

# Application of an AI Framework to Update a Quantitative Systems Pharmacology Model of CAR-T Therapy



Igor Goryanin<sup>1,2\*</sup>, Oleg Demin<sup>3</sup> & Irina Goryanin<sup>2</sup>

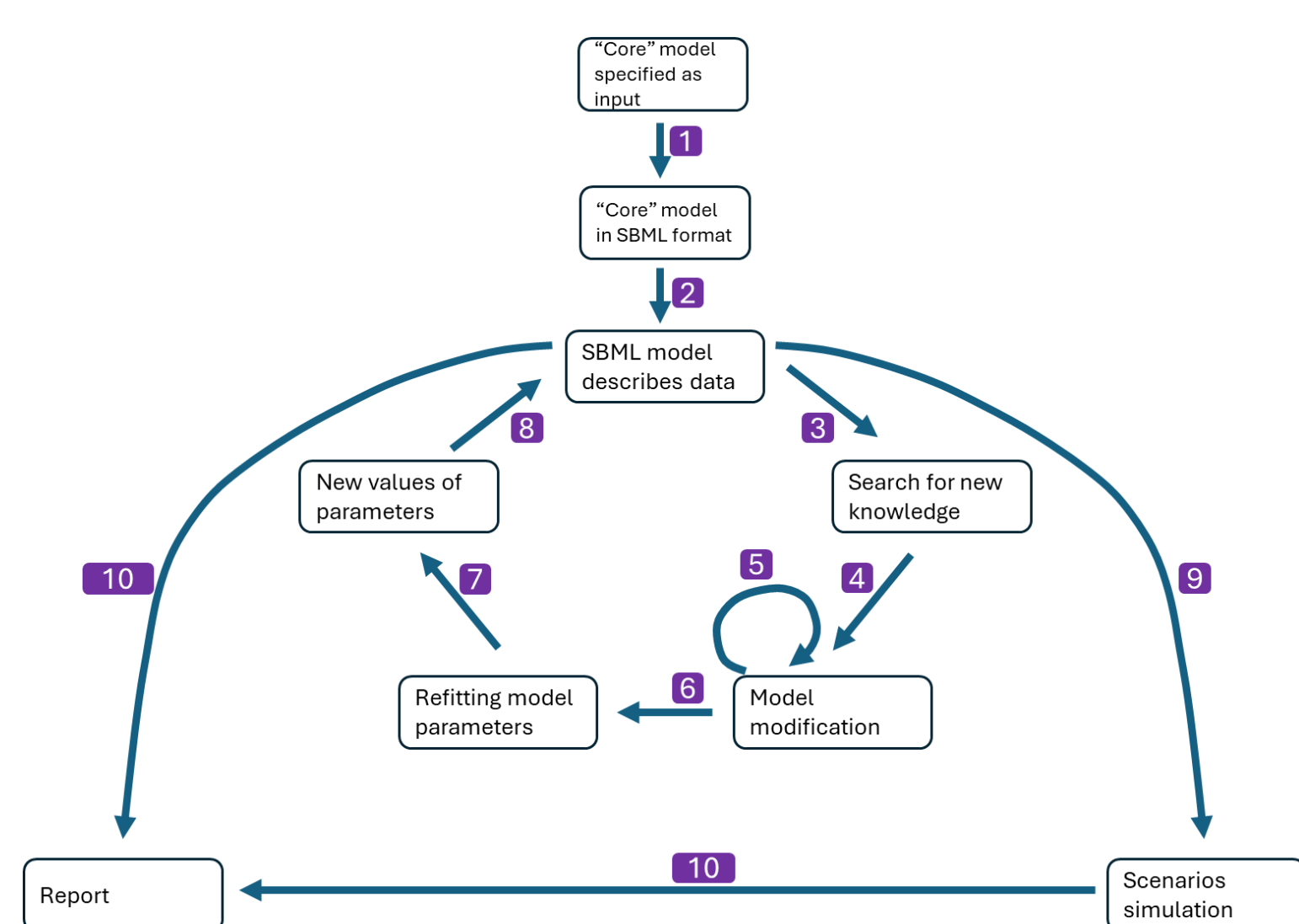
<sup>1</sup>Artificial Intelligence Institute, School of Informatics, University of Edinburgh · <sup>2</sup>IQANOVA Ltd., Edinburgh, · <sup>3</sup>InSysBio

## Introduction

Quantitative systems pharmacology (QSP) models provide mechanistic insight into drug action and disease dynamics but are typically constructed through labour-intensive, expert-dependent workflows that limit scalability. To address these challenges, we developed an AI-QSP (Artificial Intelligence–QSP) prototype that extends conventional QSP workflows by embedding automated model updating, parameter optimization, scenario generation, and verification within an AI-assisted modelling framework [1]. The present study applies this prototype to update a published CAR-T QSP model [2], with the objective of evaluating the feasibility, strengths, and limitations of AI-assisted automated model evolution.

