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# Predicting *in vivo* Target Occupancy (TO) Profiles via PBPK-TO Modeling of Warfarin Pharmacokinetics in Blood: Importance of Low Dose Data and Prediction of Stereoselective Target Interactions

Wooin Lee, Min-Soo Kim, Jiyoung Kim, Yasunori Aoki, Yuichi Sugiyama

College of Pharmacy and Research Institute of Pharmaceutical Sciences, Seoul National University, 1 Gwanak-ro, Gwanak-gu, Seoul, 08826, Korea (W.L., M-S.K., J.K.); Laboratory of Quantitative System Pharmacokinetics/Pharmacodynamics, Josai International University, 2-3-11 Hirakawa-cho, Chiyoda-ku, Tokyo 102-0093, Japan (Y.A., Y.S.); Drug Metabolism and Pharmacokinetics, Research and Early Development, Cardiovascular, Renal and Metabolism (CVRM), BioPharmaceuticals R&D, AstraZeneca, Gothenburg, Sweden (Y.A.)

#### **Running title page**

Warfarin PBPK modeling with target binding

#### **Correspondence to:**

Wooin Lee, Ph.D. College of Pharmacy and Research Institute of Pharmaceutical Sciences, Seoul National University, 1 Gwanak-ro, Gwanak-gu, Seoul, Korea 08826 Phone: +82-2-880-7873 Fax: +82-2-880-0649 E-mail: wooin.lee@snu.ac.kr

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#### **Abbreviations:**

TMDD, target-mediated drug disposition; PK, pharmacokinetic; PBPK model, physiologically-based pharmacokinetic model; VKOR, vitamin K 2,3-epoxide reductase; OAT2, Organic Anion Transporter 2; ODE, ordinary differential equation; K<sub>p</sub>, the tissue-to-blood partitioning coefficients; K<sub>d</sub>, the equilibrium dissociation constant; k<sub>a</sub>, the absorption rate constant; k<sub>on</sub>, the association rate constant; k<sub>off</sub>, the dissociation rate constant; CYP, cytochrome P450; PS, the permeability surface product; V<sub>d</sub>, the volume of distribution; CL, clearance; CL<sub>int,all</sub>, the overall intrinsic clearance; X<sub>TotalR</sub>, the total amount of the receptor; V<sub>max</sub>, the maximum rate in the Michaelis-Menten equation; CGNM, the Cluster Gauss-Newton Method; SSR, the sum of squared residuals

#### Abstract

Warfarin is well-recognized for its high-affinity and capacity-limited binding to the pharmacological target and undergoes target-mediated drug disposition (TMDD). Here, we developed a physiologically-based pharmacokinetic (PBPK) model that incorporated saturable target binding and other reported hepatic disposition components of warfarin. The PBPK model parameters were optimized by fitting to the reported blood PK profiles of warfarin with no stereoisomeric separation following oral dosing of racemic warfarin (0.1, 2, 5, or 10 mg) using the Cluster Gauss-Newton Method (CGNM). The CGNM-based analysis yielded multiple "accepted" sets for six optimized parameters, which were then used to simulate the warfarin blood PK and in vivo target occupancy (TO) profiles. When further analyses examined the impact of dose selection on uncertainty in parameter estimation by the PBPK modeling, the PK data from 0.1 mg dose (well below target saturation) was important in practically identifying the target binding-related parameters in vivo. When stereoselective differences were incorporated for both hepatic disposition and target interactions, our PBPK modeling predicted that R-warfarin (of slower clearance and lower target affinity than S-warfarin) contributes to TO prolongation following oral dosing of racemic warfarin. Our results extend the validity of the approach by which the PBPK-TO modeling of blood PK profiles can yield TO prediction in vivo (applicable to the drugs with targets of high affinity and abundance and limited distribution volume via non-target interactions). Our findings support that model-informed dose selection and PBPK-TO modeling may aid in TO and efficacy assessment in preclinical and clinical phase-1 studies.

#### Significance Statement

The current PBPK modeling incorporated the reported hepatic disposition components and target binding of warfarin and analyzed the blood PK profiles from varying warfarin doses, practically identifying target binding-related parameters *in vivo*. By implementing the stereoselective differences between R- and S- warfarin, our analysis predicted the role of R-warfarin in prolonging overall target occupancy. Our results extend the validity of analyzing blood PK profiles to predict target occupancy *in vivo*, which may guide efficacy assessment in preclinical and clinical phase-1 studies.

#### Introduction

Target-mediated drug disposition (TMDD) refers to the phenomenon in which the saturable binding of drugs to their pharmacological targets leads to nonlinear pharmacokinetic (PK) behaviors (Levy, 1994). TMDD has been frequently considered for biologics which typically interact with their targets of high specificity and affinity. Once the formation of the drug-target complex reaches saturation with either high doses or repeated dosing, the fraction of the dose binding to the target becomes disproportionately small. As such, systemic drug exposure can increase much larger than expected from a single low dose, leading to dose-dependent PK profiles that are nonlinear at low doses but linear at high doses. Compared to biologics, TMDD occurrence is less common among small-molecule drugs. Yet, TMDD cases have been increasingly reported among small-molecule drugs in recent years (An, 2017).

To enhance our mechanistic understanding of the TMDD among small-molecule drugs, it is important to tease out the relative contribution of saturable target binding to nonlinear PK profiles compared to other components in drug disposition (e.g., saturable metabolism/transport in the liver or intestine). By applying the PBPK modeling with target binding, our group recently reported that target binding, albeit not a major contributor to the nonlinear bosentan PKs, is important in capturing the observed PK profiles at low concentration ranges (Koyama et al., 2021). We also noted that the analysis of blood bosentan PK profiles obtained from a wide range of doses via PBPK modeling with target binding could practically identify target binding-related parameters of bosentan, thereby predicting the target occupancy (TO) profiles *in vivo*. These findings prompted us to pursue additional cases which may expand the validity of our approach of analyzing the blood PK profiles toward the prediction of the TO *in vivo*.

Approved for medical use in 1954, warfarin, a racemic mixture of R- and S-enantiomers, is still considered the mainstay of oral anticoagulant treatment for patients with various cardiovascular diseases. However, the safe use of warfarin remains challenging due to its narrow therapeutic window and large interpatient variability. The anticoagulant effect of warfarin is mediated by high-affinity interactions with its pharmacological target, vitamin K 2,3-epoxide reductase (VKOR), located mainly in the liver. The inhibitory potency of warfarin toward its target varied widely (ranging from nanomolar to millimolar concentrations)

(Bevans et al., 2013), but the underlying reasons for such discrepancies had remained elusive. Later, the presence of dithiothreitol *in vitro* was identified to alter the redox state of VKOR, greatly influencing the inhibitory potencies of warfarin toward VKOR (Shen et al., 2017). The target affinity of warfarin is considered to be stereoselective [S-warfarin being more potent by 3-6 times than R-warfarin, based on the relationship between dose or concentration and response (Breckenridge et al., 1974; O'Reilly, 1974; Hignite et al., 1980)]. Yet, lacking is a detailed understanding of the stereoselective warfarin-target interactions and pharmacological and clinical implications in warfarin therapy.

Saturable target binding of warfarin and its nonlinear PK profiles were noted in rats over four decades ago (Takada and Levy, 1980). Nonlinear PK profiles of warfarin in human subjects, in fact, served as the first case analyzed via TMDD-PK modeling (Levy et al., 2003). Later, a clinical study reported that the saturable target binding of warfarin could hamper the PK extrapolation from a microdose (0.1 mg) to a therapeutic dose (5 mg) (Lappin et al., 2006). The hepatic uptake of warfarin was found to be handled by Organic Anion Transporter 2 (OAT2) with stereoselective affinity and capacity (Bi et al., 2018). So far, none of the previous PK modeling of warfarin incorporated all of the reported components for hepatic warfarin disposition (i.e., metabolism, active uptake, and target binding in the liver). In addition, the previous modeling efforts mainly analyzed the data at therapeutic doses of warfarin but not at a microdose (which displayed a large deviation from dose-proportional PKs).

The current study aimed to develop an updated PBPK-TO model of warfarin by incorporating saturable target binding in addition to the metabolism and uptake components in the liver. Our analysis revisited early clinical data which measured the total warfarin levels from a wide dose range of warfarin, including a microdose. Furthermore, the stereoselective differences between R- and S-warfarin were incorporated in analyzing the warfarin blood PK profiles. We believe that our current results may offer important insights into the factors to consider in predicting and exploiting the TMDD occurrence in small-molecule drug candidates, as well as in designing preclinical studies and clinical phase-1 trials that may shed light on the target engagement *in vivo*.

#### **Materials and Methods**

#### Structure of the warfarin PBPK model

Our PBPK model for warfarin was constructed based on *in silico, in vitro*, and clinical PK data available from the literature. As depicted in Figure 1, the PBPK model included the central (blood) compartment connected to the liver, subdivided into five extrahepatic and hepatocellular compartments, and incorporated the active uptake and target binding components for warfarin. The structure of our PBPK model was similar to that reported previously, except for having the target binding components in the hepatocellular compartments (Koyama et al., 2021). To accommodate the large volume of distribution observed with warfarin, the central (blood) compartment was connected to three large-volume tissues (adipose, muscle, and skin) with the assumption of rapid equilibrium and using the tissue-to-blood partitioning coefficients ( $K_p$ ) calculated *in silico* using the method reported by Rodgers and Rowland (Rodgers and Rowland, 2006). Orally administered warfarin was assumed to be completely absorbed from the intestine to the extrahepatic compartment with a first-order rate constant  $k_a$  (/h), similar to the previous report (Bi et al., 2018). The hepatic disposition processes of warfarin were described by incorporating the following components: active influx by OAT2, metabolism by cytochrome P450 (CYP) enzymes, and target binding to VKOR.

Our PBPK model was fitted to the reported average blood PK profiles of warfarin with no stereoisomeric separation [2, 5, and 10 mg (King et al., 1995); 0.1 mg (Lappin et al., 2006)] (Figure 2A). The analysis included no interindividual variability as we had no access to individual-level data. Initially, the modeling was done using ordinary differential equations (ODEs) which did not separate R- and S-warfarin. The model included a total of 24 parameters, including six unknown and 18 fixed parameters (Table 1). Subsequent analyses  $\langle RS\#1-\#3 \rangle$  utilized the same reported blood PK dataset, but the ODEs were separated for R- and S-warfarin. Stereoselective parameters were estimated from the information available in the literature. The model included a total of 26 parameters, including six unknown (4 stereoselective parameters;  $X_{TotalR}$  and  $k_a$  kept the same for R- and S-warfarin) and 20 fixed parameters (Table 2).

