

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

ESQlabs

Stephan Schaller
Alicia Paini

Uniklinik RWTH Aachen

Lars Küpfer
Zeynep Ahenk Sayin
Bastian Kister



Istituto di Ricerche Farmacologiche Mario Negri

Domenico Gadaleta
Erika Colombo

ProtoQSAR

Rita Ortega Vallbona
Eva Serrano Candelas

Bayer

Marina García de Lomana



This project received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 963845.



This project received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 963845.

In silico PK predictions get more traction

Journal of
Medicinal
Chemistry

pubs.acs.org/jmc

Application of Machine Learning and Mechanistic Modeling to Predict Intravenous Pharmacokinetic Profiles in Humans

Xuelian Jia, Donato Teutonico, Saroj Dhakal, Yorgos M. Psarellis, Alexandra Abos, Hao Zhu, Pantaleimon D. Mavroudis,* and Nikhil Pillai*

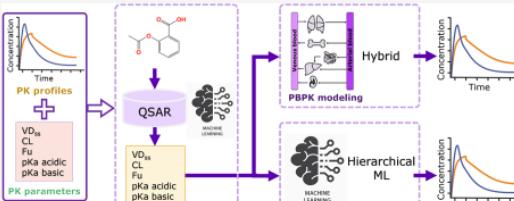
Cite This: <https://doi.org/10.1021/acs.jmedchem.5c00340>

This article is licensed under CC-BY-NC-ND 4.0



Open Access Article

ACCESS |



REVIEWED BY
Natalicia De Jesus Antunes,
State University of Campinas, Brazil
Ajay Vikram Singh,
Federal Institute for Risk Assessment (BfR),
Germany

*CORRESPONDENCE
Bo Liu,
bliu@tcd.ie

RECEIVED 01 November 2023
ACCEPTED 02 February 2024
PUBLISHED 16 February 2024

CITATION
Wu K, Li X, Zhou Z, Zhao Y, Su M, Cheng Z, Wu X, Huang Z, Jin X, Li J, Zhang M, Liu J and Liu B (2024) Application of Machine Learning and Mechanistic Modeling to Predict Intravenous Pharmacokinetic Profiles in Humans. *J. Med. Chem.* 57: 100–112. <https://doi.org/10.1021/acs.jmedchem.5c00340>

Intelligence-physiologically based pharmacokinetic (AI-PBPK) modelling

Keheng Wu¹, Xue Li¹, Zhou Zhou¹, Youni Zhao¹, M. Zhuo Cheng¹, Xinyi Wu¹, Zhijun Huang¹, Xiong Jin Mengjun Zhang³, Jack Liu¹ and Bo Liu^{1*}

¹Yinghan Pharmaceutical Technology (Shanghai) Co., Ltd, Shanghai, China; ²Jian Pharmaceutical Co., Ltd, Nanjing, China; ³School of Chemical Engineering and Technology, Wuhan, China

OSP
OPEN SYSTEMS
PHARMACOLOGY

ooo esq LABS
WE EMPOWER HEALTH CARE

Archives of Toxicology

rg/10.1007/s00204-024-03764-9

O

Article

Open Access

Article

Supporting Information

Open Access Article

Article

Supporting Information

<p

Open Access!

Systematic evaluation of high-throughput 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



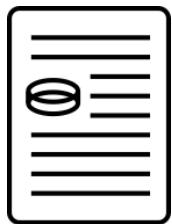
Are high-throughput PK predictions useful for real decision making?

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...**

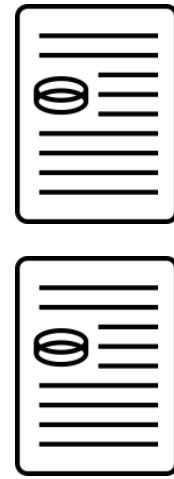
Parameters	O'Brien et al. (2006)	Xu et al. (2008)	Dawson et al. (2012)	Tolosa et al. (2012)	Thompson et al. (2012)	Gustafsson et al. (2014)	Sakatis et al. (2012)	Persson et al. (2013)	Garside et al. (2014)	Atienzar et al. (2014)	Tomida et al. (2015)
S, MF, MA	MA	MF	S	MF	MA	S	MF	MF	MA	MA	MA
No. of compounds	243	344	85	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 available	Shah et al. (2015)	Schadt et al. (2015)	Saito et al. (2016)	Aleo et al. (2019)	Khetani et al. (2012)	Proctor et al. (2017)	Vorrikk et al. (2018)	Williams et al. (2019)	Porceddu et al. (2012)	Albrecht et al. (2019)	Tolosa et al. (2019)
Longest a incubation time (h)	S, MF, MA	MA	MA	MA	MA	S	S	MA	MA	S	MA
No. of compounds	125	81	28	200	45	110	123	96	124	30	15
In vivo toxic	70	38	11	79	35	69	70	63	87	14	11
In vivo non-toxic	55	43	17	121	10	41	53	33	37	16	4
Raw data available	No	Yes	Yes	Yes	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
...



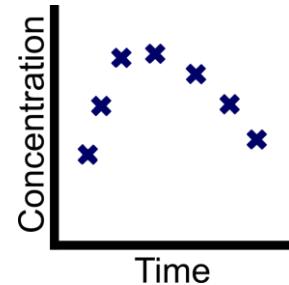
Strongest toxicity
potency value per
compound