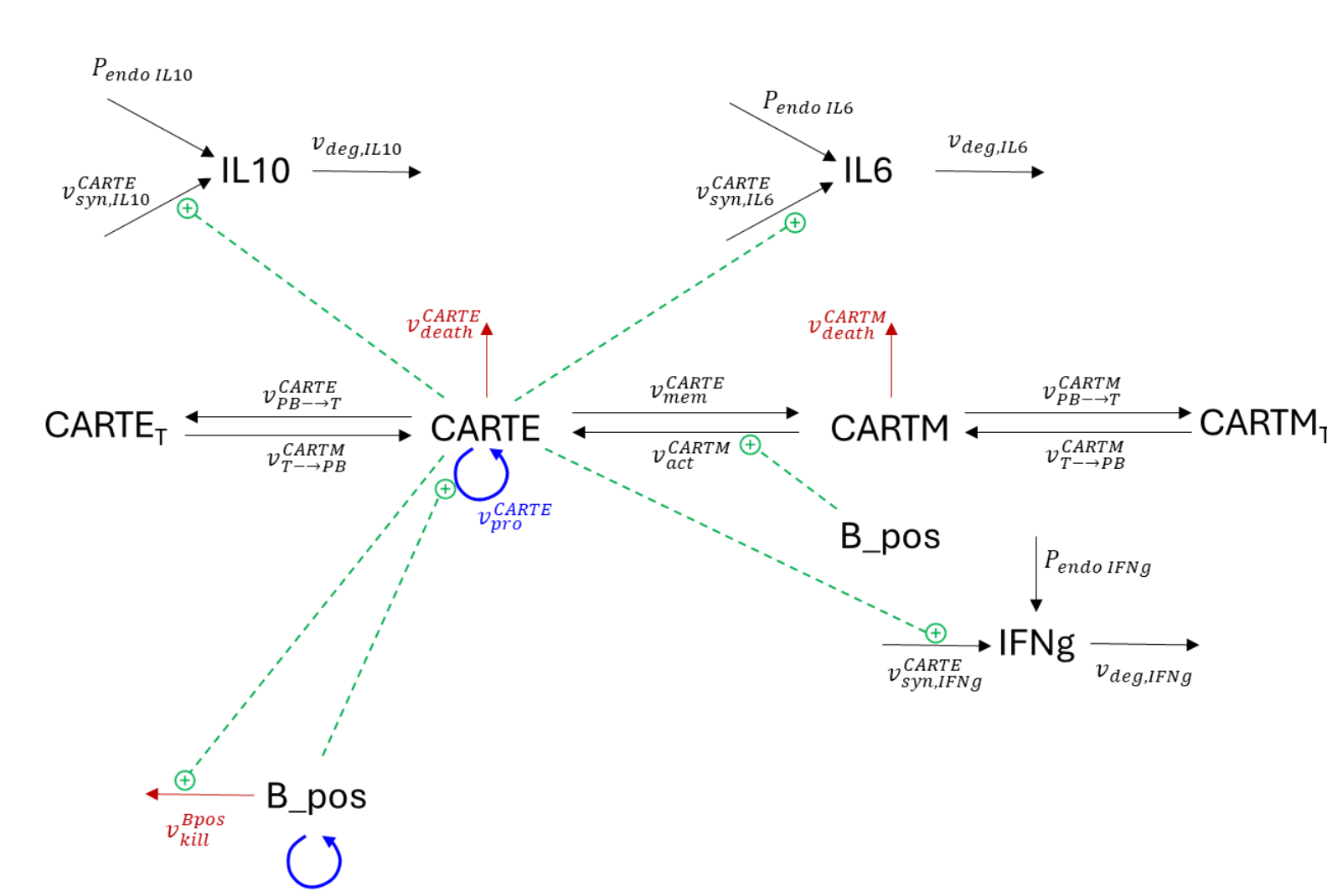
## Methods

**AI-QSP framework:** The AI-QSP prototype consists of multiple Large Language Models (LLMs) interconnected through structured prompt workflows and integrated with Python-based modelling tools executed locally. The overall architecture of the AI-assisted quantitative systems pharmacology (AI-QSP) framework is illustrated below.



