# Integrating In Vitro and In Silico Approaches Enables Accurate Prediction of Drug-Induced Liver Injury

René Geci Uniklinik RWTH Aachen/ESQlabs OSP Community Conference 2025

### Acknowledgements

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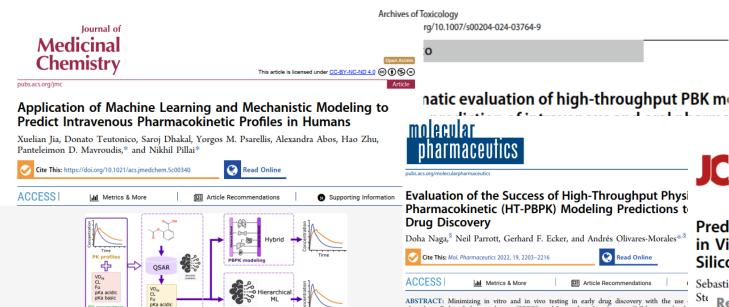








## In silico PK predictions get more traction



Natalícia De Jesus Antunes,

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Federal Institute for Risk Assessment (BfR),

Wu K, Li X, Zhou Z, Zhao Y, Su M, Cheng Z, Wu X,

luang Z, Jin X, Li J, Zhang M, Liu J and Liu B

harmacodynamic effects

based pharmacokinetic (AI-PBPK) modelling

Keheng Wu<sup>1</sup>, Xue Li<sup>1</sup>, Zhou Zhou<sup>1</sup>, Youni Zhao<sup>1</sup>, M Mengiun Zhang<sup>3</sup>, Jack Liu<sup>1</sup> and Bo Liu<sup>3</sup>\*

<sup>5</sup>Yinghan Pharmaceutical Technology (Shanghai) Co., Ltd., Shanghai, China, <sup>2</sup>Jian assays are in place for key parameters such as clearance. Pharmaceutical Co., Ltd., Nanjing, China, School of Chemical Engineering and F KEYWORDS: drug discovery, PBPK models, HT-PBPK, physicochemical properties, clearance predictions and Institute of Technology, Wuhan, China

J Pharmacokinet Pharmacodyn (2017) 44:549-565 DOI 10.1007/s10928-017-9548-7

ORIGINAL PAPER

Evaluation and calibration of high-throughput predictions of chemical distribution to tissues

Robert G. Pearce<sup>1,2</sup> · R. Woodrow Setzer<sup>1</sup> · Jimena L. Davis<sup>1,3</sup> · John F. Wambaugh<sup>1</sup> Cite This: J. Chem. Int. Model, 2019, 59, 4893-4905 pubs.acs.org/jcim

**Evaluation of the Success of High-Throughput Physi** Pharmacokinetic (HT-PBPK) Modeling Predictions to **Drug Discovery** 

Doha Naga, Neil Parrott, Gerhard F. Ecker, and Andrés Olivares-Morales \*\* S

Cite This: Mol. Pharmaceutics 2022, 19, 2203-2216

ACCESS Article Recommendations

ABSTRACT: Minimizing in vitro and in vivo testing in early drug discovery with the use physiologically based pharmacokinetic (PBPK) modeling and machine learning (ML) approaches h the potential to reduce discovery cycle times and animal experimentation. However, the prediction the potential to reduce discovery cycle times and animal experimentation. The potential to reduce discovery cycle times and animal experimentation. The potential to reduce discovery cycle times and animal experimentation. The potential to reduce discovery cycle times and animal experimentation. The potential to reduce discovery cycle times and animal experimentation. representative of a lead optimization pipeline. In this study, the prediction success of the oral (PC and intravenous (IV) pharmacokinetics (PK) parameters in rats was assessed using a "bottom-up approach, combining in vitro and ML inputs with a PBPK model. More than 240 compounds fi which all of the necessary inputs and PK data were available were used for this assessment. Different clearance scaling approaches were assessed, using hepatocyte intrinsic clearance and protein binding as inputs. In addition, a novel high-throughput PBPK (HT-PBPK) approach was evaluated to assess the scalability of PBPK predictions for a larger number of compounds in drug discovery. The results showed that bottom-up PBPK modeling was able to predict the rat IV and PO PK parameters for the majority of compounds within a 2- to 3-fold error range, using both direct scaling and dilution Zhuo Cheng<sup>1</sup>, Xinyi Wu<sup>1</sup>, Zhijun Huang<sup>1</sup>, Xiong Jin methods for clearance predictions. The use of only ML-predicted inputs from the structure did not perform inputs, likely due to clearance miss predictions. The HT-PBPK approach produced comparable results to approach but reduced the simulation time from hours to seconds. In conclusion, a bottom-up PBPK and successfully predict the PK parameters and guide early discovery by informing compound prioritization, pr

