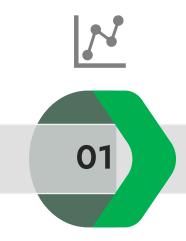


Agenda

- 1. In vivo reference databases used for training
- 2. In vitro tests, in vitro input data parameters and reference databases used for training
- **3.The prediction model** different regression equations
- 4.DA approach with defined model choice
- 5. Predictivity vs. LLNA data
- 6. Robustness and redundancy with different partial data inputs
- 7. Conclusions

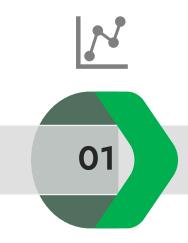
Databases of curated in vivo reference data



In vivo data

- The OECD prepared a curated reference data set (https://one.oecd.org/document/ENV/CBC/MONO(2021)11/en/pdf) on
- A) Local lymph node assay data (n = 194)
- B) Human reference data (n = 66)
- We have an extended the set to 213 chemicals with LLNA and in vitro data
- The IFRA IDEA project proposed a workflow to combine human and animal data to derive "potency values" and applied it to a list of chemicals (n = 33) (https://www.sciencedirect.com/science/article/pii/S0273230022001313)
- We extended the list with PV values (n = 139 chemicals)*
 https://www.altex.org/index.php/altex/article/view/2617

Databases of curated in vitro reference data

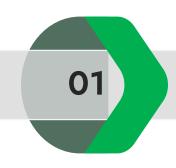


In vitro data

- Several institutions generated and collected *in vitro* data for the chemicals in the *in vivo* reference databases, mainly:
 - Kao and Shisheido (mainly h-Clat and DPRA)
 - Givaudan (KeratinoSens and kDPRA)
 - BASF (mainly kDPRA and U-Sens)
 - Procter and Gamble (Mainly DPRA)
 - Research institute for fragrance Materials (RIFM; all endpoints)
- With these large set of *in vitro* data AND *in vivo* reference data, it is possible to perform quantitative modeling
- While these data collection effort were first targeted at qualitative hazard identification,
 most of these in vitro assay also provide quantitative dose-response data

Input data: Quantitative data in KeratinoSens, h-CLAT and kDPRA





In vitro data

KeratinoSens

EC1.5 –Dose for 1.5-fold induction EC3 - Dose for 3-fold Luciferase induction IC50 for 50% reduction in cell viability

hClat

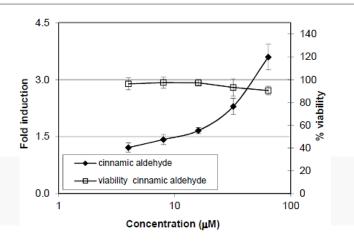
EC150 – dose for 1.5-fold induction of CD86 EC200 – dose for 2-fold induction of CD54 MIT minimum of EC150 and EC200 CV75 for 25% reduction in cell viability

Kinetic DPRA

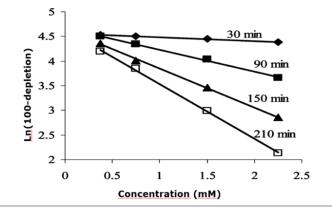
Kinetic rate for Cys-peptide depletion

D. Roberts, A. Natsch, Chem Res. Toxicol. 2009, 22,592-603.









The combined in vitro / in vivo Databases used for the Regression model





Regression Model Dataset with LLNA, KeratinoSens and kDPRA: n = 203

Dataset with LLNA, KeratinoSens, h-CLAT and kDPRA: n = 188

Dataset with OECD curated LLNA data, KeratinoSens, h-CLAT and kDPRA: n = 149

Dataset with Potency values (PV) and KeratinoSens, h-CLAT and kDPRA: n = 139

✓ All data are log transformed and normalized

Regression models



Regression

Model

Key input parameters for the equation(s) in the Regression Model:

- KS Log EC1.5norm
- KS Log IC50norm
- h-CLAT Log MITnorm
- h-CLAT Log CV75norm
- kDPRA Log kmax
- Physchem: Log VP norm

EQ 1: pEC3 =
$$0.42 + 0.40 \times \text{Log k}_{\text{max}} + 0.15 \times \text{Log EC1.5}_{\text{norm}} + 0.36 \times \text{Log IC50}_{\text{norm}} - 0.21 \times \text{Log VP}_{\text{norm}}$$