#### Parameters for the warfarin PBPK model

The hepatic permeability clearance of warfarin was considered by incorporating the active influx clearance mediated mainly by OAT2 (PS<sub>act,inf</sub> described using  $V_{max(act,inf)}$  and  $K_{m(act,inf)}$ ) along with the permeability clearance via passive influx and efflux (PS<sub>dif,inf</sub>, and PS<sub>dif,eff</sub>, respectively). The experimentally measured  $K_{m(act,inf)}$  values for R- and S-warfarin were reported to be 7.3 and 10.4 µM, respectively (Bi et al., 2018). The same study reported the  $V_{max(act,inf)}$  and PS<sub>dif,inf</sub> values (per million hepatocytes), yielding the corresponding values of 3,063 µmole/h and 12.0 L/h for an adult of 70 kg body weight (the following scaling factors were used; 118 million hepatocytes/g liver; 24.5 g liver/kg body weight). For the initial model fitting of the warfarin PK profiles,  $V_{max(act,inf)}$  was set as unknown (the lower and upper ranges set as  $10^{-2}$  and  $10^{2}$ -fold to the base value 3,063 µmole/h), and  $K_{m(act,inf)}$  was fixed as 8.85 µM (Table 1). Subsequent analyses <RS#1-#3> considered the stereoselective differences for  $K_{m(act,inf)}$  (fixed as 7.3 and 10.4 µM for R- and S-warfarin, respectively) and  $V_{max(act,inf)}$  [optimized for R-warfarin; the reported fold-difference of 0.506 was then used to calculate the corresponding value for S-warfarin, (Bi et al., 2018)] (Table 2).

The intrinsic metabolic clearance ( $CL_{int(met)}$ ) of warfarin in the hepatocellular compartment was described using  $V_{max(met)}$  and  $K_{m(met)}$ . For the model fitting of the warfarin PK profiles,  $K_{m(met)}$  was fixed as 10  $\mu$ M considering the reported  $K_{m(met)}$  values ranging from 3.9 to 24.3  $\mu$ M (Shaik et al., 2016). The previous study reported the  $CL_{int(met)}$  values of 0.1175 and 0.365  $\mu$ mol/min/mg microsomal protein for R- and S-warfarin, respectively (Bi et al., 2018). By applying the scaling factors (40 mg microsomal proteins/g liver; 24.5 g liver/kg body weight) and using the assumed  $K_{m(met)}$  value (10  $\mu$ M), the  $V_{max(met)}$  values were estimated as 4.145 and 12.88 L/h for R- and S-warfarin, respectively. For the initial model fitting of the warfarin PK profiles,  $V_{max(met)}$  was set as unknown (the lower and upper ranges set as  $10^{-2}$  and  $10^2$ -fold to the base value 8.511  $\mu$ mole/h) (Table 1). Subsequent analyses <RS#1-#3> considered the stereoselective differences for  $V_{max(met)}$  [optimized for R-warfarin; the reported fold-difference of 3.10 was used to calculate the corresponding value for S-warfarin (Bi et al., 2018)] (Table 2). The target binding of warfarin was modeled to be connected to the hepatocellular compartment [reflecting the primary location of VKOR inside hepatocytes (Hazelett and Preusch, 1988)] with the assumption that warfarin binds reversibly to VKOR in the stoichiometric ratio of 1:1 with the dissociation rate constant  $k_{off}$  and the equilibrium dissociation constant  $K_d$  (the association rate constant  $k_{on}$  was defined automatically as  $k_{off}/K_d$ ). For the initial model fitting of the warfarin PK profiles, the parameters of  $k_{off}$ ,  $K_d$ , and  $X_{TotalR}$  were set as unknown parameters [with the base values based on the previous report (Levy et al., 2003); Table 1] using the following Eqs. (1) and (2):

$$\frac{dX_{\text{FreeR}(i)}}{dt} = k_{\text{off}} \cdot X_{\text{RDcomplex}(i)} - \frac{k_{\text{off}}}{K_{\text{d}}} \cdot f_{\text{h}} \cdot C_{\text{HC}(i)} \cdot X_{\text{FreeR}(i)} \qquad \text{Eq. (1)}$$
$$\frac{dX_{\text{RDcomplex}(i)}}{dt} = \frac{k_{\text{off}}}{K_{\text{d}}} \cdot f_{\text{h}} \cdot C_{\text{HC}(i)} \cdot X_{\text{FreeR}(i)} - k_{\text{off}} \cdot X_{\text{RDcomplex}(i)} \qquad \text{Eq. (2)}$$

(Initial conditions at time zero,  $X_{FreeR(i)}(0) = X_{TotalR}/5$ ,  $X_{RDcomplex(i)}(0) = 0$ )

 $(X_{FreeR(i)}, X_{RDcomplex(i)}, and X_{TotalR(i)}$  represent the amounts of free target, drug-target complex, and total target in the *i*th hepatocellular compartment, respectively;  $f_h$  and  $C_{HC(i)}$  represent the fraction of unbound warfarin and the total concentration of warfarin in the *i*th hepatocellular compartment, respectively).

Subsequent analysis <RS#1-#3> utilized the ODEs separated for R- and S-warfarin except for Eq. (3), which was revised from Eq. (1) to consider the competitive interactions of S- and R-warfarin for the free target:

$$\frac{dX_{FreeR(i)}}{dt} = k_{off} \cdot (X_{RDcomplex(i),R-warfarin} + X_{RDcomplex(i),S-warfarin}) - \frac{k_{off}}{K_d} \cdot f_h \cdot (C_{HC(i),R-warfarin} + C_{HC(i),S-warfarin}) \cdot X_{FreeR(i)}$$
Eq. (3).  
(Initial condition at time zero,  $X_{FreeR(i)}(0) = X_{TotalR}/5$ )

 $(X_{RDcomplex(i),R-warfarin} \text{ and } X_{RDcomplex(i),S-warfarin} \text{ represent the amounts of drug-target complex by the respective R$ and S-isomers in the*i* $th hepatocellular compartment; <math>C_{HC(i),R-warfarin}$  and  $C_{HC(i),S-warfarin}$  represent the total concentration of R- and S-warfarin in the *i*th hepatocellular compartment, respectively). The analyses of <RS#2> and <RS#3> incorporated S-warfarin having the K<sub>d</sub> value three-fold lower than Rwarfarin, but assumed the stereoselective differences at the association and dissociation steps, respectively (Table 2).

#### Parameter Optimization by the Cluster Gauss-Newton Method (CGNM)

Being computationally efficient and robust in obtaining multiple possible solutions to nonlinear least-square problems, the Cluster Gauss-Newton method (CGNM) has been recently applied to the PBPK modeling of bosentan (Koyama et al., 2021) and CP-1 (Mochizuki et al., 2022; Yoshikado et al., 2022). A key assumption of the CGNM is that for some model parameters not identifiable from the data, multiple parameter combinations may provide equally as good model fits as the best model fit. Briefly, the CGNM finds multiple best-fit parameter combinations by repeating the parameter estimations from a wide range of initial iterates. Our initial analysis with the ODEs of no stereoisomeric separation uniformly and randomly generated 1,000 initial combinations of 6 unknown parameters (K<sub>d</sub>, k<sub>off</sub>,  $X_{TotalR}$ , k<sub>a</sub>,  $V_{max(met)}$ , and  $V_{max(act,inf)}$ ) with user-specified upper and lower ranges (typically,  $10^{-2}$  to  $10^2$ -fold to the base values; Table 1). Then using each of these parameter combinations as the initial iterate, the parameter combination was iteratively moved until it reached the minimum sum of squared residuals (SSR) as defined below:

$$SSR = \sum_{i=1}^{n} \left( \log_{10} y_{obs,i} - \log_{10} y_{model-predicted,i} \right)^2 \qquad \text{Eq. (4)}$$

 $(y_{obs,i})$ , the *i*th observed value;  $y_{model-predicted,i}$ , the *i*th model-predicted value)

As the above-mentioned approach using a conventional nonlinear least squares algorithm (e.g., Gauss-Newton method) is computationally intensive, the CGNM was made to remedy the computational bottleneck [see (Aoki et al., 2020) for detailed comparison with conventional algorithms].

The PBPK modeling was done by numerically integrating a set of ODEs by RxODE version 1.1.2 with default setting (Fidler M, 2022) and the CGNM implemented in R version 4.0.3, CGNM package version 0.3.1 (Aoki, 2022) with default setting except having a set number of initial parameter combinations (num\_minimizersToFind) to 1,000 and the number of iteration (num\_iteration) to 100 as suggested in the user manual. To select parameter combinations from final iterates with similarly small SSR values, the SSR values from parameter combinations were plotted in ascending order. In theory, we wish to find parameter combinations with identical minimum SSR values. However, in reality, it is often not possible with numerical artifacts. Thus, we used a heuristic called the "elbow method" to detect a sudden increase in SSR. Before we

applied the elbow method, we rejected parameter combinations that were statistically significantly worse than the minimum SSR by assuming chai square distribution of SSR (with cutoff alpha 0.05). If there were multiple sudden increases in SSR, the elbow method may not find the first sudden increase. In that case, the elbow method was repeated until similarly small SSRs were selected. The analysis was conducted using acceptedApproximateMinimizers command in the CGNM package and the resulting selections of parameter combinations were referred to as "accepted."

#### Parameter estimation uncertainty quantification by the bootstrap analysis

To quantify the parameter estimation uncertainty, residual resampling bootstrap analyses were conducted by creating 200 bootstrap datasets and re-estimating the parameters. Each re-estimation was conducted from an initial iterate randomly selected from the accepted parameter combinations. This analysis was conducted using Cluster\_Gauss\_Newton\_Bootstrap\_method command in CGNM package and the parameter distributions obtained from the bootstrap analysis were plotted as histograms.

