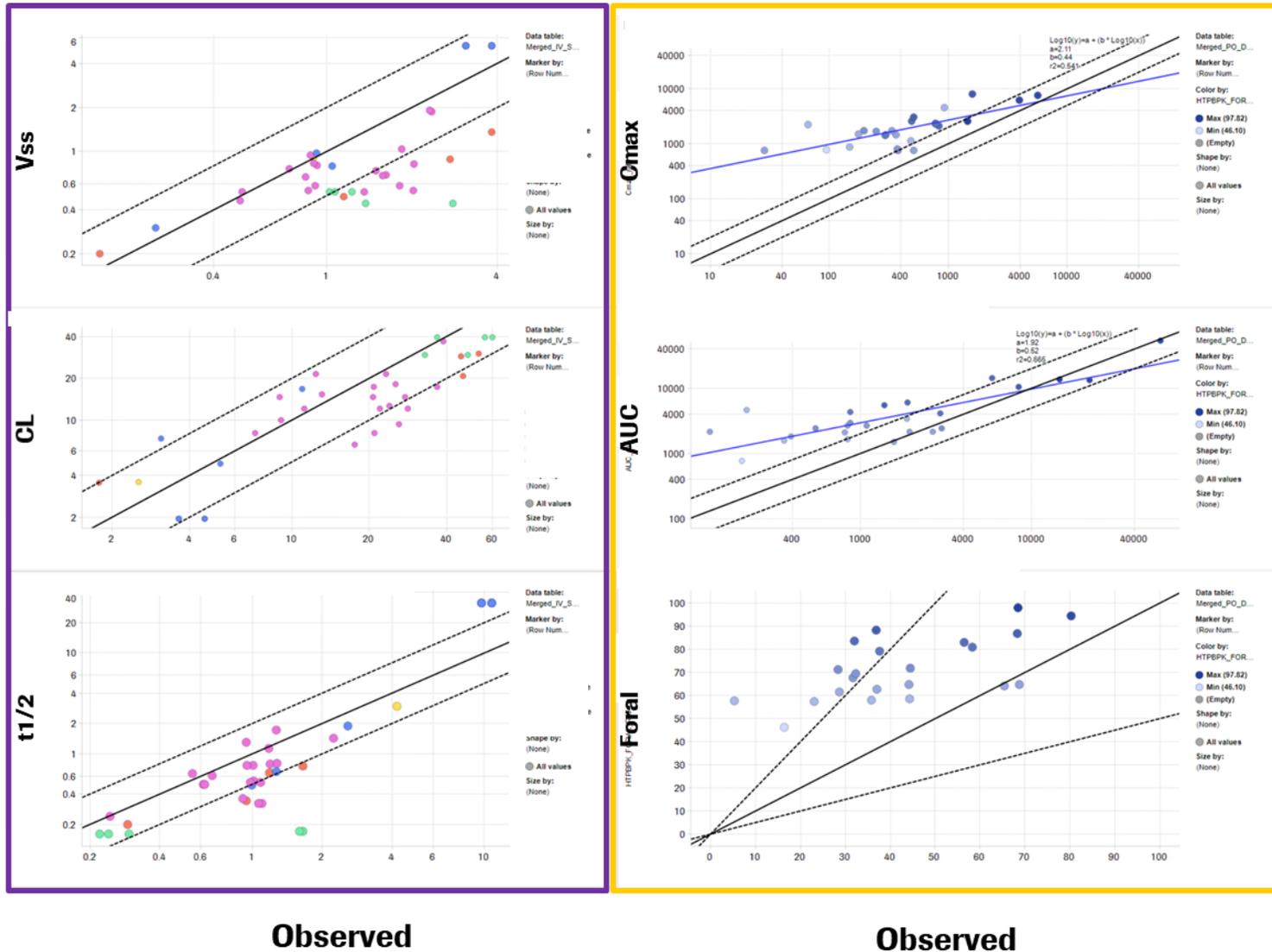
# HT-PBPK insights

## *Dose and half life predictions in humans*



# Systematic model verification

## Generating confidence in model-based approach



Most of the predictions within 2-3 fold for IV and PO parameters.

PO parameters highly correlated (good ranking)

## PoC summary

### *Model-informed drug discovery*

HT-PBPK insights  Better decision making and compound selection based on a truly multidimensional ADME optimization (e.g.,  $t_{1/2}$  vs dose)

