

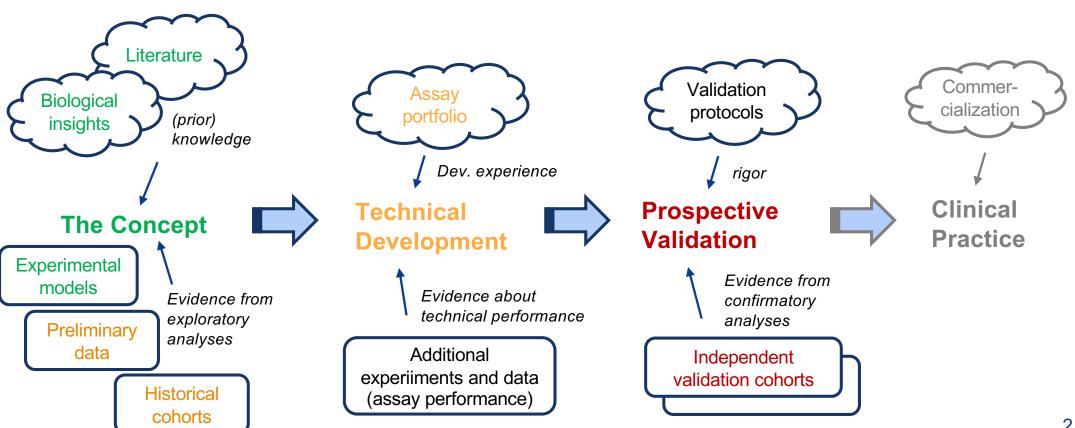
Reproducibility of Evidence Generation in Biomarker Development

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(Biomarker) Development as Evidence Generation Process. A Chain is not Stronger than its Weakest Link







1. Biomarker predictive of response to Cibisatamab CEA TCB (T-cell Bispecific)



2. Model (Exposure + Biomarker) to predict risk of CRS in PTs treated with Columvi CD20-TCB



Two Illustrative Examples



1. Biomarker predictive of response to Cibisatamab CEA-TCB (T-cell Bispecific)

- Anticipated clinical practice: Screening to increase probability of response, MSS CRC

Assay format: Multiplex rtPCR (gene expression) on FFPE biopsy

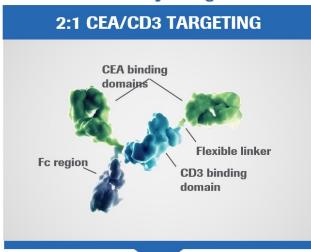
2. Model (Exposure + Biomarker) to predict risk of CRS in PTs treated with Columvi CD20-TCB

- Anticipated clinical practice: Baseline preciction of the likelihood of Gr2+ CRS after the first dose of Columvi (NHL)
- Assay format: Multi Analyte Algorithmic Assay (clinical; central lab; radiology)

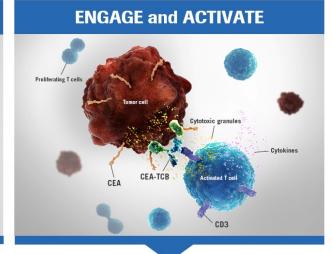
Cibisatamab, a CEA-CD3 TCB



Antibody Design



MOA as Monotherapy



Targeted T-cell activation against CEA-expressing tumors

Tight T cell-tumor cell connection

Extended half-life

Simultaneous binding to T Cells and tumor cells

Activation of T cells for potent, targeted tumor cell killing

Recruitment of additional T cells

Biomaker Hypotheses and Supportive Data



CRC MSS

CEA-TCB 160mg flat dose QW N=37

CEA-TCB 100mg flat dose QW N=20

CEA-TCB 100mg flat dose Q3W N=19

Confounding factors:

Loss of exposure, Immunogenicity, Safety

Hypothesis

CEA-TCB induces an increase in intratumoral immune cells

CEA-TCB targets cells that express CEA

CEA-TCB requires a certain threshold of CEA in the tumor to trigger anti-tumor activity.

