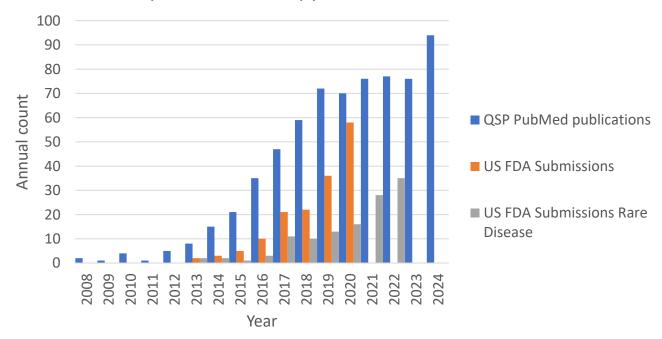




## QSP's Evolving Role in Industry

Combined with Machine Learning Opens New Frontiers for Precision Medicine

Progression in the number of annual QSP publications/supported FDA submissions#



Integrating multi-omics datasets with QSP



#### **Omics**

 Large-scale datasets capturing structure and function of bological system

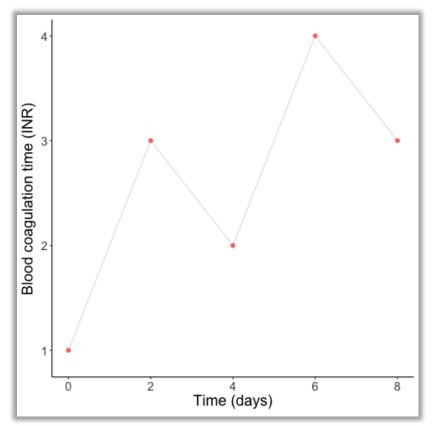
"Patient-specific multi-omics dataset when integrated with QSP models can improve the generation of virtual patient cohorts/digital twin with personalised pharmacokinetics and treatment effect that accurately represent real patients." 1

# Figure redrawn and combined from Cucurull-Sanchez, L. (2024). An industry perspective on current QSP trends in drug development. *Journal of Pharmacokinetics and Pharmacodynamics*, *51*(5). And Bai, J. P., Wang, J., Zhang, Y., Wang, L., & Jiang, X. (2023). Quantitative Systems Pharmacology for Rare Disease Drug Development. *Journal of Pharmaceutical Sciences*, *112*(9), 2313–2320. [1] Arulraj, T., Wang, H., Ippolito, A., Zhang, S., Fertig, E. J., & Popel, A. S. (2024). Leveraging multi-omics data to empower quantitative systems pharmacology in immuno-oncology. *Briefings in Bioinformatics*, *25*(3).

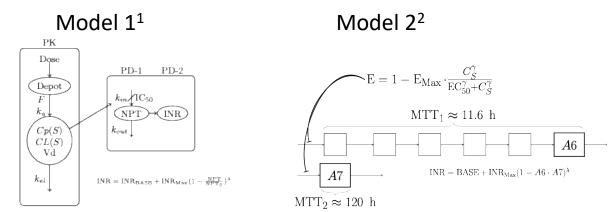
## Understanding inter-individual variability of response

Statistical analysis of clinical data

#### The data



#### **Data-driven sparse models**



 Identify influencing factors (covariates) e.g. age, bodyweight or others

However, every dataset results in different data-driven sparse model.

Which model to choose for the next analysis?

[2] The Pitfalls of Warfarin Dosing Using Different Pharmacodynamic Models: A Comparison of Two Different Warfarin Pharmacodynamic Models With Divergent Results. (n.d.), 1–30.

