



# Predictive Stability for Biologics Using Kinetic Modelling

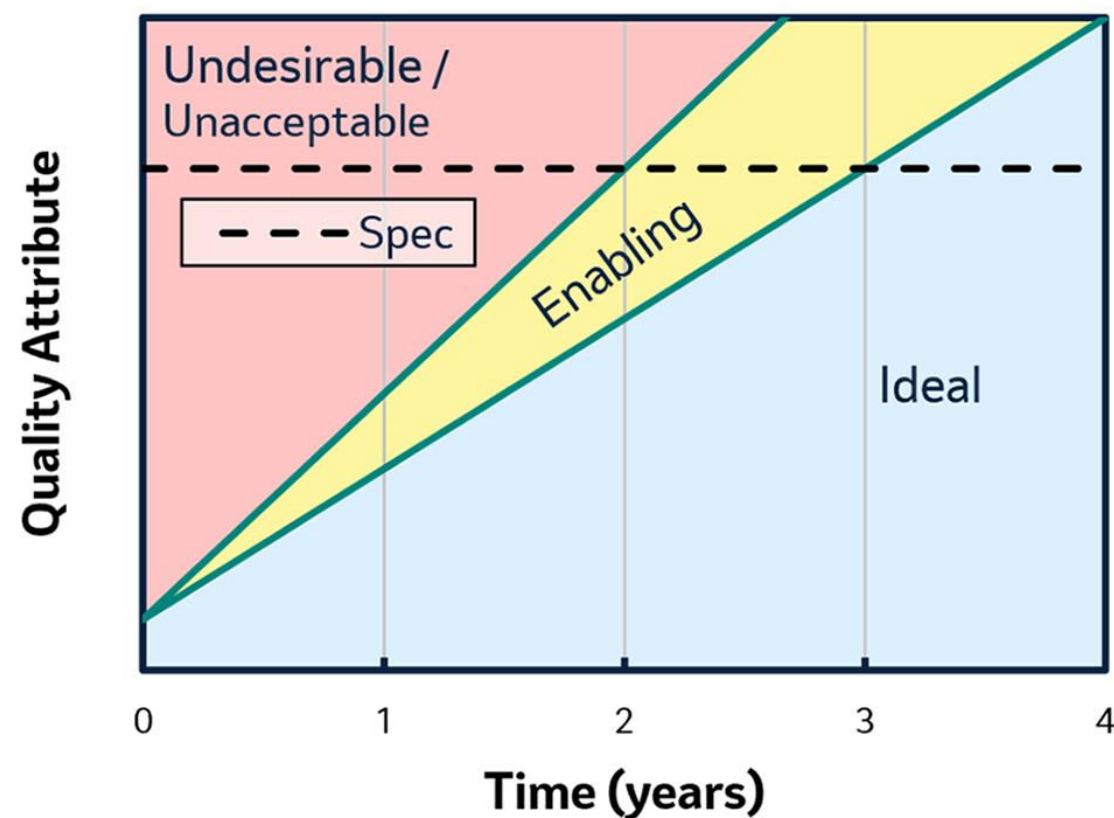
Michael Dillon, Jun Xu, Geetha Thiagarajan, Daniel Skomski, Adam Procopio

MRL, Merck & Co., Inc., Rahway, NJ, USA

# The Importance of Pharmaceutical Shelf Life

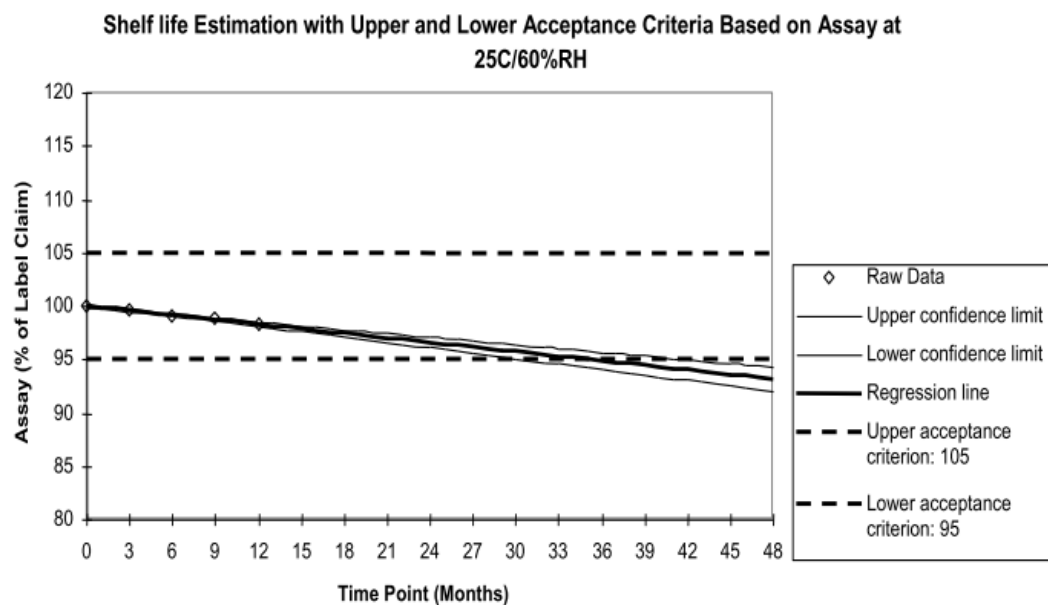
- Drug products must remain safe and effective up until patient administration
- Must establish a “shelf life” when all quality attributes stay within an acceptable specification
- Sterile pharmaceutical products generally require 2+, ideally 3+ years of shelf life, ensuring product safety, sufficient time for travel logistics, and minimization of product wastage.