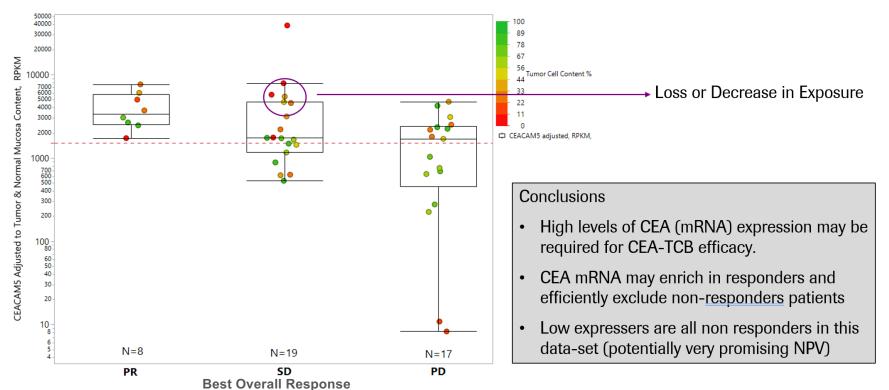
PD BM insights

- Treatment with CEA-TCB increases T-cell infiltration (activated CD8 T cells and PD1 levels) in tumors
- Treatment with CEA-TCB could lead to killing of only CEA high cells
- Tumor CEA levels appear to predict for response

CEACAM5 gene expression appears to predict for response



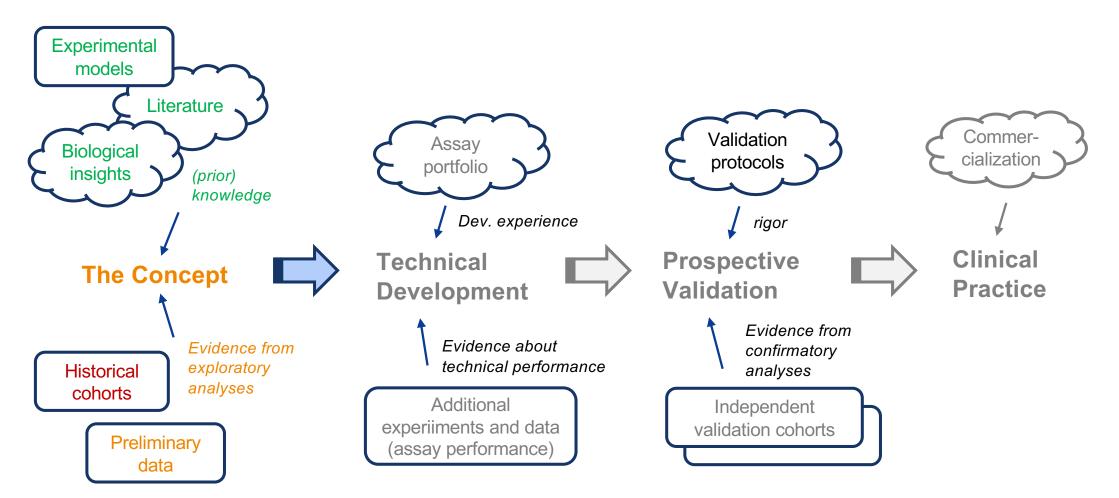
- CEA levels from IHC & RNAseq.
- Analysis of temporal pattern (visit) and expression in archival / fresh samples
- Potential role of study covariates on CEA expression. Primary tumours vs. metastases
- CEA expression in samples of different composition (tumour content, % necrotic tissue)
- Adjusting for prognostic factors and potential confounders (Stage, MSS/MSI status, Mut. load, LOE)



RECIST: PD, partial responce; SD, stable disease; PD, progressive disease

The Concept: A Victory of Prior over Likelihood...

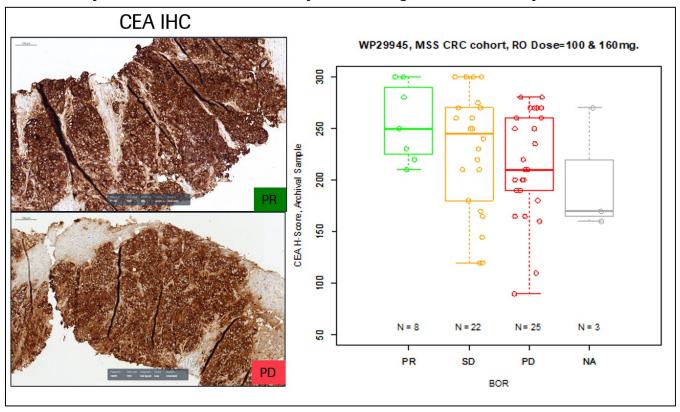


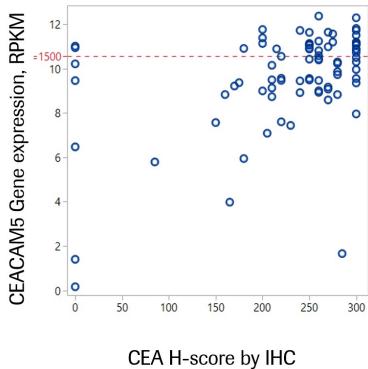


Predictive Biomarker Needs the Right Assay



IHC assay for CEA hit the limit of dynamic range: CEA levels by IHC is not Predictive Poor Correlation between IHC and GE

