



# GARD – Genomic Allergen Rapid Detection

GARDskin Dose-Response: Performance on the Reference Chemical Potency List

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**IDEA RCPL (Reference Chemical Potency List) 2<sup>nd</sup> Workshop**

September 22, 2023

SENZA  
GEN

# Overview of today's presentation

The presentation includes the following topics:

- Short introduction to the GARDskin technology (OECD TG 442E).
- GARDskin Dose-Response assay: adaptation of the validated GARDskin protocol to allow for continuous potency predictions.
- Performance of the GARDskin Dose-Response assay on the Reference Chemical Potency List

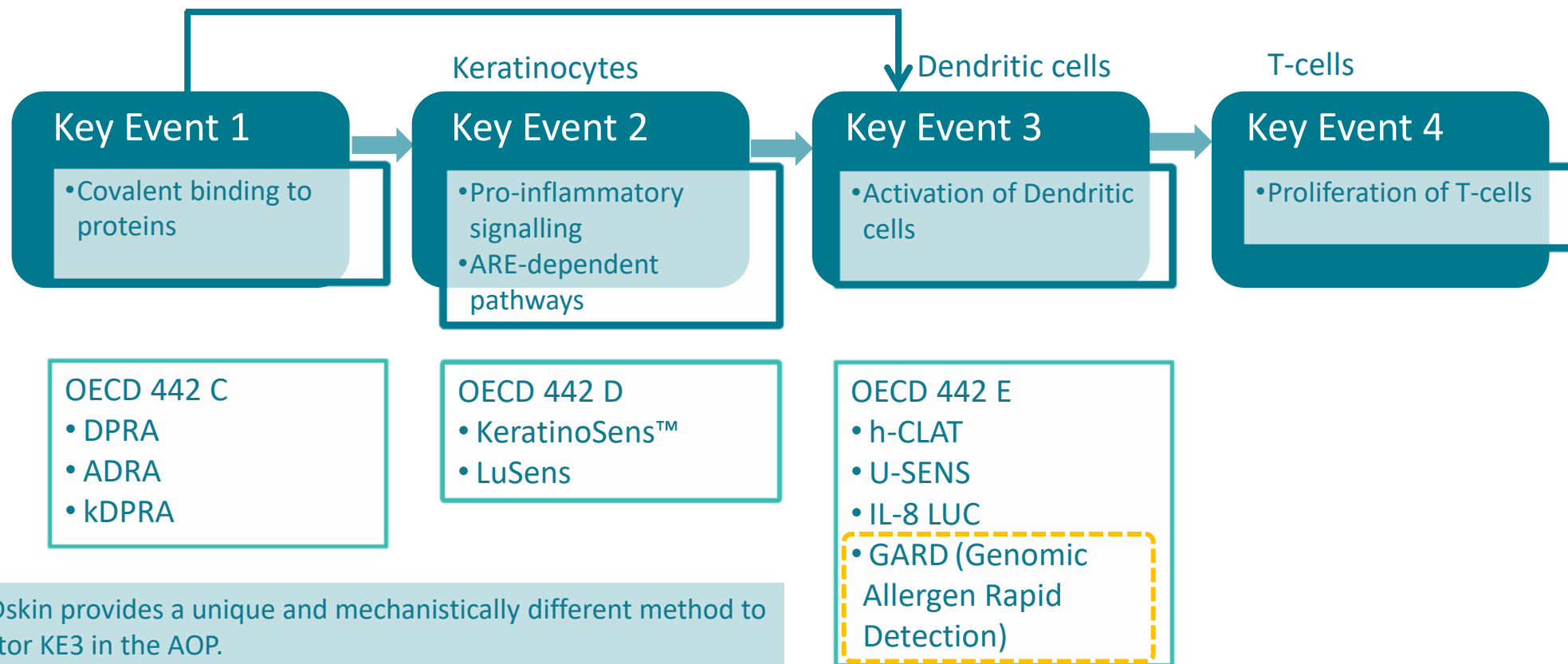


# Introduction – Testing for Skin Sensitization

OECD Test Guidelines are mapped to the AOP

AOP - Adverse Outcome Pathway

NAM - New Approach Methods (KE 1-3)



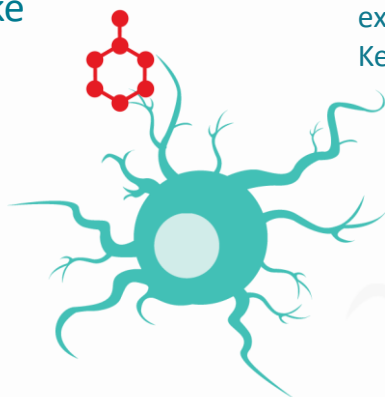
# The GARD technology platform – how it works

