

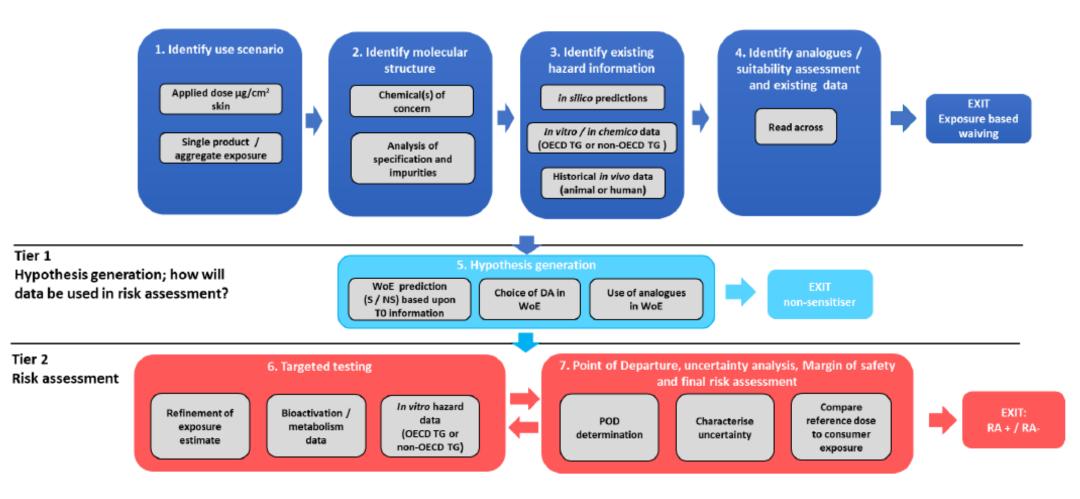
The current landscape of NAM Methods for Skin Sensitization Hazard Identification: **Progress towards Potency** Assessment

Petra Kern October 7<sup>th</sup>, 2022



# **NGRA Framework for Skin Sensitisation**

Tier 0 Identify use scenario, chemical of concern and existing information



Gilmour & Kern et al, RTP, 116, 2020 <u>https://authors.elsevier.com/a/1bRLv%7E81IJLAV</u>

65

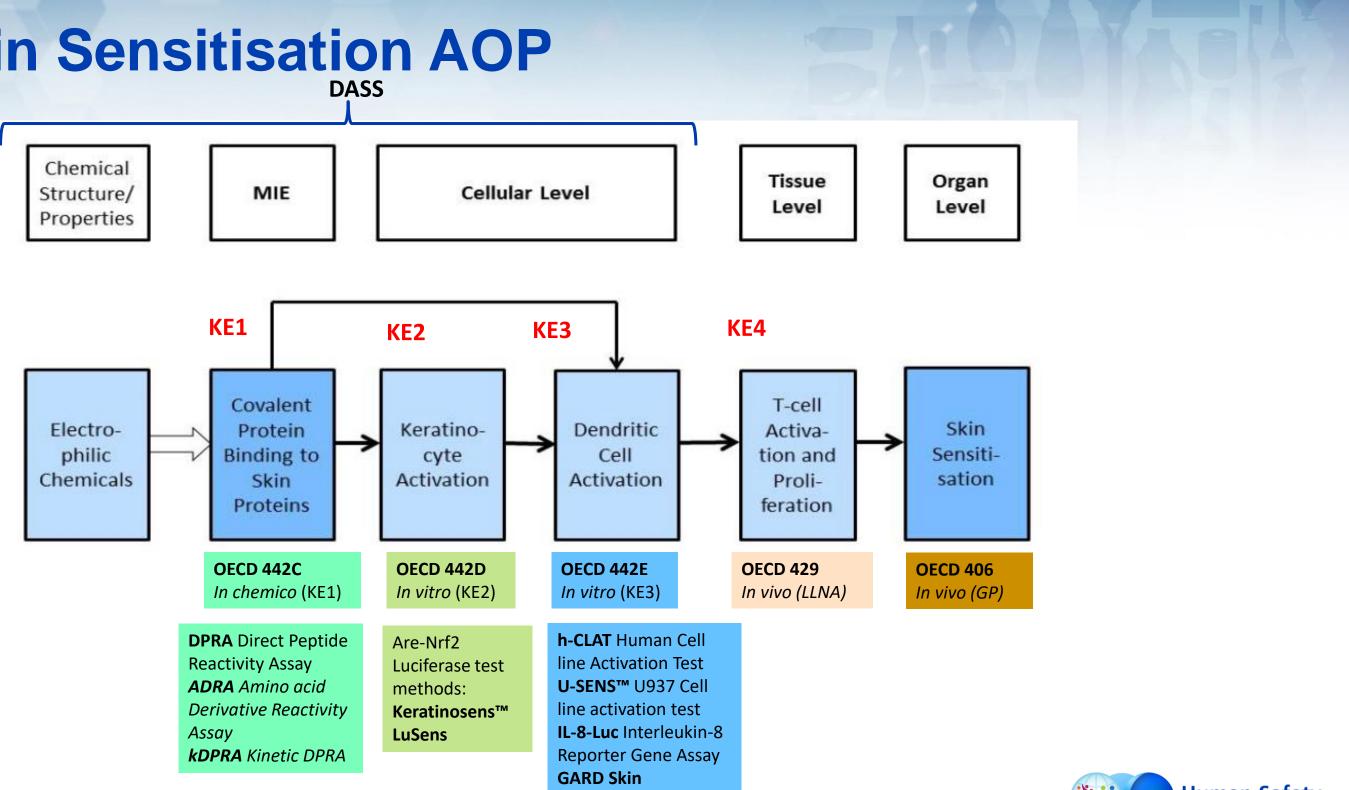


	SCG/1628/21
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	SCCS
THE S	CCS NOTES OF GUIDANCE FOR THE TESTING OF
co	SMETIC INGREDIENTS AND THEIR SAFETY
	EVALUATION
	11 <sup>TH</sup> REVISION
	Scientific Committees
	) as there is also as made to conversi and the grapher
	The SOCS adopted this guidance document at its plenary meeting on 30-31 March 2021