Prediction of Oral Bioavailability in Rats: Transferring Insights from in Vitro Correlations to (Deep) Machine Learning Models Using in Silico Model Outputs and Chemical Structure Parameters

Sebastian Schneckener, \* Sergio Grimbs, \* Jessica Hey, \* Stephan Menz, \* Maren Osmers, \*

Research Article

**Predictive Performance of Next Generation Human Physiologically** Based Kinetic (PBK) Models Based on In Vitro and In Silico Input Data

Ans Punt1, Jochem Louisse1, Karsten Beekmann1, Nicole Pinckaers1, Eric Fabian2, Bennard van Ravenzwaay2 Paul L. Carmichael<sup>3</sup>, Ian Sorrell<sup>3</sup> and Thomas E. Moxon<sup>3</sup>

<sup>1</sup>Wageningen Food Safety Research, Wageningen, The Netherlands; <sup>2</sup>BASF SE, Experimental Toxicology and Ecology, Ludwigshafen, Germany; <sup>3</sup>SEAC, Unilever, Colworth Science Park, Shambrook, Bedford, UK













Systematic evaluation of highthroughput PBK modelling strategies for the prediction of intravenous and oral pharmacokinetics in humans

Geci R, Gadaleta D, Lomana MG de, Ortega-Vallbona R, Colombo E, Serrano-Candelas E, Paini A, Kuepfer L, Schaller S (2024) Archives of Toxicology:1–18. doi: 10.1007/s00204-024-03764-9













# Are high-throughput PK predictions useful for real decision making?











### DILI is hard to predict but important

- Drug-induced liver injury (DILI) can occur via many different mechanisms
- Often idiosyncratic with only 1 20 out of 100,000 patients affected
- Many confounding factors (genetics, comorbidities, comedications etc)
- Difficult to predict with current preclinical methods
- Can lead to liver failure and patient death
- Many drug candidates fail due to liver safety in clinical studies
- Common reason for withdrawal from market after approval











# Methodology











### There are many in vitro DILI assays



Molecular assays, cell assays... different cell types... 2D, 3D...

		,		-										
Parameters	O'Brien et al. (2006)	Xu et al.	(2008)	Dawson e (2012)		Folosa et al (2012)	. Thomp- son et al. (2012)		Sakatis et al. (2012)	Persson (2013)	et al. Garside (2014)	et al. Atienzal (2014)	r et al. Tomida (2015)	et al.
S, MF, MA	MA	MF		S	1	MF	MA	S	MF	MF	MA	MA	MA	
No. of com- pounds	243	344		85	7	78	36	104	223	102	144	51	32	
In vivo toxic	146	200		64	(	66	27	83	113	66	108	40	17	
In vivo non- toxic	95	144		21		12	9	21	110	34	36	11	15	
Raw data Parameters able Longest a		Shah et al. (2015)	Schadt (2015)		Saito et (2016)		aleo et al. 2019)	Khetani et al. (2012)	Proctor et al. (2017)	Vorrink et al. (2018)	Williams et al. (2019)	Porceddu et al. (2012)	Albretcht et al. (2019)	Tolosa et (2019)
incubati S. M	F, MA	MA	MA		MA	N	1A	MA	S	S	MA	MA	S	MA
No.	of com- unds	125	81		28	2	00	45	110	123	96	124	30	15
In vi	vo toxic	70	38		11	7	9	35	69	70	63	87	14	11
In vi tox	vo non-	55	43		17	1	21	10	41	53	33	37	16	4
Raw ab	data avail-	No	Yes		Yes	Y	'es	No	Yes	No	Yes	Yes	Yes	No

**Table from:** Walker, P. A., Ryder, S., Lavado, A., Dilworth, C. & Riley, R. J. The evolution of strategies to minimise the risk of human drug-induced liver injury (DILI) in drug discovery and development. Arch Toxicol 94, 2559–2585; 10.1007/s00204-020-02763-w (2020).











