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Impact of in vitro experimental variation in kinetic parameters on physiologically based 4 5 kinetic (PBK) model simulations. 6 Ans Punt^a, Peter Bos^b, Betty Hakkert^b, Jochem Louisse^a 7 8 ^a WFSR - Wageningen Food Safety Research, Wageningen, The Netherlands 9 ^b RIVM - The National Institute for Public Health and the Environment, Bilthoven, The Netherlands 10 11 Abstract 12 In vitro toxicokinetic data are critical in meeting an increased regulatory need to improve chemical 13 safety evaluations towards a better understanding of internal human chemical exposure and 14 toxicity. In vitro intrinsic hepatic clearance (CLint), the fraction unbound in plasma (Fup), and the 15 intestinal apparent permeability (Papp) are important parameters as input in a physiologically based 16 kinetic (PBK) model to make first estimates of internal exposure after oral dosing. In the present 17 study we describe the key aspects that need to be considered when performing in vitro kinetic 18 studies and explored the experimental variation in the values for these parameters as reported in 19 literature. Furthermore, the impact that this experimental variation has on PBK-model predictions of 20 maximum plasma concentration (Cmax) and the area under the concentration time curve (AUC_{0-24h}) 21 was determined. As a result of the experimental variation in CLint, Papp, and Fup, the predicted 22 variation in Cmax for individual compounds ranged between 1.5- to 79-fold and the predicted variation in AUC $_{0.24h}$ ranged between 1.3- and 23-fold. These results indicate that there are still some 23 24 important steps to take to achieve robust data that can be used in regulatory applications. To gain

- regulatory acceptance of in vitro kinetic data and PBK models it will be important that the
- 26 boundaries in experimental conditions and the applicability domain, and of use of different in vitro

27 kinetic models are clearly described in guidance documents.

28

29 1. Introduction

30 In 2020, the European Commission launched its EU Chemicals Strategy for Sustainability under the 31 Green Deal. Key aspects of this strategy are to ban most harmful chemicals, to improve safe and 32 sustainable chemicals by design, and to obtain a better account of potential 'cocktail effects' (i.e. 33 effects upon combined exposure) of chemicals (European Commission, 2019, 2020). Such additional 34 insights in chemical safety cannot only be obtained with traditional animal testing, which is costly 35 and time-consuming, and therefore not applicable to large numbers of compounds. Therefore, there 36 is an increasing need for the regulatory use of animal-free testing strategies (Arnesdotter et al., 37 2021; Paul Friedman et al., 2020; de Boer et al., 2020). Insights in the absorption, distribution, 38 metabolism and excretion of compounds, i.e. the kinetics, have a critical role in such animal-free 39 testing strategies, particularly to improve the interpretation of in vitro toxicity results, allowing to 40 estimate the internal plasma and tissue concentrations in humans after oral, dermal, or inhalation 41 exposures, that can be related to the in vitro effect concentrations (Blaauboer, 2010; Jochem Louisse 42 et al., 2017; Coecke et al., 2013). In addition, kinetic data are important in the interpretation of data 43 from human biomonitoring studies, for example to translate measured urine concentrations of a 44 compound or its metabolite(s) to related external exposures (Zare Jeddi et al., 2021). Finally, kinetic data are key to obtain better insights in dose-, species-, and route of exposure-dependent 45 46 differences in internal exposure, as well as considerations of human interindividual variation and 47 interactions between compounds (Punt et al., 2020; Paini et al., 2021).

Given that particularly human toxicokinetic data are generally scarcely available for nonpharmaceuticals, insights in kinetics are increasingly obtained with in vitro test systems. These include approaches that capture, for example, the intestinal, dermal, or pulmonary permeability of compounds, or test systems that capture metabolic conversions, plasma or tissue binding, or influx or efflux transporter kinetics (Blaauboer, 2014; Punt *et al.*, 2017; Wilk-Zasadna *et al.*, 2015). Standalone data from such studies can, in general, not directly be used in safety evaluations, as the combined effects of different kinetic processes determines the internal exposure. Therefore, data