# *Post hoc* study design evaluation to assess the importance of dose selection for the estimation of target binding-related parameters

To assess how the study design, in terms of dose selection, can impact the estimation of target binding-related parameters ( $K_d$ ,  $k_{off}$ , and  $X_{TotalR}$ ), we investigated their estimation uncertainties with varying three-dose-level designs. The following designs were created by removing one dose arm from the full dataset: <design A> contains 2, 5, and 10 mg arms; <design B> contains 0.1, 5, and 10 mg arms; <design C> contains 0.1, 2, and 5 mg arms; <design D> contains 0.1, 2, and 10 mg arms. CGNM was used to obtain accepted parameter combinations for each dataset, and then the bootstrap analyses were conducted for  $K_d$ ,  $k_{off}$ ,  $X_{TotalR}$  for each dataset.

#### Results

# CGNM-based parameter optimization for warfarin PBPK modeling and prediction of TO profiles Our PBPK-TO modeling analyzed the reported nonlinear PK profiles of warfarin over 120 h at four warfarin dose levels (0.1, 2, 5, and 10 mg) (Figure 2A). The "accepted" parameter sets (determined by the elbow method described in the Methods section) showed nearly identical SSR values of around 0.115 (Table 3). When the CGNM runs were repeated two additional times with different initial iterates, the results were nearly identical (Table S1). Five out of six optimized parameters were distributed in a very tight range, with the "rank 1" parameter values (with the smallest SSR) and median values nearly identical. The exception was for $V_{max(act,inf)}$ , which varied widely among the accepted parameter sets. Similar to our previous study of bosentan (Koyama et al., 2021), the CGNM-based PBPK modeling of the blood warfarin PK profiles alone appeared to achieve practical identifiability for three parameters related to the target binding *in vivo* (K<sub>d</sub>, k<sub>off</sub>, and X<sub>TotalR</sub>).

For all four dose levels, the accepted parameter sets well captured the observed blood PK profiles and predicted the TO profiles in a narrow range for each dose level (Figure 2). Despite a wide variation in the  $V_{max(act,int)}$  values among the 663 sets of the accepted parameters, the accepted parameter sets yielded overlapping blood PK profiles, which appeared nearly as a single profile for each dose level (Figure 2A). Such good agreements could be explained by the calculation results showing nearly identical values of 11.93 L/h for the overall intrinsic clearance (CL<sub>int.all</sub> based on the extended clearance concept model) despite a wide variation in the  $V_{max(act,int)}$  values (Table 3). These results support that the active uptake is unlikely to be rate-determining in the overall hepatic elimination of warfarin. The 633 sets of the accepted parameter combinations also led to the simulated TO profiles, which appeared nearly as a single profile for each dose level (Figure 2B). The ranges of the accepted parameters were very narrow with the rank 1 and median values nearly identical. As an example, the rank 1 parameter combinations were used to simulate the TO profiles. The maximum TO values of 0.064, 0.818, 0.952, and 0.980 for 0.1, 2, 5, and 10 mg, respectively. The predicted TO values at 120 h post-dosing were 0.050, 0.574, 0.757, and 0.859 for 0.1, 2, 5, and 10 mg, respectively.

#### Impact of dose selection on prediction of warfarin TO profiles via PBPK-TO modeling

To examine whether and how much dose selection impacts parameter estimation and TO prediction from the blood PK data, the CGNM results were compared using four study designs of three-dose-level combinations. Similar to <ALL dataset (0.1, 2, 5, and 10 mg)>, all four study designs <designs A to D> well captured the observed blood PK profiles (Figure 3A) and predicted the TO profiles in a tight range (Figure 3B). < Design A> omitting the dose of 0.1 mg yielded the rank 1 parameter values comparable to those from <ALL dataset>, except for k<sub>off</sub> (0.0903 vs 0.0432 /h; 2.1-fold differences) and V<sub>max(act.inf)</sub> (Table 4, Figure 4A). The ranges of the final parameters were very narrow, yielding nearly identical values for the rank 1 and median values. The rank 1 parameter  $k_{off}$  value (0.0432 /h) from <design A> was comparable to the reported  $k_{off}$  value (0.0405 /h) from the previous TMDD-PK modeling which had analyzed the 2, 5, and 10 mg doses (Levy et al., 2003). For <designs B, C, and D>, which included 0.1 mg data, the accepted parameters also well captured the observed blood PK profiles of warfarin and predicted the TO profiles in a tight range (Figure 3). Unlike <design A>, the rank 1 parameter values for  $k_{off}$  was comparable between <designs B, C, and D> and <ALL dataset>: 0.0961, 0.932, 0.0901 vs. 0.0903 /h (Table 4). The bootstrap analysis informed that <design A> was associated with greater uncertainty in parameter estimation, noticeably, for the two parameters related to the target binding  $(K_d \text{ and } k_{off})$  (Figure 4B). Compared to <design A>, the uncertainty in parameter estimation was reduced to some extent in <design B> and to a greater extent in <designs C and D> which included both 0.1 and 2 mg, noticeable for X<sub>TotalR</sub> (Figure 4B).

## Warfarin PBPK-TO modeling incorporating stereoselective differences and prediction of TO profiles by individual stereoisomers

For the scenario of  $\langle RS\#1 \rangle$  (with stereoselective consideration in the hepatic metabolism and uptake processes but not in target interactions), the accepted parameter sets well captured the reported blood PK profiles of warfarin (measured with no stereoisomeric separation) at all four dose levels (sold black lines, Figure 5A). The predicted blood PK profiles for S-warfarin declined more rapidly than those for R-warfarin, in line with the calculated CL<sub>int,all</sub> values of 20.7 and 7.29 L/h for S- and R-warfarin, respectively (Table 5). At the dose levels of 0.1 and 2 mg, the simulated TO profiles for S- and R-warfarin decreased over 120 h, with a more rapid decline for S-warfarin than R-warfarin (Figure 5A). At the dose levels of 5 and 10 mg, the

TO profiles by S-warfarin declined steadily, but those by R-warfarin increased over time, attributable to the increasing engagement of R-warfarin to the target that became available from the dissociation of the target complexed with S-warfarin (Figure 5A).

The scenarios of  $\langle RS#2 \rangle$  and  $\langle RS#3 \rangle$  assumed three-fold differences in the target affinity (K<sub>d</sub>) between Rand S-warfarin (S-warfarin having a 3-fold lower K<sub>d</sub> value than R-warfarin) arising from the differences at the association and dissociation steps, respectively. In either scenario, the PBPK models captured the reported blood PK profiles of warfarin with the accepted SSR comparable to those of  $\langle RS#1 \rangle$  (Figures 5B and 5C, Table 5). For  $\langle RS#2 \rangle$  (S-warfarin with three-fold greater k<sub>on</sub> than R-warfarin), the simulation results showed that at early time points, the target engagement was dominated by S-warfarin over R-warfarin: At 2 h postdosing, the target engagement by S-warfarin was greater by 1.56-, 1.93-, 2.29- and 2.46-fold than by Rwarfarin at the 0.1, 2, 5, and 10 mg dose levels, respectively (Figure 5B). However, the target engagement by R-warfarin was predicted to be dominant from approximately 60 h post-dosing on (Figure 5B, appearing as cross-over points in the simulated TO profiles). Different from  $\langle RS#2 \rangle$ , the results from  $\langle RS#3 \rangle$  (S-warfarin assumed to have one-third k<sub>off</sub> to R-warfarin) predicted the target engagement comparable between R- and Swarfarin at early time points, especially within 1 h post-dosing (Figure 5C). The target engagement by Swarfarin stayed dominant over R-warfarin until the cross-over points at approximately 60 h post-dosing (Figure 5C).

#### Discussion

The current study developed a PBPK-TO model that can analyze the systemic warfarin PK profiles and predict TO profiles *in vivo*. Like the case of bosentan (Koyama et al., 2021), the CGNM-based analysis of the systemic warfarin PK profiles alone yielded practically identifiable target binding parameters and predicted TO profiles in a very tight range (Table 3, Figure 2). Further analyses indicated that dose selection (the inclusion of 0.1 mg dose; which leads to systemic drug exposure well below target saturation) is important in reducing the uncertainty in estimating target binding-related parameters (Figure 4, Table 4). By incorporating the stereoselective differences between R- and S-warfarin, the current PBPK-TO model predicted the target engagement of each stereoisomer under differing scenarios (Figure 5). Overall, these findings extend the validity of the approach by which the mechanistic PBPK-TO modeling captures the impact of saturable target binding on the systemic PK data and, in turn, allows for the identification of target binding parameters (thereby, TO profiles *in vivo*) based on the systemic PK data alone.

In developing the current PBPK-TO model, the two previous reports on warfarin PK modeling provided a key foundation (Levy et al., 2003; Bi et al., 2018). Bi et al. (Bi et al., 2018) provided the estimates for various parameters of the PBPK model including the handling of warfarin by OAT2. The authors reported that the active uptake of warfarin mediated by OAT2 contributes to the inter-patient variability (Bi et al., 2018). Those results are not contradictory to those from our current study, in that the inter-patient variability of CL<sub>int,all</sub> may be impacted by both PS<sub>act,inf</sub> and CL<sub>met,int</sub> (shown in Eq. (\*2), Table 3 footnote). If one compares, regarding their relative contribution to inter-patient variability associated with CL<sub>int,all</sub>, CL<sub>met,int</sub> is likely to have a greater contribution than PS<sub>act,inf</sub> which has additional terms of  $\gamma$  and PS<sub>dif,inf</sub> in Eq. (\*2). Different from the previous TMDD modeling of warfarin based on the compartmental model with the target binding component connected to the hepatocellular compartment (reflecting the primary location of VKOR in hepatocytes) (Figure 1). During CGNM-based parameter optimization in our current study, the initial parameter sets were randomly selected from the ranges covering  $10^{-2}$ - to  $10^2$ -fold to the base values from the previous reports (Tables 1 and 2). Despite having four orders of magnitude ranges in which initial iterates could be selected,

our analysis with the ODEs of no stereoisomeric separation yielded the final optimized parameters for target binding *in vivo* in a tight range indicating these parameters are identifiable from the plasma concentration data: the rank 1 and median parameter values were nearly identical, being 6.30 nM, 0.0903 /h, and 4.26 µmole for K<sub>d</sub>, k<sub>off</sub>, and X<sub>TotalR</sub>, respectively (Table 3). In the literature, the K<sub>d</sub> values for the binding of warfarin to VKOR vary widely, attributable in part to the differences in *in vitro* binding assay conditions (in particular, the presence of reducing agents altering the redox state of VKOR) (Bevans et al., 2013; Shen et al., 2017). Our current study supports the predictive utility of the PBPK-TO modeling for *in vivo* target binding parameters when the blood PK profiles are available with appropriate dose selection.

