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<u>John Wambaugh</u>¹, Nisha Sipes¹, Jon Arnot², Trevor Brown², Daniel Dawson¹, Sarah Davidson¹, Michael Devito¹, John DiBella⁴, Stephen Ferguson³, Rocky Goldsmith¹, Chris Grulke¹, Richard Judson¹, Michael Lawless⁴, Kamel Mansouri⁵, Grace Patlewicz¹, Ester Papa⁶, Prachi Pradeep^{1,7}, Alessandro Sangion², Risa Sayre¹, Rogelio Tornero-Velez¹, Barbara Wetmore¹

1. Center for Computational Toxicology and Exposure, U.S. Environmental Protection Agency (EPA), 2. ARC Arnot Research and Consulting Inc., 3. Division of the National Toxicology Program (NTP), National Institute of Environmental Health Sciences, 4. Simulations Plus, 16.
5. NTP Interagency Center for the Evaluation of Alternative Toxicological Methods, National Institute of Environmental Health Sciences., 6. Department of Theoretical and Applied Sciences, University of Insubria, Varese, 7. German Federal Institute for Risk Assessment (B

Hazard

Risk

Exposui

oxicokinetics

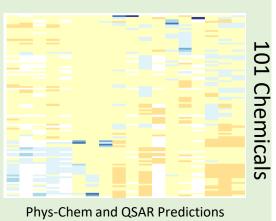
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OBJECTIVES

- We wish to understand toxicokinetics (chemical absorption, distribution, metabolism, and excretion by the body) to help assess public health risk posed by chemicals
- In silico predictions along with high throughput toxicokinetic (HTTK) methods are needed as in vivo and in vitro measurements are unavailable for thousands of chemicals in commerce and the environment

APPROACH

- This collaborative trial uses 101 chemicals with in vivo measured toxicokinetic (TK) data
- Six different sets of in silico
 (QSAR) tools for predicting TK
 were evaluated
- Predicted parameters and plasma concentrations were compared with empirical data



MAIN RESULTS

- Model predictions for in vitro measurements were generally consistent across QSARs; however, accuracy varied by chemical
- When combined with a PBTK model (httk, https://cran.r-project.org/package=httk) to predict plasma concentration, the models performed similarly across all 101 chemicals (CvTdb, https://github.com/USEPA/CompTox-PK-CvTdb)

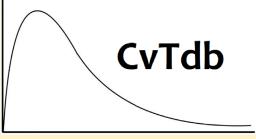
IMPACT

- Multiple QSARs exist that make reasonably accurate predictions for *in vitro* TK parameters
- This will provide key information for risk-based prioritization of many thousands of chemicals without either *in vivo* or *in vitro* TK data
- For more information, contact:
 John Wambaugh (wambaugh.john@epa.gov)

http://orcid.org/0000-0002-4024-534X

OBJECTIVES

- Four different modeling teams produced quantitative structure-activity relationship (QSAR) models for two key toxicokinetic parameters that can be measured *in vitro*: intrinsic hepatic clearance (Cl_{int} measured with hepatocyte incubations) and fraction unbound in plasma (f_{up})
- Models were evaluated for ability to reproduce the full concentration vs. time (Cvt) curve as well as summary statistics and parameters (such as half-life)
- Two additional models for chemical half-life were also evaluated



Concentration

Time

- In vivo plasma
 concentration vs. time
 data were available for
 101 chemicals from the
 CvTdb (Sayre et al. 2020)
- In vitro measurements were available for 86 chemicals (httk v2.0.4)

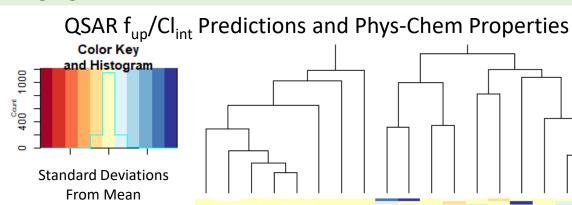
Mo	del	Team	Predictions	Mechanism	Reference
	ons Plus Predictor®	Michael Lawless, Stephen Ferguson, Nisha Sipes, and John DiBella	Level 1 (in vitro parameters)	Sum of CYP-specific Artificial Neural Network (ANN)	Sipes et al. (2017)
Pradee	ep 2020	Prachi Pradeep, Grace Patlewicz, John Wambaugh, Richard Judson	Level 1	Random forest and support vectors method	Pradeep et al. (2020)
Dawso	n 2021	Daniel Dawson, John Wambaugh, Rogelio Tornero-Velez	Level 1	Random forest, clearance organized by categories	Dawson et al. (2021)
OPI	ERA	Kamel Mansouri	Level 1	Nearest-neighbors	Mansouri et al. (2018, 2021)
IFS-C	QSAR	Jon Arnot, Trevor Brown, and Alessandro Sangion	Level 3 (Half-lives)	Fragment-based Multiple Linear Regressors (MRL)	Arnot et al. (2014
QSARIN	S-Chem	Ester Papa and Jon Arnot	Level 3	Ordinary Least Squares MLR	Papa et al. (2018)