55 obtained with the different test systems need to be integrated, e.g. with help of PBK modelling 56 (Bessems et al., 2014; J. Louisse et al., 2017; Choi et al., 2019), while taking the uptake and kinetics 57 of various ports of entry (oral, dermal and inhalation) into account. To gain confidence in the outcomes obtained with PBK models that rely on in vitro input data, it is important to understand 58 59 the robustness of the in vitro input data that are used and the combined impact of experimental 60 variation in each of the individual parameters on the model predictions. In addition, each in vitro 61 kinetic assay has its own inherent boundaries with respect to the conditions under which the in vitro 62 experiments should to be performed, including, for example, boundaries with respect to the applied 63 substrate concentration, enzyme concentration, or incubation time (Hubatsch et al., 2007; 64 Gouliarmou et al., 2018; Seibert and Tracy, 2014). There are furthermore restrictions with respect to 65 the applicability domain of different in vitro kinetic studies. For example, in vitro kinetic constants, 66 measured under linear conditions, can only be used for predictions at dose-levels that would not 67 lead to saturation of enzymes or transporters (Peters, 2012). To achieve regulatory use of in vitro kinetic studies, the robustness, experimental conditions under which the in vitro experiments need 68 69 to be performed, and applicability domain of different in vitro kinetic studies needs to become more 70 apparent.

71 Recently, Louisse et al. (2020), collected reported intrinsic hepatic clearance (CLint) values 72 from the literature for 30 compounds obtained with human hepatocytes, as well as information on 73 the experimental set-ups applied. They observed up to 100-fold differences in literature reported in 74 vitro hepatic CLint values as obtained from incubations with primary human hepatocytes, and 75 noticed that experimental set-ups applied differed for many aspects between studies. In most 76 studies, pooled hepatocytes were used, suggesting that differences between studies are not solely 77 driven by interindividual differences in biotransformation activities (Louisse et al., 2020). Apart from 78 the in vitro CLint values, the fraction unbound in plasma (Fup), and the intestinal apparent permeability (Papp) are also important parameters with which first estimates of internal 79 80 concentrations can be made for oral exposure, upon using these data as input in a PBK model (Jones

and Rowland-Yeo, 2013). Experimental uncertainties related to small differences in experimental set-ups can also be expected for these input parameters. The goal of the present study was to 1) provide an overview of the aspects that need to be taken into account when performing in vitro kinetic studies to derive these parameters for oral exposure and 2) to explore the impact of experimental variation in the in vitro kinetic results on PBK model predictions. The results are discussed with respect to the potential impact of the in vitro experimental variation on regulatory decision making and the steps required for standardization of the in vitro methods.

88

89 2. Materials and methods

90 2.1 Data collection

91 A literature search was performed to obtain an indication of the experimental variation in in vitro 92 measured CLint, Papp, and Fup. In case of CLint, the in vitro data as collected by Louisse et al. (2020) 93 were included in the present study. In this study, Louisse et al. (2020) performed a literature search 94 to obtain an indication of the experimental variation in intrinsic clearances values obtained with 95 primary hepatocytes, predominantly obtained with the substrate depletion protocol. Given that the 96 clearance data from Louisse et al. (2020) mainly covered pharmaceuticals, an additional literature 97 search was performed in the present study to expand the chemical domain to non-pharmaceuticals. 98 To this end, Scopus (www.scopus.com) was used to identify papers or databases that provide 99 relatively large datasets on in vitro metabolic clearances, measured with primary hepatocytes. 100 For non-pharmaceuticals, the R httk database (EPA) and Black et al. (2021) were identified as major 101 source for hepatic clearance data. For compounds for which two independent clearance 102 measurements were found in these initial selected data sources, an additional search was 103 performed with Google Scholar, to determine if additional clearance data could be obtained from 104 individual scientific papers.