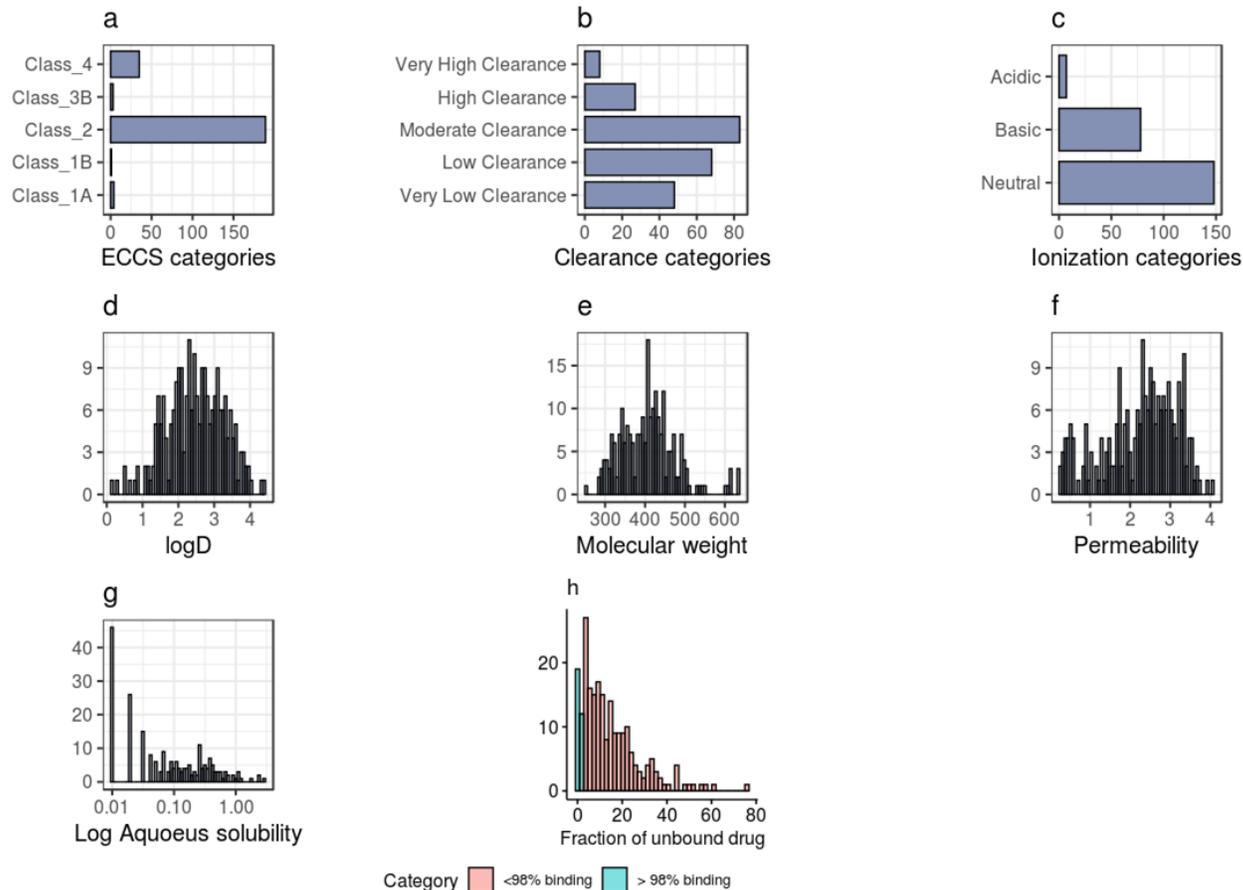


Good and predictive assays available for the project (e.g., heps)

# Not just a case study: Evaluation of early predictions

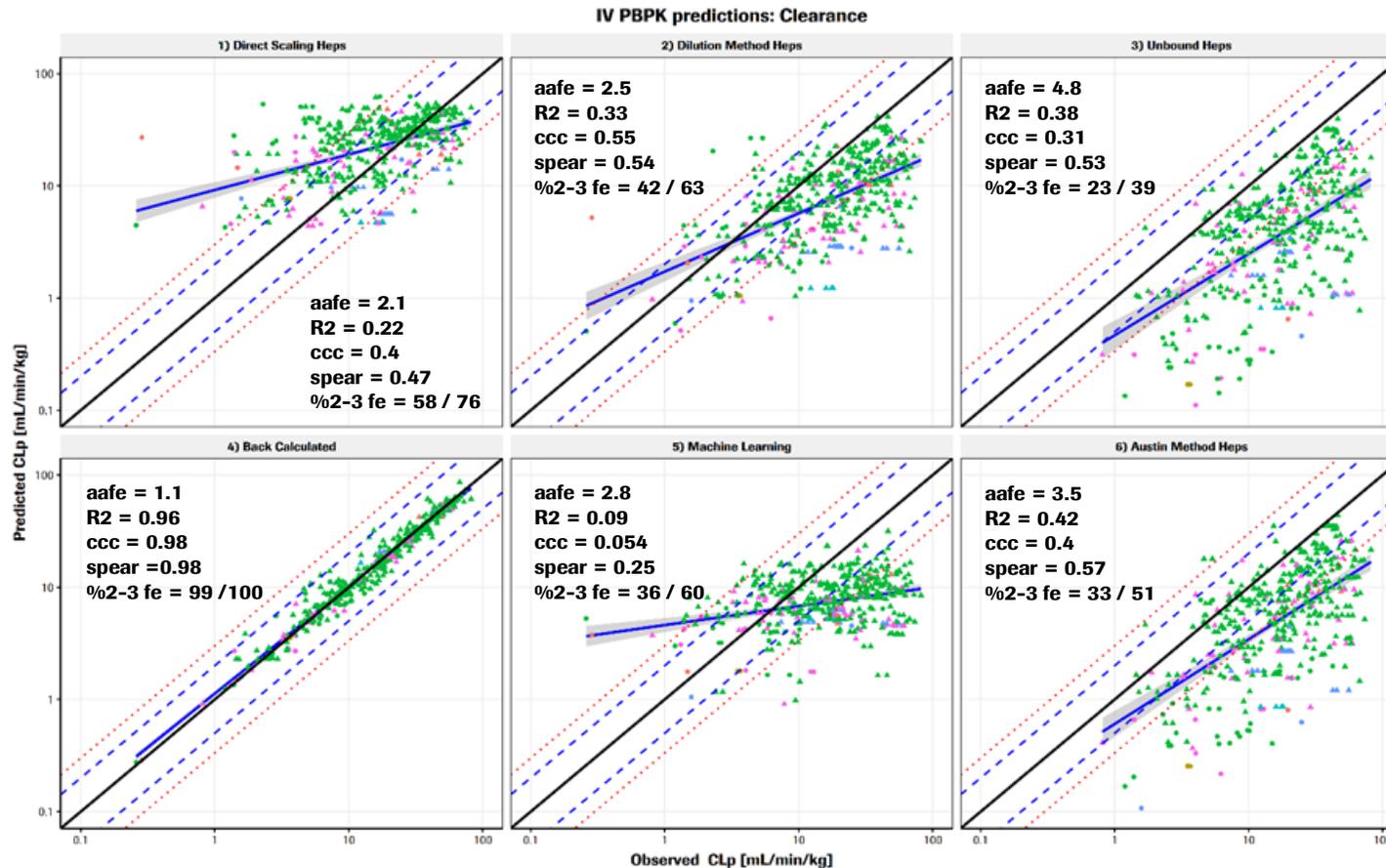
*Can we predict PK using PBPK without the learning-confirming cycle (naive predictions)?*