Peptide reactivity KeratinoSens Volatility

EQ 4: pEC3 = $0.18 + 0.36 \times \text{Log k}_{\text{norm}} + 0.21 \times \text{Log MIT}_{\text{norm}} + 0.35 \times \text{Log CV75}_{\text{norm}} - 0.19 \times \text{Log VP}_{\text{norm}}$

Peptide reactivity H-CLAT Volatility

evidence

Can be used for partial

Four different models can be applied using the '2 out of 3 approach':

- EQ1: Combining KeratinoSens with kDPRA
- EQ4: Combining h-CLAT with kDPRA
- EQ6: Combining KeratinoSens and h-CLAT
- EQ5: All evidence: Combining KeratinoSens AND h-CLAT with kDPRA

Models were trained on:

- a) LLNA EC3 values
- b) Potency values

Regression model: Spreadsheet - Application in practice

https://www.altex.org/index.php/altex/article/view/2617





Regression model

Prediction in Practice

- The key benefit of regression models is simplicity and transparency
- Using the equations from the previous slide the results can be calculated directly — no proprietary software or hidden algorithm
- For ease of application a public spreadsheet can be used
- Just enter the test results from the study report and voilà...

Chemical Identification

KeratinoSens Assay Result

kDPRA Assay Result

h-CLAT Assay Result

PoD Prediction

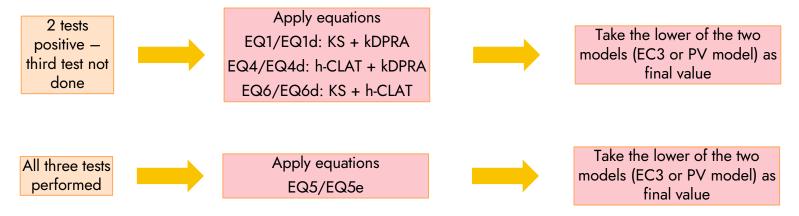
	Chemical identifier			Yellow fields only to be filled by user		
Chemical Name			Tellow fields offig to be fi	lied by diser		
CAS Nr.						
MW						
Vapor pressure (Pa)			Lognorm VP	0		
KeratinoSens ass	ay data					
Rating PM (0/1)			EC 1.5 (µM) consolidate			
EC 1.5 (μM)			LOG norm EC1.5 KS	#VALUE!		
EC 3 (μM)			EC 3 (μM) consolidated			
IC 50 (μM)			LOG norm EC3 KS	#VALUE!		
If data not in micromo	olar, enter in ppm		IC 50 (μM) consolidated			
EC 1.5 (ppm)			LOG norm IC 50 KS	#VALUE!		
EC3(ppm)						
IC 50 (ppm)			If no induction / cytotoxicity above			
			threshold, give default value = 4000			
kDPRA assay dal	ta					
Log kmax (s-1M-1)			LOG norm Kmax			
h-CLAT assays d	ata		If no induction/cytotoxicity above threshold,			
Rating PM (0/1)		give default value = 5000				
CD86 EC150 (µg/ml)			MIT (μM)	#DIV/0!		
CD54 EC200 (µg/ml)			Log norm MIT h-CLAT	#DIV/0!		
MIT (µg/ml)	0		CV 75 (μM)	#DIV/0!		
CV 75 (µq/ml)			Log norm CV75 h-CLAT	#DIV/0!		
RESULTS for models trained on LLNA data			pEC3	EC3 (%)	EC3 (DSA in µg/cm²)	
Global model KS + kDPRA Equation 1			not sufficient data	not sufficient data	not sufficient data	
Global model kDPRA + h-CLAT Equation 4			not sufficient data	not sufficient data	not sufficient data	
Global model KS + kDPRA + h-CLAT Equation 5			not sufficient data	not sufficient data	not sufficient data	
Global model KS (EC	1.5)+ h-CLAT Equa	ation 6	not sufficient data	not sufficient data	not sufficient data	
Global model KS (EC					not sufficient data	
Global model KS (EC			nded list of Potence	values (PY)		
Global model KS (EC	models traine	d on the este	nded list of Potence	values (PV) PV(%)	PV (DSA in μg/cm²)	
Global model KS (EC RESULTS for the Global model KS + kE	models traine	d on the exte	nded list of Potence pPV not sufficient data	values (PV) PV (%) not sufficient data	PV (DSA in μg/cm²) not sufficient data	
Global model KS (EC RESULTS for the Global model KS + kD Global model kDPRA	models trained PRA Equation 1d + h-CLAT Equation	d on the exte	nded list of Potency pPV not sufficient data not sufficient data	values (PY) PV (%) not sufficient data not sufficient data	PV (DSA in µg/cm²) not sufficient data not sufficient data	