In addition to the collection of CLint data, literature data were also collected to obtain an
 indication of the experimental variation in Caco-2 Papp and Fup values. To this end, Scopus

107 (www.scopus.com) was used to identify papers or databases that contain relatively large datasets of

- 108 Caco-2 Papp values or Fup values. The final selection of Caco-2 Papp data were obtained from
- Hallifax et al. (2012), Neuhoff et al. (2003), Gertz et al. (2010), Estudante et al. (2015), Larregieu and
- Benet (2014), Li et al. (2007), and Lee et al. (2017). In case of Fup, the R httk database (EPA) and
- 111 Srivastava *et al* (2021), Ye *et al*. (2016), and Ferguson *et al*. (2019) were identified as major sources.
- 112 Table 1 provides a summary of the data obtained with the literature search on in vitro intrinsic
- 113 hepatic clearance, Caco-2 Papp and Fup values for compounds from different chemical domains
- 114 (pharmaceutical, chemical, food, cosmetic). A more extensive overview of the data and references is
- 115 provided in the supporting information.
- 116

number	compound ^a	CLint			Рарр			Fup		
		mean	CV ^b	n	mean	CV ^b	n	mean	CV ^b	n
1	Antipyrine	0.19	75	8	48	93	8			
2	Disopyramide	0.28	41	8						
3	Lorazepam	0.51	74	7						
4	Dapsone	0.57	97	4						
5	Tolbutamide	1.1	120	11				0.044	50	5
6	Diazepam	1.4	110	15	29	21	3	0.028	86	9
7	Caffeine	1.6	130	10	37	22	4	0.97	42	3
8	Pindolol	1.9	29	7						
9	S-warfarin	1.9	150	5				0.013	46	9
10	Omeprazole	2.4	63	5						
11	Timolol	2.7	82	8						
12	proxen	4.1	160	6						
13	Metoprolol	4.8	77	11	33	120	10			
14	Ketoprofen	4.8	56	11						
15	Prazosin	5.2	68	6						
16	Ibuprofen	5.3	37	5						
17	Diltiazem	6.2	55	12	45	55	4	0.37	38	5
18	Quinidine	6.4	98	10	19	80	2	0.23	38	3
19	Bosentan	7	200	7				0.021	64	3
20	Clozapine	7	59	11				0.083	44	5
21	Prednisolone	7.2	130	8						
22	Sildefil	7.6	54	15						
23	Lidocaine	8.8	78	6						
24	4-Nitroaniline	9.6	100	4						

Table 1. Model compounds and the distribution of the collected CLint, Papp, and Fup values.

25	Midazolam	14	91	18	39	46	3	0.034	46	8
26	Dextromethorphan	17	120	9				0.39	23	4
27	Imipramine	17	110	19				0.17	38	5
28	3,3' ,5,5' -	18	120	4						
	Tetrabromobisphenol									
	A									
29	Phecetin	19	110	11						
30	Buspirone	21	79	6				0.2	71	3
31	Nifedipine	21	88	6				0.042	5	2
32	Desipramine	21	96	9						
33	Ketanserin	25	82	6						
34	Carvidelol	29	43	8						
35	Verapamil	30	100	15	36	81	9	0.2	38	9
36	Diclofenac	31	120	15				0.0066	69	9
37	Bufuralol	33	110	5						
38	2,5-Di-tert-	35	160	4						
	butylbenzene-1,4-									
	diol									
39	Propanolol	37	220	12						
40	Chlorpromazine	52	140	10				0.04	38	2
42	Bisphenol A	76	70	3	36	87	3			
43	Ipcozole	120	80	4						
44	Benzylparaben	370	50	4						
45	Propranolol				36	89	9	0.23	36	9
46	Fluvastatin							0.0061	42	2
47	Rosuvastatin							0.13	7.8	2

^a For the compounds highlighted in bold, the experimental variation in all three parameters, i.e.

119 CLint, Papp and Fup could be determined.

^b CV corresponds to the coefficient of variation (CV = SD/mean x 100%) and is used as indicator of

- 121 the variation in the reported kinetic values.
- 122
- 123

124 2.2 PBK model predictions

125 For the compounds for which the experimental variation in all three parameters, i.e. CLint, Papp, and

126 Fup, could be determined (see Table 1), simulations were performed to explore the impact of the

127 experimental variation on predictions of the maximum plasma concentration (Cmax) and the area

128 under the concentration time curve (AUC_{0-24h}). For these simulations, a published generic human PBK

129 model code by Jones and Rowland-Yeo (2013) was used. The original model code of Jones and

130 Rowland-Yeo (2013) was converted to R (R Core Team, n.d.) as described by Punt et al. (2021) and is

131 provided on GitHub (https://github.com/wfsrqivive/PBPK_exp_variation.git). The generic PBK model