- Ca 250 structurally diverse Roche compounds
- **Simple research questions (rats)**
  - How does PBPK predict the IV PK in rats using in vitro and ML-predicted data (ADMET predictor)
  - How does PBPK predict the oral PK in rats using in vitro and ML-predicted data (ADMET predictor)
  - How does PBPK modeling predict oral absorption (when the CL is known)



# PBPK predictions for a large number of discovery compounds

*Clearance predictions within 3 fold for 63-76% of simulations*

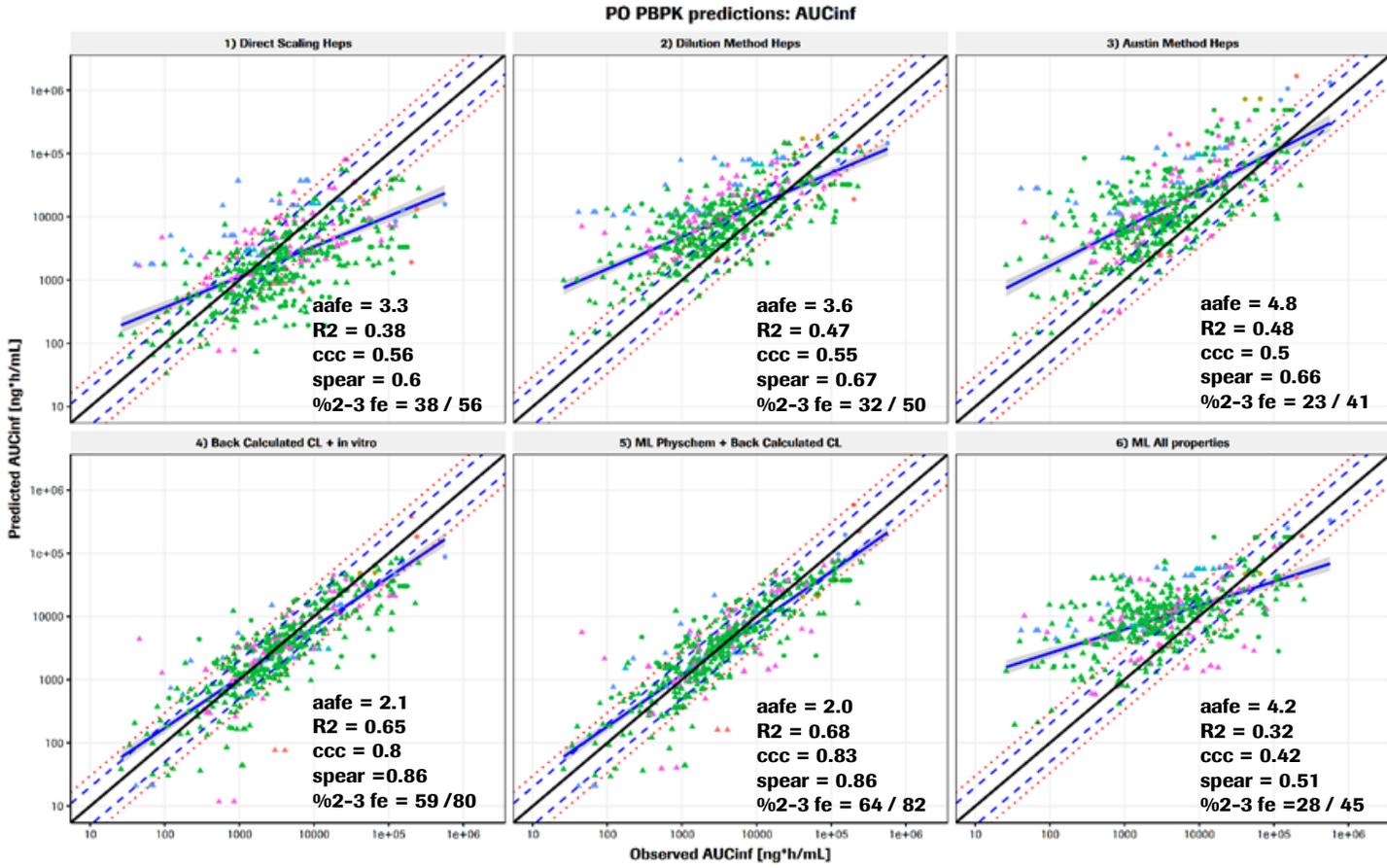


**Machine learning predictions\*** were 36% to 60% within 2 to 3 fold, however correlation is poorer than when using the in vitro data