### Data collection

In vitro studies (17x)

Cytotoxicity
Mitochondrial toxicity
BSEP inhibition

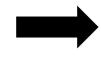
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Strongest toxicity potency value per

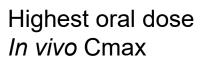


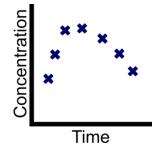






**PK Study data** 





#### **Clinical toxicity**



No DILI Less DILI Most DILI Clinical Failure

DILIrank Chen et al. (2016)



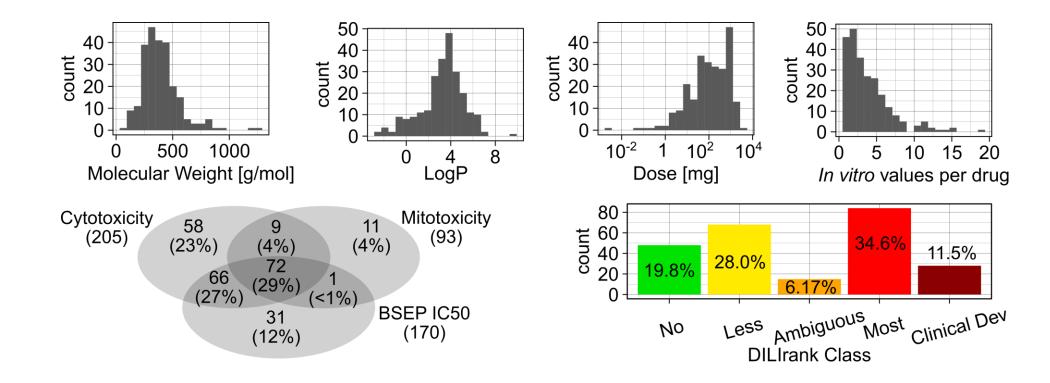








# Our integrated DILI dataset: 241 drugs













## Results



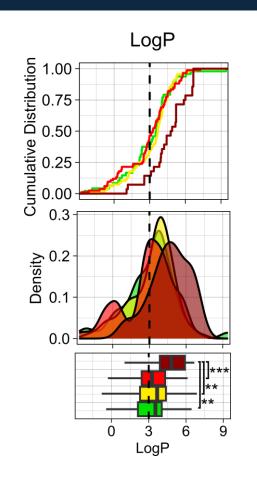


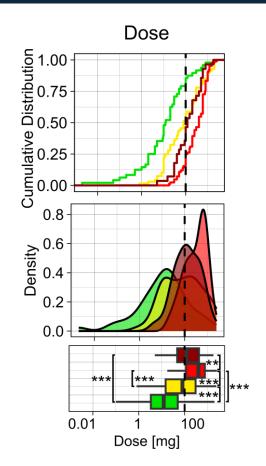




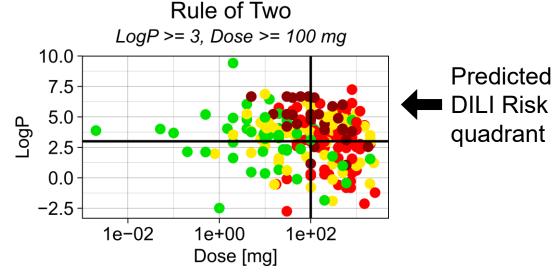