### SCCS 11th NoG 2021

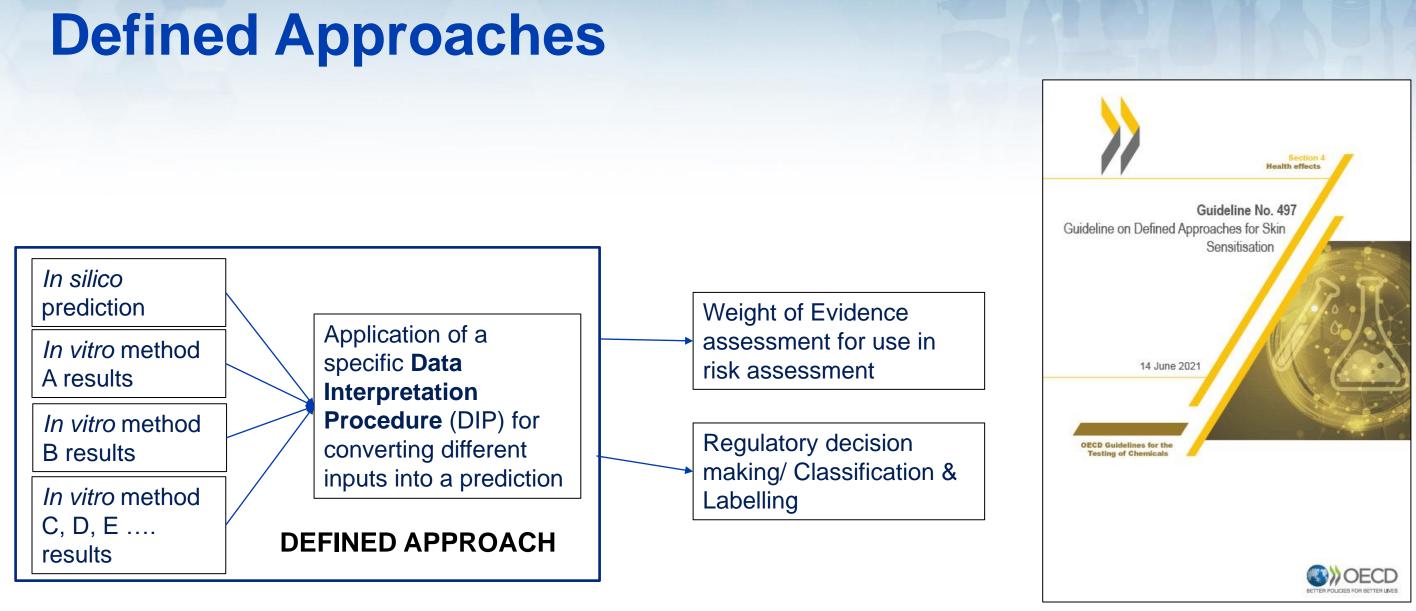


# **Skin Sensitisation AOP**



OECD, 2012. The Adverse Outcome Pathway for Skin Sensitisation Initiated by Covalent Binding to Proteins. Series on Testing and Assessment No. 168.





**OECD 497** 





# **NAM - Defined Approaches**

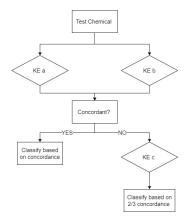
### Hazard

### Potency (GHS 1A/ 1B)

### **Potency grouping**

### **Continuous PoD values**

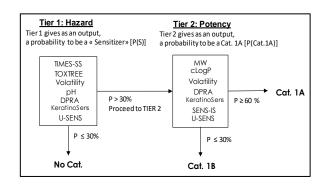
OECD (2021), Guideline No. 497



2 out of 3

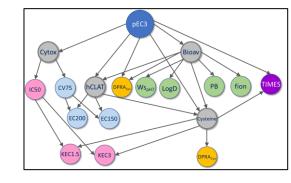
Score	h-CLAT MIT µg/mL	DPRA mean Cysteine and Lysine% depletion	DPRA Cysteine % depletion*	In silico (ITSv1: DEREK; ITSv2: OECD TB)
3	≤10	≥42.47	≥98.24	*
2	>10, ≤150	≥22.62, <42.47	≥23.09, <98.24	
1	>150, ≤5000	≥6.38, <22.62	≥13.89, <23.09	Positive
0	not calculated	<6.38	<13.89	Negative
	Potency	Total Battery Score		
	UN GHS 1A	6-7		
	UN GHS 1B	2-5		
	Not classified	0-1		