\*ADMET predictor

# PBPK predictions for a large number of discovery compounds

*Oral AUCinf in rats predictions within 3 fold for 50-56% of observations*



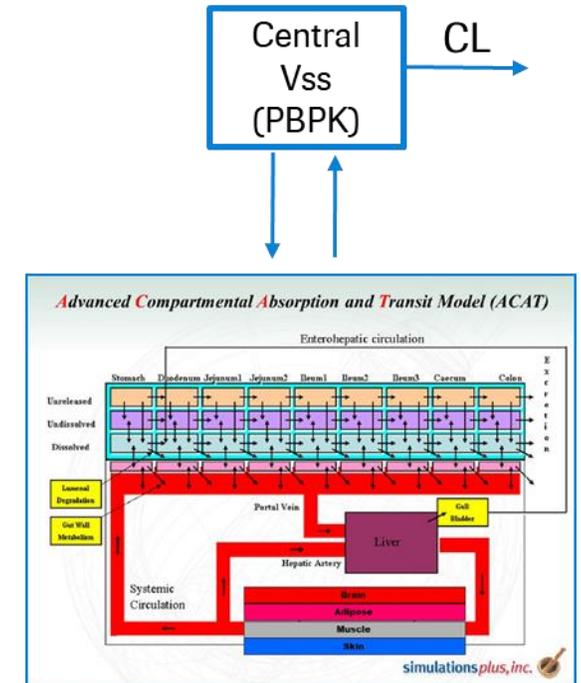
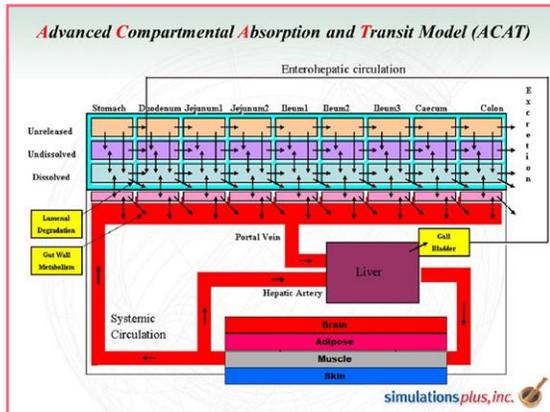
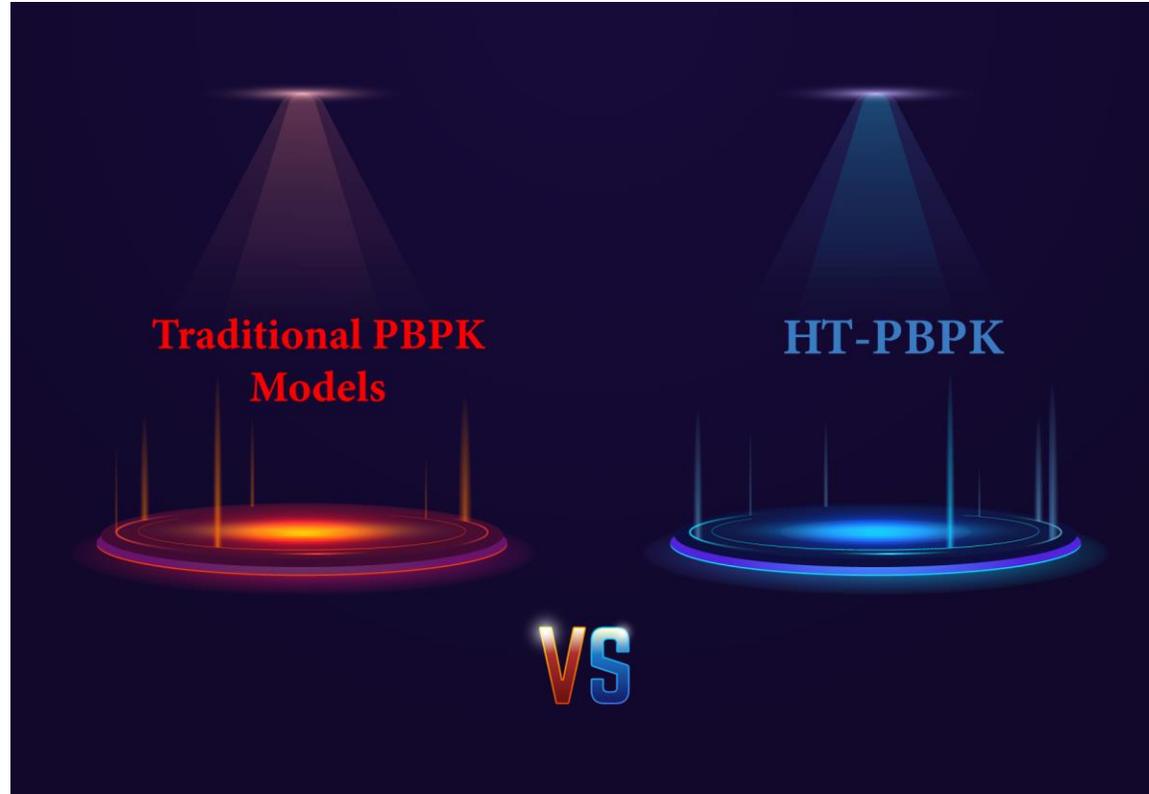
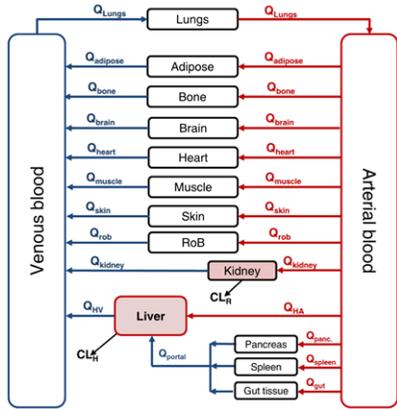
Substantial increase in prediction success of absorption model (up to 82% within 3 fold) when clearance is well predicted (back-calculated)

**Machine learning: success of 45% within 3 fold**

Naga, D., Parrott N. and Olivares-Morales A (in preparation)