The model-predicted target abundance (X<sub>TotalR</sub>) for warfarin was 4.26 µmole for 70 kg human body (Table 3). For warfarin doses of 0.1 and 2 mg (corresponding to 0.325 and 6.49 µmole, respectively), the high-affinity interaction of the drug with the target ( $X_{TotalR}$  of 4.26 µmole) may represent a significant fraction of the doses. The binding mode of warfarin to VKOR is not fully understood, and some controversies still exist as to whether or not the binding is reversible (Wu et al., 2018). When the formation of the warfarin-target complex is assumed to be reversible (thus not serving as a clearance mechanism), the high-affinity interactions between warfarin and its target may still impact the volume of distribution  $(V_d)$  by providing additional drug distribution space to which the drug initially and preferentially distributes. The  $V_d$  values calculated using non-compartmental analysis confirm such a nonlinear relationship for the blood PK dataset analyzed in the current study (Figure 6A). In theory, at a very low dose, the apparent  $V_d$  would approximate the summation of X<sub>TotalR</sub>/K<sub>d</sub> and V<sub>d</sub> via non-specific (non-target-mediated) tissue binding, V<sub>d(non-target)</sub>, as illustrated in Figure 6B. With escalating doses, the high-affinity target binding becomes saturated and no longer contributes to apparent drug distribution space (thus approximating  $V_{d(non-target)}$ ). In the case of warfarin and other drugs with targets of high affinity and abundance (i.e., small K<sub>d</sub> and large X<sub>TotalR</sub>) and limited distribution via non-specific tissue binding (i.e., small  $V_{d(non-target)}$ ), the substantial contribution of  $X_{TotalR}/K_d$  to the  $V_d$  can be expected, noticeable especially at low doses. For highly lipophilic drugs with less confined tissue distribution (i.e., large V<sub>d(non-target</sub>)), the impact of target binding would be minimal or not readily discernible (Figure 6B). For smallmolecule drugs which feature large  $X_{TotalR}/K_d$  and small  $V_{d(non-target)}$  values, it can be postulated that the PK

data at low doses, including a microdose, can provide valuable information in ascertaining the ratio of  $X_{TotalR}/K_d$ . When the dose ranges cover from low (well below target saturation; informative on  $X_{TotalR}/K_d$ ) and high doses (at target saturation; informative on  $V_{d(non-target)}$ ), the analysis of the systemic PK data alone may allow for the prediction of TO with reasonable certainty.

Our current results using warfarin imply a potentially important yet under-appreciated advantage that the PBPK modeling and microdosing approach may offer for the development of small-molecule drug candidates with potential for TMDD (Burt et al., 2020). If a drug candidate is predicted to have a significant contribution to the target binding-related component (i.e., large  $X_{TotalR}/K_d$  and relatively small  $V_{d(non-target)}$ ), our proposal is to verify the *in vivo* occurrence of the TMDD in preclinical animals by obtaining the blood PK data with ascending doses including a microdose, and intermediate and high doses (covering varying degrees of target binding). In the case of warfarin, the blood PK data in rats clearly indicated much larger  $V_d$  values in those receiving 0.1 mg/kg than those receiving 1 mg/kg (Takada and Levy, 1980). With appropriate consideration of the species differences in the target binding-related parameters (e.g.,  $X_{TotalR}, K_d$ , unbound fraction), it may be possible to identify drug candidates with a high likelihood of TMDD in humans. In such cases, the blood PK data from a microdosing study and PBPK-TO modeling can provide invaluable insights into TO profiles *in vivo*, potentially guiding the interpretation and optimization of pharmacodynamic responses in humans. The prospect of obtaining the TO profiles *in vivo* from the blood PK data alone may aid in overcoming the difficulties in translating *in vitro* potency to *in vivo* efficacy.

By incorporating the stereoselective differences in hepatic disposition and target binding between R- and Swarfarin, the current PBPK-TO model analyzed the blood PK profiles of warfarin (measured with no stereoisomeric separation) and predicted the TO profiles by individual stereoisomers under differing scenarios. Both  $\langle RS\#2 \rangle$  and  $\langle RS\#3 \rangle$  shared the assumption that S-warfarin has a 3-fold higher affinity than R-warfarin (i.e., K<sub>d,S-warfarin</sub> being one-third to K<sub>d,R-warfarin</sub>) based on the information available in the literature (Breckenridge et al., 1974; O'Reilly, 1974; Hignite et al., 1980). While  $\langle RS\#2 \rangle$  assumed that K<sub>d</sub> differences arise from the association process (i.e., k<sub>on,S-warfarin</sub> being three times to k<sub>on,R-warfarin</sub>),  $\langle RS\#3 \rangle$  assumed that K<sub>d</sub>

differences arise from the dissociation process (i.e., koff,S-warfarin being one-third to koff,R-warfarin). Currently, there is no data that experimentally verified the stereoselective differences in the binding affinity of R- and Swarfarin. Of note, Cheng et al. {Cheng, 2023 #626} applied the PK modeling with the TMDD components to the observed plasma PK profiles of S- and R-warfarin independently. The results showed 3.61-fold differences in the K<sub>d</sub> values of S- and R-warfarin (in line with the assumption of 3-fold K<sub>d</sub> differences in our current study). Molecular docking simulation predicted energetically favorable interactions for S-warfarin than for R-warfarin in binding with human VKOR (Lewis et al., 2016). Yet, it remains to be verified whether the stereoselective differences between S- and R-warfarin in interacting with VKOR involve association, dissociation, or both. In our analysis, the TO profiles by individual stereoisomers showed some differences between <RS#2> and <RS#3> (Figure 5). However, between <RS#2> and <RS#3>, little differences were observed in the summed TO profiles by R- and S-warfarin. These results may be explained by the compensatory, competitive formation of the drug-target complex between R- and S-warfarin. For instance, Swarfarin is more rapidly cleared than R-warfarin, and the equilibrium gets shifted toward the dissociation of the S-warfarin-target complex, and the dissociated target would become available to complex with R-warfarin. When the TO profiles were simulated for a typical repeated warfarin dosing regimen (10 mg for 2 days and 3 mg afterwards), the results also showed a similar profile of the compensatory formation of R-warfarin-target complex (Figure S1). As such, the dosing of racemic warfarin may prolong the target engagement and produce the target engagement and pharmacodynamic effect with a lesser degree of inter- and intra-individual variability than the dosing of single stereoisomeric warfarin.

In conclusion, we successfully developed and applied an updated PBPK-TO model to analyze the blood PK profiles of warfarin over a wide dose range, including a microdose. Our results using warfarin support the approach by which target engagement *in vivo* may be predicted with reasonable certainty from the analysis of the systemic PK data impacted by target binding. Opportunity for prediction of target engagement *in vivo* may be attainable with the model-informed selection of a dose range covering a varying extent of target saturation, in particular, by including low doses below target saturation during dose escalation of clinical phase-1 trials. Information obtained on target engagement *in vivo* can serve as a valuable guide and tool in interpreting and optimizing pharmacodynamic responses.

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#### **Data Availability Statement**

The authors declare that all the data supporting the findings of this study are contained within the paper.

#### Authorship contributions

Participated in research design: WL, YA, YS

Performed data analysis: MK, WL, JK, YA, YS

Wrote or contributed to the writing of the manuscript: WL, MK, JK, YA, YS

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#### Footnotes

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#### **Conflict of Interest**

No author has any potential conflict of interest to disclose.

#### **Figure legends**

**Figure 1.** Structure of the warfarin PBPK model incorporating saturable components for the hepatic active influx, metabolism, and target binding in the liver. Parameters are defined in the main text and Supplemental Material.

**Figure 2.** Blood PK (**A**) and TO (**B**) profiles of warfarin (racemic mixture) using the accepted parameter sets from the CGNM-based PBPK modeling of the warfarin blood PK data [2, 5, and 10 mg from (King et al., 1995) and 0.1 mg from (Lappin et al., 2006)] with the ODEs not separated for R- and S-warfarin. For each dose, open symbols represent the observed data, and lines represent the profiles with the accepted parameter sets. The accepted parameter sets (n=663) were used to draw the profiles, but the results were overlapping and appeared as a nearly single profile for each dose level.

**Figure 3.** Blood PK **(A)** and TO **(B)** profiles of warfarin using varying three-dose-level combinations: design A to D. For each dose (shown in different colors), open symbols represent the observed data, and lines represent the profiles with the accepted parameter sets. The accepted parameter sets were used to draw the profiles, but the results were overlapping and appeared as a nearly single profile for each dose level.

**Figure 4. (A)** Distribution of the accepted parameter sets from the CGNM runs using varying three-dose-level combinations: design A to D. The closed circles represent median values, and the dashed lines are drawn from the minimum to maximum values while the solid lines mark quartile values. The bandwidth represents kernel density estimated by Silverman's method. (B) Histograms for the bootstrap distribution of the accepted parameter sets from the CGNM runs using designs A to D.

**Figure 5.** Summary of the stereoselective PBPK-TO modeling (<RS #1, RS#2, and RS#3>) of R- and Swarfarin based on the warfarin blood PK data (0.1, 2, 5, and 10 mg racemic warfarin doses). (A) The <RS #1> incorporated the R- vs. S-warfarin differences in the hepatic metabolism and uptake processes but no differences in target interactions (K<sub>d</sub> values kept the same for R- and S-warfarin). (**B** and **C**) While <RS#2>

assumed that  $K_d$  differences arise from the association process (i.e.,  $k_{on,S-warfarin}$  being three times to  $k_{on,R-warfarin}$ ), <RS#3> assumed that  $K_d$  differences arise from the dissociation process (i.e.,  $k_{off,S-warfarin}$  being one-third to  $k_{off,R-warfarin}$ ). Blood PK and TO profiles of warfarin (separate profiles for S- and R-warfarin shown in purple and orange, respectively; combined profiles for both R- and S-warfarin shown in grey). For each dose, symbols represent the observed data, and lines represent the profiles with the accepted parameter sets, which appear to overlap.