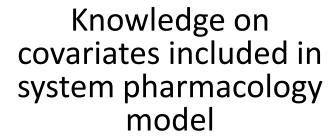
<sup>[1]</sup> Hamberg, a-K., Dahl, M.-L., Barban, M., Scordo, M. G., Wadelius, M., Pengo, V., ... Jonsson, E. N. (2007). A PK-PD model for predicting the impact of age, CYP2C9, and VKORC1 genotype on individualization of warfarin therapy. *Clinical Pharmacology and Therapeutics*, *81*(4), 529–538. https://doi.org/10.1038/sj.clpt.6100084

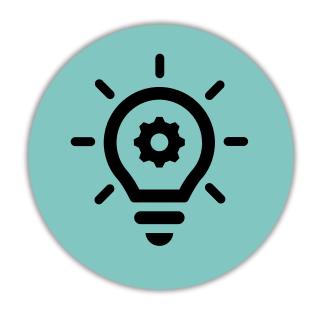
## Aim:

Leverage the knowledge in systems pharmacology models in statistical analysis

# Leveraging the knowledge in system pharmacology models





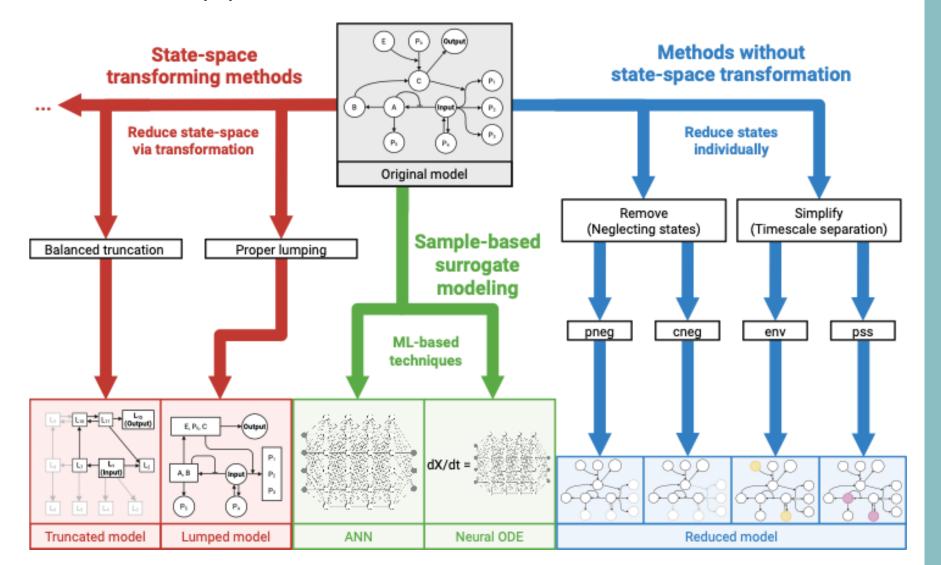


Leverage knowledge to derive theoretically-justified effective models including relevant covariates



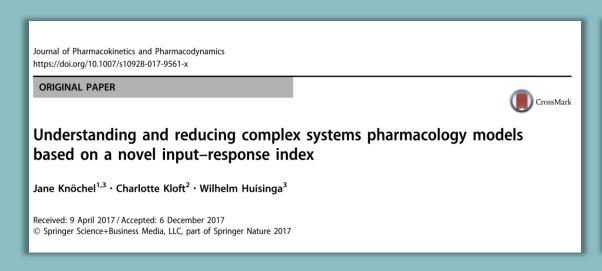
Full complexity not relevant – rather need to identify important parts

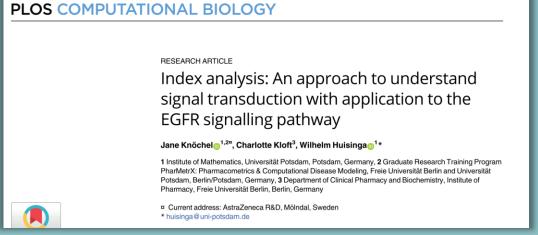
# Method Selection for Reduced Models: Which Approach Yields the Desired Outcome?



No clear guidance exists on which MOR methods suit specific scenarios or how to combine them effectively.