## Shelf Life of Biopharmaceutical Products

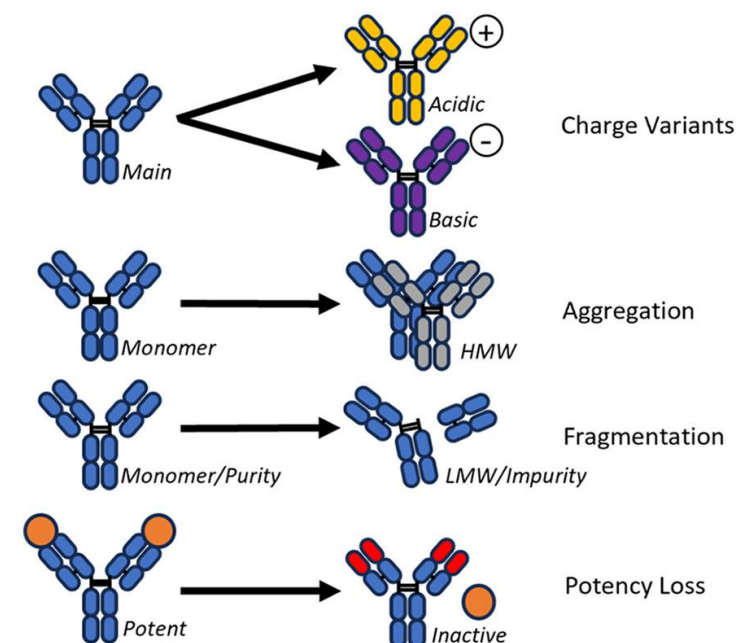


# Current Challenges of Setting Biopharmaceutical Shelf Life

- Shelf-life, or long-term stability, determination is a development bottleneck:
- Current guidance requires real time data collection with no extrapolation (commercial) or minimal extrapolation with only intended storage temp (clinical), so essentially need to wait 24M from product generation to claim you have a 2-year shelf life
- Speeding up shelf-life determination would improve CMC development timelines
- Biologics also have unique challenge of many attributes to track for product quality, and complex degradation pathways

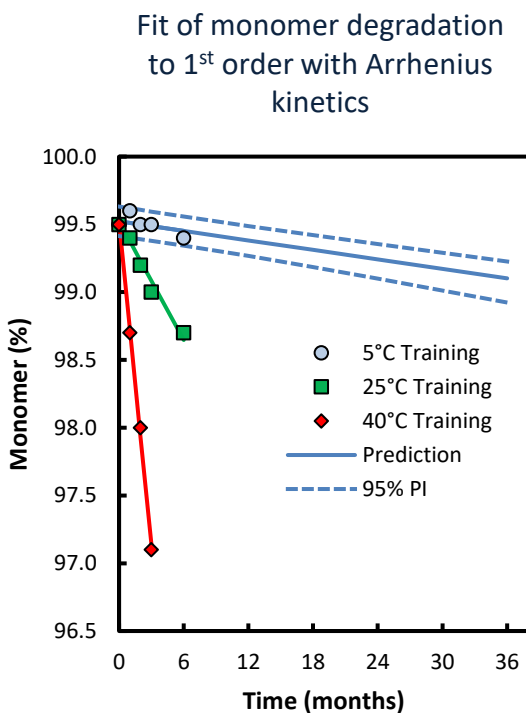


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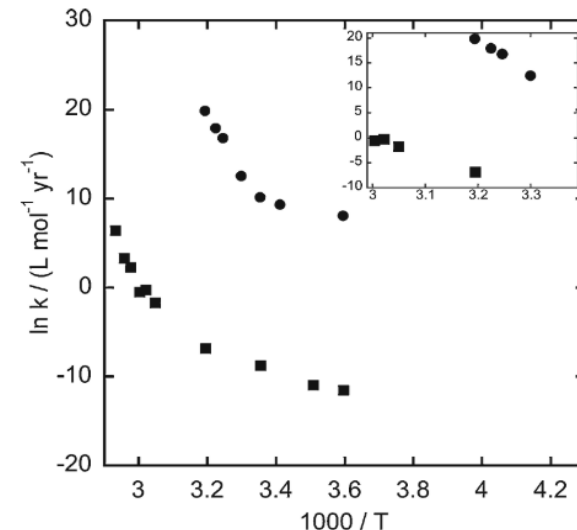


# Can we predict long-term stability using short-term data combined chemical reaction kinetics?

- Pharmaceutical degradation is generally worsened as temperature increased, so collecting multiple higher temperatures can theoretically predict degradation at lower temperatures.
- Historically, in biologics this has been considered not possible due to non-Arrhenius behavior, but recent publications have demonstrated cases for monoclonal antibodies that are well described by Arrhenius behavior
- Growing evidence we can use short term data sets at higher temperatures to predict long term, low temp trends.