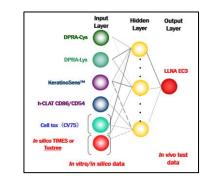
ITSv1/v2



### **Sequential Testing Strategy**

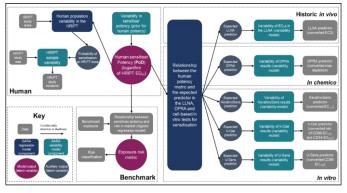
(Tourneix et al. 2019)





**BN-ITS** 

(Jaworska et al. 2015, Kern et al. 2022 in prep)

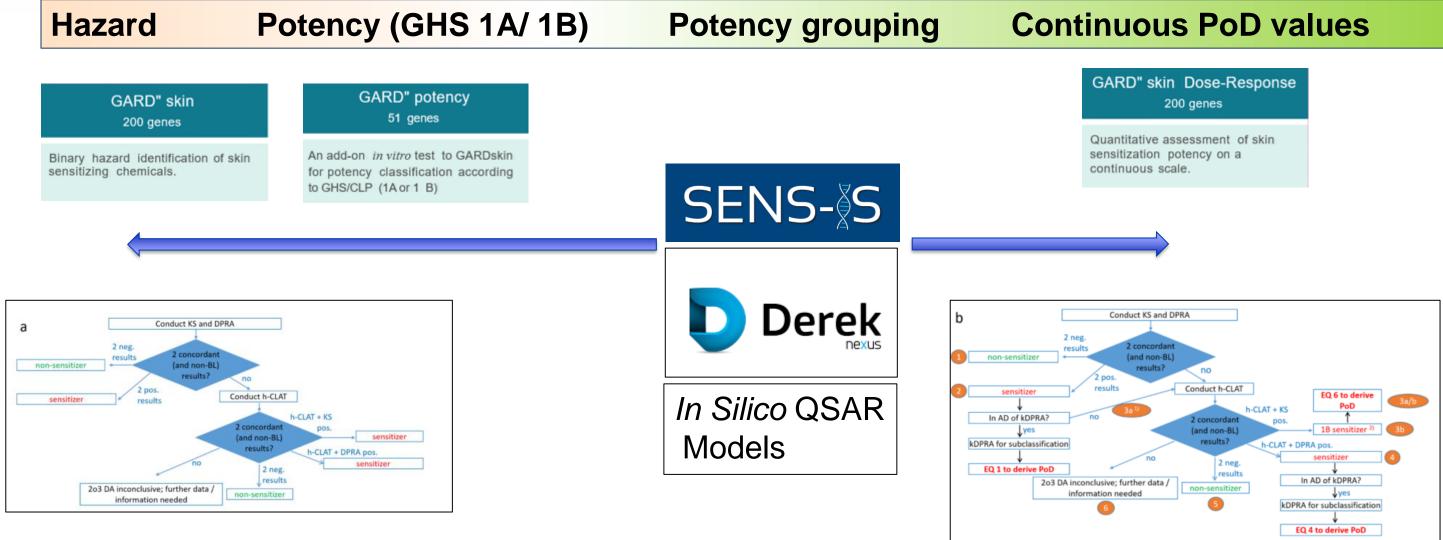


(Reynolds et al. 2019, Gilmour et al 2022) SARA

### ANN EC3 (Hirota et al 2015, 2018)



# **NAM - Defined Approaches - More Methods**

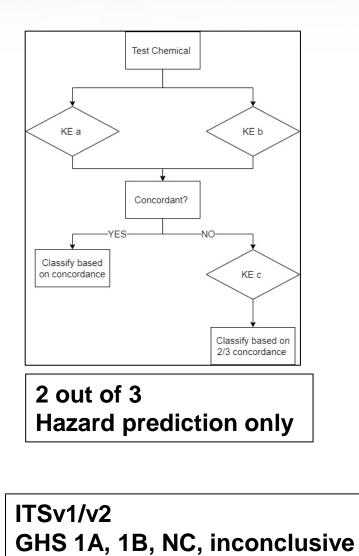


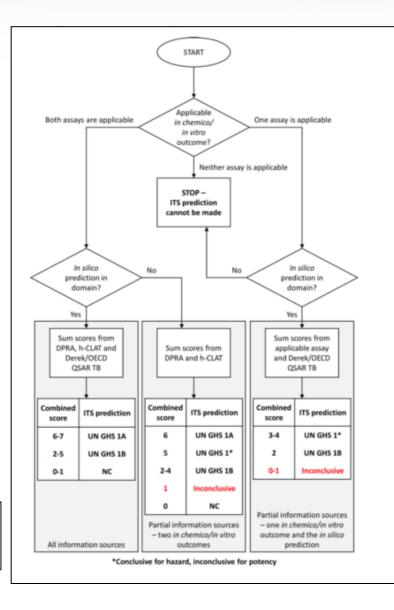
Natsch & Gerberick 2022

### DISCLAIMER: not a complete list



# **GL497 Defined Approaches**





DA/Method	Information Sources	Capability (Hazard and/or Potency)	Hazard Performance vs. LLNA	Hazard Performance vs. Human	Potency Performance vs. LLNA (Accuracy)	Potency Performance vs. Human (Accuracy)
203 DA	DPRA, KeratinoSens™, h- CLAT	Hazard	84% BA, 82% Sens, 85% Spec	88% BA, 89% Sens, 88% Spec		•
ITSv1 DA	DPRA, h-CLAT, DEREK Nexus v6.1.0	Hazard, Potency	81% BA, 92% Sens, 70% Spec	69% BA, 93% Sens, 44% Spec	70% NC, 71% 1B, 74% 1A	44% NC, 77% 1B, 65% 1A
ITSv2 DA	DPRA, h-CLAT, OECD QSAR Toolbox v4.5	Hazard, Potency	80% BA, 93% Sens, 67% Spec	69% BA, 94% Sens, 44% Spec	67% NC, 72% 1B, 72% 1A	44% NC, 80% 1B, 67% 1A
LLNA (provided for comparison)	in vivo	Hazard, Potency	849	58% BA, 94% Sens, 22% Spec	-	25% NC, 74% 1B, 56% 1A



