

Figure S1: Schematic illustrating the structure of the adapted Friberg model. G-CSF

administration was modeled as sub-cutaneous, with an absorption compartment and a central compartment. Chemotherapy was modeled as a bolus dose into a central compartment. Neutrophils were modeled as a stem cell reservoir replenished by proliferation, three transit compartments reflecting the stem cell maturation process, and a circulating neutrophil compartment. The overall mean transit time (MTT) is equal to four divided by the inter-compartment transit rate (k_{TR}) . The intercompartmental transit rate is stimulated by GCSF. Proliferation rate is equal to the transit rate multiplied by the drug effect ($SLOPE$ times drug concentration) multiplied by the feedback effect and an additive stimulatory effect of exogenous G-CSF.

Figure S2: Diagnostic plots for the final PKPD model, evaluated on the test data set. (a) DV-prediction plots for population predictions (PRED), iterative individual predictions computed with PsN proseval (ITERATIVE_IPRED) and individual predictions (IPR ED). (b) visual predictive check comparing observed data distributions. Shaded areas indicate the 95% confidence intervals around the 95th, 50th and 5th percentile of simulated data. Black lines indicate the 95th, 50th and 5th percentile of observed dat a. (c) Distribution of individual eta estimates. (d) Comparison of the new PKPD model with the literature model (Melhem et al, 2018). Prediction performance is summarized according to accuracy, precision, recall, root mean square error (rmse), and mean percent error (mpe). Variability in these error metrics was assessed across 1000 bootstrapped samples; points indicate the median and bars indicate the 5th to 95th percentile of these bootstrapped metrics. Asterisks indicate the model with the best performance on that error metric.

Figure S3: Performance of XGBoost loss functions and subsampling. (a) Comparison of observed (DV) and pre dicted values for the default (squared error) loss function, the pseudo-Huber loss function and thepseudo-H uber loss function with down-sampling and up-sampling. (b) Performance of the three training conditions on prediction performance as measured by accuracy, precision, recall, root mean square error (rmse), and mean percent error (mpe). Asterisks indicate the training condition with the best performance on that error metric. Variability in these error metrics was assessed across 1000 bootstrapped samples; points indicate the median and bars indicate the 5th to 95th percentile of these bootstrapped metrics.

(a) Enrichment versus augmentation

(b) Effect of augmentation by increasing proportions of simulated data

(c) Augmentation of selected days after treatment start

sample specified days \rightarrow size-matched random equivalent \rightarrow without up/downsampling

Figure S4: Analysis of factors impacting augmented model performance. (a) Comparison of the base ML model, the enriched model, the base ML model with augmentation (81%) and the enriched model with augmentation (81%). (b) Enriched models with different quantities of augmentation (0%, 25%, 51%, 120%, 310%, 620% additional new simulated data relative to the number of rows of the RWD data set), with simulated data randomly sampled from within the first 3 cycles of chemotherapy. (c) Enriched models with simulated data sampled from different regions of the ANC-time curve (days 0-4, days 8-12, or every fifth day of therapy after each chemotherapy dose). For control, randomly selected rows corresponding to the same fold enrichment (0.81x, 0.52x, 0.91x) are also shown (triangles), as well as size-matched randomized controls without up-sampling and down-sampling (squares). Prediction performance is summarized according to accuracy, precision, recall, root mean square error (rmse), and mean percent error (mpe). For all plots, variability in these error metrics was assessed across 1000 bootstrapped samples; points indicate the median and bars indicate the 5th to 95th percentile of these bootstrapped metrics. Asterisks indicate the training condition with the best performance on that error metric.

Figure S5: Representative patient treatment courses, with model predictions of ANC over time. At the time of the second cycle, all available data is used to predict future ANCs (open circles). Doses of chemotherapy ar e indicated by solid vertical lines, and administration of GCSF is indicated with dashed grey lines.

Table S1: Literature review for factors predictive of neutropenia

1. Joerger, M. *et al.* Evaluation of a pharmacology-driven dosing algorithm of 3-weekly paclitaxel using therapeutic drug monitoring: a pharmacokinetic-pharmacodynamic simulation study. *Clin Pharmacokinet* **51**, 607–617 (2012).

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3. Kontny, N. E. et al. Population pharmacokinetics of doxorubicin: establishment of a NONMEM model for adults and children older than 3 years. *Cancer Chemother Pharmacol* **71**, 749–763 (2013).

4. Joerger, M. *et al.* Dosing algorithm to target a predefined AUC in patients with primary central nervous system lymphoma receiving high dose methotrexate: High dose methotrexate dosing algorithm. British Journal of Clinical Pharmacology 73, 240-247 (2012).

5. Johansson, Å. M. et al. A population pharmacokinetic/pharmacodynamic model of methotrexate and mucositis scores in osteosarcoma. Ther *Drug Monit* **33**, 711–718 (2011).

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9. Razzaghdoust, A., Mofid, B. & Moghadam, M. Development of a simplified multivariable model to predict neutropenic complications in cancer patients undergoing chemotherapy. *Support Care Cancer* 26, 3691–3699 (2018).

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12. Morrison, V. A., Caggiano, V., Fridman, M. & Delgado, D. J. A model to predict chemotherapy-related severe or febrile neutropenia in cycle one among breast cancer and lymphoma patients. *JCO* 22, 8068-8068 (2004).

13. Cao, X. et al. Predicting risk of chemotherapy-induced severe neutropenia: A pooled analysis in individual patients data with advanced lung cancer. *Lung Cancer* **141**, 14–20 (2020).

14. Vendrell, I. et al. Chemoradiotherapy completion and neutropenia risk in HIV patients with cervical cancer. Medicine 97, e11592 (2018).

Table S2: Description of machine learning model features. Features shaded in grey are presentonly in hybrid models.