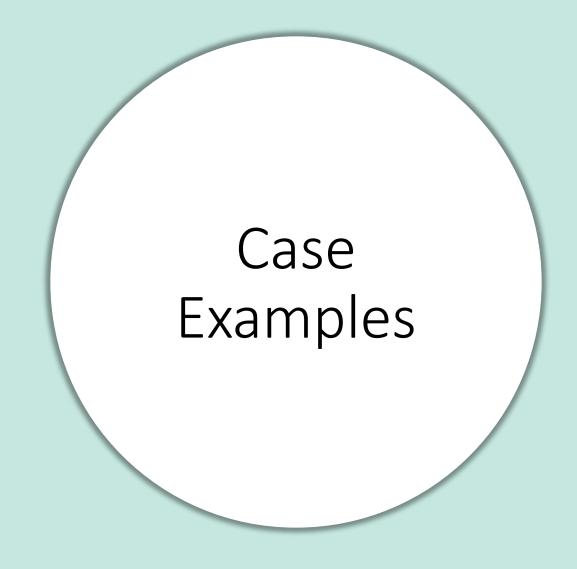
## Index Analysis: Understanding what is important



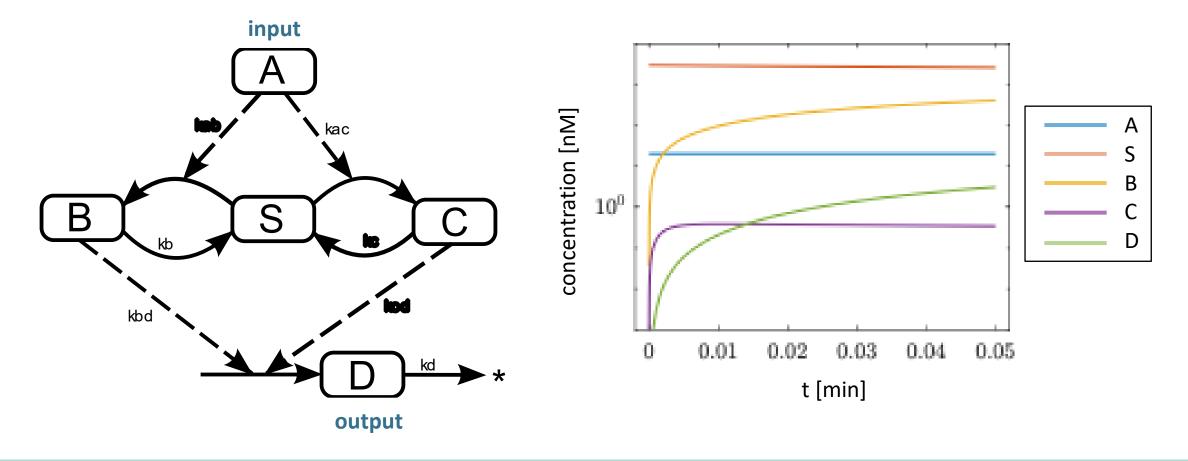


## Index Analysis-guided model order reduction

Index	Туре	Purpose	Interpretation
Ir/nir	Input-response	Assess dynamic importance of state	How relevant is a state for the input-output relationship?
Env, Pss	State classificiation	Classification based on time scale seperation	Can we simplify this state by an algebraic equation?
Pneg, Cneg	State classification	Classification of states with negligible impact on the output	Can this state be ignored?



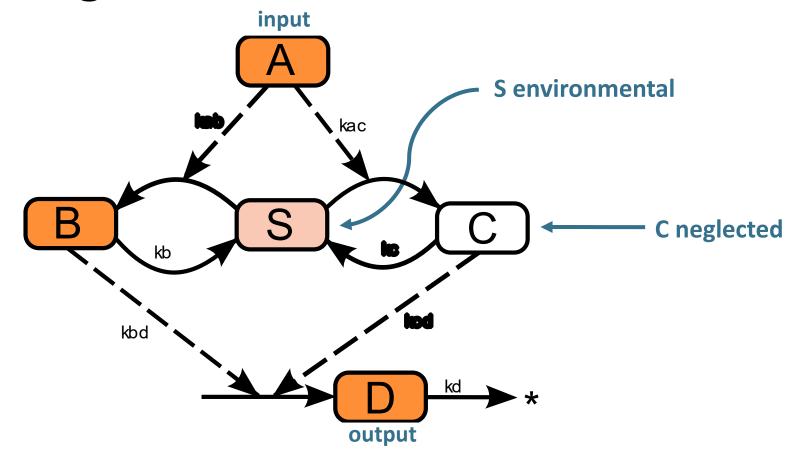
## Small example – parallel pathways



## Indices reveal appropriate reduction method

#### **Input-response indices State classification indices of C** normalised index 0.8 $10^{0}$ normalised ir-index env 0.6pss pneg 0.4cneg $10^{-2}$ threshold 0.2threshold 0.020.040.020.04t [min] t [min]