# Evaluation 1: Simple heuristic screening rules poorly predict DILI









Balanced accuracies: 50 - 70%



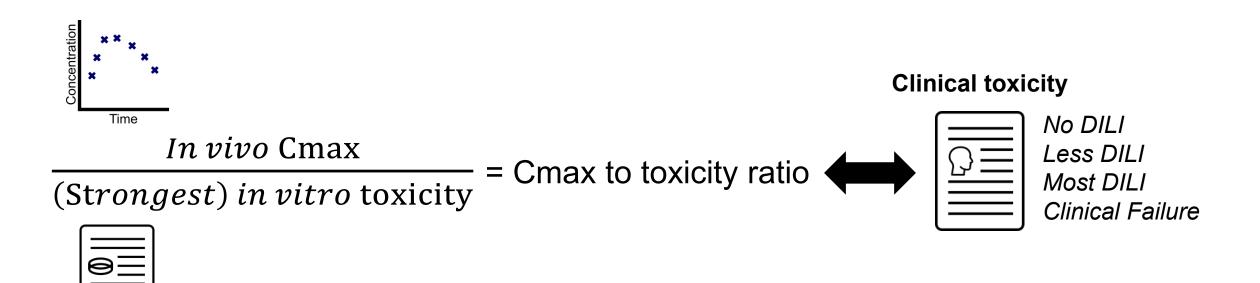








### Evaluation 2: Cmax to in vitro toxicity ratios





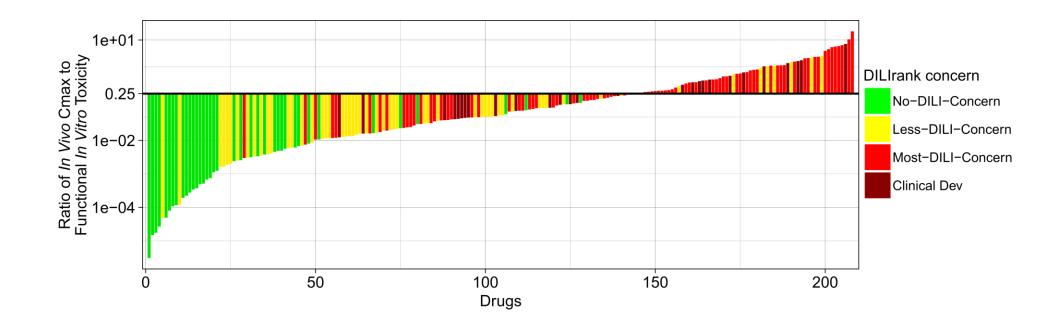








# Evaluation 2: Cmax to *in vitro* toxicity ratios strongly predict DILI





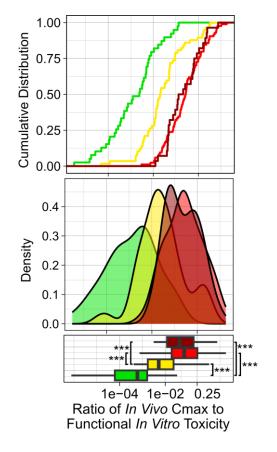


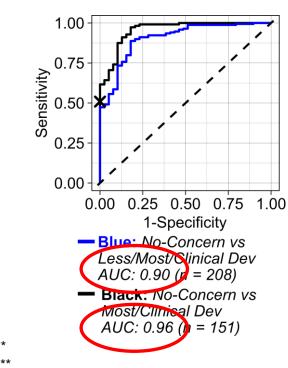






# Evaluation 2: Cmax to *in vitro* toxicity ratios strongly predict DILI







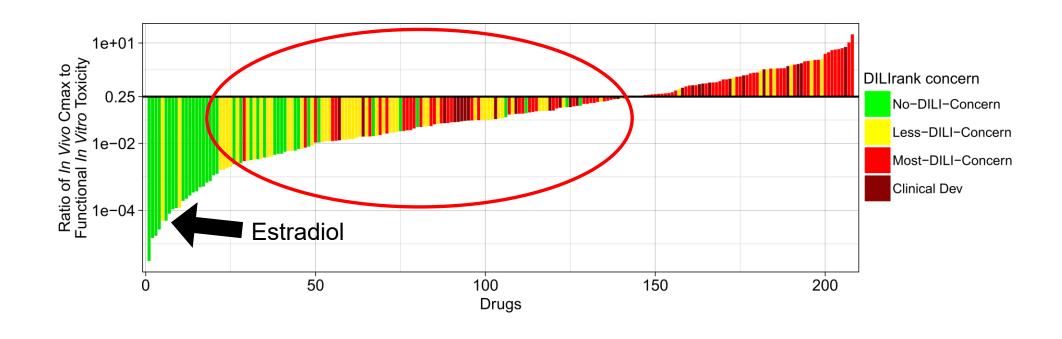








# Evaluation 2: Cmax to *in vitro* toxicity ratios strongly predict DILI





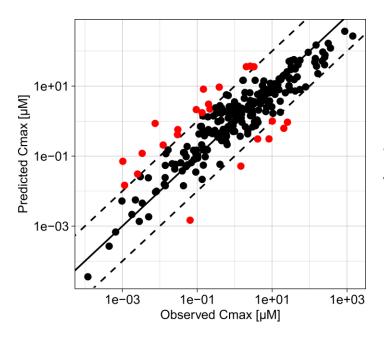