**Figure 6.** (A) Parameters (CL/F and  $V_d/F$ ) calculated via non-compartmental analysis of the observed blood PK profiles of warfarin [2, 5, and 10 mg from (King et al., 1995) and 0.1 mg from (Lappin et al., 2006)]. (**B**) A theoretical basis for the impact of dose selection on the apparent  $V_d$  for drugs that interact with targets of high affinity and abundance. Modeling-based analysis of the systemic PK data from low and intermediate doses (with varying levels of target saturation) can provide valuable information ascertaining the ratio of  $X_{TotalR}/K_d$ , thereby reducing uncertainty in the estimation of target binding parameters.

**Table 1.** List of <u>optimized</u> and <u>fixed</u> parameters in the warfarin PBPK model with the ordinary differential equations of no stereoisomeric separation. For parameter optimization by the Cluster Gauss-Newton Method (CGNM), the initial estimates were set with the upper and lower ranges as specified from  $10^{-2}$  and  $10^{2}$ -fold to the base values from the literature.

Parameter		Value/ range (min, max)	Calculation	Reference		
K <sub>d</sub> (nM)	Opt*	(0.041, 410)	Base value of 4.1 nM; 321 nM (as the total warfarin in plasma) x 0.013 $(f_{u,p})$	Target-binding-		
$k_{off}(/h)$	Opt	(0.000405, 4.05)	Base value of 0.0405 /h	related parameters from (Levy et al.,		
X <sub>TotalR</sub> (μmol)	Opt	bt (0.117, 1,170) Base value of 11.7 μmol; 0.167 μmole/ x 70 kg		2003)		
V <sub>max(met)</sub> Opt (0.08511, 851.1) (μmol/h)		(0.08511, 851.1)	Base value of 8.511 $\mu$ mol/h; the intrinsic metabolic clearance of (R) 0.4145 and (S) 1.288 L/h divided by the assumed K <sub>m(met)</sub> value (10 $\mu$ M)	Hepatic metabolism and uptake parameter		
V <sub>max(act,inf)</sub> (µmol/h)	Opt	(30.63, 306,300)	Base value of 3,063 μmol/h; averaged from (R) 4,067 μmol/h and (S) 2,059 μmol/h	from (Bi et al., 2018)		
k <sub>a</sub> (/h)	Opt	(0.1, 6)	upper bound as the gastric emptying rate of 0.1 min <sup>-1</sup> (= 6 h <sup>-1</sup> )	(Levy et al., 2003)		
V <sub>central</sub> (L)	Fixed	5.215	0.0745 L/kg x 70 kg	(Levy et al., 2003)		
K <sub>m(act,inf)</sub>	Fixed	8.85	8.85 $\mu M;$ averaged from (R) 10.4 $\mu M$ and	(Bi et al., 2018)		
$\begin{array}{l} (\mu M) \\ R_{dif} \\ (PS_{dif,inf} / \\ PS_{act,inf}) \end{array}$	Fixed	0.0355	(S) 7.3 $\mu$ M PS <sub>dif,inf</sub> of 12.0 L/h; averaged from (R) 13.4 L/h and (S) 10.6 L/h PS <sub>act,inf</sub> of 337 L/h; averaged from (R) 391 L/h and (S) 282 L/h	(Bi et al., 2018)		
$K_{m(met)}$ ( $\mu M$ )	Fixed	10	Assumed based on the reported K <sub>m</sub> values	(Shaik et al., 2016)		
$\begin{array}{c} f_{u,B} \\ f_h \end{array}$	Fixed Fixed	0.022 0.69	$f_{u,p} / R_b = 0.013 / 0.59$	(Bi et al., 2018)		
K <sub>pa</sub>	Fixed	0.0883	In silico prediction			
K <sub>pm</sub>	Fixed	0.115	In silico prediction	(Rodgers and		
K <sub>ps</sub>	Fixed	0.477	In silico prediction	Rowland, 2006)		
Q <sub>h</sub> (L/h)	Fixed	86.8	1.24 L/h/kg x 70 kg			
$Q_a(L/h)$	Fixed	15.6	0.223 L/h/kg x 70 kg			
$Q_m(L/h)$	Fixed	44.9	0.642 L/h/kg x 70 kg	(Davies and Morris,		
$Q_s(L/h)$	Fixed	18.0	0.257 L/h/kg x 70 kg	(Davies and Worris, 1993)		
$V_h(L)$	Fixed	1.22	0.0174 L/kg x 70 kg	,		
$V_a(L)$	Fixed	10.0	0.143 L/kg x 70 kg			
$V_m(L)$	Fixed	30.0	0.429 L/kg x 70 kg			
$V_{s}(L)$ $V_{he}(L)$	Fixed Fixed	7.77 0.469	0.111 L/h/kg x 70 kg 0.0067 L/kg x 70 kg	(Kawai et al., 1998)		

\* Optimized;  $f_{u,B}$ , Fraction unbound in blood;  $f_{u,p}$ , Fraction unbound in plasma;  $R_b$ , Blood-to-plasma ratio;  $f_h$ , Fraction unbound in hepatocytes; Definition of the rest of the parameters provided in the Supplemental Material.

**Table 2**. List of <u>optimized</u> and <u>fixed</u> parameters in the stereoselective warfarin PBPK model with the ordinary differential equations of stereoisomeric separation. The parameters were kept same as Table 1, except for the stereoselective parameters listed below. Out of the six optimized parameters, the two parameters ( $X_{TotalR}$  and  $k_a$ ) were assumed to be same between R- and S-warfarin.

Parameter		Value/ Range (lower, upper)	Description for stereos	elective differences a	pplied		Reference
$K_{m,(act,inf),R-warfarin}$ ( $\mu M$ ) $K_{m,(act,inf),S-warfarin}$ ( $\mu M$ )	Fixed Fixed	10.4 7.3	(Experimentally obtain	ned values reported in	the literature)		
R <sub>dif,R-warfarin</sub>	Fixed	0.0341	PS <sub>dif,inf</sub> : (R) 13.4 L/h, (				(D; at a1, 2019)
$\begin{array}{l} (PS_{dif,inf,R-warfarin} \ / \ PS_{act,inf,R-warfarin}) \\ R_{dif,S-warfarin} \\ (PS_{dif,inf,S-warfarin} \ / \ PS_{act,inf,S-warfarin}) \end{array}$	Fixed	0.0374	PS <sub>act,inf</sub> : (R) 391 L/h, (	S) 282 L/h			(Bi et al., 2018)
V <sub>max(met),R-warfarin</sub> (µmole/h)	Opt	(0.04145, 414.5)	Base value of 4.145 µr	nole/h			
			$V_{max(met),S-warfarin} = V_{ma}$ (The fold-difference of (S) 0.365 µmol/min/m	f 3.10 based on the rej		s for (R) 0.1175 and	
$V_{max(act,inf),R\text{-warfarin}} \left( \mu mole/h \right)$	Opt	(40.67, 406,700)	Base value of 4,067 µr		(Bi et al., 2018)		
			$V_{max(act,inf),S-warfarin} = V_n$ (The fold-difference of pmol/min/million hepa				
K <sub>d,R-warfarin</sub> (nM)	Opt (0.041, 410)		The target affinity of S the reported relationsh The respective assump	(Breckenridge et al., 1974; O'Reilly, 1974; Hignite et al., 1980)			
					R/S analysis scenario	)	-
				<rs#1></rs#1>	<rs#2></rs#2>	<rs#3></rs#3>	
$k_{off,R-warfarin}(/h)$	Opt	(0.000405, 4.05)	K <sub>d,S</sub> –warfarin K <sub>d,R</sub> –warfarin	Unity (assumed same for R- and S-warfarin)	,	ving one-third to R- farin)	
			k <sub>off,S-warfarin</sub> k <sub>off,R-warfarin</sub>	,	1	1/3	
			k <sub>on,S–warfarin</sub> a k <sub>on,R–warfarin</sub> a		3	1	$(^{a} k_{on} \text{ defined by } k_{off}/K_{d})$

Table 3. Summary of the accepted parameters (n=663 sets, SSR ranging from 0.11526-0.11532, Rank 1 values in bold) for the CGNM run analyzing the blood PK data from all four warfarin dose levels with no stereoisomeric consideration (results shown in Figure 2) and additional secondary parameters calculated for metabolic clearance (CL<sub>met,inf</sub>), permeability clearance (PS<sub>act,inf</sub>), and overall intrinsic clearance (CL<sub>int,all</sub>).

		Va	llue		
	Rank 1	min	max	median	
Optimized					
$K_{d}(nM)$	6.30	6.27	6.31	6.30	
k <sub>off</sub> (/h)	0.0903	0.0899	0.0906	0.0903	
X <sub>TotalR</sub> (µmole)	4.26	4.24	4.26	4.26	
V <sub>max(met)</sub> (µmole/h)	16.84	16.82	16.85	16.84	
V <sub>max(act,inf)</sub> (µmole/h)	2.76x10 <sup>11</sup>	$1.26 \times 10^{6}$	$4.96 \times 10^{16}$	$4.64 \times 10^{10}$	
k <sub>a</sub> (/h)	6.00	5.92	6.00	6.00	
Secondary (using 'rank 1	' parameters)				
$k_{on}$ (/h/ $\mu$ M)	14.33	14.28	14.39	14.33	
$PS_{act,inf}(L/h)^a$	3.12x10 <sup>10</sup>	$1.42 \times 10^5$	$5.61 \times 10^{15}$	5.25x10 <sup>9</sup>	
$CL_{met,int} (L/h)^b$	1.68	1.68	1.69	1.68	
$CL_{int,all} (L/h)^c$	11.93	11.91	11.94	11.93	

<sup>a</sup> PS<sub>act,inf</sub>, calculated as V<sub>max (act,inf)</sub>/K<sub>m (act,inf)</sub>;

<sup>b</sup> CL<sub>met,int</sub>, calculated as  $V_{max(met)}/K_{m(met)}$ ;

<sup>c</sup> CL<sub>int,all</sub>, calculated based on the extended clearance concept model,  $CL_{int,all} = (PS_{dif,inf} + PS_{act,inf}) \cdot \frac{CL_{met,int}}{PS_{dif,eff} + CL_{met,int}} Eq. (*1)$ 

PS<sub>dif,inf</sub>, calculated as PS<sub>act,inf</sub> x R<sub>dif</sub> and R<sub>dif</sub> assumed to be 0.0355 based on the literature (Bi et al., 2018);  $PS_{dif,eff}$  calculated as  $PS_{dif,inf}/0.243$  ( $\gamma$  value for anions as reported previously) (Yoshikado et al., 2016)