132 consists of 13 compartments, corresponding to the major organs in the body and an arterial and 133 venous blood compartment. The model requires chemical-specific parameters for 1) intestinal 134 uptake, 2) partition coefficients, 3) the blood:plasma ratio, 4) the fraction unbound in plasma and 5) 135 hepatic clearance. Renal clearance is described in the model based on the glomerular filtration rate 136 times the fraction unbound in plasma and does therefore not require any additional chemical-137 specific input parameter. The partition coefficients were calculated with the calculation method of 138 Rodgers and Rowland (2006). The blood:plasma ratio was assumed to be a fixed value of 1 for all 139 compounds. The input parameters for the intestinal uptake, fraction unbound in plasma and hepatic 140 clearance were obtained from in vitro experiments as described above. To explore the impact of the 141 variation in CLint, Papp, and Fup on the Cmax and AUC_{0-24h} predictions, simulations were performed with all possible combinations of CLint, Papp, and Fup for a specific compound. The codes to run 142 143 these simulations are provided on https://github.com/wfsrqivive/PBPK_exp_variation.git. The 144 simulations were performed at a low single oral dose of 0.1 mg/kg bw at which linear clearance 145 conditions can be expected for all compounds.

146To determine which of the in vitro input parameters contributed most to the predicted147variation in Cmax and AUC_{0-24h}, a global sensitivity analysis was performed with RVis. To this end, for148each compound, the R code of the PBK model was loaded into the RVis software (v0.15, using R1494.1.1). Simulations were subsequently performed within the "Sensitivity" tab, using the e-FAST150method, by adding the observed in vitro distributions (mean and CV) to the CLint, Fup and Papp151parameters. Additional details on how these simulations were performed are provided in the152supporting information.

153

155 **3. Results**

156 **3.1 Background CLint measurements and evaluation of the in vitro experimental variation.**

157 Different protocols exist to measure in vitro kinetic constants for metabolism. Incubations are most 158 frequently performed with primary hepatocytes or sub-cellular liver fractions like microsomes or S9 159 (in the presence of relevant cofactors) (Gouliarmou et al., 2018; Lipscomb and Poet, 2008; Pelkonen 160 and Turpeinen, 2007). Primary hepatocytes are considered the gold standard for performing in vitro 161 metabolism studies. Generally, experiments are performed with cryopreserved primary hepatocytes, 162 as these can be stored for a longer period making them more readily available than freshly prepared 163 hepatocytes. Cryopreserved hepatocytes retain most of the activity of freshly prepared hepatocytes 164 (Lipscomb and Poet, 2008). With a so-called "metabolite formation protocol", in vitro incubations are 165 performed at different substrate concentrations at a fixed incubation time and cell concentration 166 (Figure 1A). The formation of metabolites is then measured in these experiments, which follows the 167 Michaelis-Menten equation (Seibert and Tracy, 2014):

168	v = <u>Vmax * [compound]</u>	eq. 1
169	Km + [compound]	
170		

In this equation, the Vmax is the maximum velocity (e.g. µmol/min/10⁶ hepatocytes) and the Km is 171 172 the Michaelis-Menten constant with unit μ M (Peters, 2012). A key advantage of this approach is that 173 the kinetic constants obtained can be used to describe the formation of metabolites, and allows to 174 account for concentration dependent saturation of the enzymes. A disadvantage of this protocol is 175 that standards of the metabolites are required for quantification. Given that such standards cannot 176 be easily obtained for most compounds, the metabolic conversion of compounds is more frequently 177 measured with a so-called "substrate depletion approach" in which the disappearance of a compound 178 is measured over time to derive CLint based on the slope of the substrate depletion curve (Jones and 179 Houston, 2004). One of the most critical aspects of substrate depletion experiments is that the substrate concentration should be well below the Km, as only then the rate, v, can be simplified as 180 181 depicted in Equation 2 (Seibert and Tracy, 2014).