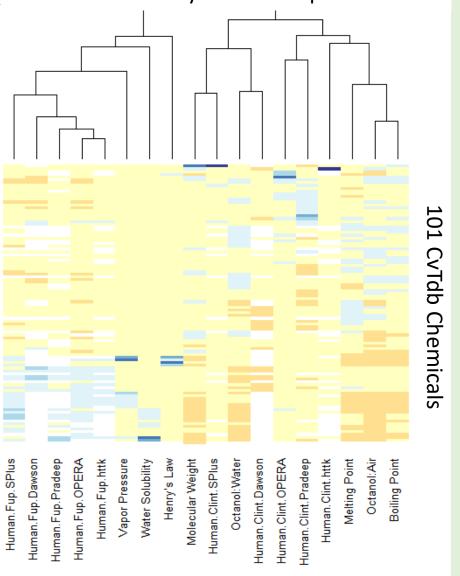
- R package "httk" (Pearce, 2017) can parameterize a physiologically-based toxicokinetic (PBTK) model based on chemical-specific values for f_{up} and Cl_{int}
- For 86 of the test chemicals, in vitro measurements were also available for comparison
- There were 101 chemicals present in the CvTdb (Sayre, 2020) as of September 2019 that had plasma concentration data following either rat or human oral or intravenous doses
 - 57 from the Toxic Substances Control Act (TSCA) active inventory
 - 20 pharmaceuticals
 - 24 pesticides
 - 99 that are found in consumer products,
 - 7 per- and poly-fluorinated substances (PFAS)
 - 64 that are part of the ToxCast screening program
- 10 chemicals could not be predicted by most models

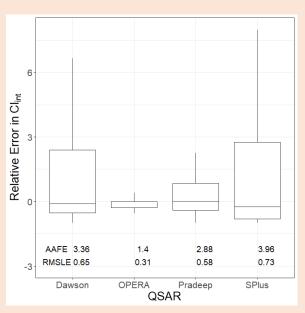
Three levels of evaluation were performed:

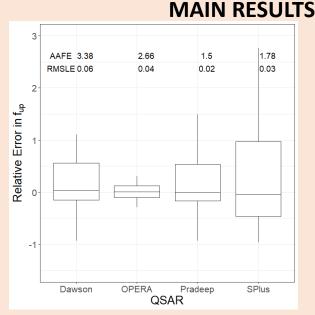
Evaluation	TK Quantities	Chemicals
Level 1	<i>In Vitro</i> TK Measurements (f _{up} , Cl _{int})	69
Level 2	TK Concentration vs. Time (all points, C _{max} , time-integral/AUC)	91
Level 3	Summary Statistics $(V_d, t_{half}, Cl_{tot})$	91

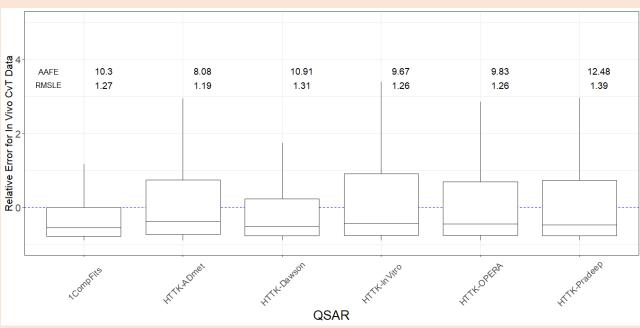
APPROACH









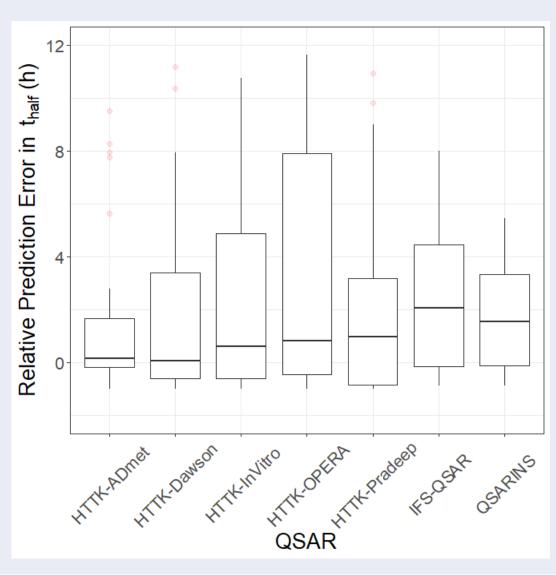


Models were evaluated against all chemicals based on Relative Predictive Error (RPE): $\frac{pred-obs}{obs}$