The framework implements an iterative workflow that integrates artificial intelligence-based knowledge interpretation, mechanistic modeling in Systems Biology Markup Language (SBML), and automated parameter optimization.

**Description of core model (Alcore):** The reference model used for validation of the AI-QSP prototype was a previously published quantitative systems pharmacology (QSP) model describing the dynamics of chimeric antigen receptor T-cell (CAR-T) therapy. The model captures key interactions between tumor cells, CAR-T cell populations, and cytokine signaling processes that regulate therapeutic response, immune activation, and treatment resistance mechanisms [2] (see scheme below):



The model describes the dynamics of antigen-positive tumor cells (Bpos), effector CAR-T cells (CARTE), and memory CAR-T cells (CARTM). CARTE proliferation is driven by antigen stimulation from Bpos. CARTE cells can differentiate into memory CAR-T cells (CARTM). Effector CAR-T cells mediate tumor killing of Bpos. Both CARTE and CARTM undergo natural death processes. Tumor cells proliferate logistically.

**AI-QSP based automatic update of Alcore QSP model:** AI-QSP was instructed to incorporate biological knowledge related to the following phenomena: T-cell exhaustion, PD-1/PD-L1 checkpoint signaling, Tumor antigen escape

The following simplified prompt illustrates the instructions used to guide the AI-assisted model update process:

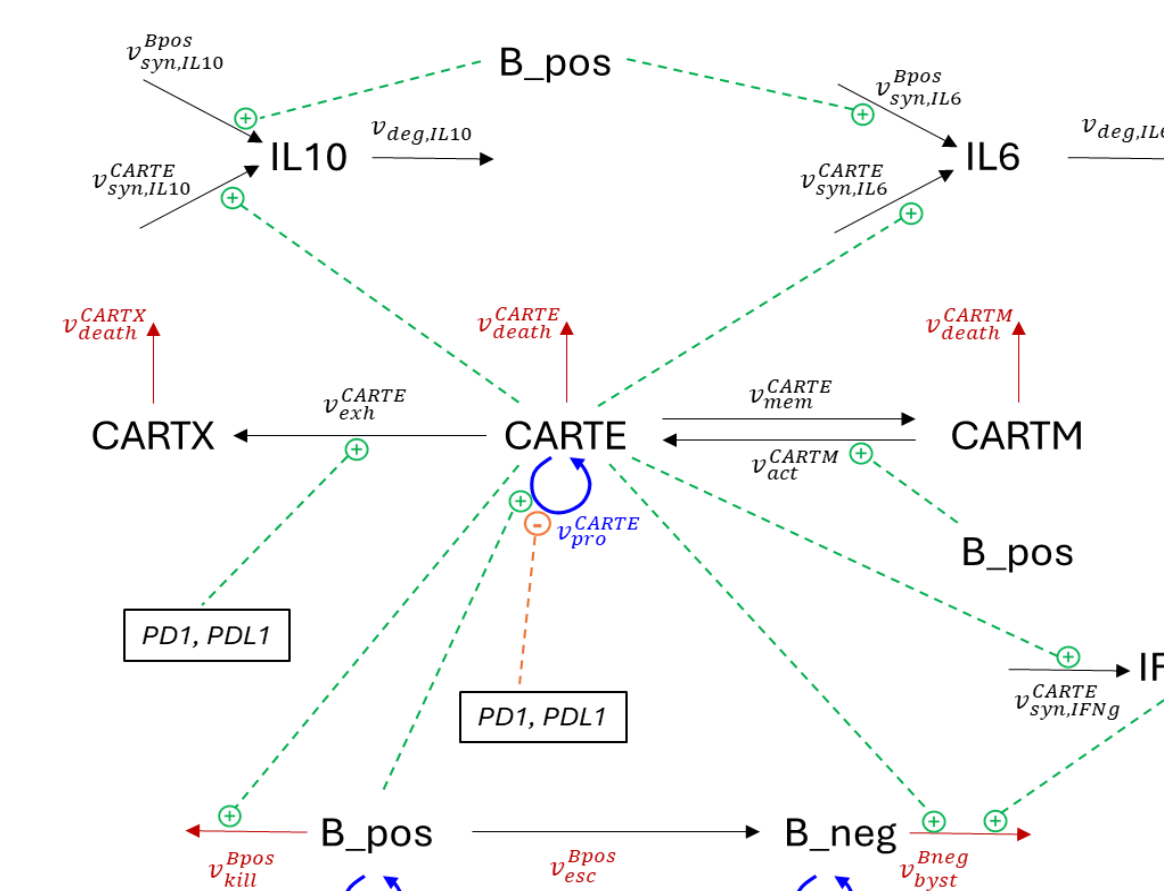
- Given an SBML model describing CAR-T therapy dynamics with the species CARTE, CARTM, B\_pos, cytokines, and tumor growth processes:
1. Identify important biological mechanisms in CAR-T therapy that are not currently represented in the model.
  2. Focus on the following mechanisms:
    - T-cell exhaustion
    - PD-1 / PD-L1 checkpoint regulation
    - tumor antigen escape
  3. Propose model extensions by:
    - introducing new state variables if required
    - defining new reactions or transitions
    - modifying rate laws if necessary
  4. Describe the proposed model updates in SBML-compatible form including species, parameters, and kinetic expressions.