October 2021

Skin sensitisation

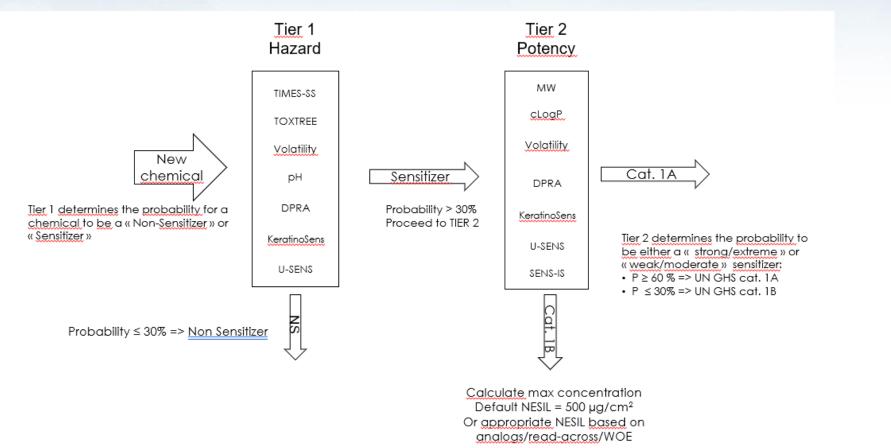




UNITED NATIONS New York and Geneva, 2021



# **Sequential Stacking Meta-Model**



- 2 Tier model: hazard ID followed by potency categorization
- GHS subcategories (1A, 1B, NC)
- Bayesian approach: probability information confidence in prediction
- LLNA training set

### Table 2

Predictive performance of the defined approach using a stacking meta-model for human and LLNA hazard data with  $\leq$  30 and  $\geq$  70% probability cut-offs.

Pro	bability cut-offs: $\leq$ 30 and $\geq$ 70% applied to the stacking meta-model	Chemicals with hazard prediction	Sensitivity (%)	Specificity (%)	Accuracy (%)	Ka
DA DA LLN LLN	predictions vs. human predictions vs. LLNA predictions vs. composite reference <sup>11</sup> iA vs. human iA vs. human predictions vs. human	97 97 97 97 105 66 <sup>b</sup>	91 (58/64) 85 (64/75) 87 (65/75) 92 (59/64) 92 (62/67) 88 (38/43)	76 (25/33) 91 (20/22) 95 (21/22) 51 (17/33) 53 (20/38) 65 (15/23)	86 (83/97) 87 (84/97) 89 (86/97) 78 (76/97) 78 (82/105) 80 (53/66)	0. 0. 0. 0. 0.
LLN	iA vs. human	66 <sup>b</sup>	91 (39/43)	39 (9/23)	73 (48/66)	0.

<sup>a</sup> Composite ref. for Human potency cat.5 + LLNA neg. = NS and cat.5 + LLNA pos. = S.

<sup>b</sup> Test set of naïve chemicals not used to develop nor challenge the defined approach for which a hazard prediction was generated using the 30/70% probability cut-offs (Del Bufalo et al., 2018).



Kappa

0.67 0.67

0.72

0.480.49

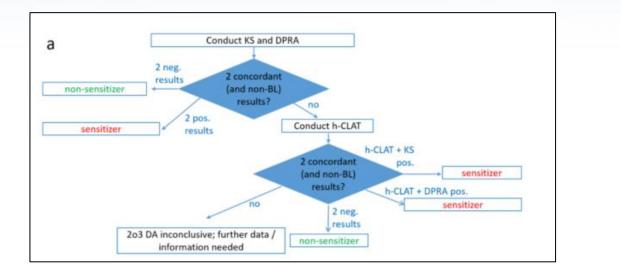
0.55

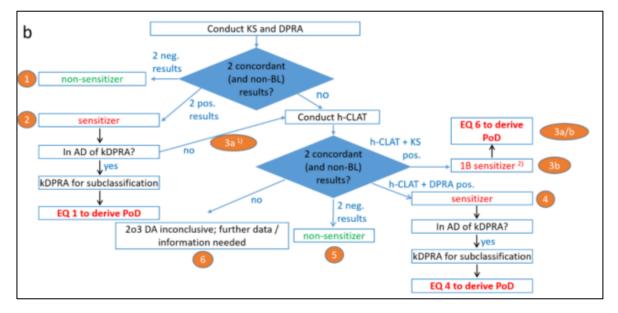
0.33





# kDPRA and "2 out of 3"





- 2 Tier model: hazard ID followed by potency prediction
- Testing sequence including GHS categories and POD determination combined with the "2 out of 3" approach
- Several multiple linear regression models
- Use of kDPRa data in combination with others NAM
- Use of an uncertainty factor to be applied
- LLNA training set