# Science and Technology: HT-PBPK modeling vs PBPK

## *A game changing technology and the core of our project*

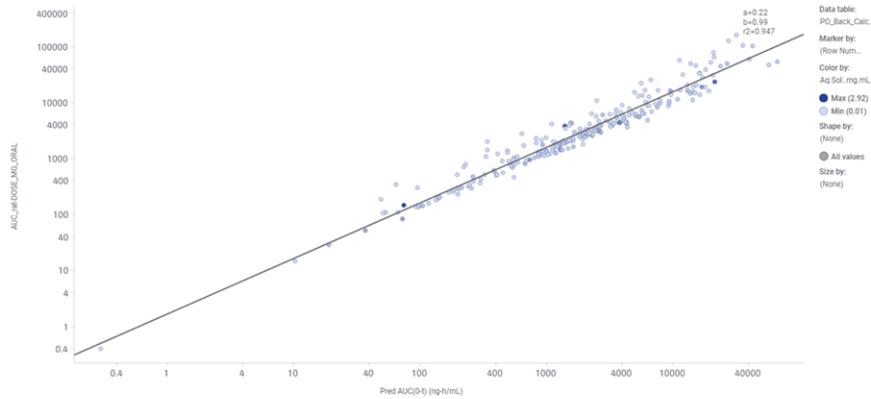


# HT-PBPK (ADMET predictor) vs PBPK (GastroPlus)

*Excellent reproducibility between the two approaches*

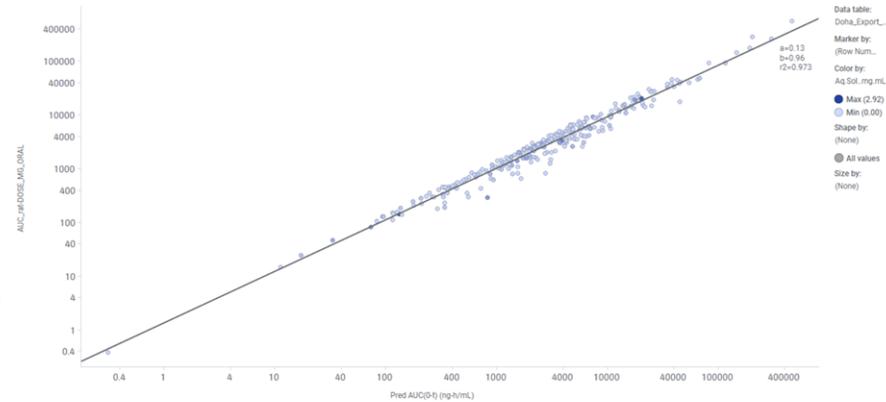
## In vitro inputs

AUC<sub>rat</sub>-DOSE\_MG\_ORAL vs. Pred AUC(0-t) (ng-h/mL)



## Machine Learning inputs

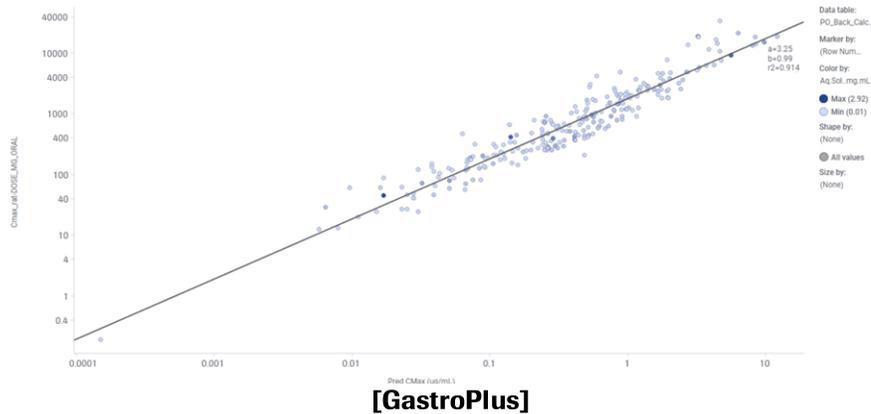
AUC<sub>rat</sub>-DOSE\_MG\_ORAL vs. Pred AUC(0-t) (ng-h/mL)



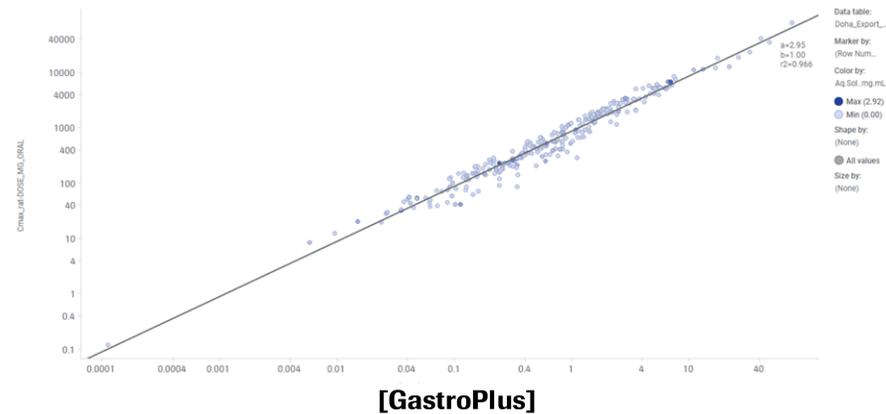
[ADMET predictor]

[ADMET predictor]

Cmax<sub>rat</sub>-DOSE\_MG\_ORAL vs. Pred CMax (ug/mL)