Considering the values of CL<sub>met,int</sub> (1.7 L/h), R<sub>dif</sub> (0.0355), and PS<sub>act,inf</sub> (>105 L/h), the value of PS<sub>dif,eff</sub> would become considerably larger than that of CL<sub>met.int</sub>, simplifying Eq.(\*1) as follows:

$$CL_{\text{int,all}} = CL_{met,int} \cdot \frac{(PS_{dif,inf} + PS_{act,inf})}{PS_{dif,eff}} = CL_{met,int} \cdot \frac{(PS_{dif,inf} + PS_{act,inf})}{PS_{dif,inf}/\gamma} = CL_{met,int} \cdot \gamma \cdot \left(1 + \frac{PS_{act,inf}}{PS_{dif,inf}}\right) \quad \text{Eq. (*2)}$$

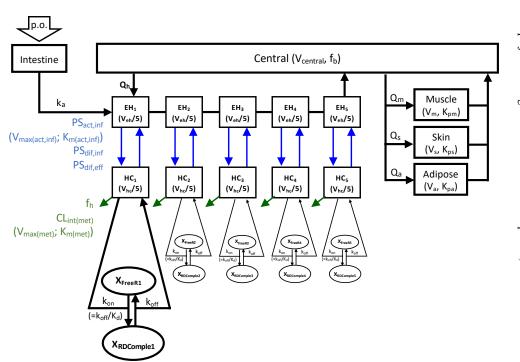
Table 4. Summary of the accepted parameters (Rank 1 values in bold; minimum, maximum, and median values in parentheses) for the CGNM runs using the blood
PK data from all four warfarin dose levels (ALL) or varying three-dose level designs (Designs A-D) and additional secondary parameters calculated for metabolic
clearance (CL <sub>met,inf</sub> ), permeability clearance (PS <sub>act,inf</sub> ), and overall intrinsic clearance (CL <sub>int,all</sub> ).

			Design					
		ALL dataset	Α	В	С	D		
Warfarin racem	ic doses (mg)	0.1, 2, 5, 10	2, 5, 10	0.1, 5, 10	0.1, 2, 5	0.1, 2, 10		
# of datapoints		36	36	36	36	36		
# of accepted para	ameter sets	663	586	469	641	645		
SSR ranges	(min, max)	(0.11526, 0.11532)	(0.0564, 0.0565)	(0.0991, 0.0992)	(0.0822, 0.0822)	(0.0820, 0.0820)		
Optimized								
	Rank 1	6.30	6.22	5.60	6.42	6.38		
K <sub>d</sub> (nM)	(min, max; median)	(6.27, 6.31; 6.30)	(6.13, 6.31; 6.22)	(5.57, 5.66; 5.60)	(6.42, 6.43; 6.42)	(6.37, 6.39; 6.38)		
	Rank 1	0.0903	0.0432	0.0961	0.0932	0.0901		
κ <sub>off</sub> (/h)	(min, max;	(0.0899, 0.0906;	(0.0425, 0.0449;	(0.0956, 0.0971;	(0.0931, 0.0932;	(0.0898, 0.0902;		
	median)	0.0903)	0.0432)	0.0961)	0.0931)	0.0901)		
	Rank 1	4.26	4.45	3.75	4.24	4.34		
X <sub>TotalR</sub> (μmole)	(min, max; median)	(4.24, 4.26; 4.26)	(4.44, 4.47; 4.45)	(3.74, 3.77; 3.75)	(4.24, 4.25; 4.24)	(4.33, 4.34; 4.34)		
max(met)	Rank 1	16.84	16.51	16.95	17.78	16.28		
μmole/h)	(min, max; median)	(16.82, 16.85; 16.84)	(16.46, 16.57; 16.51)	(16.90, 16.96; 16.94)	(17.77, 17.79; 17.78)	(16.26, 16.28; 16.28		
	Rank 1	2.75x10 <sup>11</sup>	2.83x10 <sup>8</sup>	4.23x10 <sup>9</sup>	4.65x10 <sup>10</sup>	1.87x10 <sup>9</sup>		
V <sub>max(act,inf)</sub> (µmole/h)	(min, max;	$(1.26 \times 10^6, 4.96 \times 10^{16};$	$(2.51 \times 10^4, 2.49 \times 10^{11};$	$(3.85 \times 10^5, 2.78 \times 10^{16};$	$(5.02 \times 10^7, 9.44 \times 10^{15};$	$(2.53 \times 10^7, 5.16 \times 10^1)$		
µmole/n)	median)	$4.64 \times 10^{10}$ )	$5.17 \times 10^{6}$ )	$4.45 \times 10^9$ )	$3.43 \times 10^{10}$ )	$2.38 \times 10^{10}$ )		
	Rank 1	6.00	5.58	6.00	6.00	6.00		
<sub>ka</sub> (/h)	(min, max; median)	(5.92, 6.00; 6.00)	(5.19, 6.00; 5.58)	(5.94, 6.00; 6.00)	(6.00, 6.00; 6.00)	(6.00, 6.00; 6.00)		
Secondary (using	g 'rank 1' parameters)							
κ <sub>on</sub> (/h/μM)		14.3	6.94	17.2	14.5	14.1		
PS <sub>act,inf</sub> (L/h)		$3.12 \times 10^{10}$	$3.19 \times 10^7$	$4.78 \times 10^{8}$	5.26x10 <sup>9</sup>	$2.11 \times 10^8$		
CL <sub>met,int</sub> (L/h)		1.68	1.65	1.69	1.78	1.63		
CL <sub>int,all</sub> (L/h)		11.93	11.70	12.01	12.60	11.54		

**Table 5.** Summary of the CGNM runs  $\langle RS\#1-\#3 \rangle$  analyzing all four warfarin dose levels with stereoselective considerations applied (as described in Table 2): the accepted parameters (Rank 1 values in bold; minimum, maximum, and median values in parentheses) and additional secondary parameters calculated for metabolic clearance ( $CL_{met,inf}$ ), permeability clearance ( $PS_{act,inf}$ ), and overall intrinsic clearance ( $CL_{int,all}$ ).

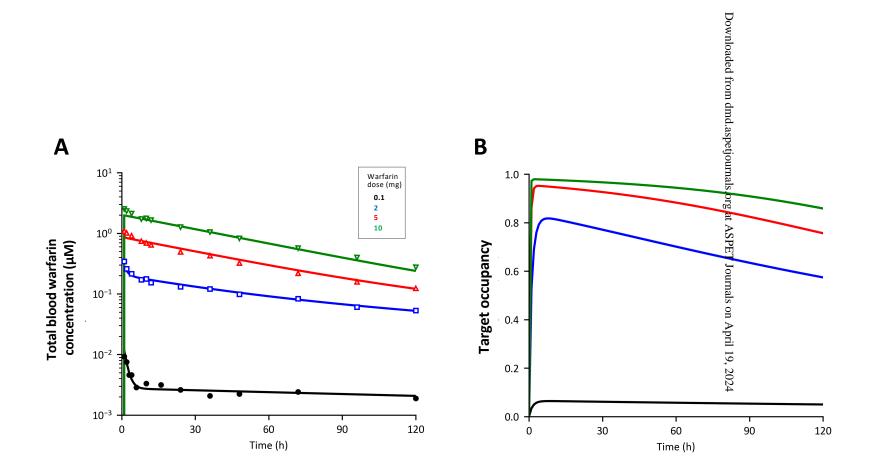
		RS#			RS#2	RS#3		
		(n=361; SSR 0.10	/		109241-0.109241)	(n=357; SSR 0.108873-0.11102)		
		R-warfarin	S-warfarin	R-warfarin	S-warfarin	R-warfarin	S-warfarin	
Optimized								
K <sub>d</sub> (nM)	Rank 1	6.03		8.94	2.98	9.00	3.00	
	(min, max; median)	(5.93, 6.13; 6.03)		(8.93, 8.94; 8.94)	$(K_{d,R-warfarin}x1/3)$	(8.80, 9.16; 9.00)	$(K_{d,R-warfarin}x1/3)$	
	Rank 1	0.09	5	0.0	)858	0.141	0.047	
k <sub>off</sub> (/h)	(min, max; median)	(0.094, 0.102; 0.0095)		(0.0893, 0.0894; 0.0894) (Same for R- and S-warfarin)		(0.137, 0.159; 0.141)	(k <sub>off,R-warfarin</sub> x1/3)	
X <sub>TotalR</sub>	Rank 1	3.96		3.98		3.94		
(µmole)	(min, max; median)	(3.90, 4.02; 3.96)		(3.98, 3.98; 3.98)		(3.87, 4.01; 3.94)		
	Rank 1	9.9	30.69	10.5	32.55	10.5	32.55	
V <sub>max(met)</sub> (μmole/h)	(min, max; median)	(9.8, 10.0; 9.9)	$egin{pmax(met), R-warfarin\ x3.10) \end{pmax}$	(10.5, 10.5; 10.5)	$(V_{max(met),R-warfarin} x3.10)$	(10.4, 10.6; 10.5)	$(V_{max(met),R-warfarin} x3.10)$	
¥7	Rank 1	4.72x10 <sup>11</sup>	2.39x10 <sup>11</sup>	6.16x10 <sup>13</sup>	3.12x10 <sup>13</sup>	6.77x10 <sup>10</sup>	3.43x10 <sup>10</sup>	
V <sub>max(act,inf)</sub> (μmole/h)	(min, max; median)	$(8.19 \times 10^4, 5.02 \times 10^{15}; 6.08 \times 10^9)$	$(V_{max(act,inf),R-warfarin} x0.506)$	$(6.50 \times 10^8, 2.66 \times 10^{16}; \\ 8.94 \times 10^{10})$	$(V_{max(act,inf),R-warfarin} x0.506)$	$(4.20x10^4, 3.22x10^{16}; 4.52x10^9)$	$(V_{max(act,inf),R-warfarin} x0.506)$	
	Rank 1	6.00	)	6.00		6.00		
k <sub>a</sub> (/h)	(min, max; median)	(5.25, 6.00; 6.00)		(6.00, 6.00; 6.00)		(4.83, 6.00; 6.00)		
econdary (u	ising 'rank 1' paramete	/						
k <sub>on</sub> (/h/μM)		15.8		9.60 28.8		15.7 (Same for R- and S-warfarin)		
PS <sub>act,inf</sub> (L/h)	)	$4.54 \mathrm{x10}^{10}$	3.27x10 <sup>12</sup>	$5.92 \times 10^{12}$	$4.27 \times 10^{12}$	6.51x10 <sup>9</sup>	4.69x10 <sup>9</sup>	
CL <sub>met,int</sub> (L/h		0.99	3.07	1.05	3.25	1.05	3.26	
CL <sub>int,all</sub> (L/h)	)	7.29	20.7	7.73	21.9	21.9 7.76		

