Evaluating Several *in vitro* Disposition Models for use in High-throughput Toxicokinetic Research

Steven Lasee [1], Johanna Nyffeler [2], Brett R Blackwell [3], Joshua Harrill [3], Felix Harris [4], Jonathan Haselman [3], John Nichols [3] and Daniel L. Villeneuve [3]

(1)Oak Ridge Institute for Science and Education (ORISE) participant at U.S. Environmental Protection Agency, (2)CCTE, U.S. Environmental Protection Agency, (3)U.S. Environmental Protection Agency, (4)ORAU student contractor at U.S. Environmental Protection Agency, United States

Steven Lasee I lasee.steven@epa.gov I 920-264-4909

Introduction

- *In vitro* high-throughput screening assays are increasingly adopted as part of a tiered testing strategy for chemical hazard evaluation.

- It is important to understand chemical behavior within *in vitro* assay systems to accurately predict the bioavailable chemical concentration at a calculated nominal *in vitro* potency.

- Several *in vitro* distribution models have been developed to predict chemical partitioning using physiochemical properties along with assay-specific parameters (Figure 1).

- Final model outputs are then applied to the nominal point-of-departure (POD) to calculate a free chemical concentration, which will then be used for *in vitro*-to-*in vivo* extrapolation (IVIVE).

Modeled Materials

- Models were run with parameters from the Rainbow trout gill cell line (RTgill-W1) in the OECD test guideline 249 (OECD TG249) assay miniaturized to 384-well format.

- These exposures were conducted using 231 environmentally relevant chemicals (log K_{OW} Range -2.63 to 7.61, RTgill-W1 cell line, 384-well format) as part of a separate project.

- A subset of 12 chemicals will be empirically measured to compare with and validate model outputs. These chemicals span a range of physicochemical properties (log K_{OW} -1.31 – 5.76) and include 17 beta-estradiol, pyrene, malathion, imidacloprid, 4-nonylphenol, ethanolamine, bisphenol A, Fluoxetine hydrochloride, diethyl phthalate, benzaldehyde, methoxychlor, and triazophos (Figure 2, black outlined points).
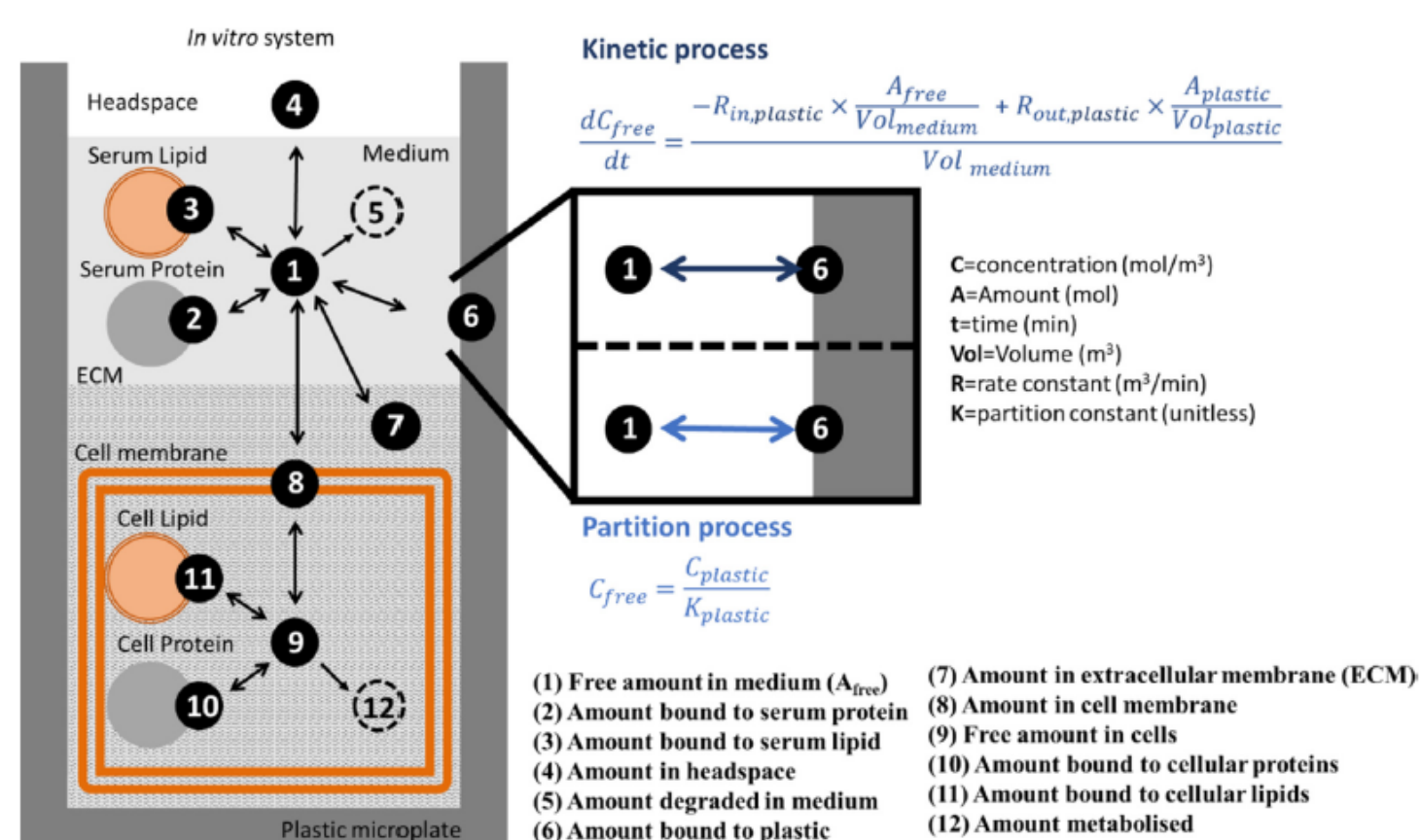
Models