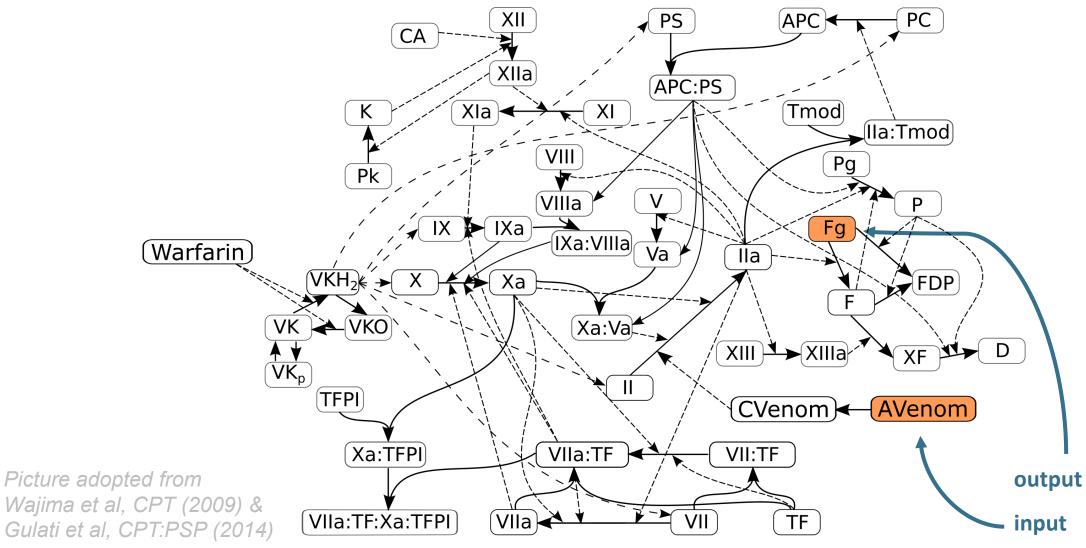
## Indices guide the model order reduction



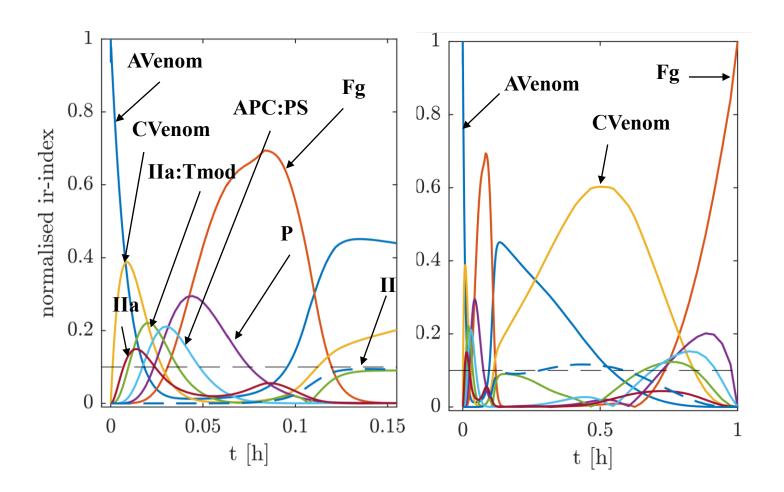
orange – dynamical states; light orange – environmental states; white – neglected states