Non-Arrhenius rate constants for aggregation of bG-GSF (circles) and mAb (squares) (*reproduced from Wang & Roberts. AAPS Journal. 2013.*)



Increasing number of publications shows capability of Arrhenius models to predict long-term stability

scientific reports

OPEN Long-term stability predictions of therapeutic monoclonal antibodies in solution using Arrhenius-based kinetics

Drago Kuzman<sup>1</sup>, Marko Bunc<sup>1</sup>, Miha Ravnik<sup>1,2</sup>, Fritz Reiter<sup>1</sup>, Lan Zagar<sup>1</sup> & Matjaž Bončina<sup>1,2</sup>

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Predicting the Long-Term Stability of Biologics with Short-Term Data

Michael Dillon,<sup>\*</sup> Jun Xu, Geetha Thiagarajan, Daniel Skomski, and Adam Procopio

Cite This: *Mol. Pharmaceutics* 2024, 21, 4673–4687

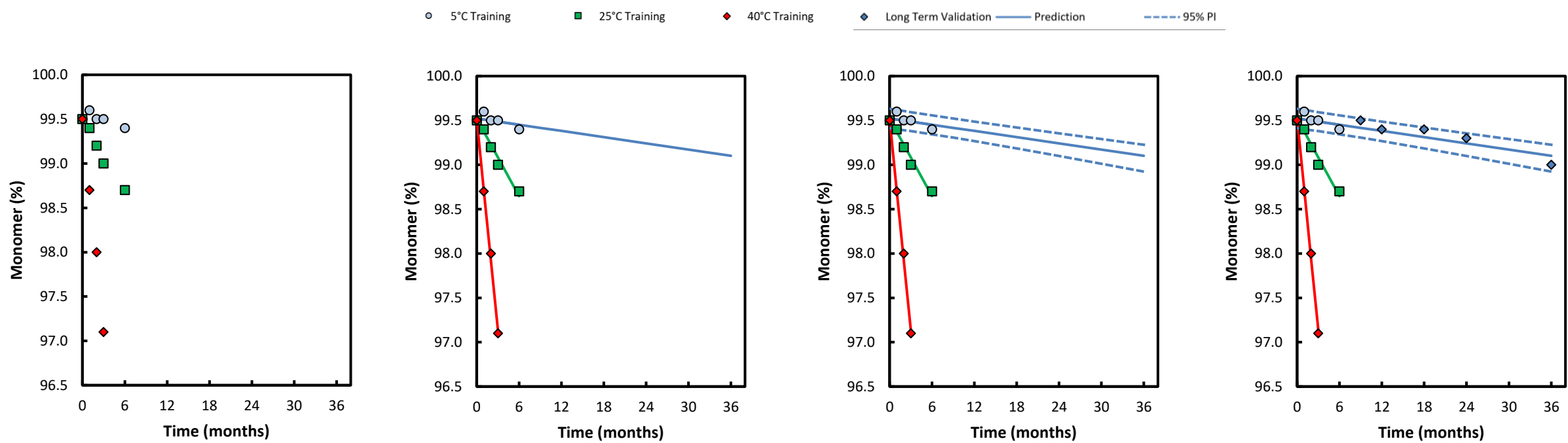
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scientific reports

OPEN A universal tool for stability predictions of biotherapeutics, vaccines and in vitro diagnostic products

M. Huelsmeyer<sup>1</sup>, D. Kuzman<sup>1</sup>, M. Bončina<sup>1</sup>, J. Martinez<sup>2</sup>, C. Steinbrügger<sup>1</sup>, J. Weusten<sup>1</sup>, C. Calero-Rubio<sup>2</sup>, W. Buche<sup>2</sup>, B. Niederhaus<sup>1</sup>, Y. Vantsevelde<sup>1</sup>, M. Hrynnyk<sup>2</sup>, P. Balcells<sup>3,4</sup>, H. Achard<sup>1,5</sup>, S. Augusto<sup>1,5</sup>, M. Guillois<sup>1,5</sup>, C. Piszczolinski<sup>1,5</sup>, M. Gerasimov<sup>1,5</sup>, C. Neyra<sup>1,5</sup>, D. Ponduri<sup>1,5</sup>, S. Ramesh<sup>1,5</sup> & D. Clément<sup>1,5</sup>

# Prediction Workflow



# Model Algorithm

Load Data

Solve for Model  
Parameters and RMSE

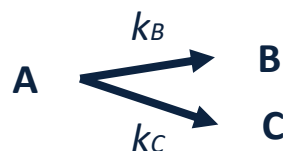
Monte Carlo Simulation  
for 95% Prediction  
Intervals

Calculate Upper and  
Lower Estimates

## Kinetic Model Equations

### Parallel Reactions

Monomer  $\rightarrow$  HMW + LMW,  
Main  $\rightarrow$  Acidic + Basic



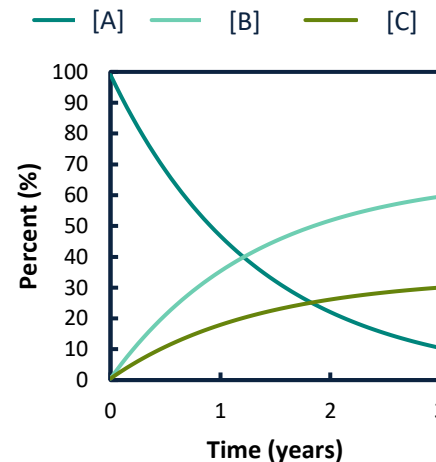
$$\frac{d[A]}{dt} = -(k_B(T) + k_C(T)) [A]$$

$$\frac{d[B]}{dt} = k_B(T)[A] + [B]_0$$

$$\frac{d[C]}{dt} = k_C(T)[A] + [C]_0$$

$$k_B(T) = k_B(T_{ref})e^{-\frac{E_{A,B}}{R}\left(\frac{1}{T} - \frac{1}{T_{ref}}\right)}$$

$$k_C(T) = k_C(T_{ref})e^{-\frac{E_{A,C}}{R}\left(\frac{1}{T} - \frac{1}{T_{ref}}\right)}$$