Figure 1 – Basic diagram of in vitro disposition and modeling

Proença, S., Escher, B. I., Fischer, F. C., Fisher, C., Grégoire, S., Hewitt, N. J., ... & Kramer, N. I. (2021). Effective exposure of chemicals in in vitro cell systems: A review of chemical distribution models. *Toxicology in Vitro*, 73, 105133.

Primary Information Needed for Models

- Well plate parameters
— Volume, well bottom area, fill, time, material
> 145 µL, 8.35 mm², 120 µL, 24 h, polypropylene

- Cell/biological/serum parameters
— Protein, lipid, and DOM content, pH, Ionic strength, temp, cell number
> 0.05, 0.05, 0, 7.4, 0.104 M, 19°C, 22500

- Chemical Traits
— Log K_{OW}, Log K_{AW}, water solubility, MW
> Generated using **CompTox dashboard**

— Polyparameter linear free energy relationships(PP-LFERs)
> Generated using **UFZ-LSER database**

Model Predictions

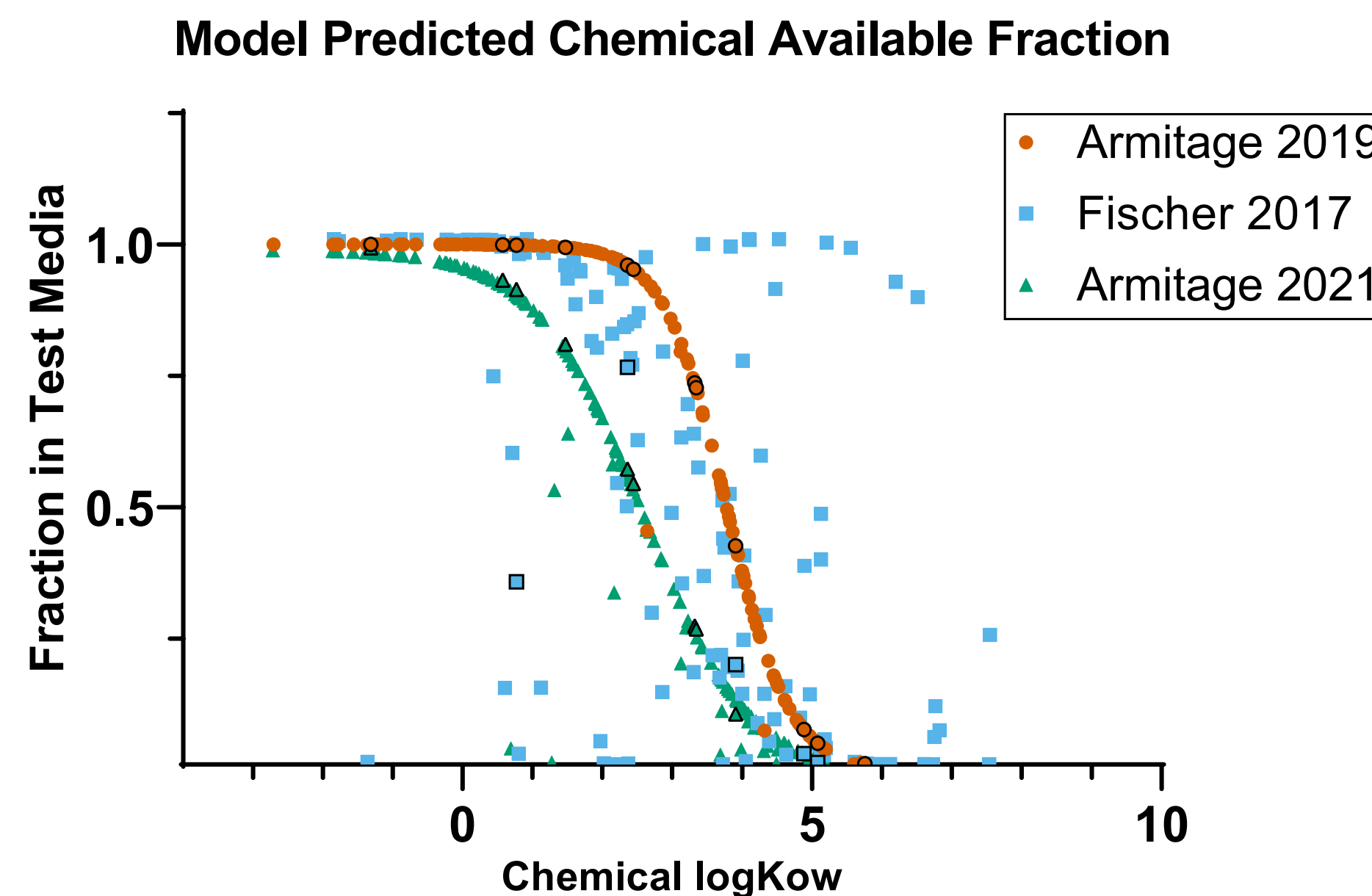### Model Predicted Chemical Available Fraction