Transcriptomic read-out of the biological response

**Biological system:** Dendritic-like cell line (KE3)

**Readout:** Gene expression (genes and toxicity pathways)

Dendritic-like  
cell line

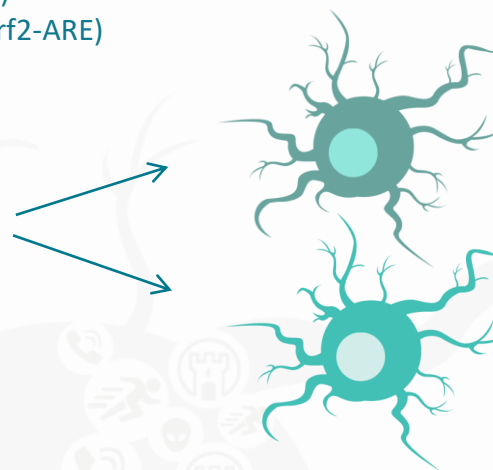


ex: h-CLAT (CD86/CD54)  
KeratinSens (Keap1-Nrf2-ARE)

↑  
Cellular  
responses



GARDskin



Sensitizer

Non-sensitizer

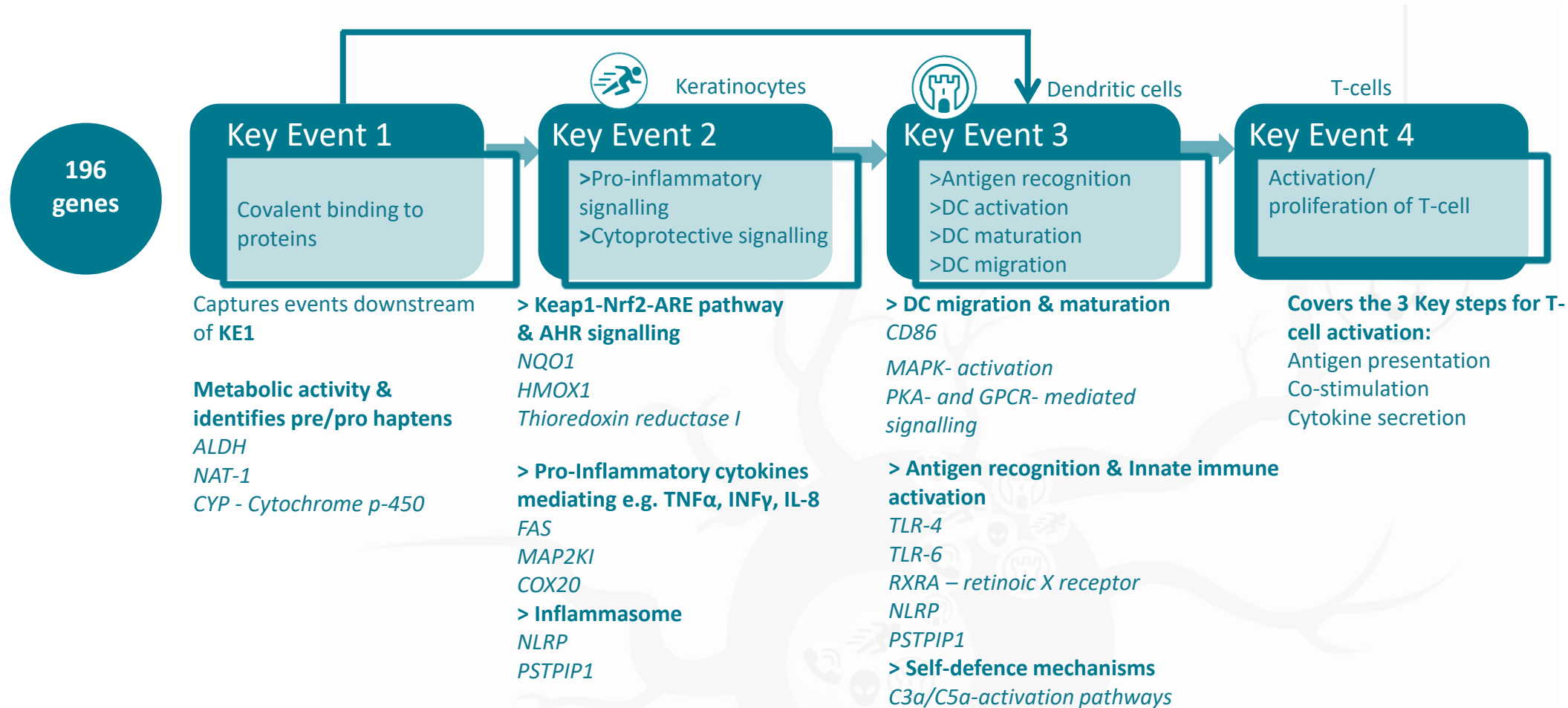
Gene expression of biomarker signatures  
GARDskin: 196 genes.