# In silico predicted Cmax is similar to in vivo observed values



90% of Cmax values predicted within 10-fold











### Evaluation 3: In silico predicted Cmax

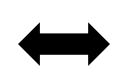


*In vivo In silico* Cmax

(Strongest) in vitro toxicity

= Cmax to toxicity ratio







No DILI Less DILI Most DILI Clinical Failure





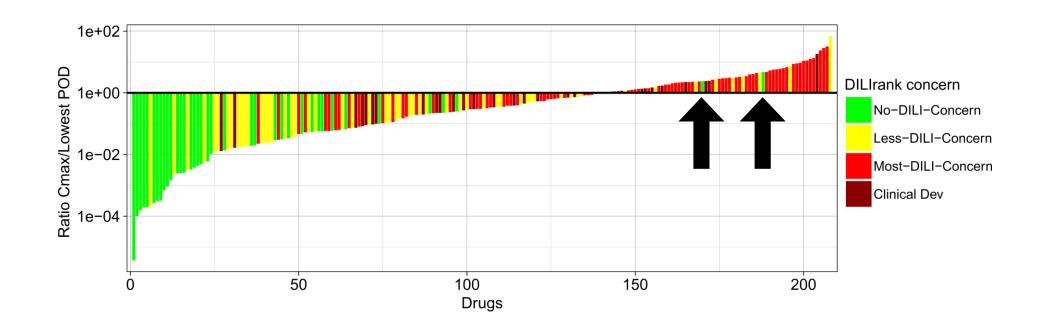








# Evaluation 3: *In silico* predicted Cmax enables prospective DILI evaluation





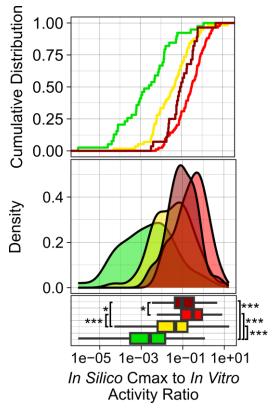


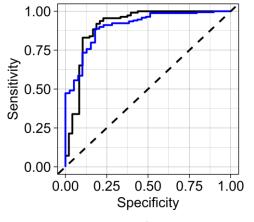






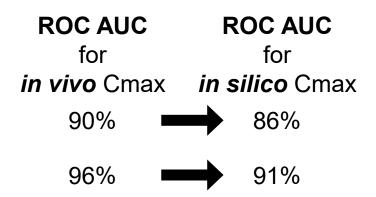
# Evaluation 3: *In silico* predicted Cmax enables prospective DILI evaluation