Figure 2 – Fraction of chemical in test media outputs from the 3 models run (Armitage 2019, Fischer 2017, and Armitage 2021). 12 test chemicals are represented with black outlines.

Displayed Models
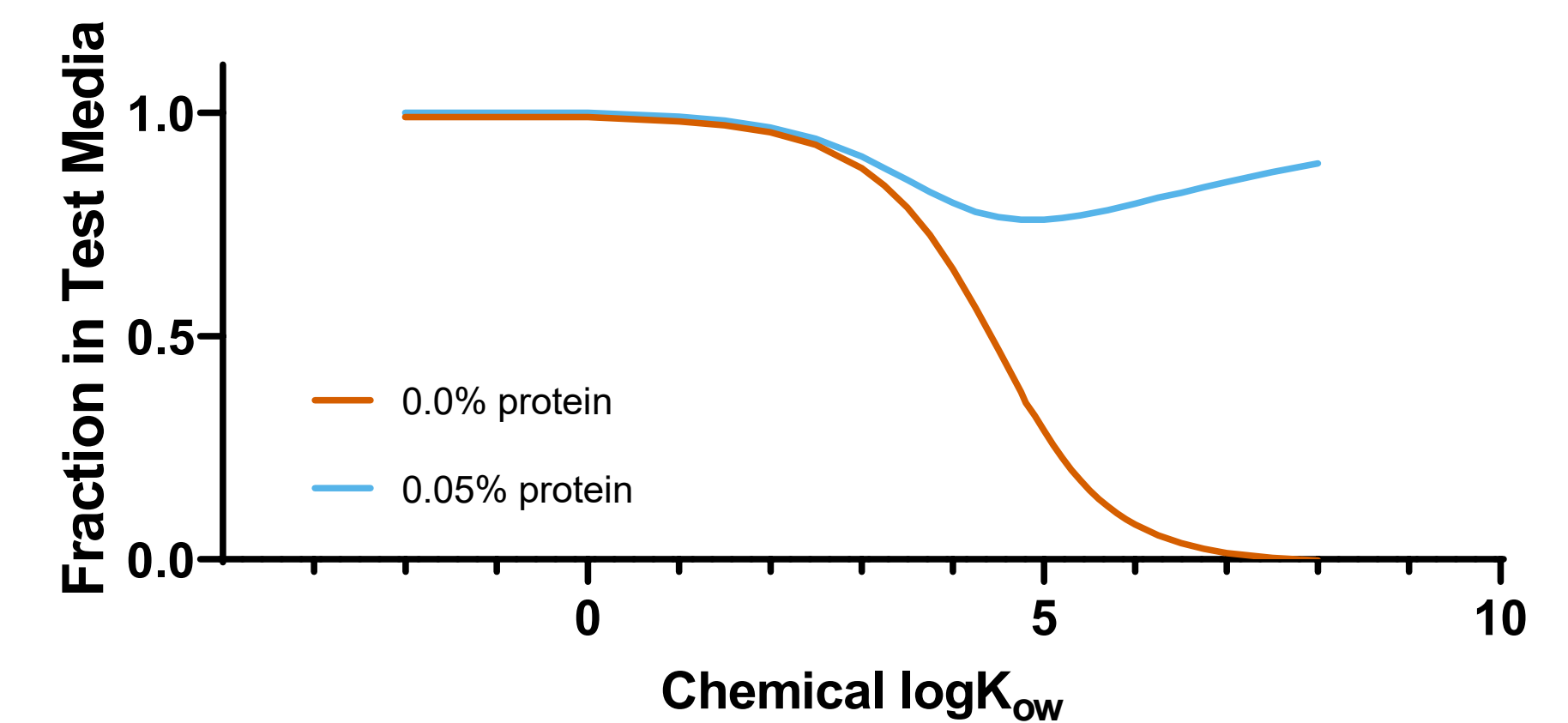
Armitage 2019 (Figure 2)-update of the 2014 Armitage model-
- K_{OW} Focused