### Single Reaction/ Degradation

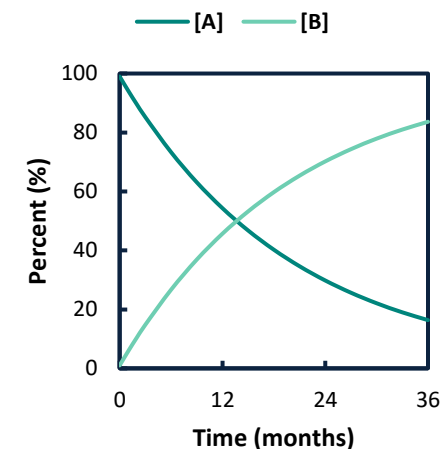
CE-SDS  $\rightarrow$  LMW, Potency, PS80



$$\frac{dA}{dt} = -k(T)[A]$$

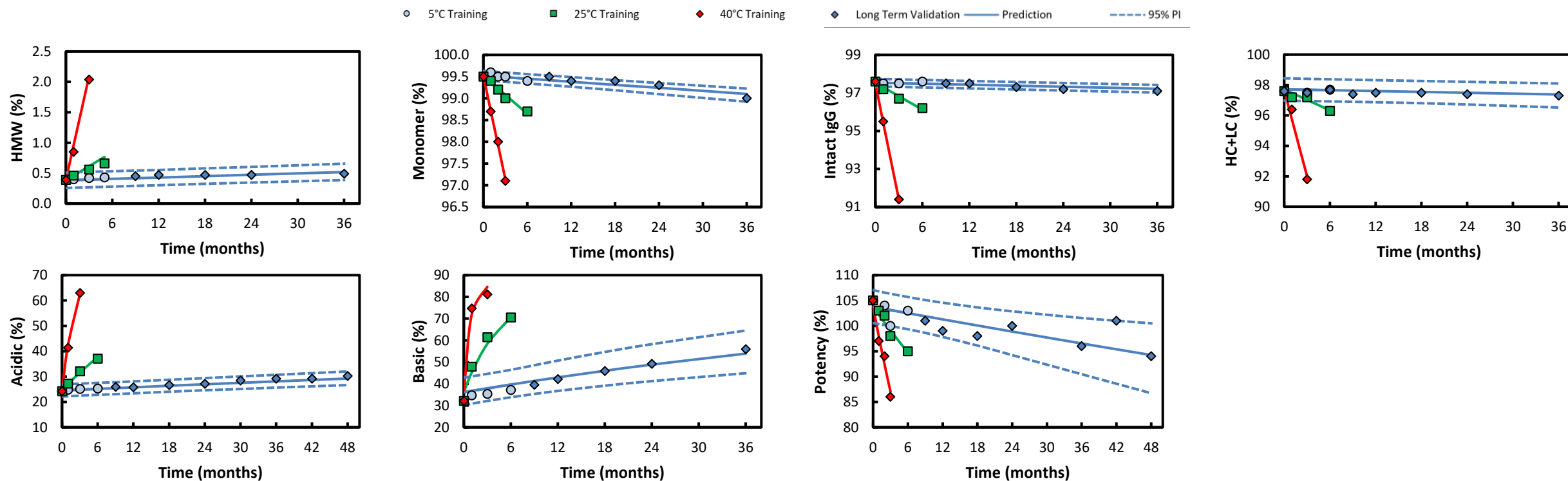
$$\frac{dB}{dt} = k(T)[A]$$

$$k(T) = k(T_{ref})e^{-\frac{E_A}{R}\left(\frac{1}{T} - \frac{1}{T_{ref}}\right)}$$



# Examples of Biologics Quality Attribute Predictions

- Biologics require prediction of not just one, but multiple quality attributes to set shelf-life,
- In each case below, kinetic model was trained on only 6M of data from 5, 25, and 40C data sets. Then predicted out to 36+ months (solid and dashed lines). Then real long-term data from IND/BLA filings (diamonds) compared alongside, showing excellent agreement with predictions
- Shown for key quality attributes of HMW (aggregates), monomer, Intact IgG, HC+LC, charge variants, and potency



# Model Validation on Multiple Drug Products

- Drug product (DP) validation set comprised of mAbs, ADCs, conforms, fusion protein
- IgG1 and IgG4
- Liquid and Lyophilized formulations
- Concentration range
  - Low: < 25 mg/mL
  - Medium: >25 and < 100 mg/mL
  - High: ≥ 100 mg/mL