**Synthetic data and model calibration:** a synthetic dataset was generated using simulations of the reconstructed Alcore QSP model. Model calibration was performed by the AI-QSP framework's optimization engine. The objective was to minimize the log-transformed root mean square error (log-RMSE) between the model simulations and the synthetic benchmark data.

A random-restart global search strategy, implemented in Python with Tellurium and NumPy, was used to sample 200 candidate parameter vectors within plausible biological bounds. The full calibration comprised 19 parameters: seven kinetic parameters governing CAR-T and tumor dynamics, plus six cytokine production and stimulation parameters, three cytokine degradation rate constants, two antigen-recognition parameters, and one baseline degradation constant.

## Results

**Generation of updated QSP model and analysis of its structure:** Applying several cycles described in AI-QSP workflow updated version of CART QSP model (**Alupdate2**) was generated on the basis of Alcore QSP model



Key Process-Level Differences

Process	Alcore	Alupdate2
Tissue migration (CARTE, CARTM)	✓ Present	X Absent
Exhaustion transition (CARTE -> CARTE_EX)	X Absent	✓ Rcn_CARTE_Exhaustion
Antigen-negative tumour growth	X Absent	✓ Rcn_Bneg_growth
Bystander killing of B_neg	X Absent	✓ Rcn_Bneg_Bystander_Killing
Antigen escape (B_pos -> B_pos_esc)	X Absent	✓ Rcn_Antigen_Escape
CAR-T proliferation (antigen-driven)	✓ k_prolif + CARTE + B_pos/K_prolif + B_pos	✓ V + same expression
Tumour killing (saturable)	✓ k_kill + CARTE + B_pos/K_kill + B_pos	✓ V + same expression
Cytokine synthesis (IL-6, IL-10, IFN-gamma)	✓ Present	✓ Present (volume-scaled)

The Alupdate2 model differs from the Alcore model in both **state variables** and **biological processes**. Indeed, there are 3 groups of variables/processes in these model versions:

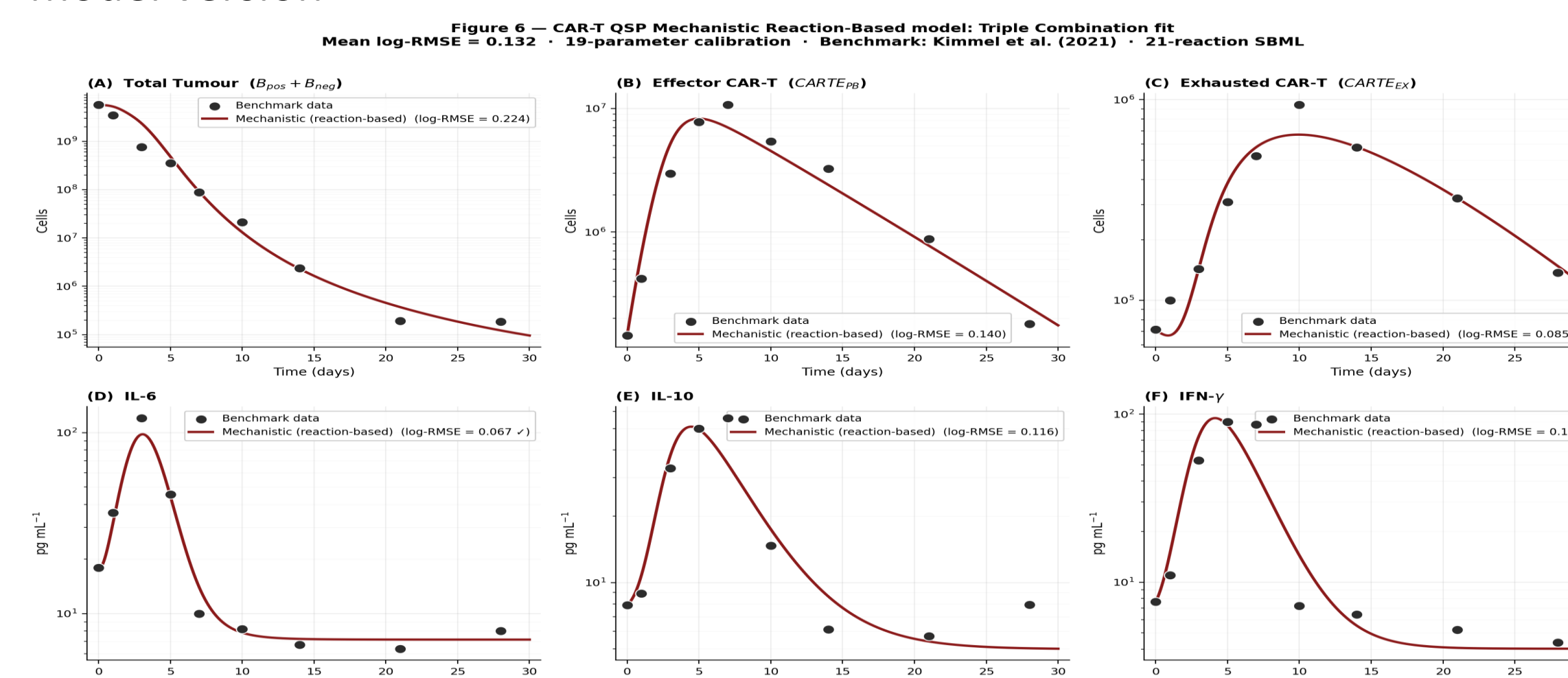
- Group 1: Included in Alcore version only
- Group 2: Included in "Alupdate2" version only
- Group 3: Included in both versions

**AI-QSP based automatic calibration of Alupdate2 :** Initially, Alupdate2 was applied for calibration against the synthetic dataset. Calibration converged to poor solutions, likely due to structural limitations in the right-hand side rate expressions introduced during the AI-guided extension step.