Blue: No-Concern vs Less/Most/Clinical Dev AUC: 0.86

— Black: No-Concern vs Most/Clinical Dev AUC: 0.91













### Evaluation 4: *In vitro* BSEP inhibition data

JOURNAL ARTICLE

#### Measures of BSEP Inhibition In Vitro Are Not Useful Predictors of DILI

Rosa Chan, Leslie Z Benet 🗷

Toxicological Sciences, Volume 162, Issue 2, April 2018, Pages 499–508,

https://doi.org/10.1093/toxsci/kfx284 🤊

Published: 20 December 2017



















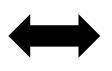


### Evaluation 4: In vitro BSEP inhibition data



#### **Clinical toxicity**

 $\frac{In\ vivo\ Cmax}{In\ vitro\ BSEP\ IC50} = Cmax\ to\ toxicity\ ratio$ 





No DILI Less DILI Most DILI Clinical Failure





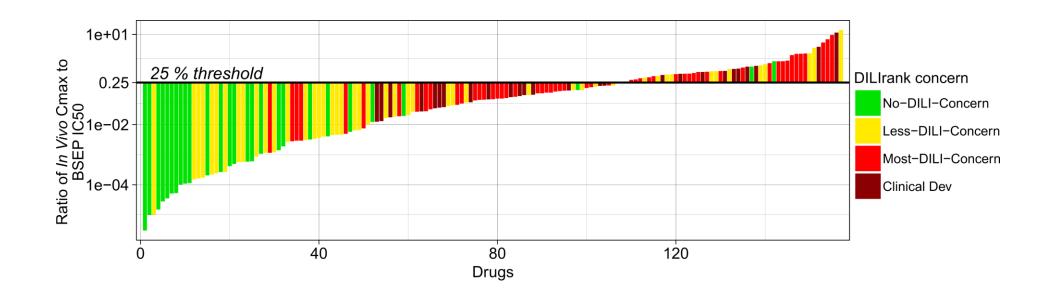








# Evaluation 4: Inclusion of BSEP inhibition improves DILI predictivity





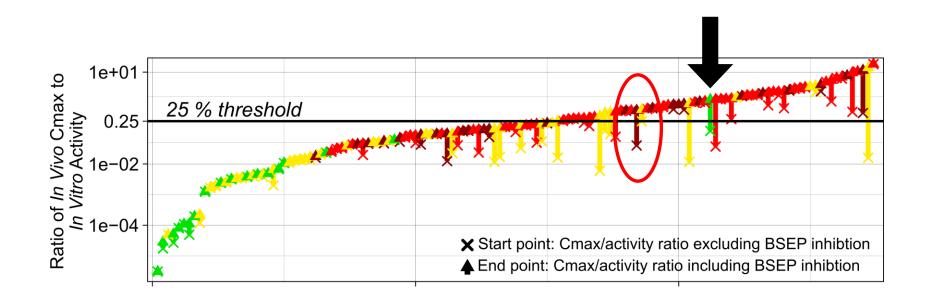








# Evaluation 4: Inclusion of BSEP inhibition improves DILI predictivity













### Mifepristone

Case Reports > Hepatology. 2019 Jun;69(6):2704-2706. doi: 10.1002/hep.30465 (2019).

Epub 2019 Mar 8.

#### Cholestatic Drug-Induced Liver Injury Caused by Mifepristone

Katalina Funke <sup>1</sup>, Don C Rockey <sup>1</sup>

Affiliations + expand

PMID: 30561784 (9) DOI: 10.1002/hep.30465 (9)

Case report Open access Published: 03 February 2023

#### Mifepristone induced liver injury in a patient with Cushing syndrome: a case report and review of the literature

Taylor A. Ault, David R. Braxton, Rebecca A. Watson, Alan O. Marcus & Tse-Ling Fong

Journal of Medical Case Reports 17, Article number: 33 (2023) Cite this article

**3553** Accesses **8** Citations **1** Altmetric Metrics

#### Case Report



Gastroenterol Res. 2019;12(3):181-184

#### Mifepristone: An Uncommon Cause of Drug-Induced Liver Injury

Ishani Shaha, d. Tyler Putnama, Evan Daughertyb, Neil Vyasc, Keng-Yu Chuange

#### Abstract

Mifepristone is frequently used in large doses for management of Cushing's syndrome. This is a case of a 35-year-old woman with Cushing's syndrome, who presented with abdominal pain and jaundice. A month prior to admission, she had been started on a daily dose of 1,200 mg mifepristone. After evaluating for various other causes of liver injury, biopsy revealed cholestatic pattern of liver disease, likely associated with drug-induced hepatotoxicity. Mifepristone was discontinued and her symptoms resolved. We believe this is one of the first few reported cases of drug-induced liver injury (DILI) associated with mifepristone use.

Keywords: Chemical and drug-induced liver injury; Mifepristone; Cushing's syndrome

#### Case Report

A 35-year-old woman presented to our hospital with generalized abdominal pain for a month. Pain was described as dull, constant and unrelated to eating or activity. She also complained of nausea, vomiting, yellowing of her skin and generalized itching. Her medical history was significant for Cushing's syndrome, for which she was being treated with mifepristone. She was initially started on 300 mg of mifepristone 3 months prior to presentation, which was increased to 600 mg after 3 weeks, followed by 900 mg 3 more weeks later, and most recently 1,200 mg about a month prior to presentation. Her only other medication was levothyroxine, which she had been taking at a stable dose for more than 10 years. She denied tak-