Drug Product	Molecule	mAb Subtype	State	Conc (mg/mL)
A	mAb	IgG4	Liquid	Medium
B	mAb	IgG1	Liquid	Medium
C	mAb coform	IgG1 + IgG4	Liquid	Low
D	mAb	IgG1	Liquid	High
E	mAb	IgG4 Human	Liquid	High
F	ADC	IgG1	Liquid	Low
G	ADC	IgG1	Lyophilized	Low
H	mAb	IgG4	Liquid	Low
I	mAb	IgG4	Lyophilized	Low
J	mAb	IgG4	Liquid	High
K	mAb	IgG1	Liquid	High
L	mAb	IgG4	Liquid	Low
M	mAb coform	IgG1 + IgG4	Liquid	Low
N	mAb	IgG4	Liquid	Medium
O	mAb	IgG1	Liquid	Medium
P	mAb	IgG1	Liquid	Medium
Q	mAb coform	IgG1 + IgG4	Liquid	Low
R	Fusion Protein	N/A	Lyophilized	Medium

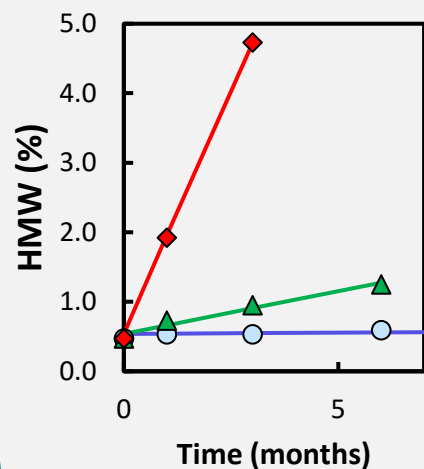


# Model Validation on Multiple Drug Products – HMW Example

- For each DP, model trained on its own 6M data from 5, 25, 40C → determine kinetic parameters → predict into future
- Compared 36M predictions against real measured 36M data from filings, showing excellent agreement (right bar chart)

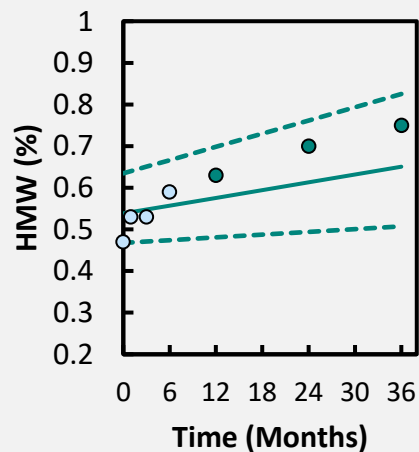
## Use 6M Data (5, 25, 40C) to predict Long Term 5C Stability

○ 5C    ▲ 25C    ◆ 40C  
— 5C Pred    — 25C Pred    — 40C Pred



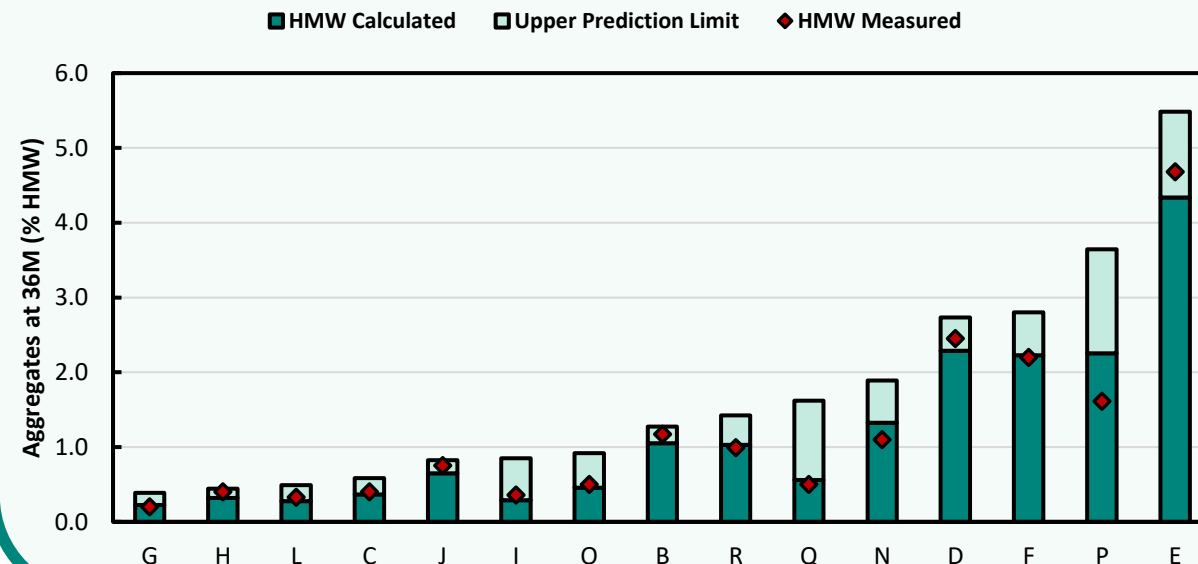
Kinetic Model +  
Monte Carlo sim  
for error  
estimates

● Measured    — Predicted  
--- 95% C.I.