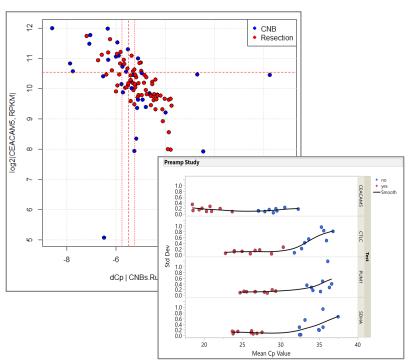


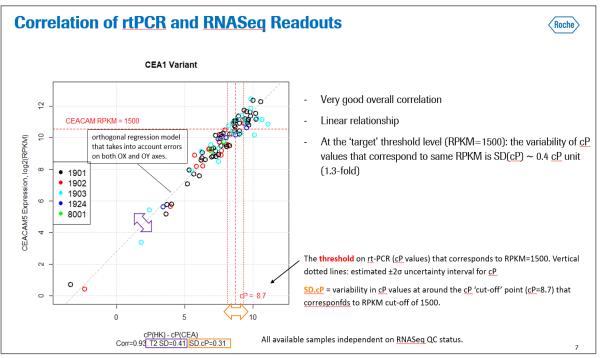


Roche

Development of a Multiplex qRT-PCR Assay

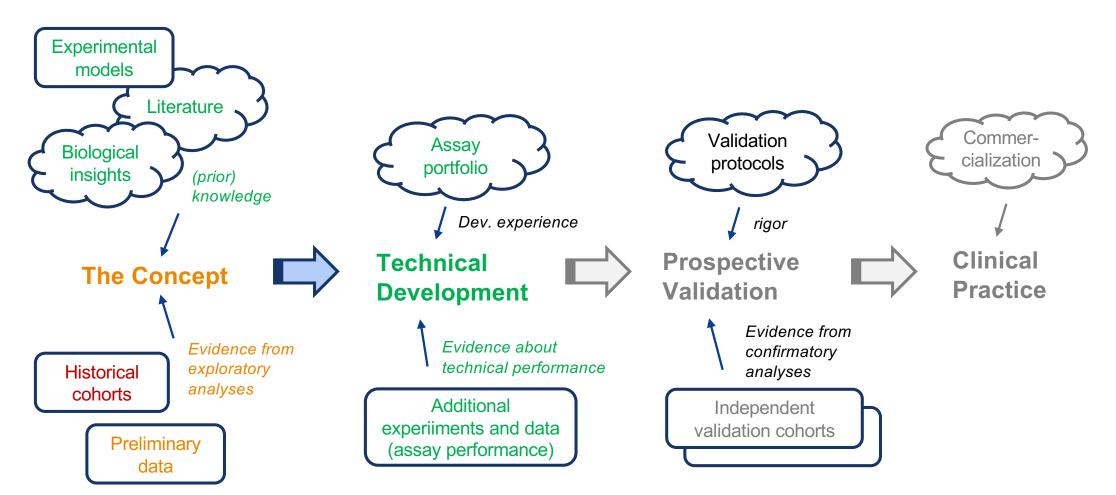
- Selection of housekeeping gene panel on historical & external cohorts (RNAseq and Nanostring).
- Clinical samples re-run with 3 designed Thermo Fisher probes (Almac).
- QC workflow and assay design finalized on external samples from Almac (N~100).
- Prevalence study and cutoff selection.
- First technical validation on the clinical samples (N~50, qRT-PCR).
- Second technical validation on a cohort of separately acquired samples (N~125). gRT-PCR and RNAseg.