Highest oral dose
In vivo Cmax



PK Study data



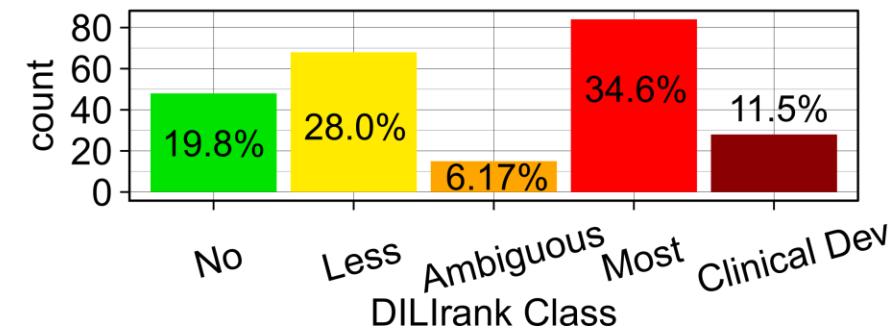
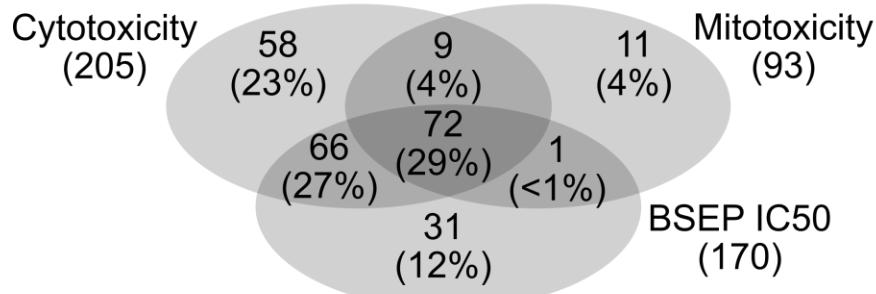
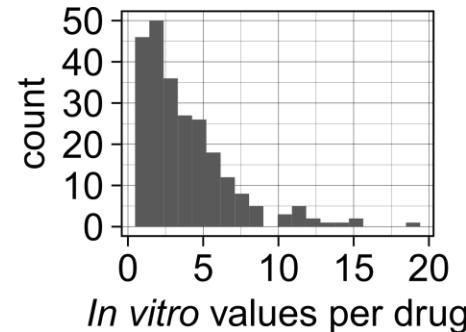
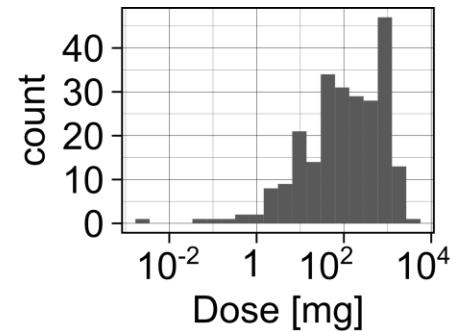
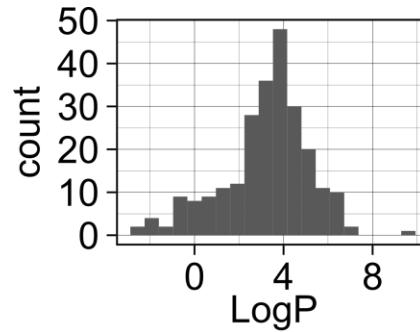
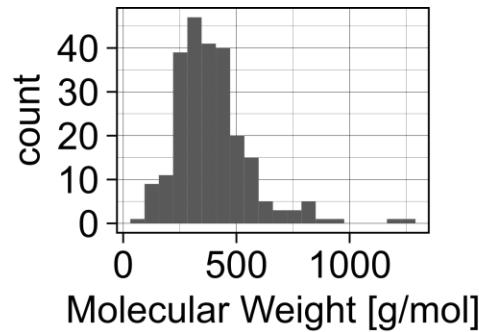
Clinical toxicity



DILIrank
Chen et al.
(2016)

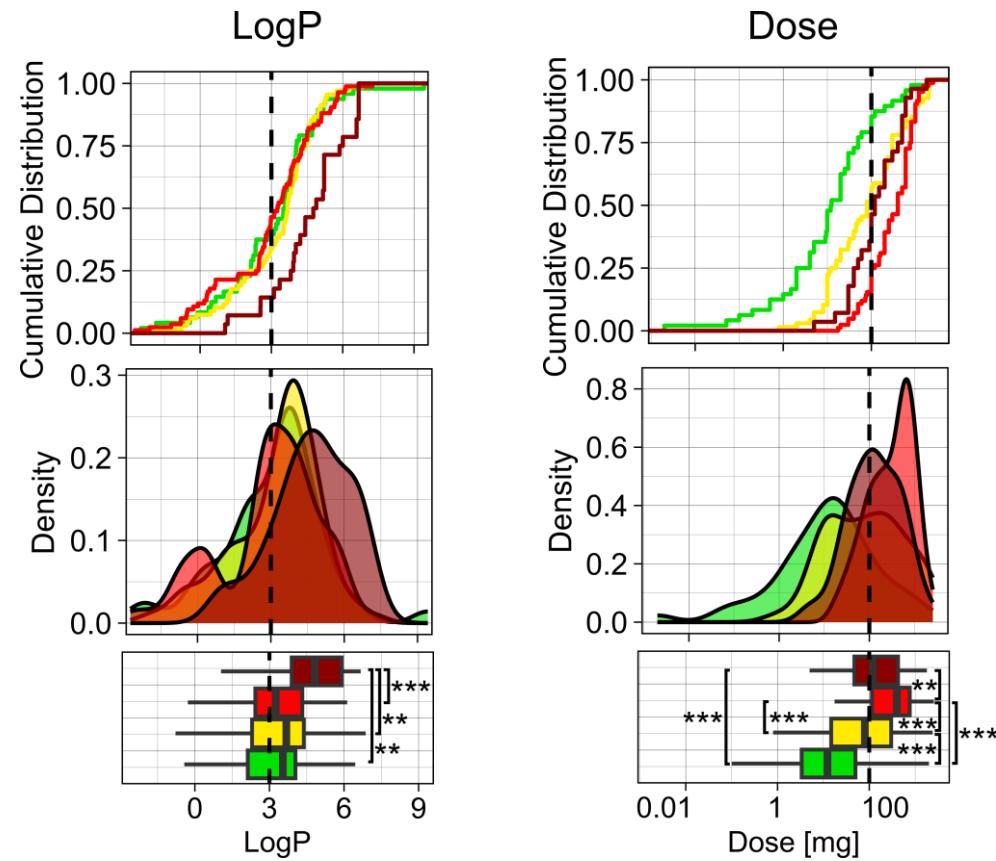
No DILI
Less DILI
Most DILI
Clinical Failure

Our integrated DILI dataset: 241 drugs

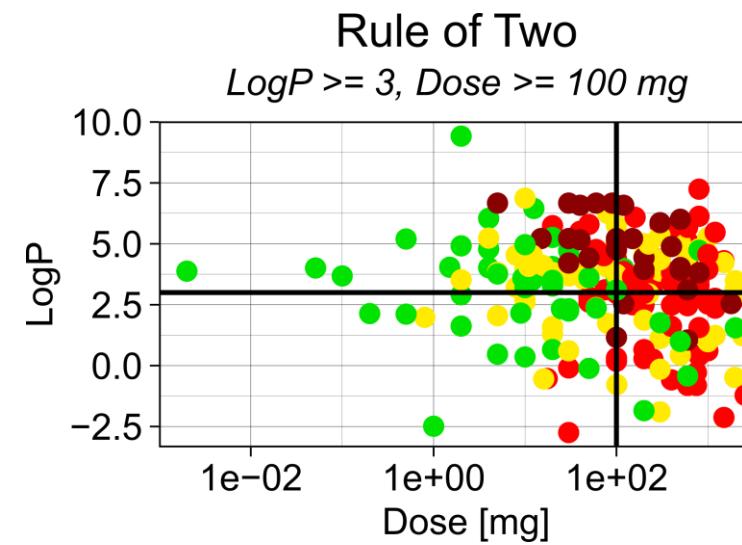


Results

Evaluation 1: Simple heuristic screening rules poorly predict DILI

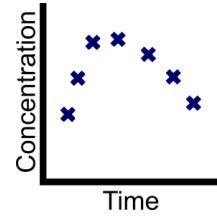


No-DILI-Concern Most-DILI-Concern
Less-DILI-Concern Clinical Dev

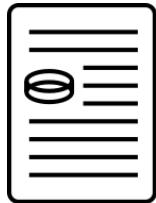


Balanced accuracies: 50 - 70%

Evaluation 2: Cmax to *in vitro* toxicity ratios



$$\frac{\text{In vivo Cmax}}{(\text{Strongest}) \text{ in vitro toxicity}} = \text{Cmax to toxicity ratio}$$