## Validation on bio DPs with 36M data (mAbs, co-forms, ADCs, & fusion protein)

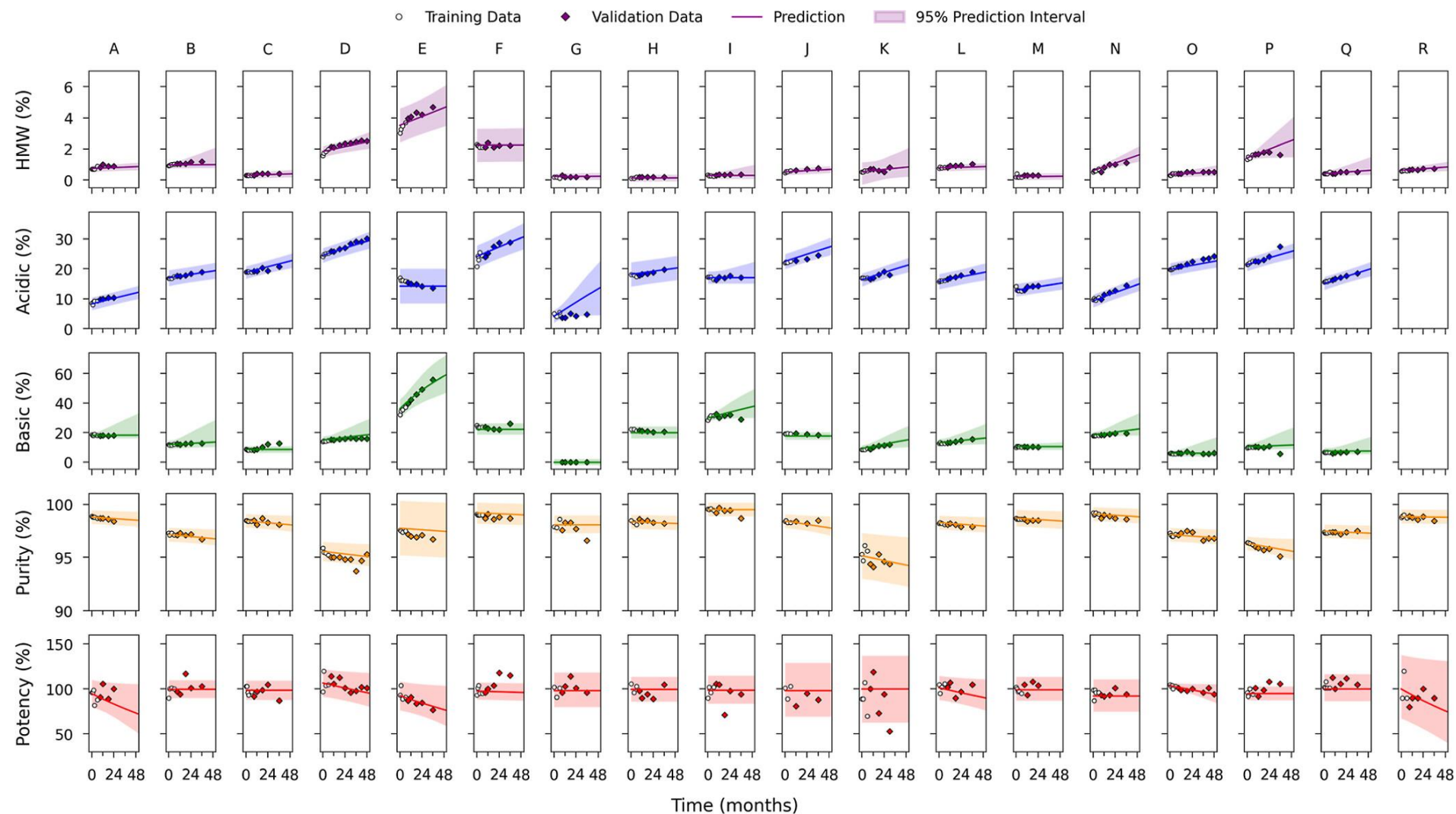
### 36 Month Aggregate (HMW) - Measured vs Predicted