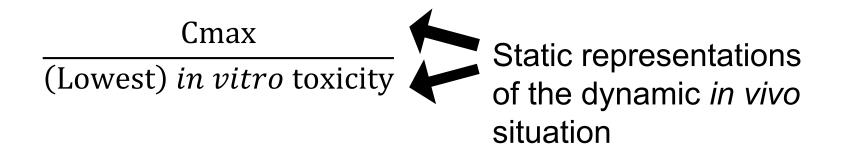








## Evaluation 5: Dynamic effect modelling





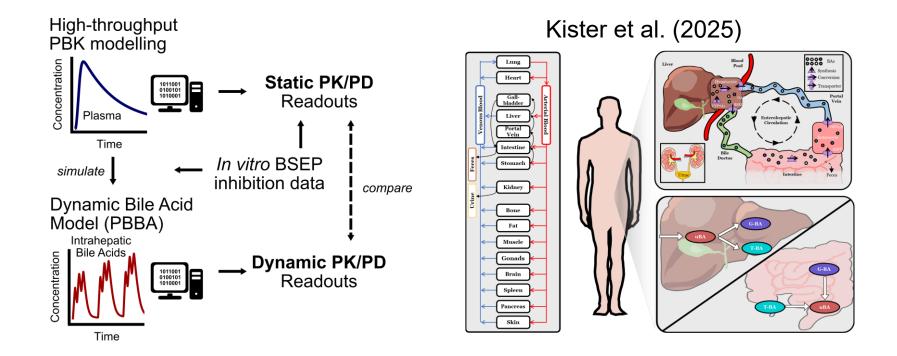








# Evaluation 5: Dynamic modelling gives more realistic insights on *in vivo* bile acid perturbations



**Bile acid model:** Kister, B., Blank, L. M., Pollmanns, M., Wirtz, T. H. & Kuepfer, L. A physiologically-based model of bile acid metabolism in humans. *bioRxiv*, 2025.07.19.665677; 10.1101/2025.07.19.665677 (2025).



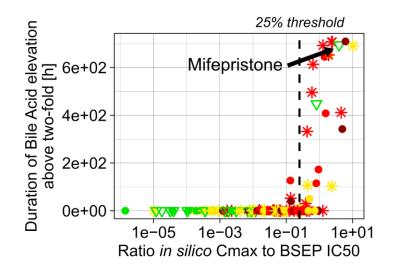


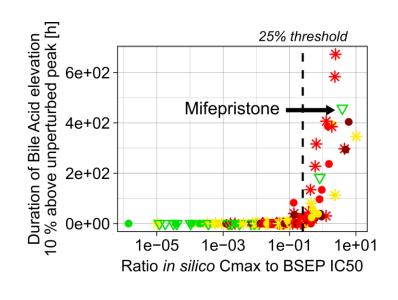






# Evaluation 5: Dynamic modelling gives more realistic insights on *in vivo* bile acid perturbations





#### DILIrank concern

- No-DILI-Concern
- Less-DILI-Concern
- Most-DILI-Concern
- Clinical Dev

#### DILI pattern

- \* Cholestatic
- △ Contradiction
- ☐ Hepatocellular
- ∇ Safe
- Unknown



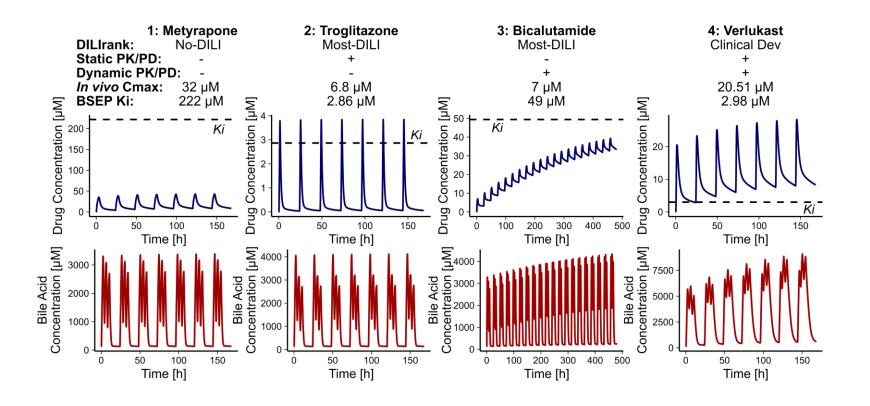








# Evaluation 5: Dynamic modelling gives more realistic insights on *in vivo* bile acid perturbations













### Limitations

- Heterogeneous literature data with incomplete endpoint coverage per drug
- Immune-mediated, metabolite-driven, and gene-regulatory mechanisms are underrepresented
- Retrospective sources lack formulation details and dosing schedules
- Key confounders (co-medications, comorbidities, genetics) are largely unavailable
- Ideal thresholds are probably endpoint-specific