	LLNA Result				
Prediction 2o3 DA with kDPRA	NC (n =26)	1B (n = 85)	1A (n = 38)		
NC	21	16	0		
1B	3	34	7 (4) <sup>a</sup>		
1A	1	14	26 (29)		
Correct	84%	53%	79% (88%)		
Under	NA	25%	21% (12%)		
Over	16%	22%	NA		
Inconclusive	n = 8	n =21	n = 5		

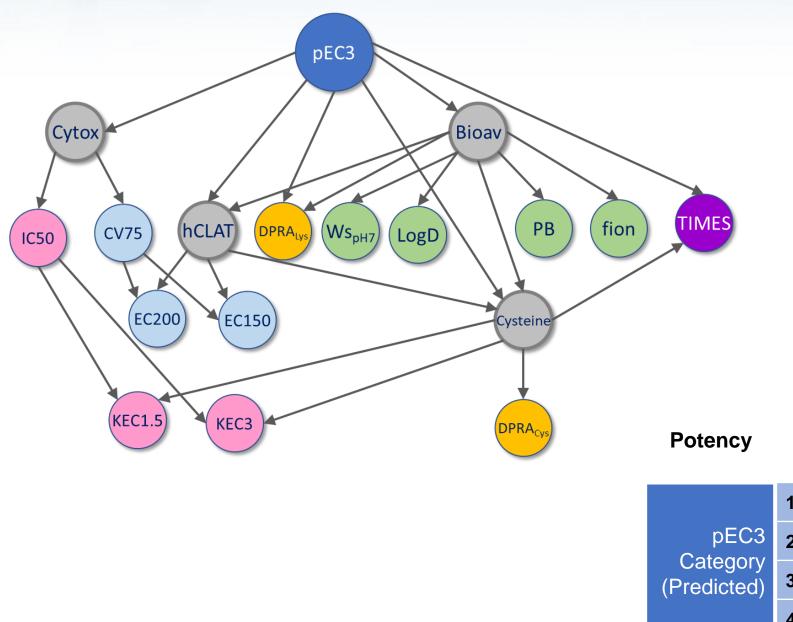
Tab. 2: GHS sub-classification of the chemicals in the OECD database by the 2o3 DA combined with kDPRA

<sup>a</sup> The values are based on applying only the prediction model of the kDPRA and 2o3 DA. In brackets are given the values if taking the AD of the kDPRA into account and applying Scenario 3a in Figure 1 (Using EQ6 for chemicals outside of AD of kDPRA).

### tency prediction ories and POD t of 3" approach els n others NAM



# **BN-ITS Defined Approach**



- Bayesian network model: captures conditional dependencies between variables
- Hazard ID and Potency evaluation
- Target data: LLNA potency categories based on EC3 values (NS, weak, moderate, strong)
- Prediction of potency categories and uncertainty evaluation using probability distribution and Bayes factors
- Conversion to EC3 values (continuum POD) possible

Potency		pEC3 Category (Experimental)						
		1	2	3	4			
	1	62	6	2	2			
pEC3	2	3	31	7	0			
Category (Predicted)	3	5	8	48	9			
	4	3	4	13	34			

Accuracy = 74% Accuracy +1/-1 = 93%Over-predicted = 15%Under-predicted = 11%





### ANN

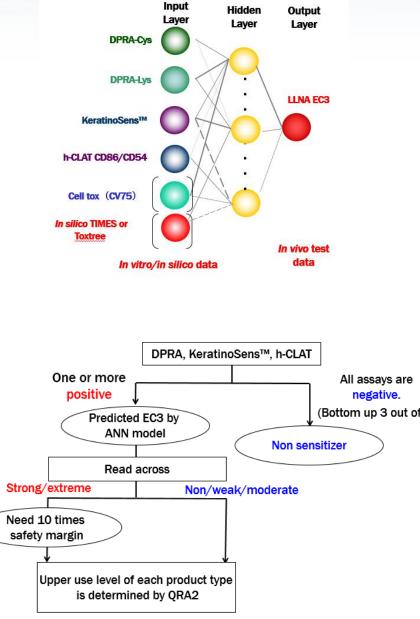


TABLE 5 Correlations between LLNA EC3 classified into four categories and predicted LLNA classification obtained with ANN models 1, 2, 4 and 6 (n = 134)

		LLNA classificatio	on (in vivo)		
	Potency category	Extreme or strong (26)	Moderate (37)	Weak (31)	NS (40)
(A) ANN model 1 (Min(h-CLAT&cell toxicity)/ DPRA/ KeratinoSens™)	Extreme or strong Moderate Weak Negative, predicted EC3 > 100%	19 6 1 0	3 17 15 2	0 7 23 1	0 0 24 16
	Accuracy (%) Overpredicted (%) Underpredicted (%)	56.0 25.4 18.7			
(B) ANN model 2 (h-CLAT/ DPRA/ KeratinoSens <sup>™</sup> / cell toxicity)	Extreme or strong Moderate Weak Negative, predicted EC3 > 100%	21 4 1 0	3 15 17 2	0 10 19 2	0 0 24 16
	Accuracy (%) Overpredicted (%) Underpredicted (%)	53.0 27.6 19.4			
(C) ANN model 4 (h-CLAT/ DPRA/ KeratinoSens/cell toxicity""/TIMES-M)	Extreme or strong Moderate Weak Negative, predicted EC3 > 100%	20 6 0 0	4 25 6 2	0 9 21 1	0 1 14 25
	Accuracy (%) Overpredicted (%) Underpredicted (%)	67.9 20.9 11.2			
(D) ANN model 6 (h-CLAT/DPRA/ KeratinoSens/cell toxicity <sup>™</sup> / Toxtree)	Extreme or strong Moderate Weak Negative, predicted EC3 > 100%	22 3 1 0	4 18 13 2	0 10 20 1	0 1 20 19
	Accuracy (%) Overpredicted (%) Underpredicted (%)	59.0 26.1 14.9			