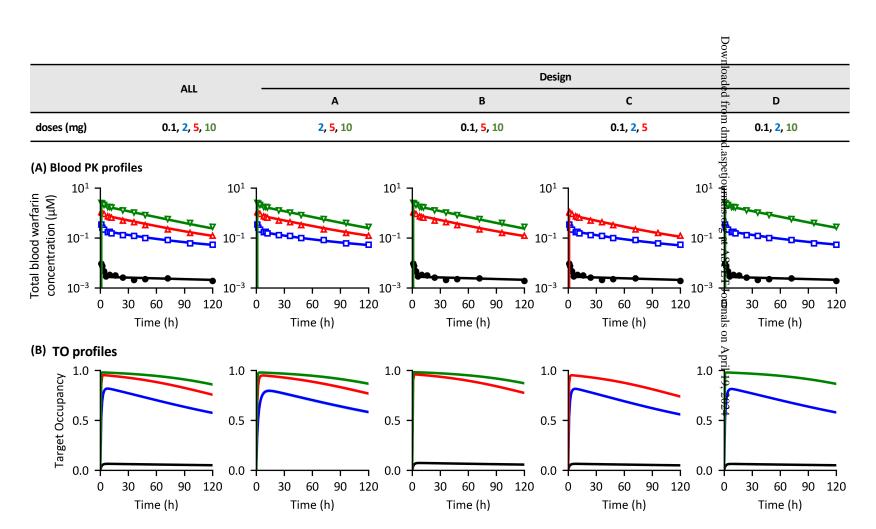
Figure 1



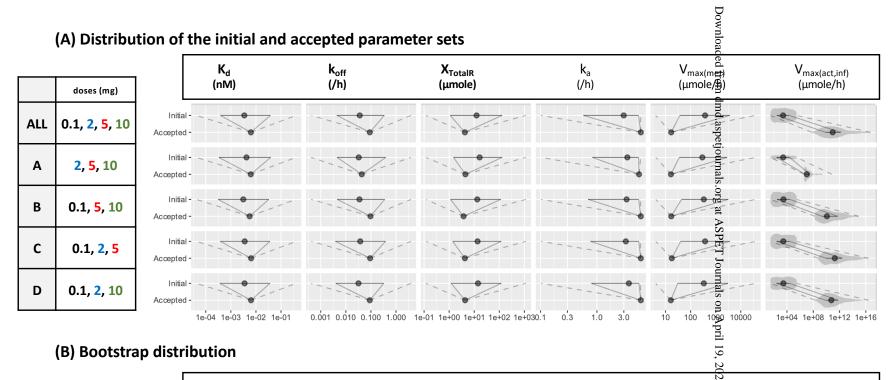
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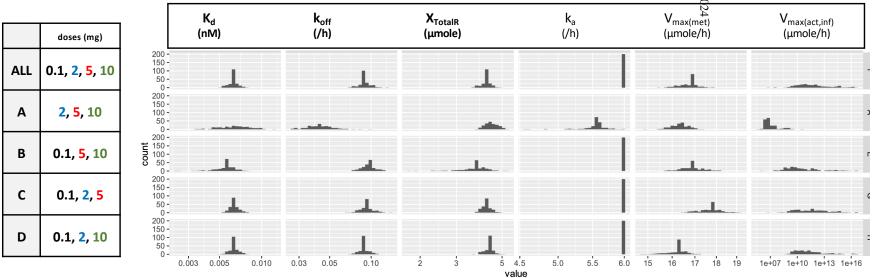






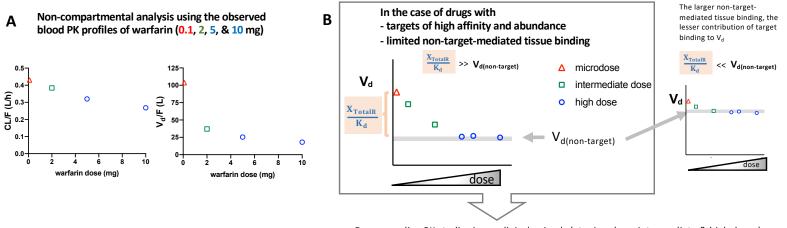
#### Figure 4





### Figure 5

	K <sub>d,S</sub> –warfarin K <sub>d,R</sub> –warfarin	k <sub>off,S-warfarin</sub> k <sub>off,R-</sub> warfarin	k <sub>on,S-warfarin</sub> k <sub>on,R-warfarin</sub>	Blood PK and TO profiles
(A) RS#1	1	1	1	Blood PK TO TO
(B) RS#2	1/3	1	<b>3</b> Differences at the <u>association</u> step	Blood PK TO $TO$ $IO_{10}^{0,1}O_{10}^{$
(C) RS#3	1/3	<b>1/3</b> Differences at the <u>dissociation</u> step	1	Blood PK TO $TO$ $IO_{1, Mg}$



Dose-scending PK studies in preclinical animals (at microdose, intermediate & high doses) may verify the occurrence of TMDD & identify target binding parameters *in vivo* 

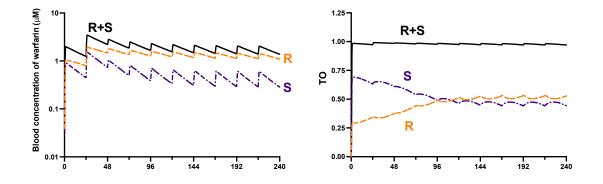
**Supplemental Figure** 

# Predicting *in vivo* Target Occupancy (TO) Profiles via PBPK-TO Modeling of Warfarin Pharmacokinetics in Blood: Importance of Low Dose Data and Prediction of Stereoselective Target Interactions

Target Interactions

Wooin Lee, Min-Soo Kim, Jiyoung Kim, Yasunori Aoki, Yuichi Sugiyama

**Figure S1.** Simulated PK and TO profiles of R- and S-warfarin in subjects receiving repeated warfarin dosing (10 mg for 2 days and 3 mg afterwards) using the rank 1 parameter set of the CGNM run <RS#2>



**Supplemental Material** 

# Predicting *in vivo* Target Occupancy (TO) Profiles via PBPK-TO Modeling of Warfarin Pharmacokinetics in Blood: Importance of Low Dose Data and Prediction of Stereoselective Target Interactions

Wooin Lee, Min-Soo Kim, Jiyoung Kim, Yasunori Aoki, Yuichi Sugiyama

Table S1. Summary of the accepted parameters (rank 1, maximum, minimum, and median values) for the CGNM repeat runs #1 and #2 analyzing all four warfarin dose levels and additional secondary parameters calculated for metabolic clearance (CL<sub>met,inf</sub>), permeability clearance (PS<sub>act,inf</sub>), and overall intrinsic clearance (CL<sub>int,all</sub>).

		Repeat	run #1		Repeat run #2				
_	(N=678 sets; SSR, 0.11527-0.11527)				(N=659 sets; SSR, 0.11526-0.11538)				
	Rank 1	min	max	median	Rank 1	min	max	median	
Optimized									
$K_{d}(nM)$	6.30	6.28	6.31	6.30	6.30	6.26	6.33	6.30	
$k_{off}$ (/h)	0.090	0.090	0.090	0.090	0.090	0.090	0.091	0.090	
$X_{TotalR}(\mu mole)$	4.26	4.25	4.26	4.26	4.26	4.25	4.28	4.26	
Vmax(met) (µmole/h)	16.84	16.83	16.84	16.84	16.84	16.81	16.86	16.84	
$V_{max(act,inf)}(\mu mole/h)$	3.31*10 <sup>8</sup>	$2.43*10^{7}$	$2.14*10^{16}$	$3.43*10^{10}$	1.63*10 <sup>14</sup>	5.82*10 <sup>5</sup>	$2.99*10^{16}$	$2.43*10^{10}$	
k <sub>a</sub> (/h)	6.00	6.00	6.00	6.00	6.00	5.86	6.00	6.00	
Secondary (using 'ran	k 1' paramet	ers)							
$k_{on}$ (/h/ $\mu$ M)	14.33	14.26	14.37	14.33	14.33	14.21	14.40	14.33	
PS <sub>act,inf</sub> (L/h)	3.73*10 <sup>7</sup>	$2.75^{*}10^{6}$	2.41*10 <sup>15</sup>	3.88*10 <sup>9</sup>	1.84*10 <sup>13</sup>	$6.58*10^4$	$3.38*10^{15}$	$2.74*10^{9}$	
$CL_{met,int}\left(L/h\right)$	1.68	1.68	1.69	1.68	1.68	1.68	1.69	1.68	
CL <sub>int.all</sub> (L/h)	11.93	11.93	11.94	11.93	11.93	11.92	11.95	11.93	

 $PS_{act,inf}, calculated \ as \ V_{max\,(act,inf)}/K_{m\,(act,inf)}; PS_{dif,inf}, calculated \ as \ PS_{act,inf} \ x \ R_{dif} \ and \ R_{dif} \ assumed \ to \ be \ 0.0355 \ based \ on \ N_{max\,(act,inf)}/K_{m\,(act,inf)}; PS_{dif,inf}, calculated \ as \ PS_{act,inf} \ x \ R_{dif} \ and \ R_{dif} \ assumed \ to \ be \ 0.0355 \ based \ on \ N_{max\,(act,inf)}/K_{m\,(act,inf)}; PS_{dif,inf}, calculated \ as \ PS_{act,inf} \ x \ R_{dif} \ and \ R_{dif} \ assumed \ to \ be \ 0.0355 \ based \ on \ N_{max\,(act,inf)}/K_{m\,(act,inf)}; PS_{dif,inf}, calculated \ as \ PS_{act,inf} \ x \ R_{dif} \ and \ R_{dif} \ assumed \ based \ base$ the literature (Bi et al. 2018);

PS<sub>dif,eff</sub>, calculated as PS<sub>dif,inf</sub>/ 0.243 (γ value for anions as reported previously) (Yoshikado et al., 2016); CL<sub>met,int</sub>, calculated as V<sub>max(met)</sub>/K<sub>m(met)</sub>;