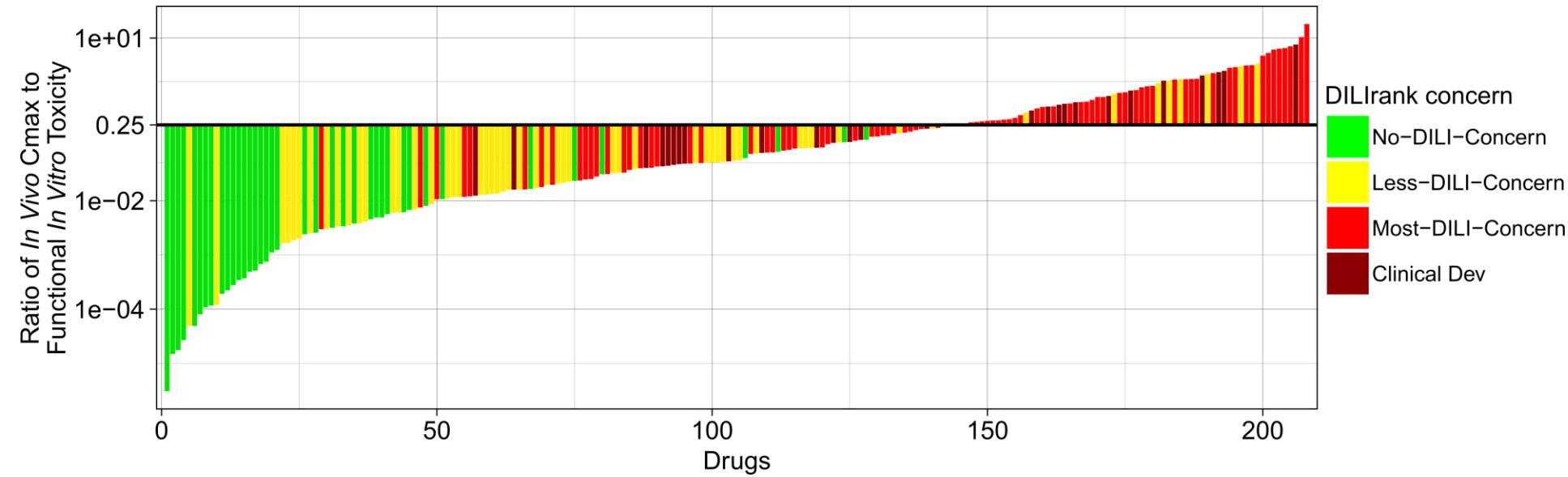


Clinical toxicity

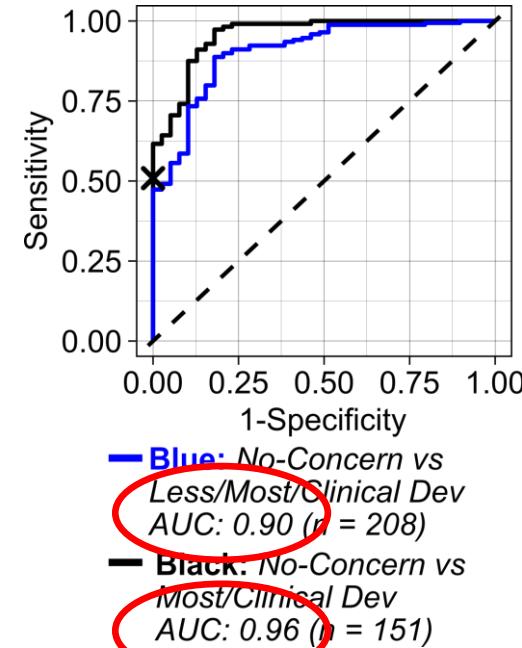
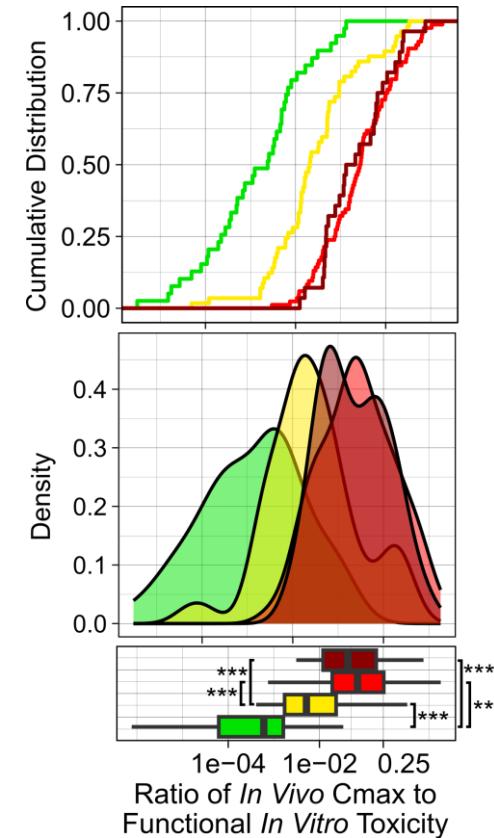