### JHIJEID

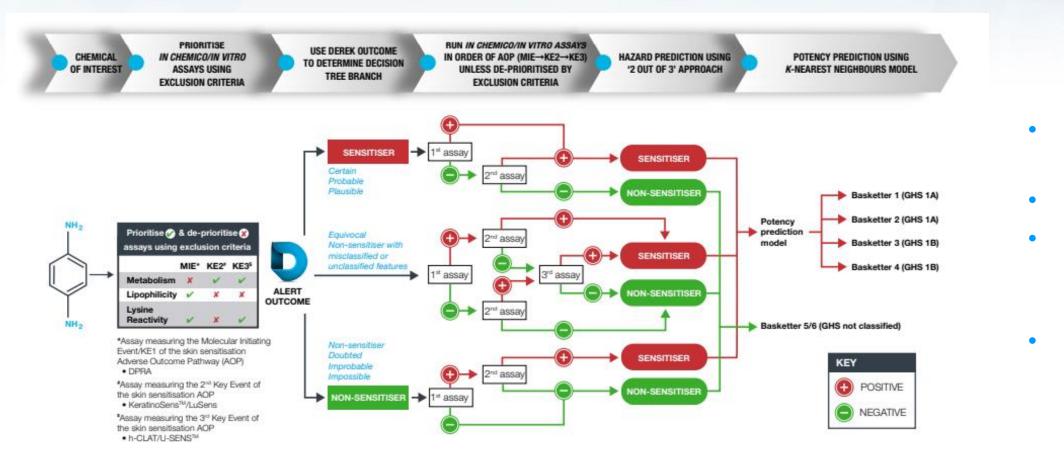
•

2 Tier model: hazard ID followed by potency prediction LLNA EC3% predicted – continuous value No categorization No probability information LLNA training set

Applied at EPA for isothiazolinone RA



# **DEREK NEXUS (LHASA)**



### Table 7

The skin sensitisation potency predictivity of the DA (and LLNA) compared to both LLNA and human reference data.

	Benchmark data	Potency category			GHS classification				
		n	Over-predicted	Correctly predicted	Under-predicted	n	Over-predicted	Correctly predicted	Under-predic
-	DA vs LLNA DA vs Human LLNA vs Human	174 <sup>a</sup> 79 <sup>b</sup> 89	20% 14% 25%	59% 68% 54%	21% 18% 21%	174ª 79 <sup>b</sup> 79	12% 10% 20%	73% 76% 65%	15% 14% 15%

\* 20 chemicals with a hazard prediction not given a potency prediction by the DA.

<sup>b</sup> 23 chemicals with a hazard prediction not given a potency prediction by the DA.

### (Macmillan & Chilton 2019)

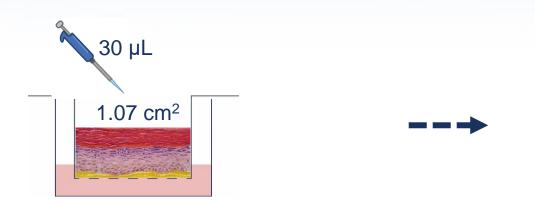
Tiered approach: Hazard ID and potency categorization 6 categories Combination of DEREK alerts with "2 out of 3" and a nearest

neighbour prediction model Updated with EC3 prediction

licted



# **SENS-IS** assay versus Weight of Evidence Skin **Sensitisation Potency Categories**



### **62 SENS-IS biomarkers** (ARE, SENS-IS, Irritation genes)

Concentration leading to Pos.	Potency category	Dose per uni		
0.1%	Extreme	28 µg/cm <sup>2</sup>		
1%	Strong	280 µg/cm²		
10%	Moderate	2803 µg/cm <sup>2</sup>		
50%	Weak	14000 µg/cm <sup>2</sup>		
100%	Very Weak	28000 µg/cm <sup>2</sup>		

	Category Name	Human Cat. (µg/cm²)	
	Extreme	<25	
WoE-based Skin sensitization	Strong	25 - 500	
Potency Categorization	Moderate	500 - 2,500	
USRR TOOLSOX	Weak	2,500 - 10,000	
BLOOD RECHA	Very Weak	> 10,000	
174	Non Sensitizer	Negative	



nit area	
2	
<sup>2</sup>	
1 <sup>2</sup>	



# **SENS-IS** assay versus Weight of Evidence Skin **Sensitisation Potency Categories**

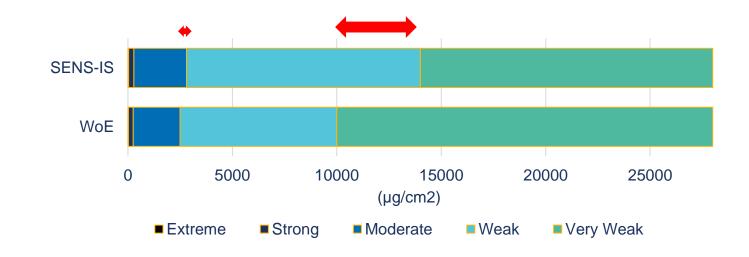
SENS-IS WoE	Extreme	Strong	Moderate	Weak	Very Weak	NS
Extreme	2	2	0	1	0	0
Strong	1	12	5	1	0	0
Moderate	0	5	18	6	3	2
Weak	1	1	14	27	5	6
Very Weak	0	0	7	17	2	12
NS	0	0	0	4	1	19
	_					