Techical Development: Solid Performance



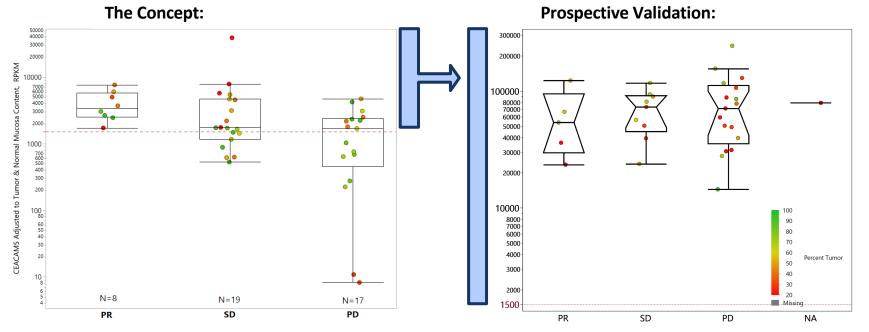


Phase 1b/2 Study to Optimize Benefit-Risk Profile





- Biomarker selection (CEACAM5 gene expression) to maximize ORR
- Gazyva pretreatment (2000 mg -d13/12) to mitigate ADAs



BOR, Best Overall Response (RECIST): PD, partial responce; SD, stable disease; PD, progressive disease





- CEACAM5 gene expression was identified as a candidate biomarker that may further increase ORR, optimize benefit-risk and enable accelerated clinical development.
- A screening IVD assay (multiplex qRT-PCR on FFPE biopsy) successfully developed and utilized in a Ph 1b trial
- Biomarker does not seem to hold predictive value

Insufficient initial evidence:

- \rightarrow Low N
- → complex interrelation of confounders?



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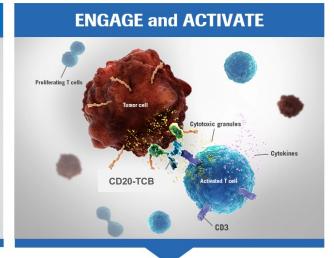
Columvi, a CD20-CD3 TCB



Antibody Design

CD20 binding domains Flexible linker CD3 binding domain

MOA as Monotherapy



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Extended half-life

Simultaneous binding to T Cells and tumor cells

Activation of T cells for potent, targeted tumor cell killing

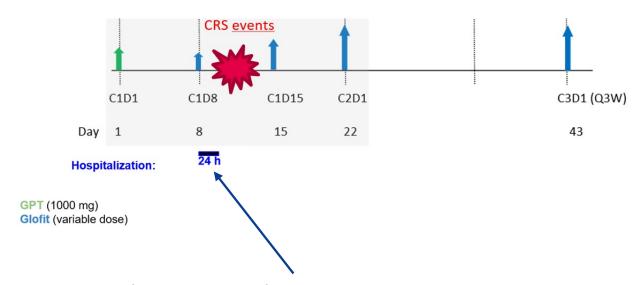
Recruitment of additional T cells

References: Tian et al. J Hematol Oncol (2021) 14:75





Identify a meaningful size patient subset (at least 20-25%) with high (>90%) likelihood of staying free of Grade 2+ CRS, for whom outpatient monitoring would be appropriate



Application of CRS-RS may inform investigator decision in clinical trials in future to wave hospitalization requirement for "low risk" patients

Strategy of Model Development and Validation



Training Dataset

Flat- & Split- Dose Cohorts: All available studies, dose groups and schedules All available histologies

- Formulation of the model

- List of risk factors (CRS understanding)
- Parsimonious predictive model

re model

Pre-selected Dose(s) & Schedule

 Validation of the model formulation
 Sellection of the model decision cutoff and NHL histologies

Model Validation & Cutoff

Selection Dataset

Prospective Validation Datasets

Pre-selected Dose & Schedule

- Validation of decision cutoff
- Observation: model performance and behaviour in relevant subgroups

Due to study design limitations and data availability, the model may need to be developed based on the data across several studies and dose groups / regiments.

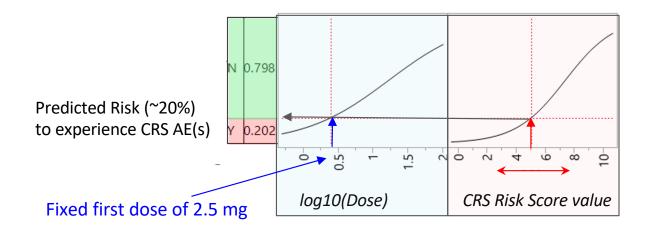
- Lack of randomization or stratification → potentially strong confounding & mis-balance of many characteristics
- Strong effect of Dose on CRS to be considered → any room for the predictive model to add value?
- \circ Several prognostic/predictive factors may be known \rightarrow any room for the predictive model to add value?

