# ADaM@: End-to-end automation of Pharmacometric (Roche) modelling in drug development, from dataset building to output generation

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Background

The 3 pillars of ADaMO



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- The Automated Datasets, Models and Outputs (ADaMO) initiative seeks to automate and streamline pharmacometric processes used for informing decision-making in drug development
- The manual creation of datasets for modelling, development of population models and respective reports are complex, arduous and time-consuming processes
  - the time spent in these activities tends to be longer than the time invested in using the models to inform the clinical development of compounds

- The ADaMO initiative has been developed in a validated computational environment [1, 2], Scinteco improve, where data, models and outputs are generated and stored
- ADaMO consists of three pillars that cover the end-to-end Pharmacometric modelling process
  - **pillar I**: automated dataset request and creation
  - **pillar II**: automated model building
  - **pillar III**: automated output creation

## Pillar I: A dataset for population modelling is produced using scripts generated automatically

The process starts with the user completing a data request form in a user-friendly web app, indicating the variables to be included in the dataset (e.g. demographic variables, subjects and dependent variable with definition of units, formulas and imputation rules). After reviewing the request, a data scientist triggers the automatic generation of SAS scripts in a validated GCP compliant environment where data is generated and stored [1,2]. Finally, the dataset undergoes QC and the user is automatically notified that the dataset has been created. In this pillar, automation simplifies and speeds-up the process of dataset request and creation, providing increased robustness as the scripts generated are reusable.



Order Details Data Order CPDS Activities			M&S Data Order									
Selected variables		Expand All Collapse All Sear	ch for Variable									
Expand All Collapse All	Search for Variable	Name	Labels	Unit	Modules	Formula	Default Attribute Param	Time Dependent	Туре	Imputatio		
		Core variables										
Name	Labels	Demography Variables										
▲ Core variables		AGE	Age	vear	DM		Baseline		Continuous	-99		
✤ Demography Variables			rige						Continuedo			
<ul> <li>Observation variables</li> </ul>		BSA	BSA	m^2	VS	DuBois	Baseline		Continuous	median		
BLQ	Below limit of quantification flag											
COMMENT	Data comments	BMI	BMI	kg/m^2	VS		Baseline		Continuous	mean		
С	Flag for exclusion											
DV	Dependent variable	HGT	Height	cm 🗸	VS		Baseline HEIGHT		Continuous	median		

#### Screenshots of the interface of the data order tool

#### Pillar II: A PK model is developed automatically using NONMEM

A heuristic algorithm is being developed to create a population PK model and optimise its components (e.g. structural, inter-individual variability, residual error models) automatically with the goal of reaching a final PK model developed in NONMEM [3]. For this purpose, an initial NONMEM model is generated from scratch using the open-source R package assemblerr (https://uupharmacometrics.github.io/assemblerr) [4], and its parameters are estimated using NONMEM directly in R using PharmR, an R wrapper for Pharmpy (https://pharmpy.github.io) [5]. Thereafter, the automatic process continues with the model being modified (e.g. structural model challenged) and a series of candidate models being generated. These are tested and the best model is selected based on pre-specified statistical criteria. In this pillar, automation speeds-up PK model development and it increases its robustness by using predefined algorithms.





For detailed information on model development algorithms, check the Pharmpy manual available at https://pharmpy.github.io



### Pillar III: A modelling report is pre-populated automatically

A series of R markdown scripts and an R library have been created which allow direct incorporation of model outputs (e.g. GOF plots, parameter tables, VPC) into a word report. By automatically combining the structure of a report with model outputs (main tables and figures), the reporting process has been substantially speeded up resulting also in fewer typographical and carry over errors.

Synopsis		Screenshots of the generated report							
Introduction	4 4		-						
Treatment assignments Number of patients per treatment group		Model schematic	Parameter	Estimate	RSE	CI95	Shrinkage	Description	Units
Demographic information		IV infusion	CL	0.0082	5.060	0.00736-0.00897	-	Clearance	L/h
Number of patients by sex Demographic data	Base Model information		V1	3.2700	2.980	3.08-3.46		Central Volume	L
Modelling process	Model	Peripheral Q Central	Q	0.0221	8.850	0.0183-0.0259		Transfer rate	L/h
Model Selection Criteria	;; 1. Based on: run1a	v2 ← V1	V2	2.2200	8.220	1.86-2.57	12	Peripheral volum	le L

#### Conclusion

- A solution to automate end-to-end Pharmacometric modelling has been developed
- The current scope of ADaMO includes classical PK models for a single entity in pillar II, and pillars I and III already go beyond this scope, supporting more advanced PK and PK/PD analyses
- While the full potential of the solution will only be achieved through the integration of all three pillars in one



computational environment, it is possible to use each component on its own

• Automation boosts quality, reproducibility and frees time for pharmacometricians to use the model outcomes to influence clinical trials, address more complex modelling tasks and increase the number of supported projects

## References

[1] Improve – Modeling and simulation platform. PAGE (2016). Abstr 6073.

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[3] Development of a tool for fully automatic model development (AMD). Chen et al. PAGE (2022). Abstr 10091.

[4] Pharmpy and assemblerr - Two novel tools to simplify the model building process in NONMEM. Nordgren et al. PAGE (2021). Abstr 9656.

[5] Pharmpy: a versatile open-source library for pharmacometrics. Nordgren et al. PAGE (2022). Abstr 10096.

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