

Immunogenicity Publication Bias and Its Consequences for Predictive Models

A Call for Transparent Reporting

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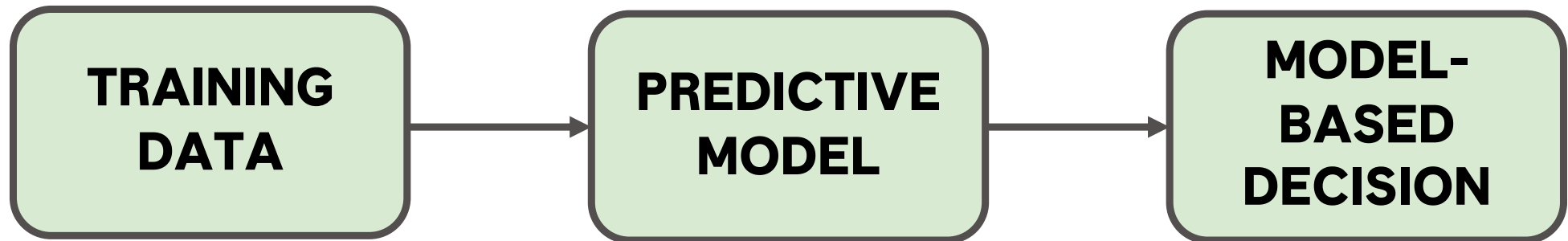
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Predictive models have potential to derisk immunogenicity early

But do we give them the chance to reflect the reality of early-phase development?

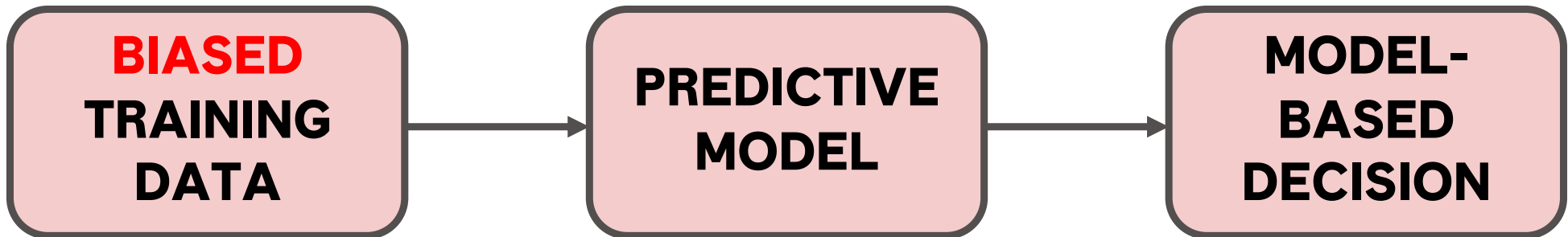


Guides:

- Candidate selection and ranking
- Protein engineering
- Trial design ...