Global model KS (EC RESULTS for the Global model KS + kE Global model kDPR/ Global model KS + kE	models trained PRA Equation 1d A+h-CLAT Equation PRA+h-CLATE	d on the external on 4d quation 5d	nded list of Potency pPV not sufficient data not sufficient data not sufficient data	PV (%) not sufficient data not sufficient data not sufficient data	PV (DSA in µg/cm²) not sufficient data not sufficient data not sufficient data	
Global model KS (EC RESULTS for the Global model KS + kD Global model kDPRA	models trained PRA Equation 1d A+h-CLAT Equation PRA+h-CLATE	d on the external on 4d quation 5d	nded list of Potency pPV not sufficient data not sufficient data	values (PY) PV (%) not sufficient data not sufficient data	PV (DSA in µg/cm²) not sufficient data not sufficient data	
Global model KS (EC RESULTS for the Global model KS + kE Global model KS + kE Global model KS + k-1	models trained PRA Equation 1d A + h-CLAT Equation PRA + h-CLAT E CLAT Equation 6c	d on the external on 4d quation 5d	nded list of Potence pPV not sufficient data not sufficient data not sufficient data not sufficient data	PV (%) not sufficient data not sufficient data not sufficient data not sufficient data	PV (DSA in µg/om²) not sufficient data not sufficient data not sufficient data not sufficient data	
Global model KS (EC RESULTS for the Global model KS + kE Global model kDPR/ Global model KS + kE	models trained PRA Equation 1d A + h-CLAT Equation PRA + h-CLAT E CLAT Equation 6c	d on the external on 4d quation 5d	nded list of Potency pPV not sufficient data not sufficient data not sufficient data	PV (%) not sufficient data not sufficient data not sufficient data	PV (DSA in µg/cm²) not sufficient data not sufficient data not sufficient data	
Global model KS (EC RESULTS for the Global model KS + KE Global model KS + KE Global model KS + h-1 Global model KS + KE	models trained PRA Equation 1d A + h-CLAT Equation PRA + h-CLAT E CLAT Equation 6c	on 4d quation 5d d	nded list of Potence pPV not sufficient data not sufficient data not sufficient data not sufficient data	values (PY) PV (x) not sufficient data not sufficient data not sufficient data not sufficient data	PV (DSA in µg/cm²) not sufficient data	
Global model KS (EC RESULTS for the Global model KS + kE Global model KS + kE Global model KS + k-1	models trained PRA Equation 1d A + h-CLAT Equation PRA + h-CLAT E CLAT Equation 6c	on 4d quation 5d d	nded list of Potence pPV not sufficient data not sufficient data not sufficient data not sufficient data	values (PY) PV (x) not sufficient data not sufficient data not sufficient data not sufficient data	PV (DSA in µg/cm²) not sufficient data not sufficient data not sufficient data not sufficient data	

Automated model choice in a Defined Approach

The Regression approach makes multiple predictions — based on

- a) the training dataset (LLNA EC3 or potency values (PV)) and
- b) based on input data (all tests, partial evidence)

For OECD approval – the approach selects one outcome based on the input data:



This approach is coded into the Excel-Spreadsheet, so that, depending on the available data, one final value will automatically be generated (i.e. it is a DEFINED APPROACH (DA).

Regression model: Predictivity

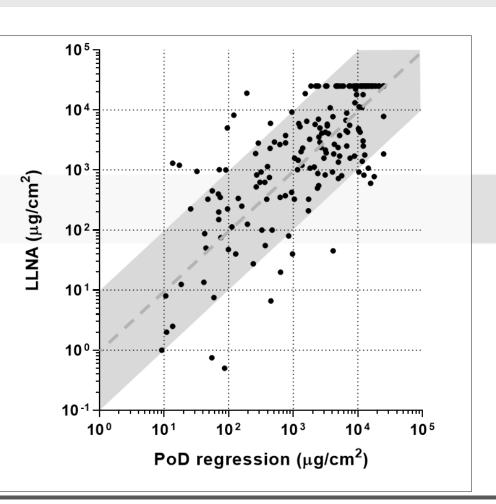




Prediction

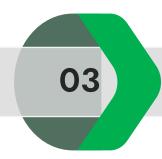
Overall predictivity vs. LLNA EC3 data

- All chemicals with all three tests available
- Compared versus OECD MLLP LLNA EC3 data or other LLNA data according [1] in case no OECD MLLP EC3 is available
- Grey dashed line: line of identity
- Grey area area of less than 10-fold misprediction