 182
 v = <u>Vmax * [compound]</u> = CLint*[compound]
 eq. 2

 183
 Km

 184

185 The obtained CLint values can therefore only be used in situations where no saturable metabolism is 186 to be expected. This can be explored with in vitro range finding experiments at different concentrations to determine at which concentrations saturation of metabolism occurs (Sjögren et al., 187 2012; Nichols et al., 2018). First estimates of the internal concentrations with a PBK model can be used 188 189 to determine if these saturable conditions are likely to be reached in the liver. Other aspects that need 190 to be considered when performing in vitro metabolic clearance studies are e.g. the protein amount in the incubation mixture, whether or not serum is added to the incubation, number of time points and 191 sampling schedule, the percentage of test item consumption at the end of the incubation, and aspects 192 193 related to the analytical techniques that are used to analyse the sample (Louisse et al., 2020a; 194 Gouliarmou et al., 2018).

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Figure 1. Examples of A) Michaelis–Menten kinetics with a Km of 25 μ M and Vmax values of 100 nmol/min/10⁶ hepatocytes and B) a metabolic clearance study with a t1/2 of 30 min and a CLint of ln(2)/30 = 0.02 ml/min/10⁶ hepatocytes when performed in an incubation that contains 10⁶ hepatocytes per ml.

203 Figure 2 shows the experimental variation in in vitro metabolic clearance studies as obtained 204 from the literature. For the majority of the compounds, the CLint measurements varied over a 100-205 fold, generally ranging between values that are 5-fold higher and 20-fold lower than the mean of a 206 specific compound. The results from Figure 2, also reveals that the variation in CLint is consistent 207 over the different compounds. This is corroborated by a Levene's test on equal variances, revealing 208 no statistical differences in the variance for most of the compounds (Results provided in the 209 supporting information). This consistency in experimental variation over a range of different 210 compounds provides an indication of the variation that can be expected from in vitro metabolic 211 clearance studies with primary hepatocytes.

212



213

Figure 2. Variation in in vitro CLint (μL/min/10⁶ cells) measurements. The histogram depicts the
combined distribution of the variation over the different compounds. The values represent the
normalized CLint values, corresponding to the CLint values obtained for a specific compound, divided
by the mean of these values for the specific compound.

218

3.2 Background Caco-2 Papp measurements and evaluation of the in vitro experimental variation.

The Caco-2 cellular model of intestinal absorption is one of the most frequently used in vitro cell models to study the rate of transport of compounds over the intestinal cell membrane. Although Cacocells are derived from a human colon carcinoma, the cells mimic the epithelial barrier of the small intestine when cultured in a monolayer (Hubatsch *et al.*, 2007). For in vitro Papp measurements, the cells are grown in a so-called Transwell system, in which the cells are seeded on a permeable filter

225 insert and are cultured for about 21 days to form a monolayer. To measure the cellular transport of a 226 compound, the cell culture medium at the apical compartment of the Transwell is replaced by a 227 transport buffer in which the compound is dissolved and the cell culture medium at the basolateral 228 compartment is replaced by the transport buffer, often containing bovine serum albumin to mimic 229 the blood compartment (Hubatsch et al., 2007). A critical aspect of Papp measurements is that the 230 experiments are performed under a concentration gradient, otherwise diffusion cannot take place. 231 This means that the time-range in which the absorption studies are performed need to be optimized 232 to make sure that less than 10% of the compound is diffused to the basolateral compartment (also 233 called sink-conditions) (Usansky and Sinko, 2005). Such sink conditions provide the best 234 representation of the physiological conditions, as a concentration gradient between the gut lumen 235 and the plasma will exist in vivo due to distribution of the chemical in the body after absorption. In 236 addition, it should be noted that Caco-2 experimental results often vary between labs and with 237 batches of cells. Therefore, a range of reference substrates should be included in the experimental 238 setup to normalize the results. A final important experimental aspect that can affect the Papp 239 measurement is the pH gradient that is applied between the apical and basolateral compartment. A 240 pH gradient of 6.5-7.4 provides the best representation of the physiological conditions between the 241 intestine and blood (Neuhoff et al., 2003).

Figure 3 shows the experimental variation in in vitro reported Papp values. For the three compounds for which most Caco-2 Papp measurements are available (i.e. metoprolol (13), verapamil (35), and antipyrine (1)), the variation in Papp values appears to range over 40 to 60-fold, ranging between values that about 3 to 4-fold higher and about 15-fold lower than the mean Papp of a specific compound. For the remaining compounds, less data was available and the results revealed a 1.5 to 5fold variation.