Honda GS, Pearce RG, Pham LL, Setzer RW, Wetmore BA, Sipes NS, et al. (2019) Using the concordance of *in vitro* and *in vivo* data to evaluate extrapolation assumptions. PLoS ONE 14(5): e0217564.

Fischer 2017 (Figure 2)
- Polyparameter linear free energy relationships (PP-LFERs) focused

Fischer, F. C., Henneberger, L., Schlichting, R., & Escher, B. I. (2019). How to improve the dosing of chemicals in high-throughput *in vitro* mammalian cell assays. Chemical research in toxicology, 32(8), 1462-1468.

Armitage 2021 (Figure 2)
- K_{OW} Focused

Armitage JM, Sangion A, Parmar R, Looky AB, Arnot JA. Update and Evaluation of a High-Throughput *In Vitro* Mass Balance Distribution Model: IV-MBM EQP v2.0. Toxics. 2021; 9(11):315.

Fischer 2018 (Figure 3)
- Media Protein vs. K_{OW}

Fischer, F. C., Cirpka, O. A., Goss, K. U., Henneberger, L., & Escher, B. I. (2018). Application of experimental polystyrene partition constants and diffusion coefficients to predict the sorption of neutral organic chemicals to multiwell plates in *in vivo* and *in vitro* bioassays. Environmental science & technology, 52(22), 13511-13522.

Discussion

Figure 3 – Chemical fraction in Media vs. chemical log K_{OW} in two media of differing protein content using the model by Fischer et al. 2018

- Chemical sorption to the walls of multiwell plates was found to be potentially very high in experiments where the media lack protein in chemical with higher K_{OW} (Figure 3).

- The models only work for chemicals with known physiochemical traits. This data can be hard to come by, difficult to consolidate, and much of it modeled itself.

- Accurate parameters will often need to be identified and calculated/input manually into the models for optimal accuracy. Well plate measurements vary slightly from brand to brand.

- The Armitage vs. Fischer models predictions commonly showed discrepancies (Figure 2). This is likely due to different input parameters (i.e., K_{OW} vs. PP-LFERs)used in calculating distribution.

- The three models mostly agreed on low log K_{OW} chemical fraction in the media. As log K_{OW} increases model agreement decreases, potentially due to additional factors quantified by PP-LFERs (i.e. dipolarity/polarizability, H-bond donor properties, molar volume, etc.).

Future Work

- Calculate outputs from additional models (e.g., Fisher 2019) to compare with our current model outputs and future experimental data.

- Gather measurement from well plate studies for a subset of 12 chemicals (K_{OW} = -1.31 – 5.76) and qualify model outputs with those experimental measurements. These exposures will be run using RTgill-W1 and the OECD TG249 assay miniaturized to the 384-well format over 24 hours.

- Determine if certain chemical groups' (from our 231 test chemicals, e.g. organophosphates, chemicals with a log K_{OW} > 1, pharmaceuticals, etc.) distributions are better predicted by any one model using results of modeling and empirical measurements.

- Final outputs of the selected model will be used to adjust *in vitro* PODs and compare IVIVE estimates with known *in vivo* PODs.