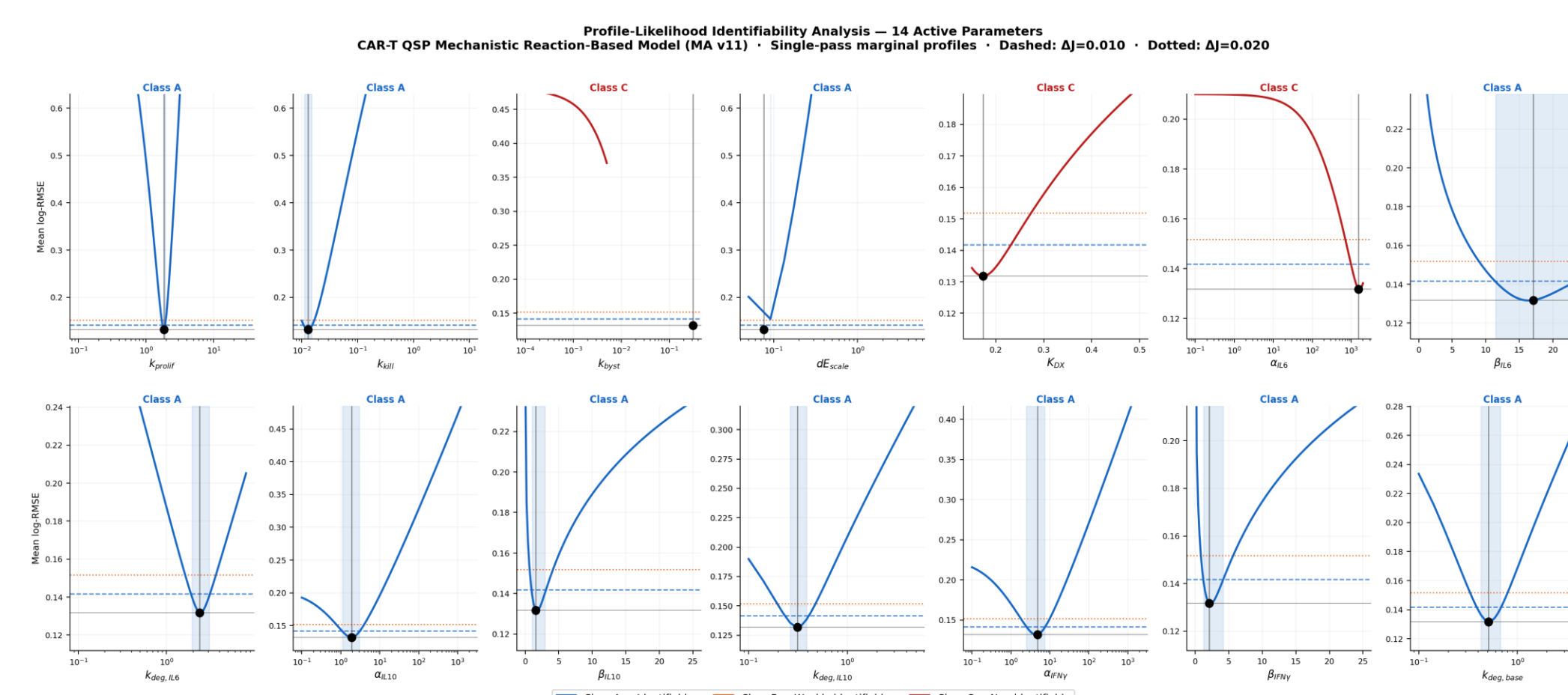
This failure is itself an informative outcome: it demonstrates that AI-generated structural extensions, even when technically correct at the SBML level, may not be immediately calibratable and require further adaptive refinement.

In response, the AI-QSP framework was re-engaged to adaptively modify the rate expressions of the problematic processes, producing **Alupdate3** — with revised kinetic formulations for the exhaustion and bystander killing pathways that improve the conditioning of the optimisation landscape

**Calibration of Alupdate3 :** AI-QSP framework was applied to successfully calibrate Alupdate3 model version



**Global Sensitivity and identifiability analysis of Alupdate3 :** A Sobol' variance-based GSA was performed on all 19 calibrated parameters using a Saltelli quasi-random sample of N = 1024 base vectors (40,960 total model evaluations). First-order (S<sub>1</sub>) and total-order (S<sub>T</sub>) Sobol' indices were computed. Following GSA analysis, profile-likelihood identifiability was assessed for the 14 active parameters using single-pass marginal profiles evaluated across each parameter's full bound range:



Ten of 14 parameters were classified as identifiable, with finite bounded confidence intervals; four parameters were non-identifiable

## Conclusions

An AI-based framework for automated updating of QSP models was developed and evaluated in the context of CAR-T therapy modelling. The results demonstrate that AI-assisted workflows can accelerate model extension while maintaining mechanistic interpretability and expert oversight. The AI-QSP framework provides a scalable approach for iterative QSP model development and supports integration of diverse biological and clinical data sources. This work establishes a generalizable paradigm for transparent, data-driven evolution of mechanistic pharmacology models. Model credibility was assessed using ASME V&V 40 and ICH M15 principles, including global sensitivity and profile-likelihood analyses

## References

1. Goryanin I, Goryanin I, Demin O. Revolutionizing drug discovery: Integrating artificial intelligence with quantitative systems pharmacology *Drug Discovery Today*. 2025;30(9):104448.
2. Hardiansyah et al. Quantitative systems pharmacology model of CAR-T cell therapy. *Clinical and Translational Science*. 2019;12(4):343–349.
3. Goryanin I, Demin O., Checkley S., Goryanin I. An AI-Assisted Workflow for Reconstruction, Extension, and Calibration of Quantitative Systems Pharmacology Models. Submitted to CPT and BioRxiv, available on request [goryanin@iqanova.org](mailto:goryanin@iqanova.org), [www.iqanova.org](http://www.iqanova.org)