Figure 3. Variation in in vitro Caco-2 Papp (cm⁻⁶/s) measurements. The histogram depicts the combined distribution of the variation over the different compounds. The values represent the normalized Papp values, corresponding to the Papp values obtained for a specific compound, divided by the mean of these values for the specific compound.

254

3.3 Background Fup measurements and evaluation of the in vitro experimental variation.

256 Various methods have been developed to measure Fup, of which the equilibrium dialysis test system 257 being most commonly applied. For these experiments, so-called equilibrium dialysis devices are 258 used, which consists of a bas plate and different dialysis inserts. Each of dialysis inserts consists of 259 two chambers separated by a dialysis membrane. The human plasma, generally containing 2 to 5 μ M 260 of the substrate, is added to one chamber and phosphate-buffered saline (PBS) to the other (Ryu et 261 al., 2021). The concentrations in the two chambers is monitored until an equilibrium is reached. The 262 equilibrium dialysis techniques particularly poses challenges with measuring the fraction unbound 263 for highly bound compounds. For these compounds the levels in the receiving PBS chamber will be 264 close to the limit of detection, resulting in unmeasurable Fup values. For highly bound compounds, 265 modified equilibrium dialysis have therefore been proposed, including bidirectional equilibrium dialysis, dilution methods and pre-saturation methods (Ferguson et al., 2019; Wambaugh et al., 266

267 2019).

To obtain insights in the variation in Fup measurements, a literature search was performed to find reported Fup values for a range of compounds. Figure 4 reveals the experimental variation in in vitro derived Fup values for a range of compounds. Given that the Fup values can only range between 0 and 1, as the Fup is a fraction, the extent of variation in the Fup estimates appears to be less than
observed for CLint and Caco-2 Papp values as described above. The largest experimental variation is
observed for diclofenac (34) with Fup values ranging from 0.0015-0.02, corresponding to a 13-fold
range.



Figure 4. Variation in in vitro Fup (unitless) measurements. The histogram depicts the combined distribution of the variation over the different compounds. The values represent the normalized Fup values, corresponding to the Fup values obtained for a specific compound, divided by the mean of these values for the specific compound.

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3.4 Impact of the combined variation in CLint, Papp and Fup on the PBK model-predicted Cmax

282 and AUC_{0-24h}.

283 For the six compounds within the dataset for which CLint, Papp and Fup data from different studies 284 were available, the combined effects of the experimental variation in the three input parameters on 285 the PBK model predictions were determined. The results of these predictions are depicted in Figure 286 5. For every chemical, each available CLint value was combined with each available Papp value, and 287 each CLint-Papp combination was in turn combined with each available Fup value for a specific 288 compound. Figure 5 reveals that the impact of the variation in experimental conditions on the PBK-289 model predictions is different for each compound. The lowest variation in Cmax and AUC_{0-24h} predictions occurs for the low-clearance compound diazepam (6), revealing only a 1.5-fold range in 290 291 predicted Cmax values and 1.3-fold range in predicted AUC_{0-24h}. The highest variation in both Cmax 292 and AUC_{0-24h} predictions occurs for the high-clearance compound verapamil (35), revealing a 79-fold

range in predicted Cmax and a 16 -fold range in predicted AUC_{0-24h}. A high variation in AUC_{0-24h} of 23-



fold is also observed for caffeine (7).





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3.5 Relative contribution of the different input parameters to the variation in predicted Cmax and AUC_{0-24h} values.

301 Figure 6 depicts the results of the global sensitivity analysis that was performed to determine which 302 of the three input parameters (i.e. CLint, Papp, and Fup) contribute most to the variation in Cmax 303 and AUC_{0-24h} predictions as observed in Figure 5. Experimental variation in CLint had the highest 304 impact on AUC_{0-24h} predictions for all compounds and for three out the six compounds also on the 305 Cmax predictions (caffeine (7), diltiazem (17) and verapamil (35)). The observed variation in Cmax 306 predictions for these compounds, can thus largely be attributed to the variation in CLint. The 307 experimental variation in uptake parameter Papp had no influence on the AUC_{0-24h} predictions, but 308 does have an impact on the Cmax predictions of two out of the six compounds (diazepam (6) and 309 quinidine (18)). The relative sensitivity towards experimental variation in Fup values was found to be 310 lower than for CLint.