- No DILI
- Less DILI
- Most DILI
- Clinical Failure

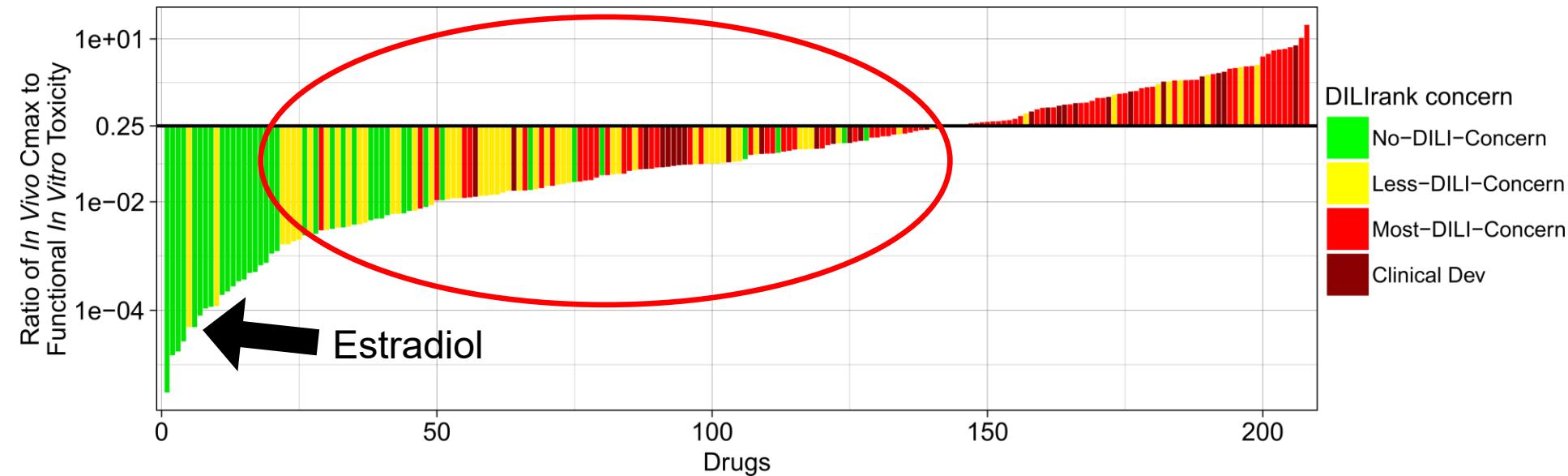
Evaluation 2: Cmax to *in vitro* toxicity ratios strongly predict DILI



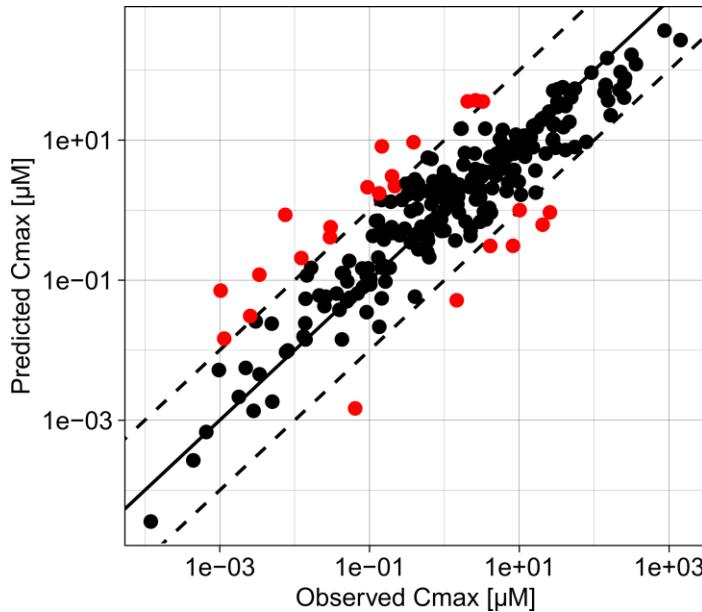
Evaluation 2: Cmax to *in vitro* toxicity ratios strongly predict DILI



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

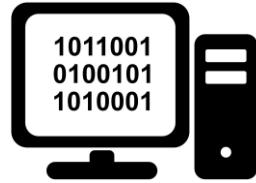


In silico predicted Cmax is similar to *in vivo* observed values

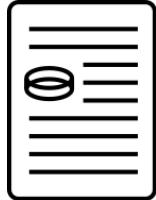


90% of Cmax
values predicted
within 10-fold

Evaluation 3: *In silico* predicted Cmax



$$\frac{\text{In vivo } \text{In silico Cmax}}{(\text{Strongest}) \text{ in vitro toxicity}} = \text{Cmax to toxicity ratio}$$