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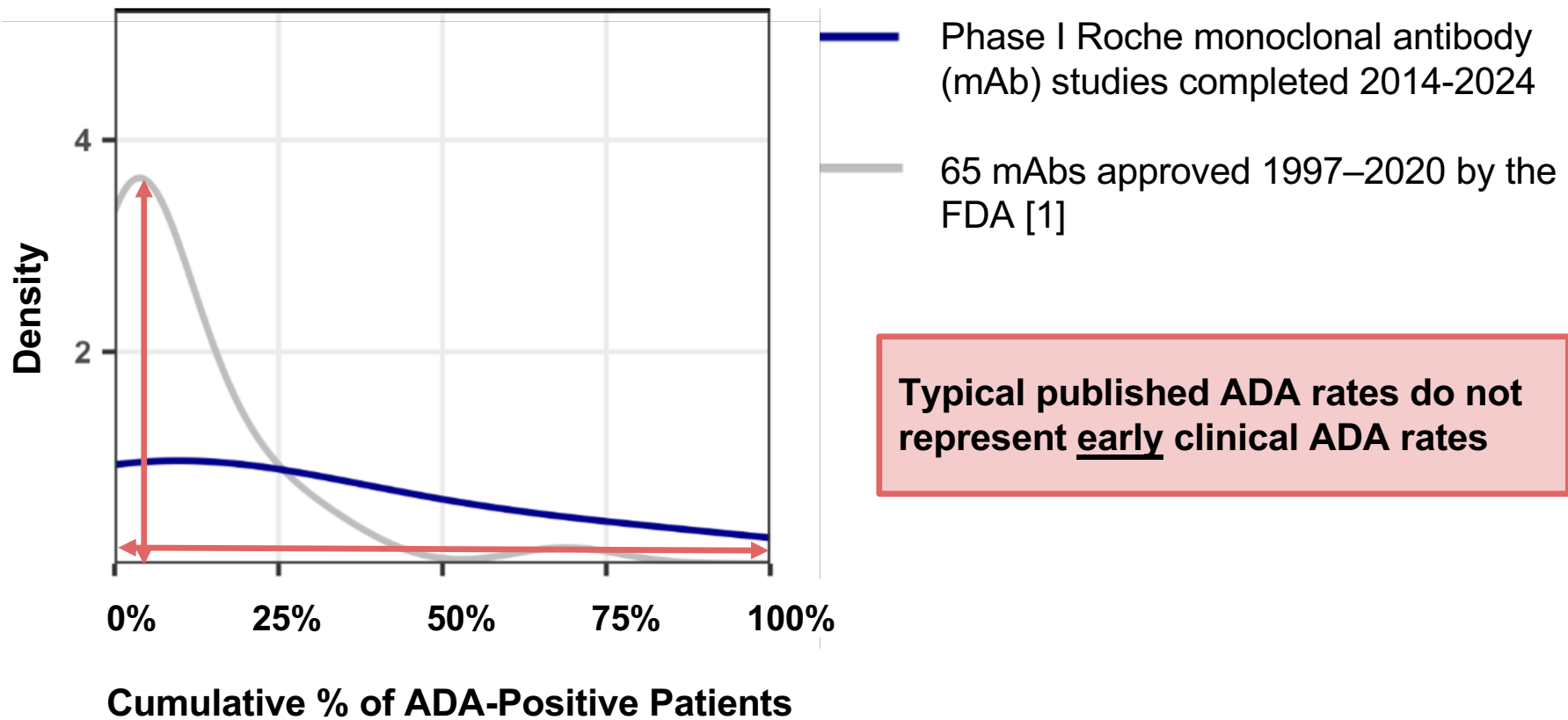


Misguides:

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Published Anti-Drug Antibody (ADA) Data vs. Phase I Reality