Figure 6. Relative sensitivity of the Cmax (A) and AUC_{0-24h} (B) prediction to the variation in CLint,

Papp and Fup, as obtained with the RVis global sensitivity analysis. The relative sensitivity

314 respresents the relative contribution of each of the three parameters to the variation in Cmax or

AUC_{0-24h} as observed in Figure 5. For example, in case of caffeine (7), the variation in CLint accounted

for 82% of the total variation in Cmax predictions, whereas variation in Fup and Papp contributed

with 14% and 0.6%, respectively. The remaining 3.4% variation is caused by the interaction between

318 these different parameters as depicted in the supporting information.

319

311

321 4. Discussion

322 With the present study we described various aspects that need to be taken into account when 323 performing in vitro CLint, Caco-2 Papp and Fup kinetic studies and explored the experimental 324 variation observed with these parameters and the impact that this experimental variation has on 325 PBK-model predictions of Cmax and AUC_{0-24h}. As a result of the observed experimental variation in 326 CLint, Papp, and Fup, the PBK-predicted Cmax for compounds for which these three parameters 327 were available, was found to range between 1.5- to 79-fold and the AUC_{0-24h} ranged between 1.3and 23-fold. The extensive variation in Cmax and AUC_{0-24h} predictions, as observed for some of the 328 329 compounds, indicates that the in vitro kinetic data are currently not robust enough to make reliable 330 predictions of the in vivo kinetics of a compound without means to evaluate the adequacy of a 331 specific in vitro kinetic parameter or PBK-model prediction.

332 To gain confidence in in vitro kinetic parameters and PBK model predictions, comparisons 333 with in vivo experimental animal or human kinetic data are currently being requested in various 334 regulatory guidelines (e.g. SCCS, 2018; EMA, 2018; OECD, 2021). This approach of model evaluations 335 against in vivo data is at present, however, mainly successful within the pharmaceutical domain as 336 only for pharmaceuticals sufficient clinical data are available (EMA, 2018; Punt et al., 2017). For many other chemical domains the availability of experimental animal or human in vivo kinetic data is 337 338 limited, and evaluations against in vivo kinetic data is often not possible. For a transition to next 339 generation (animal-free) regulatory risk evaluations to happen, other means to gain confidence in 340 the in vitro kinetic data and PBK-model predictions are therefore urgently needed. Application of 341 uncertainty factors to the in vitro-based PBK-model predictions might be one way to take the uncertainties related to the in vitro experimental variation into account. The results of the present 342 343 study indicate, however, that large uncertainty factors may then be required to cover the impact of 344 potential experimental variation. It will therefore be more critical to improve the robustness of in 345 vitro kinetic data and to improve the possibilities within regulatory risk evaluations to evaluate the 346 quality of in vitro kinetic data and the adequacy of an in vitro study design.

347 As described in the present study, each in vitro kinetic test system has its own set of 348 inherent boundaries and restrictions with respect to how the data can be used in a regulatory 349 context. Critical to the in vitro experimental setup are e.g. the selection of the substrate 350 concentration, the incubation time, or concentration of enzyme that is used (Louisse et al., 2020). In 351 addition, considerations of the loss of a chemical due to sticking to the plastic or from evaporation 352 are important to take into account in the experimental setup (Groothuis et al., 2015). At present, various protocols for performing in vitro kinetic studies to derive values for CLint, Papp, and Fup are 353 354 available in the scientific literature (e.g. Watanabe et al., 2018; Cai and Shalan, 2021; Hubatsch et al., 355 2007) and describe these critical aspects that need to be considered. Our study shows that a next 356 step would be to formalize these literature available protocols and to describe the applicability 357 domain/use in a regulatory context. It should, however, be noted that most of the protocols have 358 been developed within the pharmaceutical domain and also most experience with the predictive 359 performance of the different in vitro kinetic studies comes from the pharmaceutical domain. 360 Compounds, like pesticides, biocides, industrial chemicals, cosmetic ingredients and food related 361 compounds generally have a broader range of physicochemical properties than pharmaceuticals and 362 can contain, for example, compounds that are highly lipophilic or volatile (Andersen et al., 2019; 363 Ferguson et al., 2019). Recently, Black et al. (2021) also observed that a starting concentration of 1 364 μ M, that is generally applied for pharmaceutical compounds for metabolic clearance studies, may be 365 insufficient to achieve first-order reaction conditions for some non-pharmaceuticals. These are all 366 aspects that need to be considered when formalizing existing protocols. At present, there are no 367 guidance documents available that arrange these type of considerations. Recently, the OECD published a guidance document on a workflow for characterising and validating PBK models (OECD, 368 369 2021). The quality of the in vitro input data is not explicitly taken into account in this guidance 370 document yet. The results of the present study indicate that the quality of the model predictions will 371 be as good as the quality of the input data. The development of guidelines on the design of in vitro