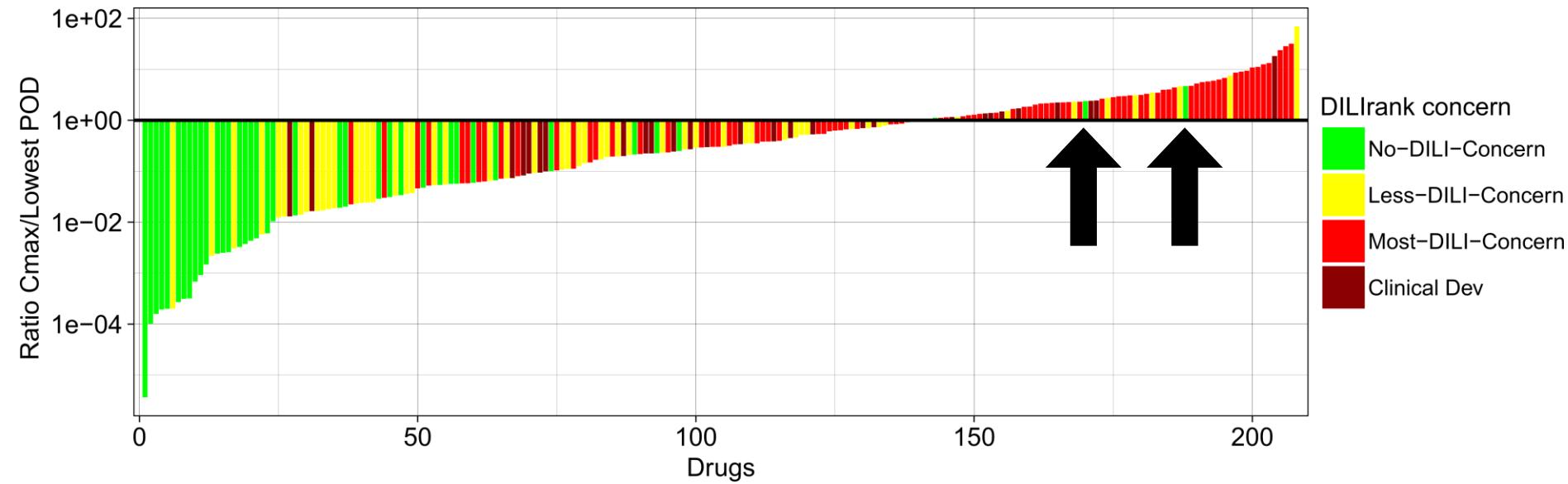


Clinical toxicity

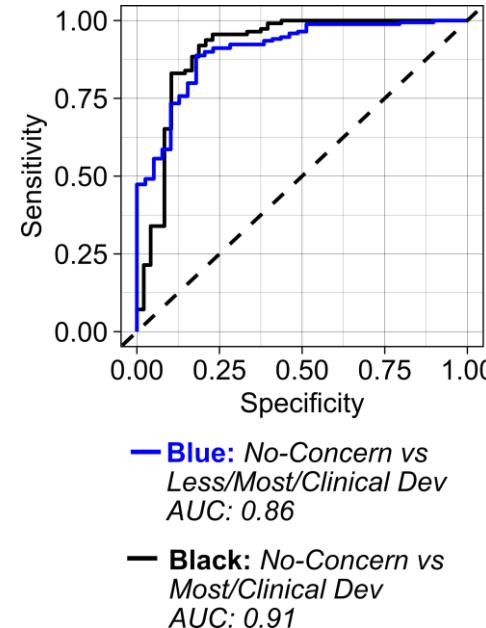
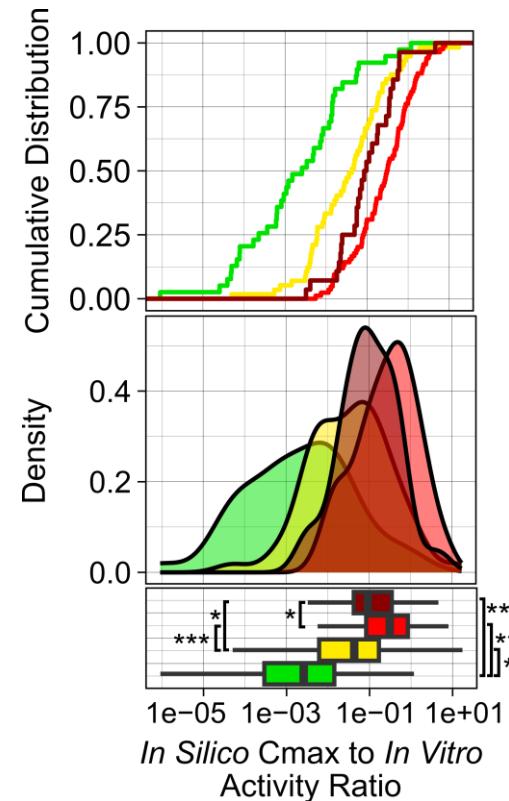


No DILI
Less DILI
Most DILI
Clinical Failure

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



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



ROC AUC for <i>in vivo</i> Cmax	ROC AUC for <i>in silico</i> Cmax
90% → 86%	96% → 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> 

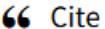
Published: 20 December 2017



PDF



Split View



Cite



Permissions



Share ▾

Evaluation 4: *In vitro* BSEP inhibition data



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

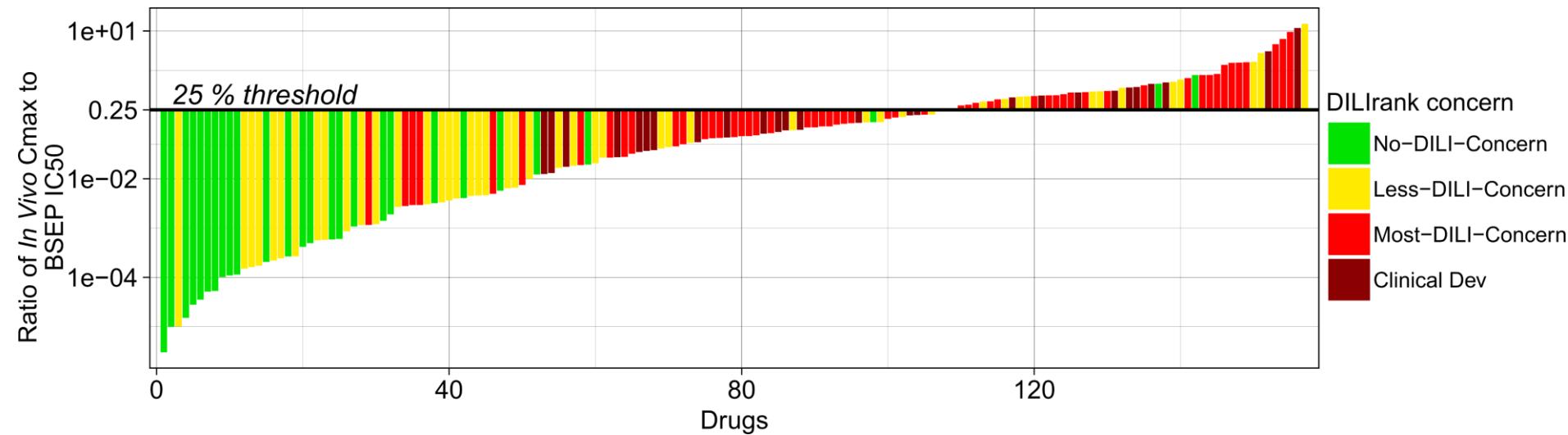


Clinical toxicity

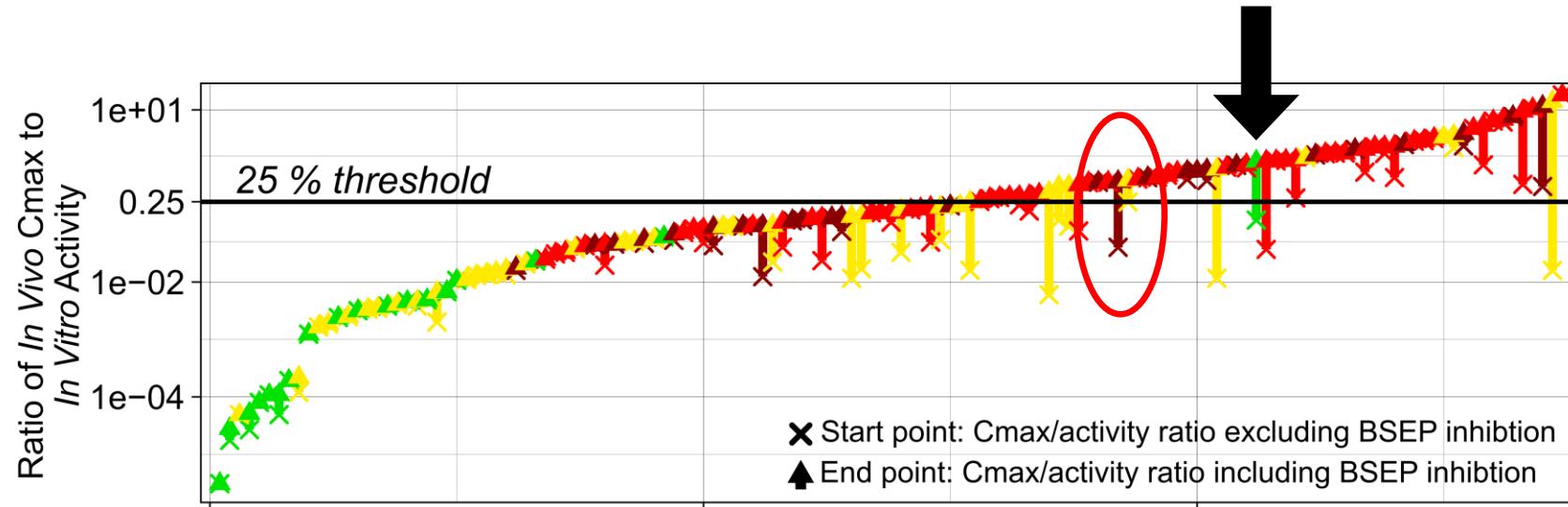


No DILI
Less DILI
Most DILI
Clinical Failure

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 ⓘ
Epub 2019 Mar 8.