### Conclusions

- 1. Available in vitro toxicity assays are already very useful for predicting DILI
- ... even better predictivity when more toxicity mechanisms are covered
- 2. Exposure (Cmax) is key
- ... high-throughput PBK modelling allows prospective predictions before any clinical studies have been performed
- 3. BSEP inhibition is an important mechanism of DILI
- 4. Dynamic models capture time-dependent effects and yield more realistic *in vivo* insights than static metrics, although those are good first approximations











# Thank you for your attention!











## In vitro toxicity alone is a poor predictor



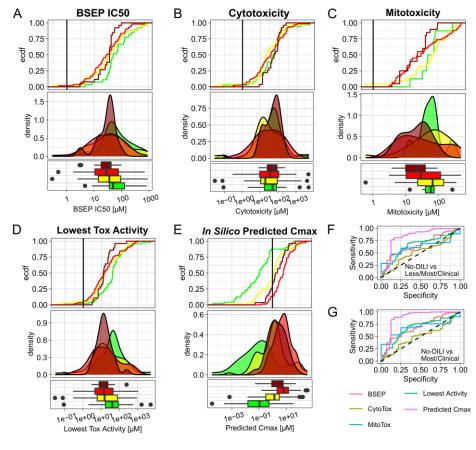








# Per assay ratios





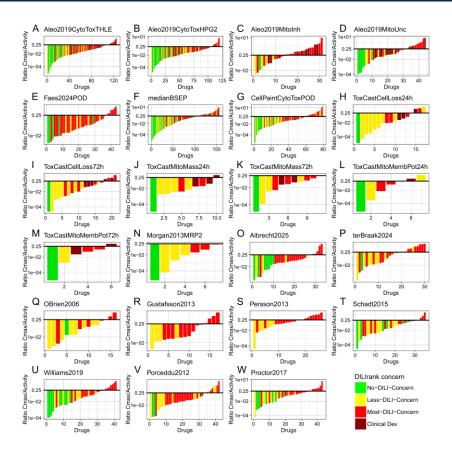








### Per assay ratios





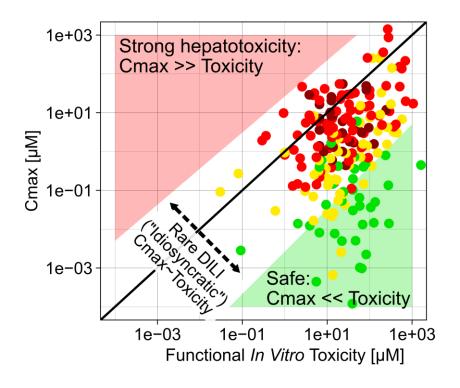








# Dose & Idiosyncratic DILI





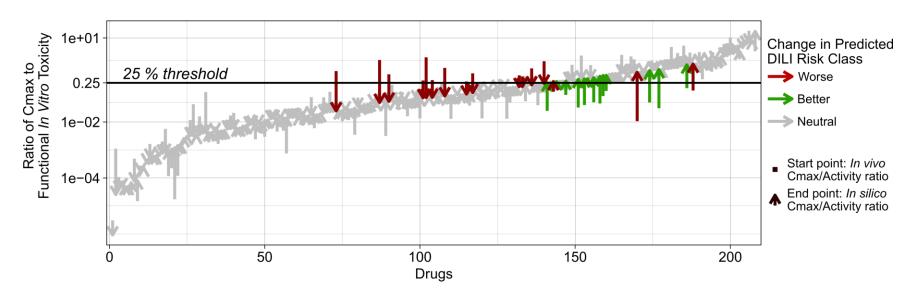








# In silico predicted Cmax enables prospective DILI evaluation



14% of drug DILI risk classifications changed when using in silico predicted Cmax instead of in vivo observed values











# BSEP inhibition seems associated with "Less DILI" classification