kinetic studies will therefore be a critical follow up step to this guidance document to gainconfidence in PBK model predictions.

374 Apart from guidance documents on the design of in vitro kinetic studies, guidance 375 documents will also be needed with respect to the applicability of different in vitro kinetic studies 376 with respect to meeting specific regulatory needs. The in vitro kinetic data discussed in the present 377 study, can for example only be used to make first tier estimates of plasma concentrations of the 378 parent compound after oral exposure (Jones and Rowland, 2013). Simulations of inhalation and 379 dermal exposure will require additional kinetic input data on in vitro lung and dermal absorption to 380 mimic these respective exposure routes. The first tier estimates of plasma Cmax and AUC_{0-24h} after 381 oral exposures do also not yet take the contribution of metabolites, possible saturation of 382 biotransformation enzymes, possible involvement of transporters, or possible extrahepatic 383 metabolism into account. At present it remains particularly difficult to determine when additional 384 kinetic processes, like transporter kinetics or extrahepatic metabolism, need to considered for a 385 specific compound (Sager et al., 2015). Additional research is still needed to define the 386 characteristics of chemicals that require the inclusion of these additional kinetic processes (Punt et 387 al., submitted).

388 Whereas the present study focussed on the impact of variation in reported in vitro CLint, 389 Fup and Papp values on PBK model predictions, other in vitro kinetic parameters could be relevant 390 as well. Metabolic clearance is, for example, not only measured with primary hepatocytes, but also 391 with liver microsomes and S9. In addition, in situations where dose-dependent kinetics are of 392 importance, the Michaelis-Menten constants (Km and Vmax) need to be derived from the in vitro 393 metabolism studies. Moreover, in vitro transporter kinetic data (e.g. intestine, kidney and liver 394 transporters) are important for the kinetics of some compounds. A similar description of 395 experimental boundaries and the applicability domain will be needed for each of these studies. Apart from the in vitro kinetic data, in silico predictors of different kinetic parameters have been 396 397 developed as well. Particularly the prediction of partition coefficients (determining the distribution

398 of compounds in different organs) depends on the use of these calculators, as these parameters are 399 difficult to obtain with in vitro experiments. Recently, Punt et al. (submitted) revealed that 400 significant differences can occur as a result of the use of different calculators. For example, the 401 calculation method of Berezhkovskiy (Berezhkovskiy, 2008) led frequently to underpredictions of the C_{max} of acidic compounds (pKa<6), whereas the calculation method of Schmitt (Schmitt, 2012) 402 403 appeared to perform less well for highly lipophilic compounds (Punt et al., submitted). The 404 calculation method of Rodgers and Rowland (Rodgers and Rowland, 2006) performed overall best, 405 and was also applied in the present study to predict the partition coefficients of the different 406 compounds.

407 Overall the results of the present study indicate a strong impact of experimental variation in 408 CLint, Papp and Fup on Cmax and AUC_{0-24H} predictions. This implies that steps need to be taken to 409 reduce experimental variability and the associated uncertainty in order to increase the confidence in 410 these in vitro kinetic data for regulatory use. To this end, it will be crucial that the in vitro 411 experiments are performed in a standardized way and thereby meet the regulatory needs. In 412 addition, the chemical and regulatory applicability domains of the in vitro test systems and kinetic 413 models need to be clearly described. Therefore, it is important that existing protocols are formalized in guidance documents to improve harmonisation of testing procedures and correct usage of test 414 415 findings.

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