Off

**Approximate** 

38/68 predicted to be stronger sensitizers by SENS-IS

30/68 predicted to be weaker sensitizers by SENS-IS





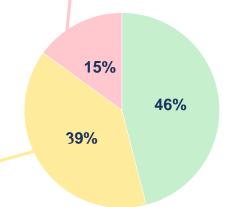
Na et al. reg. Tox pharm. 2022

Exact match



13/26 predicted to be stronger sensitizers by SENS-IS

13/26 predicted to be weaker sensitizers by SENS-IS



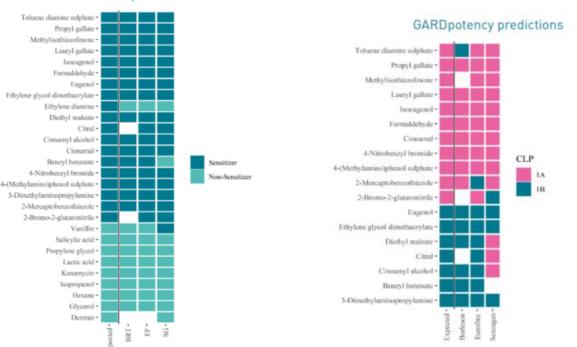


# **GARD Skin Sensitisation Assay Portfolio**

From binary hazard identification to quantitative potency information on a continuous scale

OECD TG 442e

GARD" skin	GARD" potency	GARD" skin Dose-Response
200 genes	51 genes	200 genes
Binary hazard identification of skin sensitizing chemicals.	An add-on <i>in vitro</i> test to GARDskin for potency classification according to GHS/CLP (1A or 1 B)	Quantitative assessment of skin sensitization potency on a continuous scale.



# and a second sec

	GARD	LLNA
Response value	DV	SI
Binary Threshold	DV = 0	SI = 3
Readout	$cDV_0(DV_0Concentration)$	EC3 Concentra

### Gradin et al. 2021





Performance statistics:GARDskin accuracy:94%GARDpotency accuracy:88%GARD Defined Approach:86%



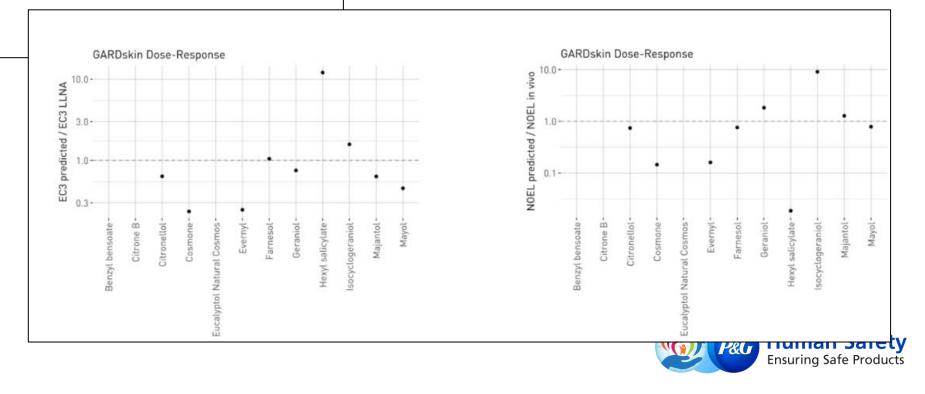
ation

# **RIFM – GARD Evaluation**

Test Item	Name	Predicted LLNA EC3 (%) <sup>I</sup>	Reference LLNA EC3 (%) <sup>1</sup>	Predicted HP Cat	Reference HP cat <sup>II</sup>	Predicted NOEL (µg/cm²)	Reference NOEL (µg/cm²) <sup>II</sup>
S1	Farnesol	5.02 (2.46, 10.3)	4.8	4 (0.357)	3	2090 (795, 5490)	2755
S2	Citronellol	27.6 (8.14, 93.9)	43.5	5 (0.481)	5	21800 (3560, 134000)	29528
S3	Iso-cyclo Geraniol	39.4 (10.2, 100)	25	5 (0.547)	4	35500 (4660, 271000)	3898
S4	Geraniol	12.2 (4.75, 31.2)	16.2	4 (0.38)	4	7070 (1840, 27100)	3875
S5	Citrone B	Non-Sens	64.98	Non-Sens	4	Non-Sens	2780
S6	Majantol	18.5 (6.29, 54.5)	29.2	5 (0.406)	4	12600 (2600, 60900)	9900
S7	Hexyl salicylate	2.17 [1.13, 4.17]	0.18	4 (0.285)	4	658 (270, 1600)	35433
S8	Cosmone	3.86 [1.96, 7.59]	16.4	4 [0.338]	5	1450 (589, 3590)	10000
S9	Evernyl	4.68 (2.32, 9.45)	19	4 (0.352)	5	1890 (736, 4880)	11810
S10	Eucalyptol Natural Cosmos	Non-Sens	65.9	Non-Sens	4	Non-Sens	590
S11	Mayol	19.9 (6.6, 60.3)	44	5 (0.42)	5	13900 (2760, 70300)	17717
S12	Benzyl benzoate	Non-Sens	17	Non-Sens	5	Non-Sens	20690