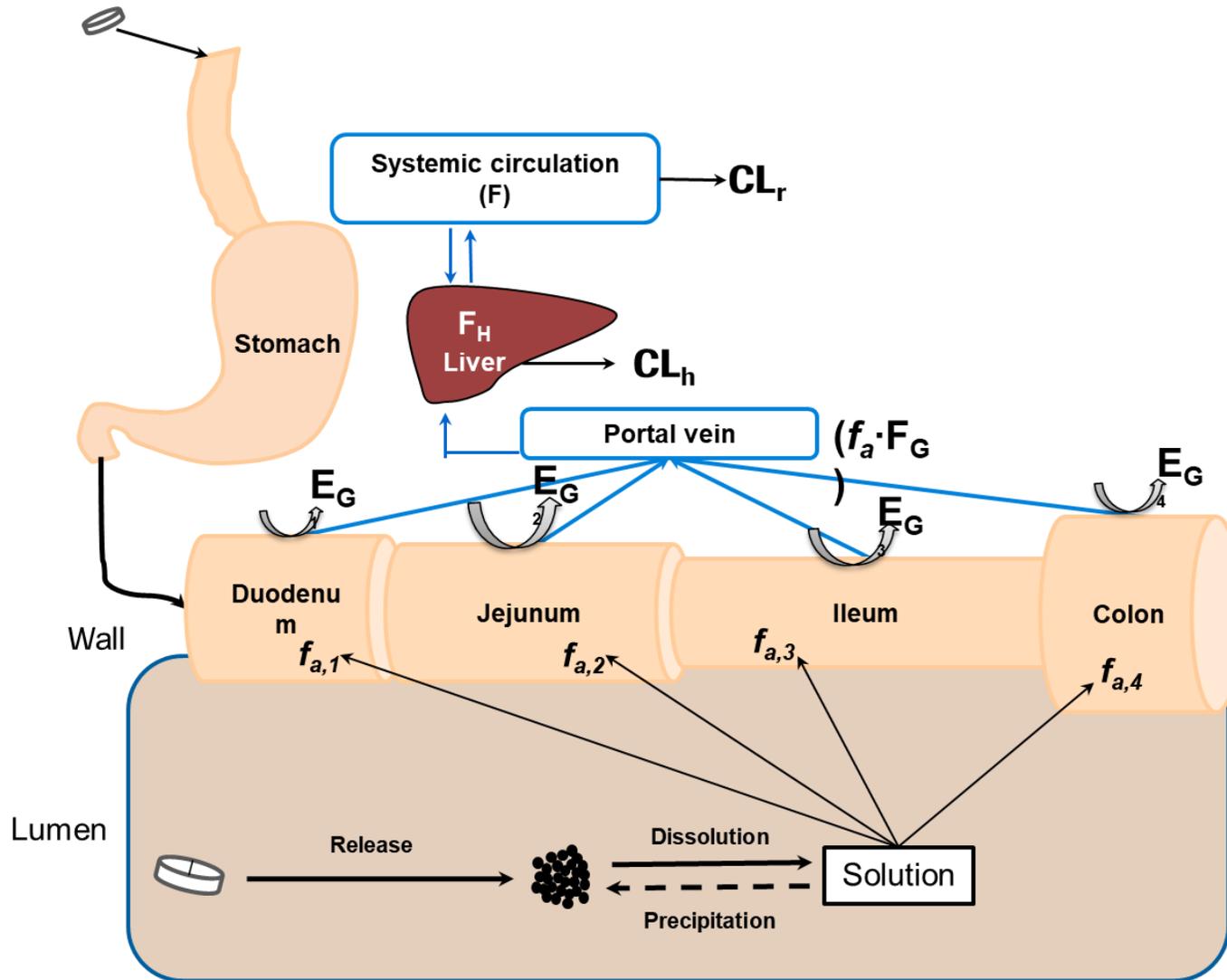
Cmax<sub>rat</sub>-DOSE\_MG\_ORAL vs. Pred CMax (ug/mL)



[GastroPlus]

[GastroPlus]

# What can be predicted with HT-PBPK?



**Species:** rat and human  
**Dosage form:** IR tablet or IV Bolus  
**Pharmacokinetics**

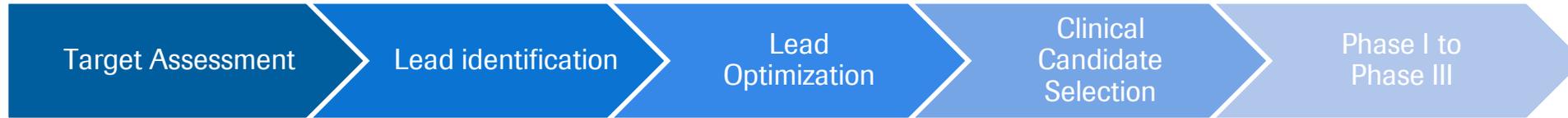
- **PK profiles:** single dose and steady state
- **PK parameters:** AUC,  $C_{max}$ ,  $t_{1/2}$ ,  $CL_{hepatic}$  (IVIVE),  $CL_{total}$  from NCA (renal + metabolic), Bioavailability ( $F_b$ ), fraction absorbed ( $F_a$ ),  $V_{ss}$  (Rodgers-Rowland-Lukakova)

**PK/PD**

- **Dose** needed to reach a given efficacious concentration ( $C_{eff}$ ) as:
  - Coverage
  - $C_{max}$
  - $C_{min}$

# A paradigm shift in the early PBPK strategy

*Focus on speed, ranking and compound prioritization from design to optimization*



## High-throughput PBPK predictions

- Focus on compound optimization and ranking
- Rely on predictive models of properties (machine learning) for design compound
- Reduced learn and confirm cycle (at the project level)
- Constant PBPK prediction monitoring per project