The Predictive Model



- CRS-RS: CRS Risk Score is introduced as a weighted sum of (binarized \rightarrow 0/1) risk factor conditions
- The 8-parameter score can be reduced to a 5parameter score CRS-RS.5p for aggressive NHL histologies
- The final predictive model combines the CRS-RS & Columvi dose to estimate the expected probability of CRS event

log(Odds Gr2+ CRS) ~ log(Dose) + CRS Risk Score

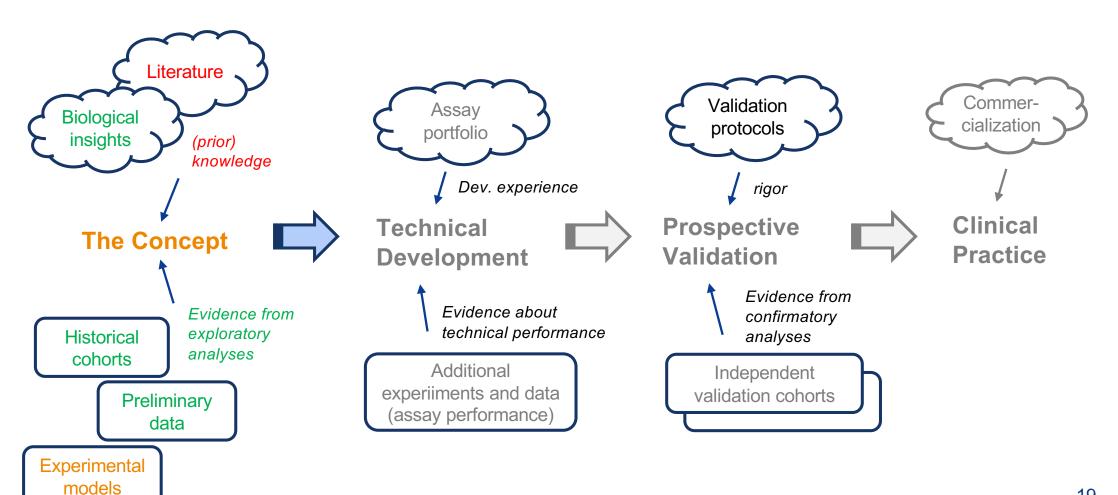


CRS-RS

Parameter & CutOff	Weight	
LDH > 280 U/I	0.5	
WBC > 4.5*10 ⁹ Cells/l	0.5	
Age > 64 yrs	1	
Cardiac comorbidity	0.5	
BM Infiltration	1	CRS-RS.5p
Atypical cells in PB	1	/
Ann Arbor Stage = III or IV	2	
SPD >= 3000 mm ²	2	

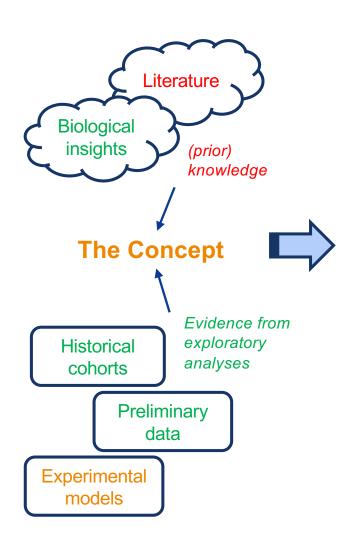
The Concept: Primarily Evidence-Driven

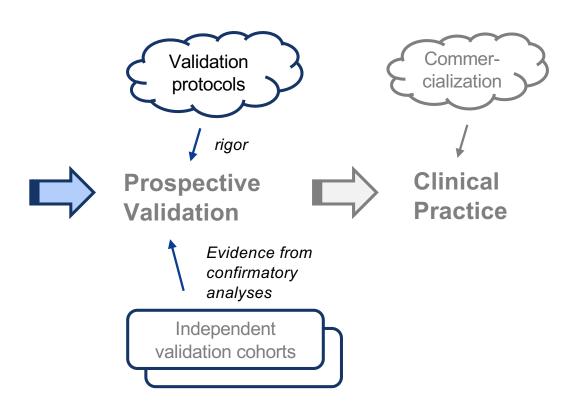




Technical Development: -



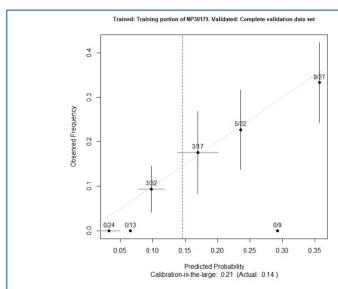




Prospective Trial GO43321 NIS to Validate the Model



- A prospective clinical study to determine the predictive performance of the CRS-RS.5p model
- Across clinical trials utilizing glofitamab in patients with aggressive non-Hodgkin lymphoma (excluding MCL)
- Whether the PTs are at low or high risk of developing Grade ≥ 2 CRS following the first 2.5-mg columvi dose
- N = 240 (GO43321) + 190 (2 additional prospective data collections, Roche Ph I trials)