Cholestatic Drug-Induced Liver Injury Caused by Mifepristone

Katalina Funke ¹, Don C Rockey ¹

Affiliations + expand

PMID: 30561784 ⓘ DOI: 10.1002/hep.30465 ⓘ

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

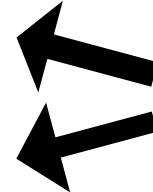
Taylor A. Ault, David R. Braxton, Rebecca A. Watson, Alan O. Marcus & Tse-Ling Fong 

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

3553 Accesses | 8 Citations | 1 Altmetric | [Metrics](#)

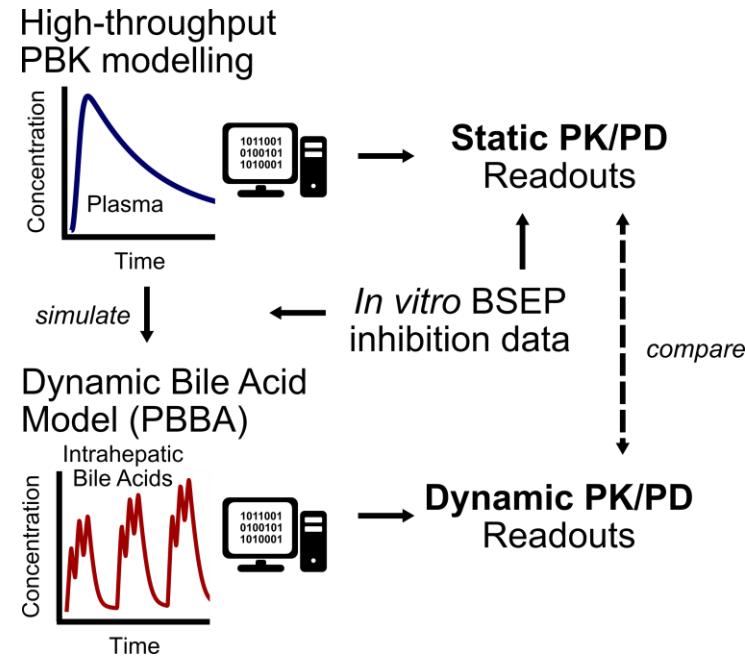
Evaluation 5: Dynamic effect modelling

$$\frac{C_{max}}{\text{(Lowest) } in \text{ vitro \ toxicity}}$$

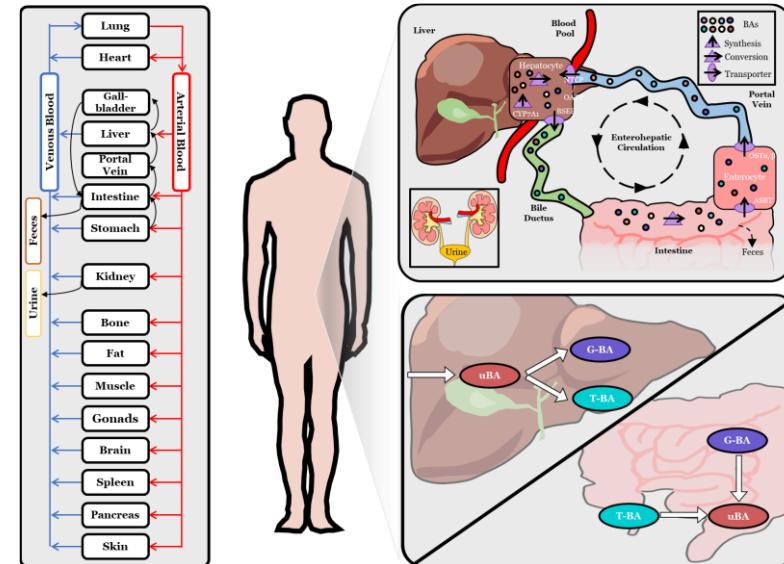


Static representations
of the dynamic *in vivo*
situation

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

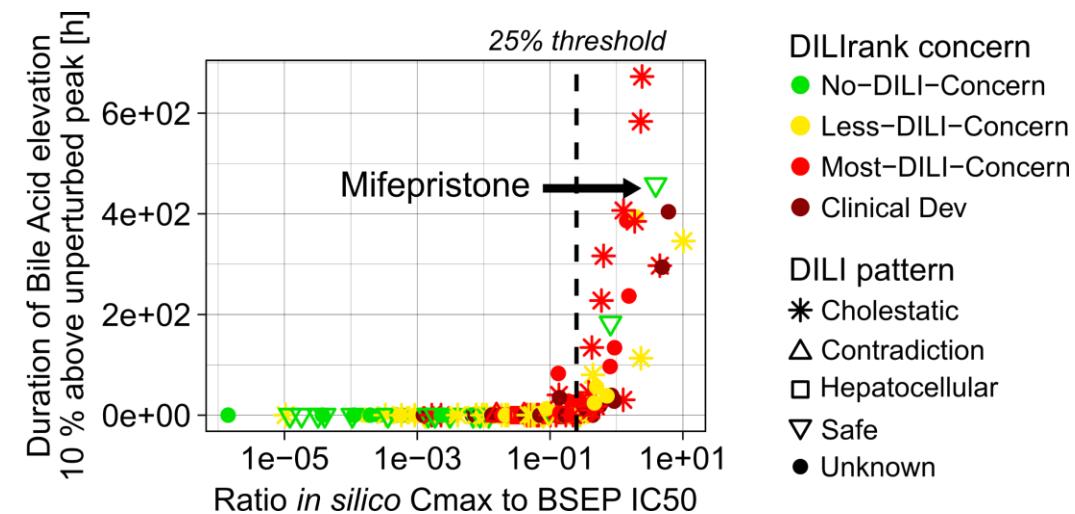
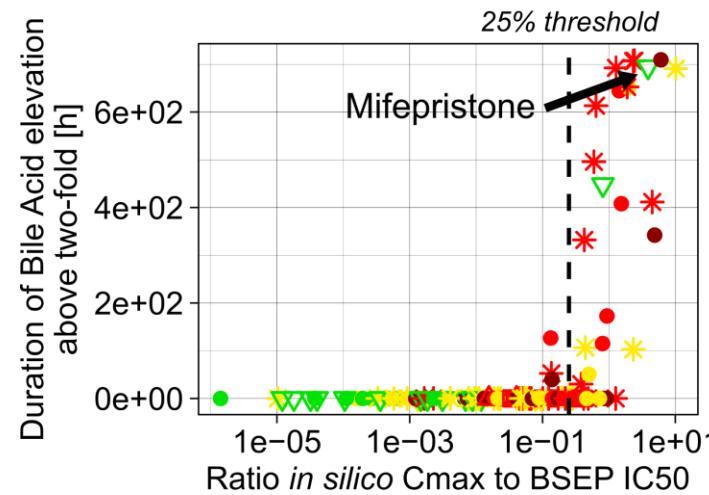