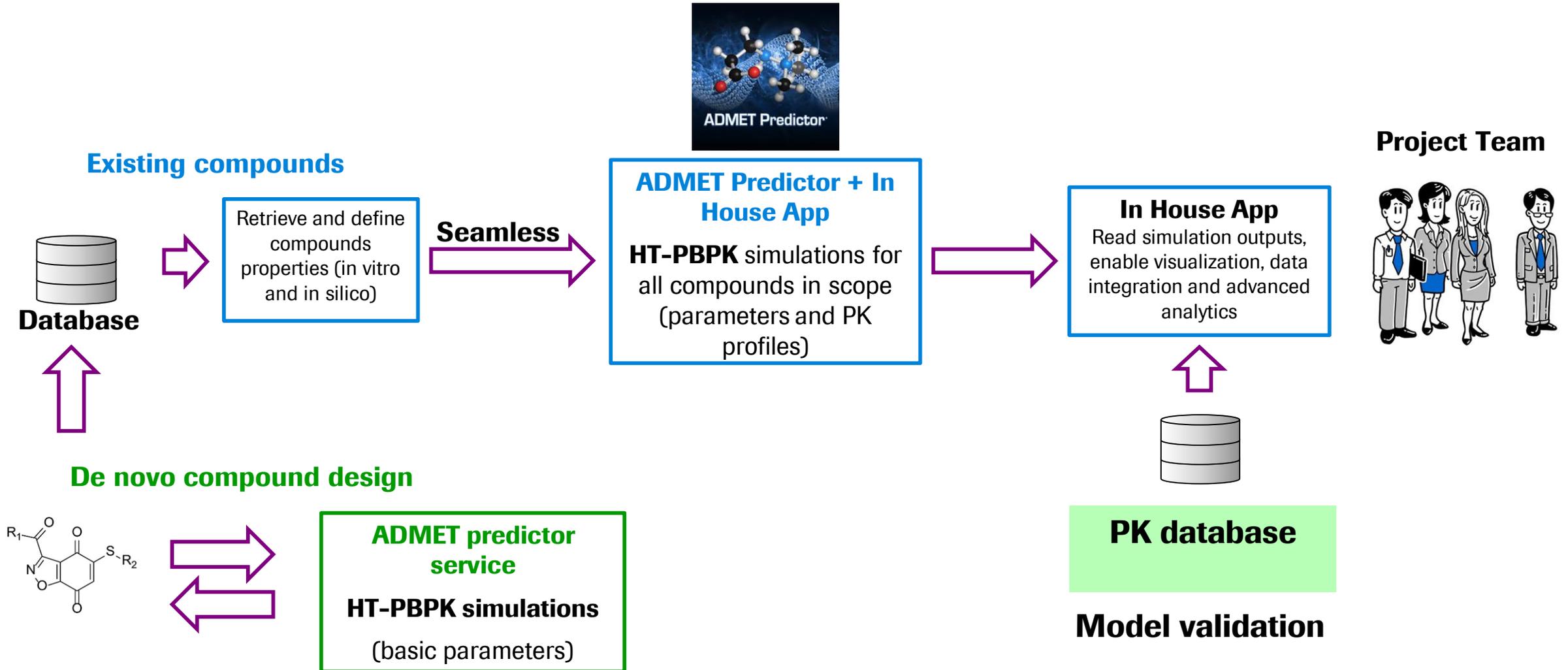
## Tailored PBPK modeling

- Single or limited compounds before EIH
- Traditional learn and confirm approach still apply (single species or two species validation)
- Further applications (DDIs, Biopharmaceutics, etc.)

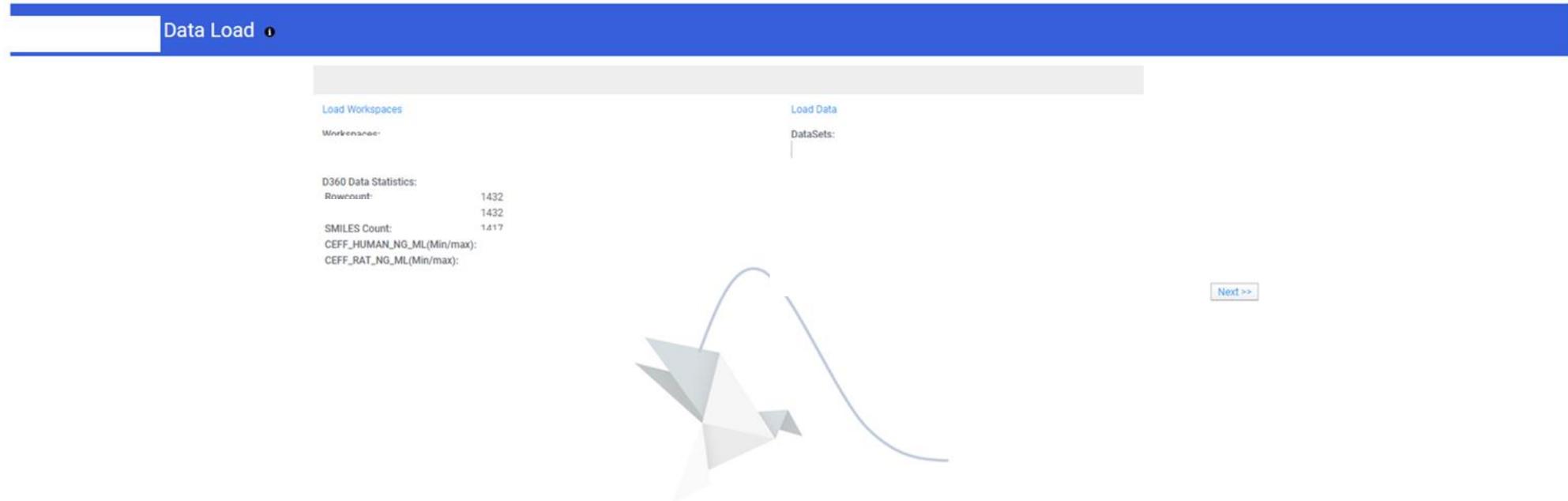


# Implementation of HT-PBPK in pRED

*In house app and ADMET predictor service for de novo compounds*



# In house app for HT-PBPK simulations



## The App provides a simplified way:

- To interact with the ADMET predictor - guided analysis
- To retrieve and generate input data set
- To visualize the results

The landing page allows the user to log onto our central data repository select the data set or rerun a query.