# Model Validation on Multiple Drug Products – Multiple Attributes

Excellent agreement with  
real long-term data within  
95% prediction intervals

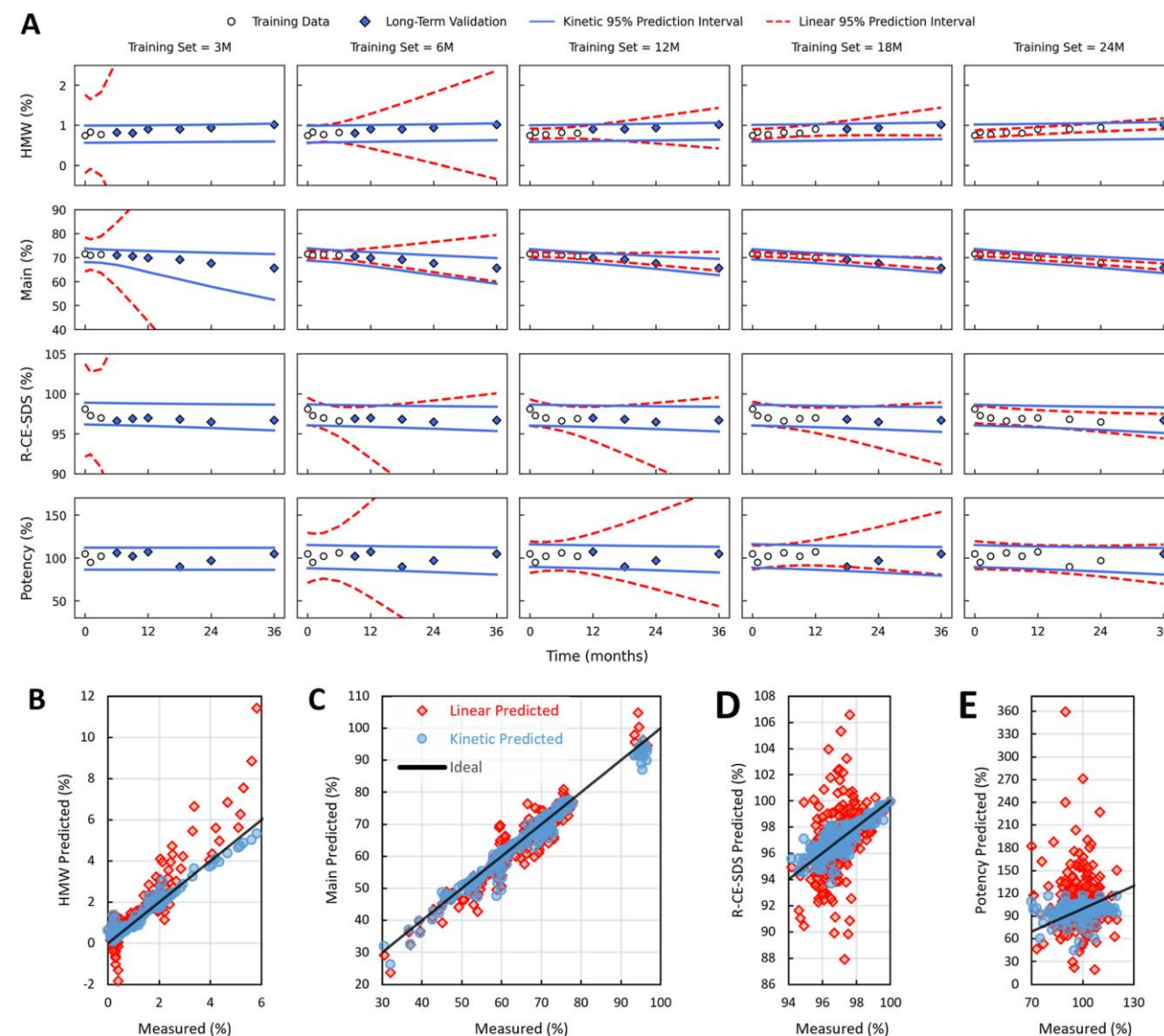
Models trained up to 6M 5,  
25C, and 3M 40C. For clarity,  
only 5C data and predictions  
shown here.



# Kinetic Models Shows Improved Prediction to Linear Regression at Early Timepoints

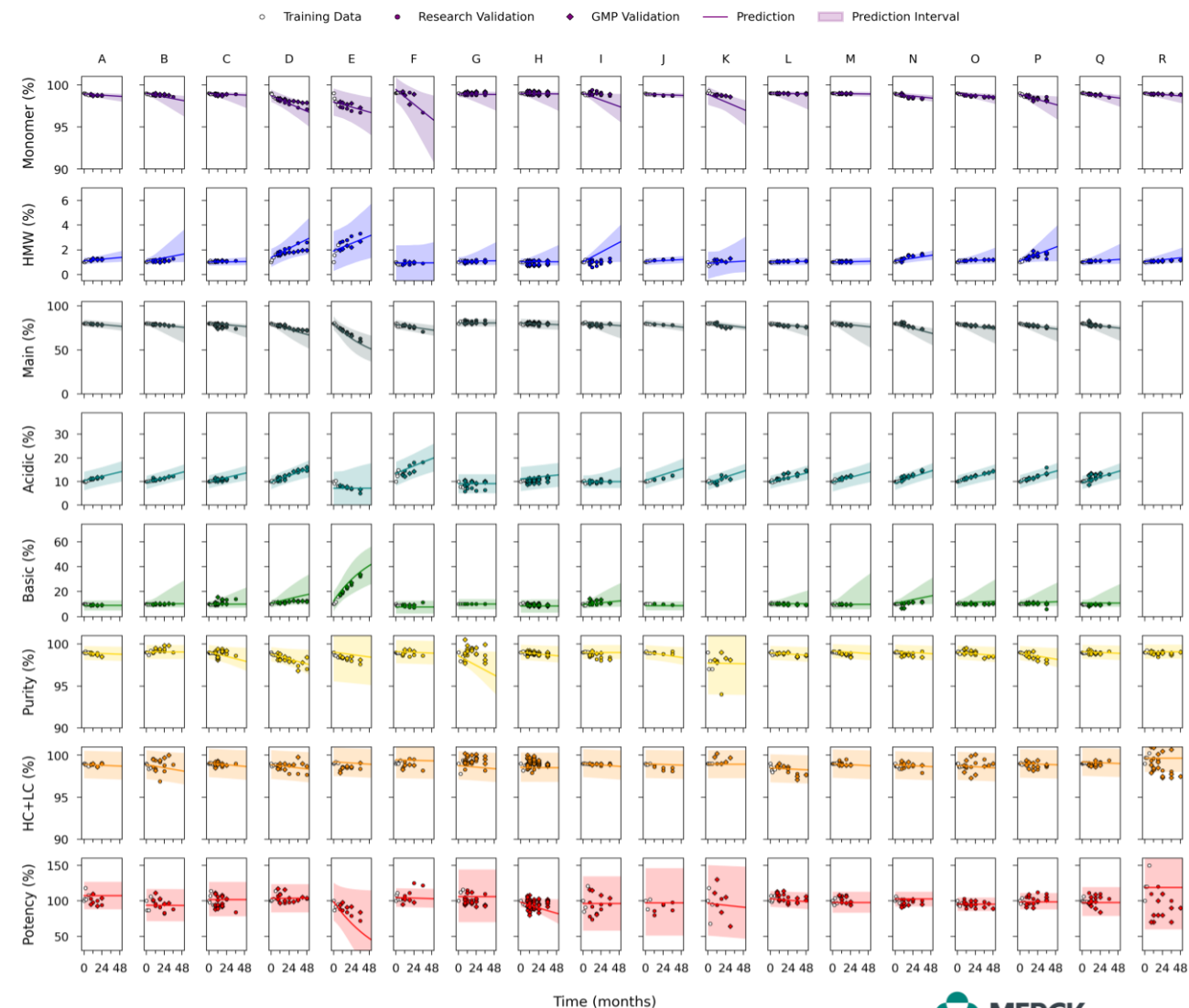
Linear regression on 5C (intended storage) condition is current industry standard to set shelf life. We wanted to compare if our model could yield earlier, more accurate predictions