 $CL_{int,all}, \text{ calculated as } \bullet_{max(met)} \land Sm(met),$   $CL_{int,all}, \text{ calculated based on the extended clearance concept model,}$   $CL_{int,all} = \left(PS_{dif,inf} + PS_{act,inf}\right) \cdot \frac{CL_{met,int}}{PS_{dif,eff} + CL_{met,int}} = \left(1.0355 \cdot PS_{act,inf}\right) \cdot \frac{CL_{met,int}}{PS_{act,inf} \cdot \frac{0.0355}{0.243} + CL_{met,int}}$ 

#### **Supplemental Equations**

#### Nomenclature/Abbreviations

C, the total concentration of the drug;  $C_{central}$ , the drug concentration in the central compartment;  $C_{EH(i) (i=1-5)}$ , the drug concentration in the i<sup>th</sup> hepatic extracellular compartment; C<sub>HC(i) (i=1-5)</sub>, the drug concentration in the i<sup>th</sup> hepatocellular compartment; Cadipose, Cmuscle, and Cskin, the drug concentration in the adipose, the muscle, and the skin compartments, respectively; V<sub>central</sub>, V<sub>eh</sub>, and V<sub>hc</sub>, the volume of the central compartment, the hepatic extracellular compartment, and the hepatocellular compartment, respectively; V<sub>a</sub>, V<sub>m</sub>, and V<sub>s</sub>, the volume of the adipose, the muscle, and the skin compartment, respectively; Qh, Qm, Qs, and Qa, the blood flow rate to the liver, the muscle, the skin, and the adipose, respectively; K<sub>m,act,inf</sub> and V<sub>max,act,inf</sub>, the Michaelis-Menten constant and the maximum velocity for the active influx through the basolateral membrane of hepatocytes; K<sub>m(met)</sub>, V<sub>max(met)</sub>, the Michaelis-Menten constant and the maximum velocity for the hepatic metabolism; fu,B and fh, the fraction of the unbound drug in blood, and in the hepatocellular compartment, respectively; Rdif, the ratio of the influx intrinsic clearance via passive diffusion across the sinusoidal membrane of hepatocytes (PS<sub>dif,inf</sub>) to the influx intrinsic clearance via active uptake across the sinusoidal membrane of hepatocytes (PS<sub>act,inf</sub>); PS<sub>dif,eff</sub>, the efflux intrinsic clearance via passive diffusion across the sinusoidal membrane of hepatocytes, calculated as  $PS_{dif,inf}/\gamma$  ( $\gamma = 0.243$  for anions); k<sub>a</sub>, the absorption rate constant; k<sub>off</sub> and k<sub>on</sub>, the dissociation and association rate constant of the drug to the target, respectively;  $K_d = k_{off}/k_{on}$ , the dissociation equilibrium constant of the drug to the target; K<sub>pa</sub>, adipose-to-blood drug concentration ratio; K<sub>pm</sub>, muscle-to-blood drug concentration ratio;  $K_{ps}$ , skin-to-blood drug concentration ratio;  $R_b$ , blood to plasma drug concentration ratio; TO, the ratio of target occupancy; Xa, the amount of the drug absorbed; XTotalR, the total amount of the target receptor assumed to be equally divided into the five serially placed hepatocellular compartments;  $X_{\text{FreeR(i)}}$  (i=1-5) and  $X_{\text{RDcomplex(i)}}$  (i=1-5), the amount of the unoccupied (free) target receptor and the target receptor-drug complex in the i<sup>th</sup> hepatocellular compartment, respectively.

#### [Intestine]

 $\frac{dX_a}{dt} = -k_a \cdot X_a$  (The bioavailability was assumed to be unity based on the previous report, Bi et al. (2018))

[Central compartment]

$$V_{\text{central}} \cdot \frac{dC_{\text{central}}}{dt} = Q_{\text{h}}(C_{\text{EH5}} - C_{\text{central}}) - Q_{\text{m}}\left(C_{\text{central}} - \frac{C_{\text{muscle}}}{K_{\text{pm}}}\right) - Q_{s}\left(C_{\text{central}} - \frac{C_{\text{skin}}}{K_{\text{ps}}}\right) - Q_{a}\left(C_{\text{central}} - \frac{C_{\text{adipose}}}{K_{\text{pa}}}\right)$$

[Liver]

Hepatic extracellular compartment [EH(1) to EH(5)]

For EH(1),

$$\begin{aligned} \frac{V_{eh}}{5} \cdot \frac{dC_{EH(1)}}{dt} &= k_a \cdot X_a + Q_h \cdot \left(C_{central} - C_{EH(1)}\right) - \frac{0.2 \cdot V_{max(act,inf)} \cdot f_{u,B} \cdot C_{EH(1)}}{K_{m(act,inf)} + f_{u,B} \cdot C_{EH(1)}} - \frac{0.2 \cdot V_{max(act,inf)} \cdot R_{dif}}{K_{m(act,inf)}} \cdot f_{u,B} \cdot C_{EH(1)} \\ &+ \frac{0.2 \cdot V_{max(act,inf)} \cdot \frac{R_{dif}}{0.243}}{K_{m(act,inf)}} \cdot f_h \cdot C_{HC(1)} \end{aligned}$$

For EH(i), i=2-5,

$$\begin{split} \frac{v_{eh}}{5} \cdot \frac{dC_{EH(i)}}{dt} &= Q_h \cdot \left(C_{EH(i-1)} - C_{EH(i)}\right) - \frac{0.2 \cdot V_{max(act,inf)} \cdot f_{u,B} \cdot C_{EH(i)}}{K_{m(act,inf)} + f_{u,B} \cdot C_{EH(i)}} - \frac{0.2 \cdot V_{max(act,inf)} \cdot R_{dif}}{K_{m(act,inf)}} \cdot f_{u,B} \cdot C_{EH(i)} \\ &+ \frac{0.2 \cdot V_{max(act,inf)} \cdot \frac{R_{dif}}{0.243}}{K_{m(act,inf)}} \cdot f_h \cdot C_{HC(i)} \end{split}$$

Hepatocellular compartment [HC(1) to HC(5)]

For HC(i), i=1-5,

$$\frac{v_{hc}}{5} \cdot \frac{dC_{HC(i)}}{dt} = \frac{0.2 \cdot V_{max(act,inf)} \cdot f_{u,B} \cdot C_{EH(i)}}{K_{m(act,inf)} + f_{u,B} \cdot C_{EH(i)}} + \frac{0.2 \cdot V_{max(act,inf)} \cdot R_{dif}}{K_{m(act,inf)}} \cdot f_{u,B} \cdot C_{EH(i)} - \frac{0.2 \cdot V_{max(act,inf)} \cdot G_{L243}}{K_{m(act,inf)}} \cdot f_{h} \cdot C_{HC(i)} - \frac{0.2 \cdot V_{max(act,inf)} \cdot G_{L243}}{K_{m(act,inf)}} \cdot f_{h} \cdot C_{HC(i)}$$

[Distribution compartments (muscle, adipose, and skin)]

$$V_{\rm m} \cdot \frac{dC_{\rm muscle}}{dt} = Q_{\rm m}(C_{\rm central} - \frac{C_{\rm muscle}}{K_{\rm pm}})$$
$$V_{\rm a} \cdot \frac{dC_{\rm adipose}}{dt} = Q_{\rm a}(C_{\rm central} - \frac{C_{\rm adipose}}{K_{\rm pa}})$$
$$V_{\rm s} \cdot \frac{dC_{\rm skin}}{dt} = Q_{\rm s}(C_{\rm central} - \frac{C_{\rm skin}}{K_{\rm ps}})$$

[Target binding]

For i = 1-5,

$$\frac{\mathrm{d}X_{\mathrm{FreeR}(i)}}{\mathrm{d}t} = k_{\mathrm{off}} \cdot X_{\mathrm{RDComplex}(i)} - \frac{k_{\mathrm{off}}}{K_{\mathrm{d}}} \cdot f_{\mathrm{h}} \cdot C_{\mathrm{HC}(i)} \cdot X_{\mathrm{FreeR}(i)}$$

$$\frac{dX_{RDcomplex(i)}}{dt} = \frac{k_{off}}{K_d} \cdot f_h \cdot C_{HC(i)} \cdot X_{FreeR(i)} - k_{off} \cdot X_{RDcomplex(i)}$$

$$\frac{\mathrm{dRO}}{\mathrm{dt}} = \frac{1}{X_{\mathrm{TotalR}}} \left\{ \frac{k_{\mathrm{off}}}{K_{\mathrm{d}}} \cdot f_{\mathrm{h}} \left( C_{\mathrm{HC}(1)} \cdot X_{\mathrm{FreeR}(1)} + C_{\mathrm{HC}(2)} \cdot X_{\mathrm{FreeR}(2)} + C_{\mathrm{HC}(3)} \cdot X_{\mathrm{FreeR}(3)} + C_{\mathrm{HC}(4)} \cdot X_{\mathrm{FreeR}(4)} + C_{\mathrm{HC}(5)} \cdot X_{\mathrm{FreeR}(5)} \right) - k_{\mathrm{off}} \left( X_{\mathrm{RDcomplex}(1)} + X_{\mathrm{RDcomplex}(2)} + X_{\mathrm{RDcomplex}(3)} + X_{\mathrm{RDcomplex}(4)} + X_{\mathrm{RDcomplex}(5)} \right) \right\}$$

Other equations

$$\begin{split} PS_{dif,inf} &= R_{dif} \cdot PS_{act,inf} \\ PS_{dif,eff} &= PS_{dif,inf} / \gamma \\ CL_{met,int} &= V_{max(met)} / K_{m(met)} \\ CL_{int, all} &= \left( PS_{dif,inf} + PS_{act,inf} \right) \cdot \frac{CL_{met,int}}{PS_{dif,eff} + CL_{met,int}} \end{split}$$

For the analysis <RS#1-3>, the equations were duplicated and separated for R- and S-warfarin except for the following equations considering competitive interactions of S- and R-warfarin for the free target;

For i=1-5,

 $\frac{dx_{FreeR(i)}}{dt} = k_{off} \cdot (X_{RDcomplex(i),R-warfarin} + X_{RDcomplex(i),S-warfarin}) - \frac{k_{off}}{K_d} \cdot f_h \cdot (C_{HC(i),R-warfarin} + C_{HC(i),S-warfarin}) \cdot X_{FreeR(i)})$