Kister et al. (2025)



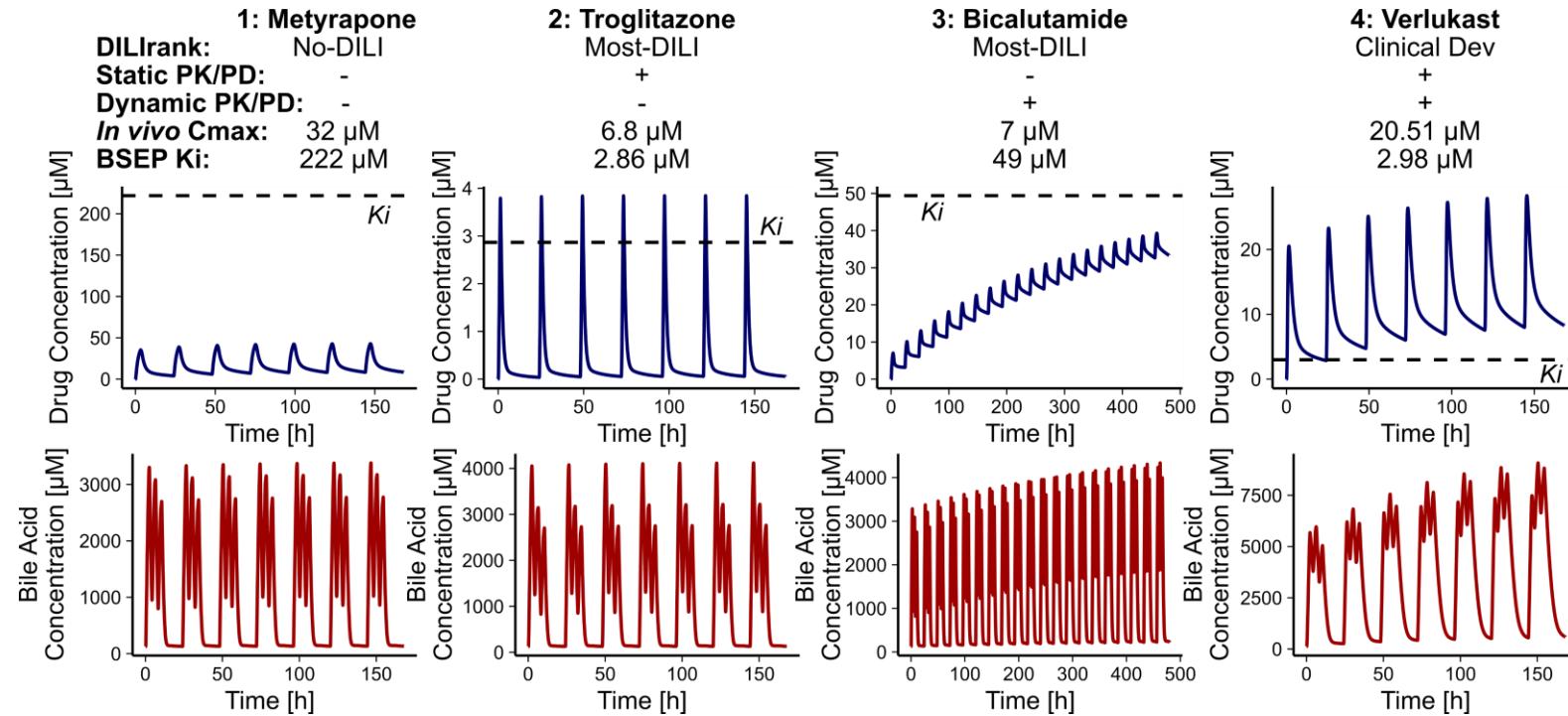
Bile acid model: Kister, B., Blank, L. M., Pollmanns, M., Wirtz, T. H. & Kuepfer, L. A physiologically-based model of bile acid metabolism in humans. *bioRxiv*, 2025.07.19.665677; 10.1101/2025.07.19.665677 (2025).

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



- DILIrank concern
 - No-DILI-Concern (green circle)
 - Less-DILI-Concern (yellow triangle)
 - Most-DILI-Concern (red circle)
 - Clinical Dev (dark red circle)
- DILI pattern
 - Cholestatic (asterisk)
 - Contradiction (open triangle)
 - Hepatocellular (open square)
 - Safe (open inverted triangle)
 - Unknown (black circle)