- A) Kinetic model using 5, 25, and 40C data (blue lines) shows more precise prediction compared to linear regression on just 5C (red) when limited timepoints available
- B) Comparison of HMW predicted vs measured for linear model (red diamond) and kinetic model (blue circle). Kinetic model closer to ideal scenario of 1 to 1 agreement (black line), indicating more accurate model.
- C) Same as above for Charge variants – main
- D) Same as above for R-CE-SDS purity
- E) Same as above for Potency (ELISA)



# Modeling Can Predict Overall Product Success, Not Just a Single Batch

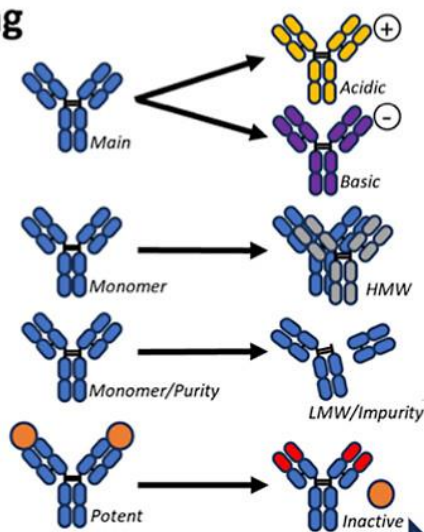
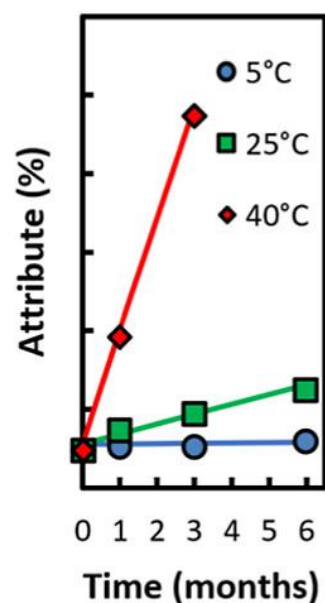
- In figure to right, model trained on single non-GMP probe stability batch and generated prediction intervals
- All future data, including future GMP batches for the product plotted within cell (normalized to same initial value).
- Future data remains within worst case prediction intervals, suggesting prediction estimates from early non-GMP probe stability batch can predict future batch success, i.e. overall product success
- Caveats: must be same formulation, process, and analytical methods when extending these extrapolations



# Summary

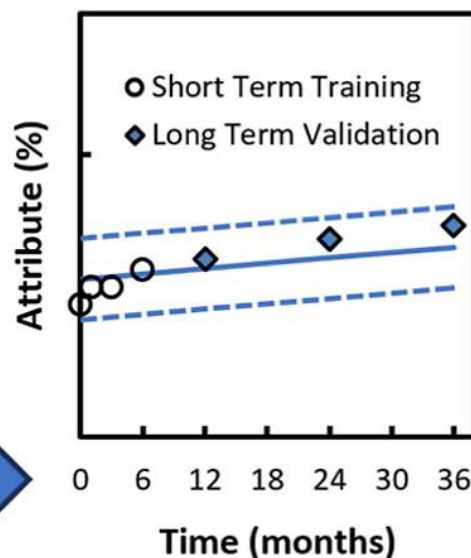
- A kinetic model was developed to predict long-term stability using short term data from accelerated temperatures
- Model rigorously validated on 18 biologics drug products of varying properties and with multiple quality attributes
- Model showed excellent agreement with long term training data and improved prediction compared to standard linear regression

## Short Term Training



Kinetic Model

## Long Term Prediction & Validation



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Article

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# Thank you!!

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Thank you very much your attention and attending this talk!

A VERY special thank you to the analytical teams who have generated the data in the IND/BLA filings leveraged to support this analysis

And a huge thank you to my co-authors on this work: Daniel Skomski, Jun Xu, Geetha Thiagarajan, and Adam Procopio

And thank you to all my colleagues who have contributed data, scientific discussion, or supported the effort, including but not limited to:

Swathi Damodaran

Kyle Fergie

Amanda Christon

Mariah Mcdonald

Xi Zhao

Zhiyuan Ruan

Aparna Chakravarti

Daniel Fesenmeier

Jiaying (Ingrid) Liu

James Forder

Federico Ferrari

Jordan Berger

Rui Fang

Smita Raghava

Jainik Panchal

Ralf (Joe) Carillo

Alex Pavon

Michael Heslinga

Yogita Krishnamachari

Nicole Buist

Wei Xu

Sachin Mittal

Rubi Burlage

And the broader SPD and BARD teams!