Error bars represent:

- Y-axis: ±SE of observed frequencies and measure the precision of observed frequency summary in every bin
- X-axis: ±1.5 * standard deviation (SD) of predicted probabilities and correspond to a typical width of the distribution of predicted probabilities in every bin

The points on the plot are annotated by the number of Grade ≥ 2 events / number of cases in the corresponding bin. Red dashed line: probability of CRS of Grade ≥ 2 predicted by the model that corresponds to Dose=2.5mg and CRS-RS.5p=4. Gray dashed line: the diagonal that corresponds to the perfect calibration.

94% of patients from the validation cohort are CRS-RS.5p – evaluable as provide complete set of baseline risk parameter values required to estimate CRSRS.5p risk score.

- True Positive Rate (aka Sensitivity) ~ 0.85 .. 0.90
- Negative Predictive Value (aka NPV) ~ 0.95 .. 0.98
- Detected fraction of low CRS risk patients ~ 50 %

			Validatio	n.Data.Set	N					NPV	P.NPVgreater0.9
			NP30179	Validation	145	0.96 (0	.024),	95%CI 0.88	to	0.99	0.071
	NP30179	Validation	+ G043921	+ YO42610	340	0.97 (0	.013),	95%CI 0.93	to	0.99	0.00057
IP-weighted:	NP30179	Validation	+ G043921	+ Y042610	320	0.98	(0.011)	, 95%CI	.94	to 1	0.00057
				G043921	168	0.98	(0.017)	, 95%CI	0.92	to 1	0.0077
		GO43921	(prospec	tive part)	74	0.97	(0.026)	, 95%CI	.86	to 1	0.095

ř.	Validation.Data.Set			PPV		Sensitivity	Specificity	Prevalence	DetectionRate	
		NP30179 Validation	145	0.23	(0.048)	0.85 (0.08)	0.54 (0.045)	0.14 (0.029)	0.52 (0.041)	
	NP30179 Validation -	+ GO43921 + YO42610	340	0.18	(0.029)	0.86 (0.056)	0.53 (0.029)	0.11 (0.017)	0.51 (0.027)	
IP-weighted:	NP30179 Validation -	+ GO43921 + YO42610	320	0.16	(0.029)	0.9 (0.056)	0.53 (0.029)	0.093 (0.016)	0.51 (0.028)	
		G043921	168	0.17	(0.041)	0.88 (0.083)	0.54 (0.04)	0.095 (0.023)	0.5 (0.039)	
	G043921	(prospective part)	74	0.17	(0.062)	0.86 (0.13)	0.55 (0.061)	0.095 (0.034)	0.49 (0.058)	

Model to Predict CRS after Columvi



- 5-parameter risk score was developed to predict risk of Gr2+ CRS in aNHL patients after the first dose of Columvi.
- Model uccessfully validated in a prospective, multi-centric cohort
- Utilization of the model in clinical practice requires technical development and additinal validation of the risk score

Rather weak initial evidence:

- \rightarrow Low N
- → Training across data sets of varying exposure

Strong performance across data sets and conditions:

→ Yet enough room for the risk parameters to demonstrate predictive power on top of exposure



Final Considerations



Biomarker in clinical research: **Evidence of a MoA / PD / PK may be sufficient to support research** or clinical development cycle (*biomarker data: the molecule does what it is supposed to do*) ...

...but may be insufficient when a preditive power in a particular classification / prediction clinical context is desired (biomarker-based prediction of clinical performance)

Why?

1- Victory of Prior over Likelihood:

quite weak data-driven evidence in exploratory research

2- Genuine incompleteness of predictive models

Relevant parameters may be not collected or exist as latent factors Complex ,playground' with several (potentially) disturbing covariates

prior likelihood

$$P(\theta|x) \sim P(\theta) * P(x|\theta)$$