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

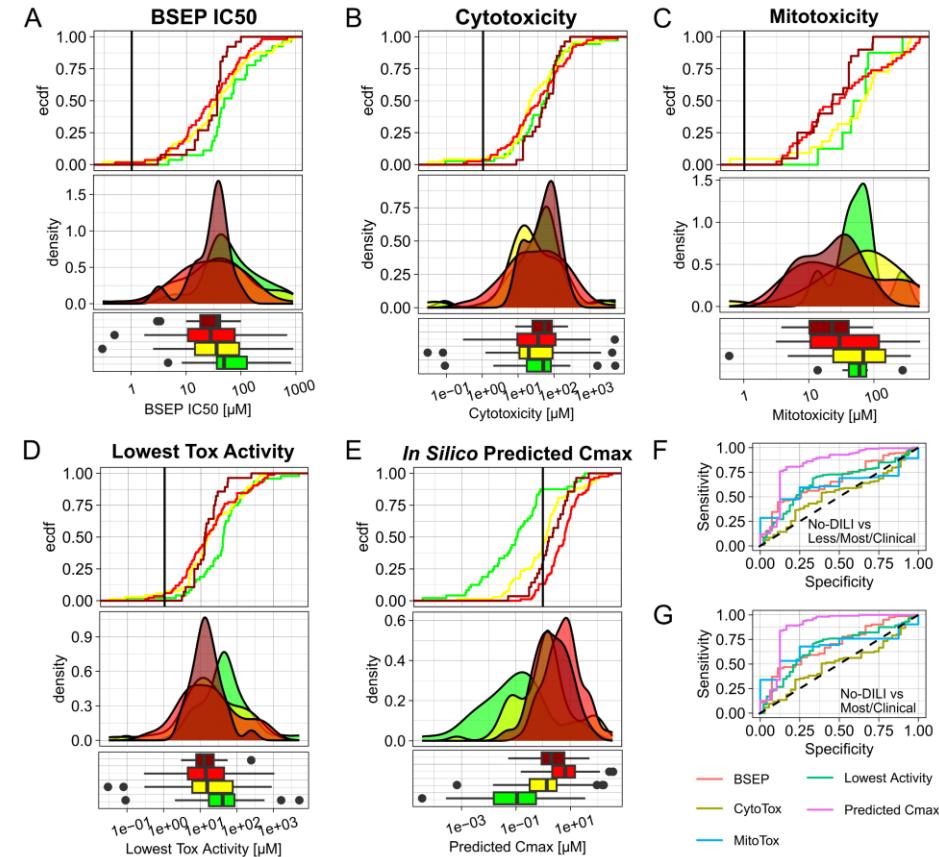
Conclusions

- 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**

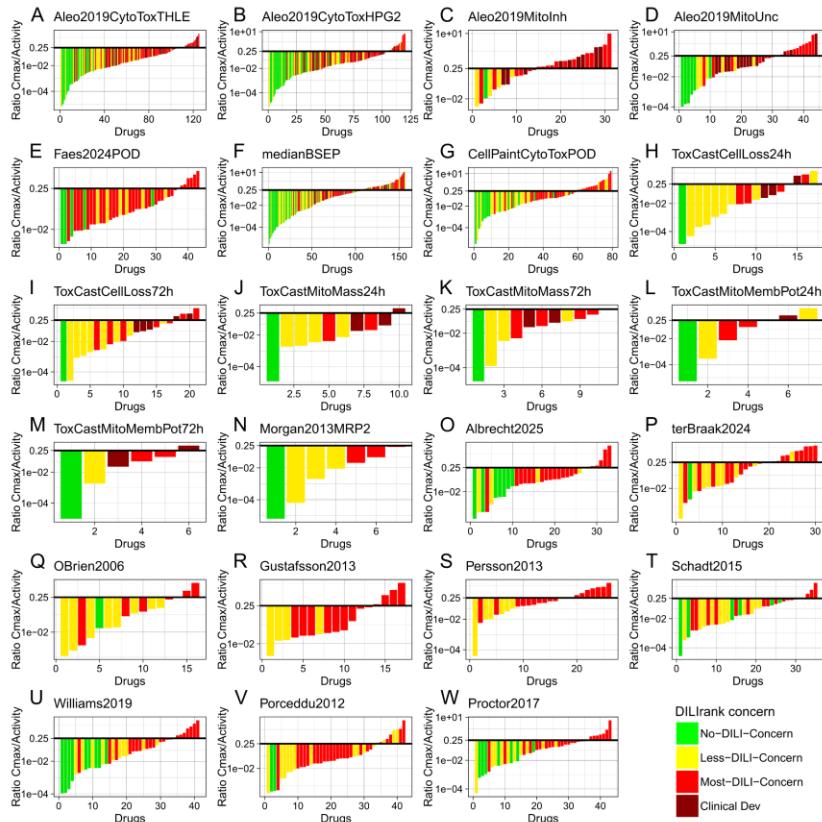
Thank you for your attention!

In vitro toxicity alone is a poor predictor

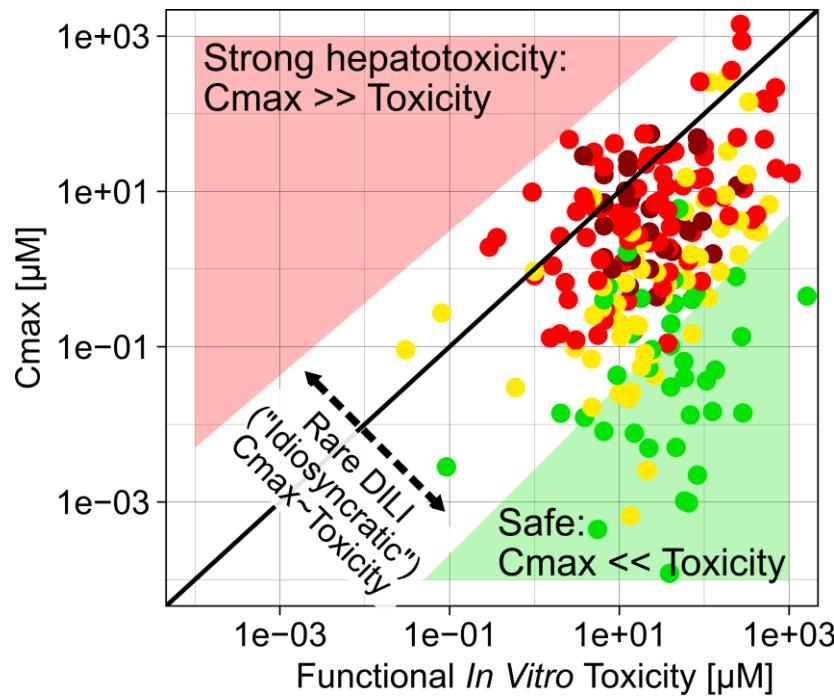
Per assay ratios



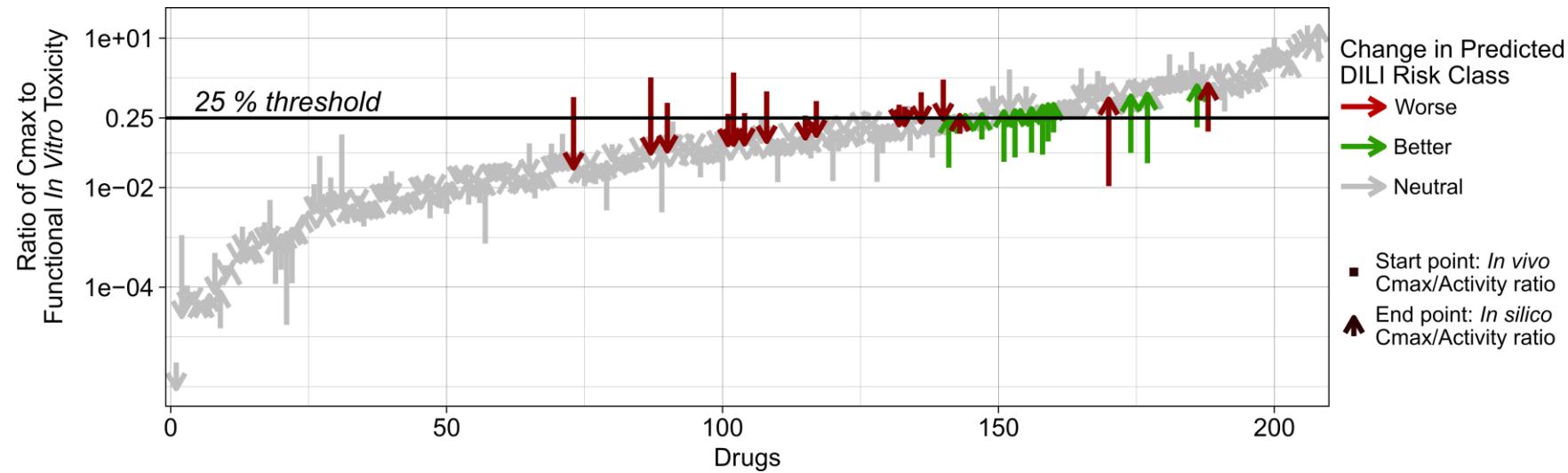
Per assay ratios



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