- Here we have evaluated all observed time points equally, neglecting phase (absorption/distribution/metabolism) and measurement accuracy. Other analyses focusing on key statistics (such as peak and time-integrated concentration) will be examined elsewhere
- Maximum likelihood empirical one-compartment model fits provide an estimate of ideal performance
- At left are box-and-whiskers plots showing the distribution of RPE across all 99 chemicals for which predictions were available (no model predicted Oxoacetic acid--water (1/1) or Nitrite)
- The upper and lower extent of the box for each model indicates the 25th to 75th quantiles, the midline indicates the median (50th quantile) and vertical line indicates 1.5x the range of the box.

IMPACT/SIGNIFICANCE

- TK information, such as elimination half-life (t_{half}, plotted below), is critical for understanding chemical risk
- EPA is continuing to accumulate chemical-specific TK data, both:
 - In vivo (CvTdb, Sayre (2020))
 - In vitro (Wetmore (2012, 2015), Wambaugh (2019))
- However, several thousand chemicals remain in need of TK info; the QSARs evaluated here provide options to fill this gap
- Overall, the HTTK PBTK model performed similarly when using TK QSARs for Cl_{int} and f_{up} as when the actual *in vitro* measured data were used ("HTTK-InVitro" in figure at right)
- These QSARs will enable public health risk-based prioritization of chemicals in commerce and the environment



REFERENCES

- Arnot, Jon A., Trevor N. Brown, and Frank Wania. "Estimating screening-level organic chemical half-lives in humans." *Environmental Science & Technology* 48.1 (2014): 723-730. https://doi.org/10.1021/es4029414
- Dawson, Daniel E., et al. "Designing QSARs for Parameters of High-Throughput Toxicokinetic Models Using Open-Source Descriptors." *Environmental Science & Technology* (2021). https://doi.org/10.1021/acs.est.0c06117
- Mansouri, Kamel, Grulke, C.M., Judson, R.S. et al. OPERA models for predicting physicochemical properties and environmental fate endpoints. J Cheminform 10, 10 (2018). https://doi.org/10.1186/s13321-018-0263-1
- Mansouri, Kamel; Chang, Xiaoqing; Allen, David; Judson, Richard; Williams, Antony; Kleinstreuer, Nicole (2021): OPERA models for ADME properties and toxicity endpoint. SOT 2021 meeting Poster. https://doi.org/10.23645/epacomptox.14470728.v1
- Papa, Ester, et al. "Development of human biotransformation QSARs and application for PBT assessment refinement." Food and Chemical Toxicology 112 (2018): 535-543. https://doi.org/10.1016/j.fct.2017.04.016
- Pearce, Robert G., et al. "httk: R package for high-throughput toxicokinetics." *Journal of Statistical Software* 79.4 (2017): 1. https://doi.org/10.18637/jss.v079.i04
- Pradeep, Prachi, et al. "Using chemical structure information to develop predictive models for in vitro toxicokinetic parameters to inform high-throughput risk-assessment." *Computational Toxicology* 16 (2020): 100136. https://doi.org/10.1016/j.comtox.2020.100136
- Sayre, Risa R., John F. Wambaugh, and Christopher M. Grulke. "Database of pharmacokinetic time-series data and parameters for 144 environmental chemicals." *Scientific Data* 7.1 (2020): 1-10. https://doi.org/10.1038/s41597-020-0455-1
- Sipes, Nisha S., et al. "An intuitive approach for predicting potential human health risk with the Tox21 10k library." *Environmental Science & Technology* 51.18 (2017): 10786-10796. https://doi.org/10.1021/acs.est.7b00650
- Wambaugh, John F., et al. "Assessing toxicokinetic uncertainty and variability in risk prioritization." *Toxicological Sciences* 172.2 (2019): 235-251. https://doi.org/10.1093/toxsci/kfz205
- Wetmore, Barbara A., et al. "Integration of dosimetry, exposure, and high-throughput screening data in chemical toxicity assessment." *Toxicological Sciences* 125.1 (2012): 157-174. https://doi.org/10.1093/toxsci/kfr254
- Wetmore, Barbara A., et al. "Incorporating high-throughput exposure predictions with dosimetry-adjusted in vitro bioactivity to inform chemical toxicity testing." *Toxicological Sciences* 148.1 (2015): 121-136. https://doi.org/10.1093/toxsci/kfv171