## Large-scale QSP model – the blood coagulation network

Brown snake envenomation



## The input-response indices in action Brown snake venom effect on Fibrinogen

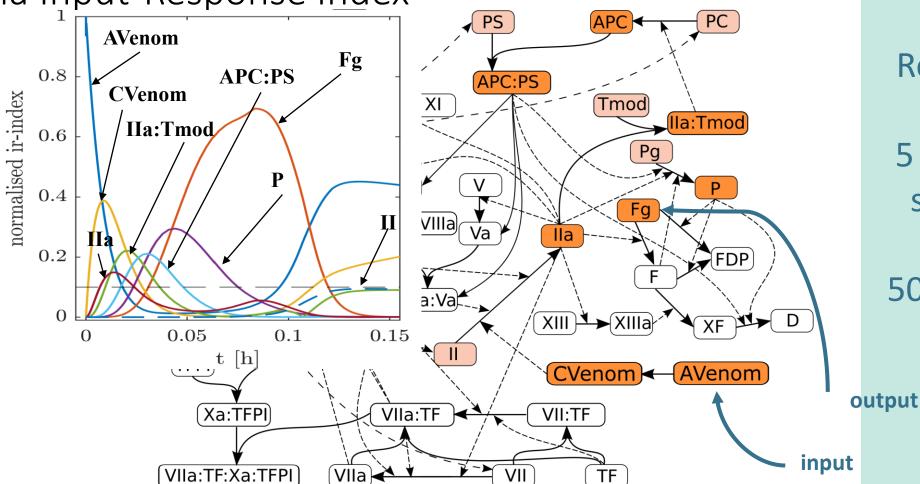


Demonstrates how the signal moves through the network!

Let's combine
this with the
graphical
illustration of the
model!

Understanding Signal Propagation and Key Molecular Players

via Input-Response Index



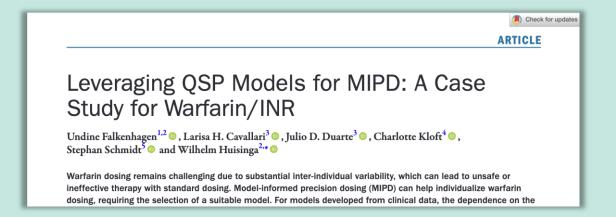
Reduced model: 8 dynamical, 5 environmental state variables

50 state variables neglected

orange – dynamical states; light orange – environmental states; white – neglected states

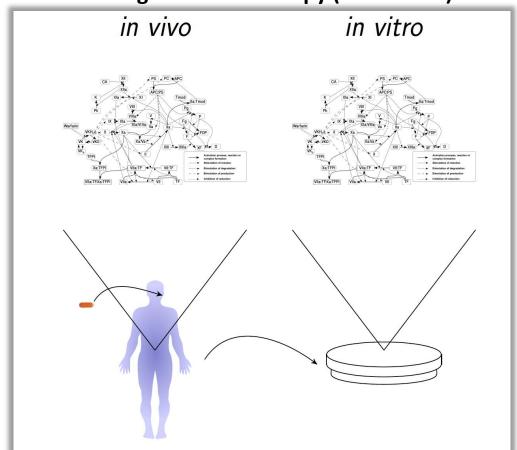
# Theoretical Models for Optimizing Warfarin Therapy



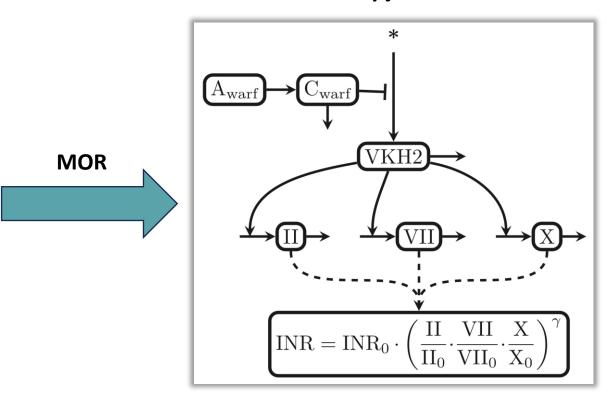


## Resulting Theoretical Model Size Allows Statistical Analysis of Clinical Data

#### **Modelling Warfarin Therapy (2x60 ODEs)**



#### Theoretically justified models



## Acknowledgement

Financial support:

**Graduate Research Training Program PharMetrX** 



#### Collaboration partners:

Potsdam University: Institute of Mathematics
Prof. Dr. Wilhelm Huisinga
Dr. Undine Falkenhagen
Johannes Tillil

Freie Universität Berlin: Institute of Pharmacy Prof. Dr. Charlotte Kloft