Regression model: Predictivity for case studies





Prediction

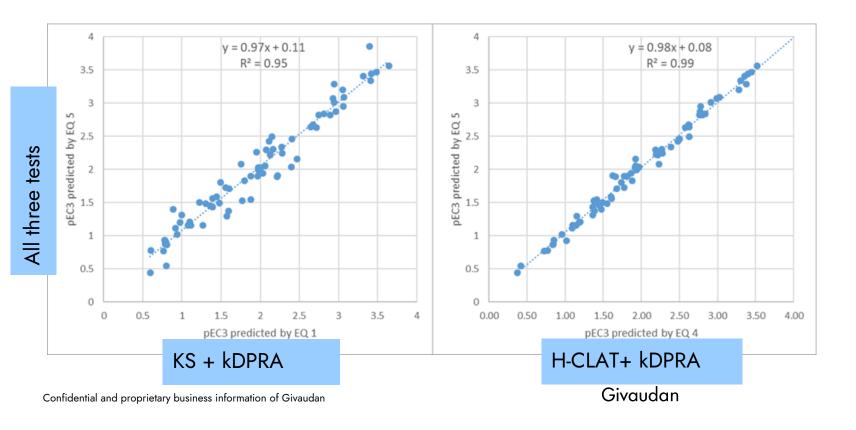
- Chemicals with at least 5 LLNA studies in OECD DB as case studies
- For these the certainty of the LLNA value is high
- Overall accurate prediction of these chemicals with strong in vivo evidence.
 Mostly within variability of the LLNA studies
- Similar predictivity with different models
- Flexibility which model to apply

	LLNA EC3 1)	LLNA studies (n)	LLNA EC3 range	EQ1	EQ4	EQ5
Aniline	NC	14	13.25 - (> 100)	60	52	57
Penicillin G	31.3	8	11.2 - 46.5	>100	>100	>100
Hydroxycitronellal	21.1	8	18.8 - 33	18.7	11.3	10.9
Geraniol	16.1	6	5.6 - 57	18.3	14.3	14.2
Eugenol	11.6	16	3.8 - 16.6	19.9	6.8	10.4
alpha-hexyl cinnamic aldehyde	10.8	29	1.2 - 33.8	5.9	(25)	17.4
Lilial	8.6	5	3 - 18.6	20.5	9.3	12.5
Citral	5.8	16	1.5 - 26.8	9.4	5.0	4.8
Formaldehyde	3.8	15	0.35 - 14.5	1.5	0.8	1.0
3- dimethylaminopropylamine	3.5	7	1.8 - (>10)	40	37	32
Isoeugenol	1.3	31	0.5 - 6.4	1.8	(4.6)	4.2
Cinnamic aldehyde	1	12	0.5 - 3.1	1.0	0.8	0.8
Hydroquinone	0.19	20	0.07 - 1.67	0.9	0.4	0.4
PPD	0.11	10	0.06 - 0.2	3.5	1.9	1.7
DNCB	0.054	20	0.012 - 0.096	0.18	0.19	0.17
Kathon CG	0.008	10	0.005 - 0.063	0.05	0.05	0.05
Oxazolone	0.002	7	0.001 - 0.003	1.5	0.5	0.7

Predicted EC3

Regression model: Robustness and redundancy

- The data on predictivity and case studies show that
 - Similar predictions for individual chemicals with EQ1, EQ4 and EQ5
 - The overall fold-misprediction is quite similar by different models
- Further illustrated by individual predictions for chemicals positive in three tests