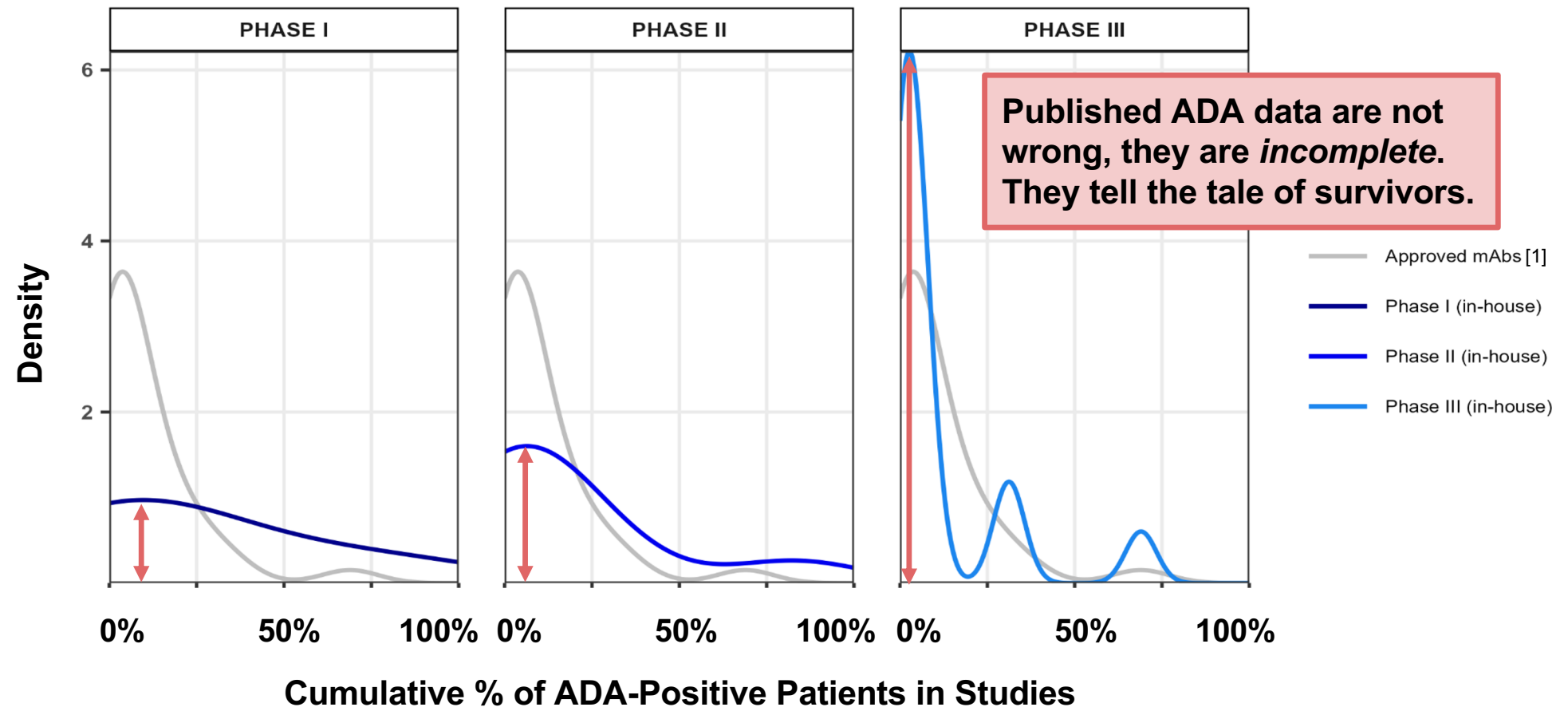
A clear mismatch in the ADA risk profile - and yet, we want to use models for early-phase prediction



[1] Vaisman-Mentesh *et al. Front Immunol.* 2020;11:1951.

Explaining the Gap: “Survival of the Fittest”

Attrition of high ADA risk compounds & lack of publishing of their ADA data drives publication bias



Simulate ADA Time-Course

Empirical ADA Incidence Time Course Model, Closed Solution to 2 State Markov Model

$$y = y_{\max} - (y_{\max} - b) \cdot \exp\left(-\frac{k_{np}}{y_{\max}} \cdot (t - t_{\text{lag}})\right)$$

**Structural Time-Course
Parameters:**

t_{lag} = onset time
 k_{np} = transition rate
 b = baseline positivity

Learned from NHP data

Peak ADA Incidence:

y_{\max} = maximum
cumulative ADA incidence

**Calibrated on the 2 in-
Human datasets**

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10000 simulations

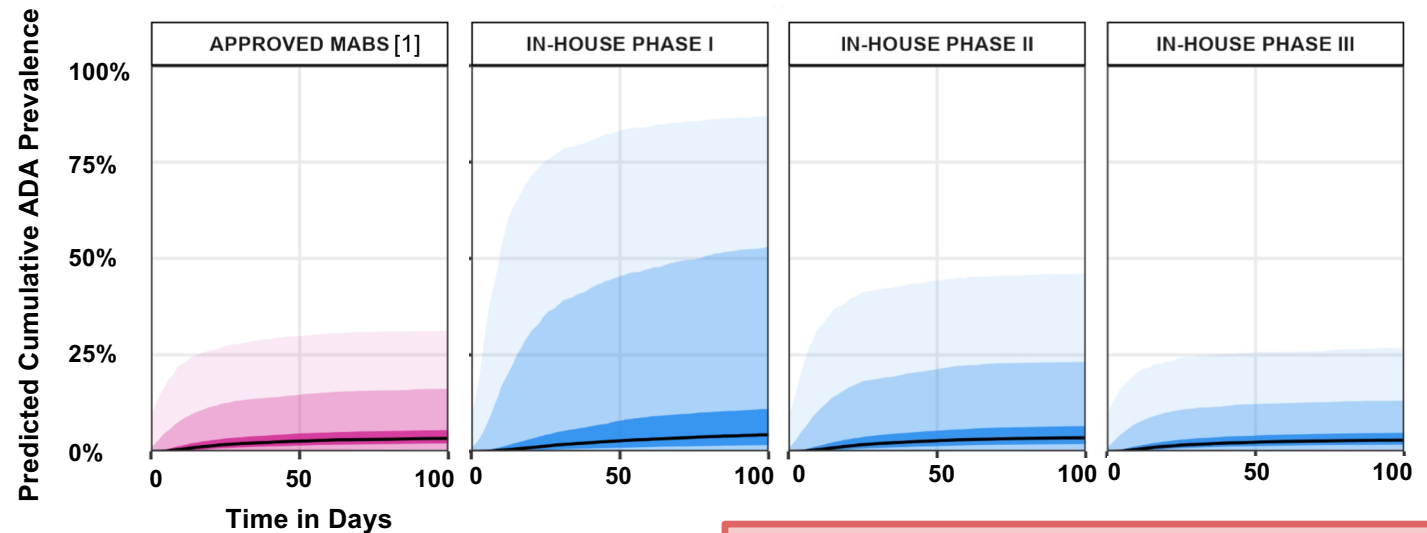
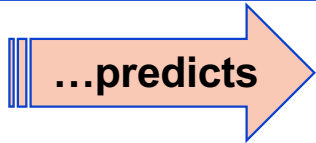
Each represents a compound

Compare predicted IG dynamics

Biased ADA Data Produce Biased Immunogenicity Predictions

We underpredict early-phase ADA risk if we rely on typical published ADA resources

Our Empirical Model



Confidence intervals (percentile ranges):

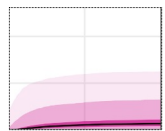
- 10%-90%
- 25%-75%
- 40%-60%

Median

Training the model on published ADA data predicts median time courses and variability reflective of Ph 3 – not Ph 1 – compounds.

A Simple Thought Experiment:

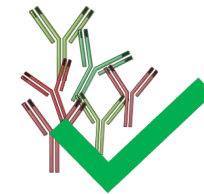
Imagine early research decisions are informed by predicted ADA incidence.



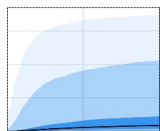
Model trained on public ADA data



- Only Low ADA incidence
- Narrow range



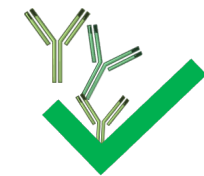
HIGH-RISK COMPOUNDS NOT FLAGGED EARLY



Model trained on representative development data



- Higher ADA incidence
- Realistic Uncertainty



HIGH IMMUNOGENICITY RISK BECOMES VISIBLE EARLIER

! Not as standalone decision rule



Combined with PK, assay, and safety data

Call to Action

Two commitments to improve predictive immunogenicity models

Critically Evaluate Model Training Data


 Are the training data representative of the model's context of use?

 Demand transparency on data sources and limitations.

 Remember: public datasets mainly reflect surviving compounds

Share IG Data, Including Early Phase

 Include: Publish data from *terminated programs*.

 Beyond Incidence, include:

- detailed assay data (cut-points, validation),
- ADA impact on PK and safety
- Relevant covariates

 Support cross-industry data sharing (e.g. ABIRISK [2]).



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Dragomir Dragonov
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Citations

- [1]** Vaisman-Mentesh A, Gutierrez-Gonzalez M, DeKosky BJ, Wine Y. *The molecular mechanisms that underlie the immune biology of anti-drug antibody formation following treatment with monoclonal antibodies*. Front Immunol. 2020;11:1951.
- [2]** Hassler S, Bachelet D, Duhaze J, et al. *Clinicogenomic factors of biotherapy immunogenicity in autoimmune disease: A prospective multicohort study of the ABIRISK consortium*. PLoS Med. 2020;17(10):e1003348.

Doing now what patients need next