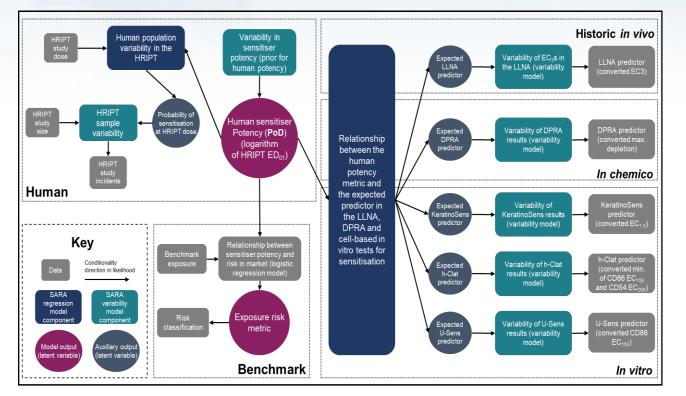
1) 11) LLNA EC3 values were provided by RIFM.

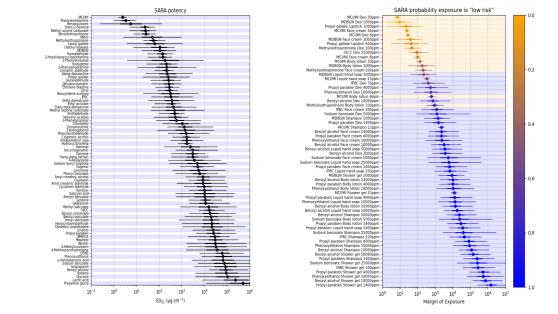
Human NOEL and HP cat were obtained from Basketter (2016) and API





# **SARA Defined Approach**





Unileve

- Bayesian statistics to infer a probability that a consumer exposure to some chemical can be considered low risk (SARA risk metric) for induction
- Uses a database of public NAM data, and historic LLNA and HRIPT data
- The PoD metric is a dose with a 1% chance of human skin sensitisation (ED01)
- The model accounts for variability in the data
- Incorporates benchmark exposure
- SARA can also predict hazard, GHS categories, POD (continuous scale)



### **Training sets and Performance**

- NAM/ DA not trained / built with human data
- LLNA dataset used for all (most) as training set
  - Potency categories or EC3 continuous values
  - Similar data used for all DA/ models (applicability domain)
- Human benchmarks incorporated in some to determine risk
- Performances evaluated against LLNA
  - OECD LLNA reference database (168, 123 with 1A/1B) or others
  - Comparable performance (for hazard, potency difficult to compare)
  - Better for hazard than potency (drops with more categories)
- Relevance to humans / Performances against human data
  - Some NAM/ DA evaluated against human data
  - OECD human reference database (66, 55 with 1A/1B)





# **Use for QRA/ NGRA: Conversion of Prediction into POD**

Potency Category	LLNA EC3 % ranges (ECETOC)	LLNA EC3 % conversion to µg/cm <sup>2</sup> (based on LLNA dosing*)	Default NESIL μg/cm <sup>2</sup> to be used as POD
Extreme (Potent)	< 0.1	< 25	1
Strong	≥ 0.1 - < 1	≥25 - <250	10
Moderate	≥ 1 - < 10	≥250 - <2500	100
Weak	≥ 10 - ≤ 100	≥2500 - <25000	1000
GHS 1A	< 2%	< 500	< 500
GHS 1B	> 2%	> 500	> 500

- Conversion of LLNA categories or EC3% to  $\mu$ g/cm<sup>2</sup> using a conversion factor (1% = 250)  $\mu$ g/cm<sup>2</sup>)
- GHS categorization models limited in deriving POD (only < or > 500  $\mu$ g/cm<sup>2</sup>)
- Some methods (Bayesian) allow confidence evaluation around predicted value
- Genomic methods unique conversion approaches
- PoD metric of SARA is a dose with a 1% chance of human skin sensitisation (ED01)



# Some final Comments...

- NAM/ DA remain categorical for most, but progress was made towards better potency prediction (ie. Continuous values)
  - What is sufficient?
- Progress made towards POD setting for QRA.
- Conversion to POD not uniquely done
- Conservatism / confidence in prediction differs between NAM/ DA
- Bayesian DAs enable experimental data variability to be modelled and uncertainty in POD & risk metrics can be factured into decision making
- Shortcomings of the animal reference standard must be acknowledged
- Human biological and mechanistic relevance of the DA needs to be established



### **Thanks to the CE Skin Tolerance Task Force and colleagues!**

**Kao** Enriching lives, in harmony with nature.

**JHIJEIDO** 





ESTĒE IAUDFR COMPANIES

> L'ORÉAL Research & Innovation



Dermo-Cosmétique

Beiersdorf

Henkel

MOËT HENNESSY • LOUIS VUITTON





### CHANEL