# In house App



**Data Load** ⓘ

Load Workspaces      Load Data

Workspaces:      DataSets:

Rowcount: 21  
SRN Count: 21  
SMILES Count: --  
CEFF\_HUMAN\_NG\_ML(Min/max):  
CEFF\_RAT\_NG\_ML(Min/max):

Next >>

Downloading

Trying to download

Starting...

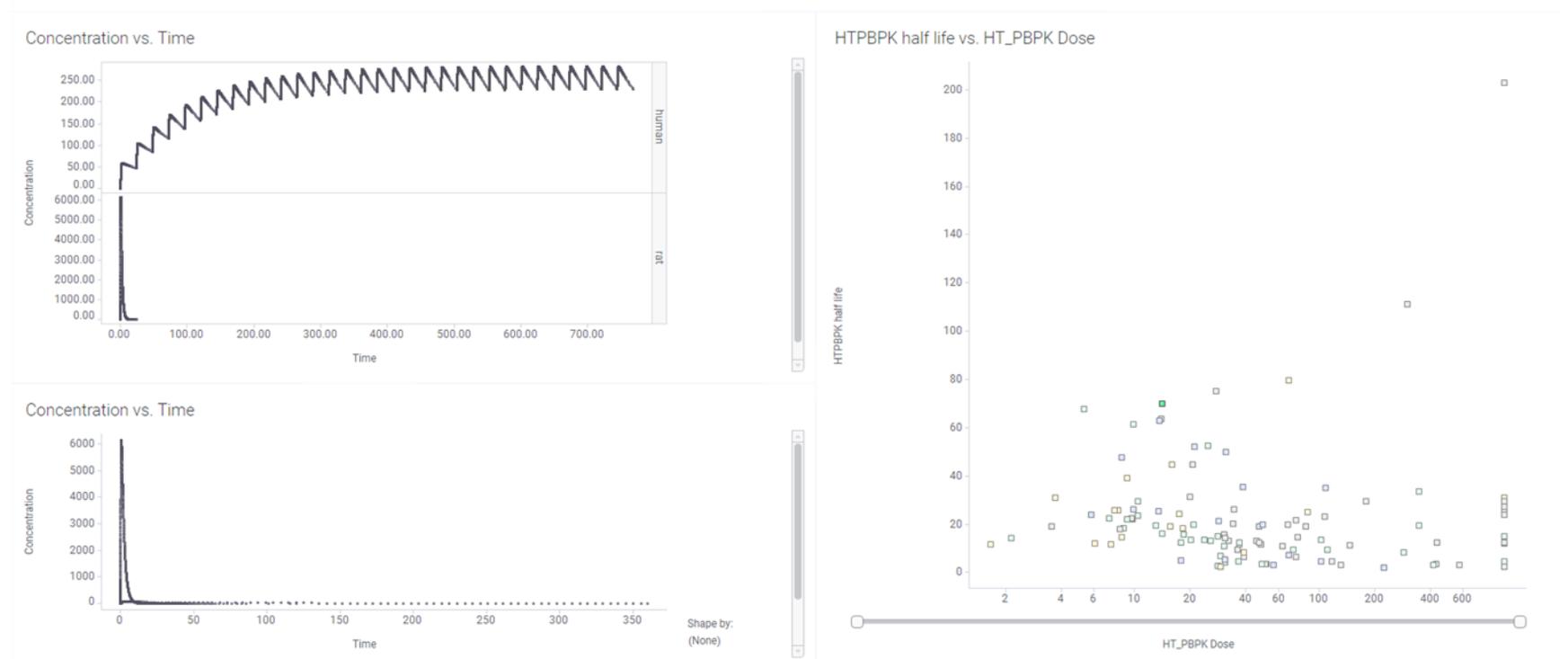
Cancel

Show details

# Pre-defined results visualization

The interface to the ADMET predictor is designed according to Roche specification.

Once the data is loaded one is able to filter the data, set prediction parameters and select the desired prediction



**The data retrieval and cleaning is fully automated, visualization are readily shared to project teams**

# Conclusions

- HT-PBPK simulations are now available for small molecule project teams using our in house data as input (in vitro, ML, etc.)
- The simulation process is seamless by creating an internal workflow and connecting ADMET predictor to our systems
- Simulations are easy to set up with minimal user intervention
- Pre-allocated visualization allow project teams to gain insights that are not generally available without PBPK modeling (bioavailability, half-life, Vss, etc.)
- Integration within our data systems allow for almost automatic model development and evaluation (e.g., PK predictions and learn-confirm cycles)

# Acknowledgements

## **DMPK and M&S**

- Neil Parrott
- Nenad Manevski
- Holger Fischer
- Matthias Wittwer
- Doha Naga
- Andrea Morger
- Kenichi Umehara

## **pRED Informatics**

- Yaniv Cohen
- Peter Curle

## **Small Molecule Research**

- Michael Reutlinger
- Giuseppe Cecere

*Doing now what patients need next*