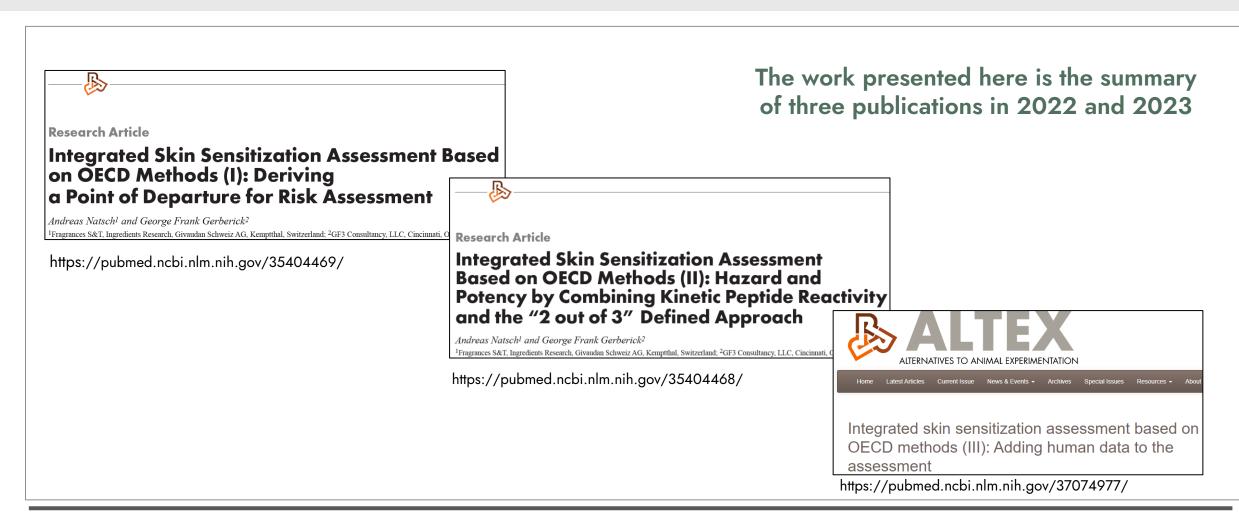
- This indicates data-redundancy
- Partial evidence is sufficient
- Having a third positive tests often does not change the assessment

Conclusions

- All the key event-based test guidelines (except classical GARD in TG) deliver next to hazard identification dose-response
 data which contribute to potency prediction
- Regression models are a **facile** and **transparent** way to integrate these data to derive a **Point-of-Departure** for quantitative risk assessment (QRA2)
- Already with these three tests there is data redundancy, and two tests often give very similar predictions to three tests
 - This may indicate we are in a 'as good as it can get' situation for the prediction model
- The simple public spreadsheet makes application of the regression model straightforward
- These are in vitro-only Defined Approach —in vitro data directly leads to the PoD*
- '2 out of 3' DA (TG497) combined with kDPRA (TG442D) give
 - Hazard ID
 - GHS potency class
 - PoD from the same data! No additional testing!

^{*}DA does not yet include in silico evaluation, structural alert and read-across. These additional lines of evidence can then be used to refine the assessment and assess uncertainty (they are not 'used up' in the DA)

Publications



Acknowledgements

Frank Gerberick, GF3 consultancy

Co-drafting of the publications and discussions

Givaudan, Fragrance S&T, Kemptthal, Switzerland:

- Roger Emter (Keratinosens Develpment, validation and database)
- Tina Haupt (kDPRA validation and database)

BASF

- Britta Wareing (kDPRA validation and database)
- Susanne Kolle (kDPRA validation and 2o3 validation)

OECD DASS expert group

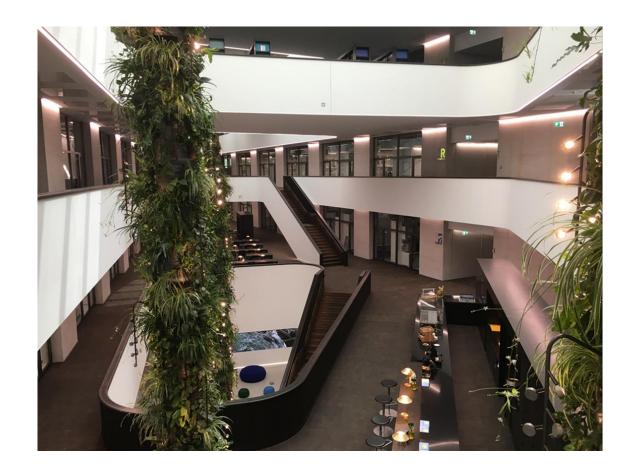
Data curation and compilation:

The IMS team



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Thank you

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Givaudan

Human by nature