Full transparency: Identities of genes being measured available in peer-reviewed scientific literature.

See for example: Johansson et al. (2011) A genomic biomarker signature can predict skin sensitizers using a cell-based in vitro alternative to animal tests. BMC Genomics.

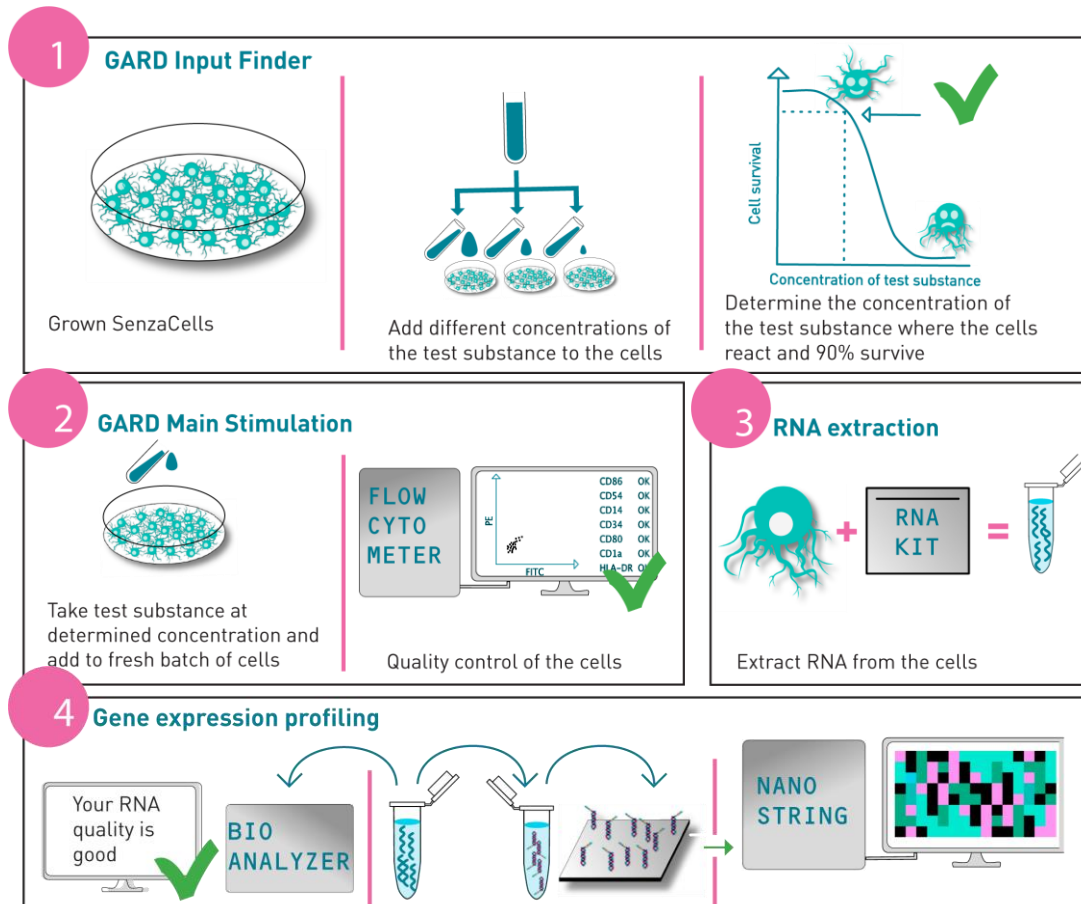
# The GARD technology platform – how it works

Genes cover mechanistically relevant toxicity pathways



Genes and pathways in the prediction signature are aligned with multiple key events in the AOP

# How to GARD<sup>®</sup> your products in 6 Steps



**Importantly: All genes contribute to a final classification, but with different weights**

**Prediction algorithm:**

$$DV = b + \sum_{i=1}^n w_i x_i$$

n: number of variables (n for GARDskin:196)

b: constant (SVM intercept)

$W_i$ : weight for variable i

$X_i$ : Normalized gene expression data for variable i

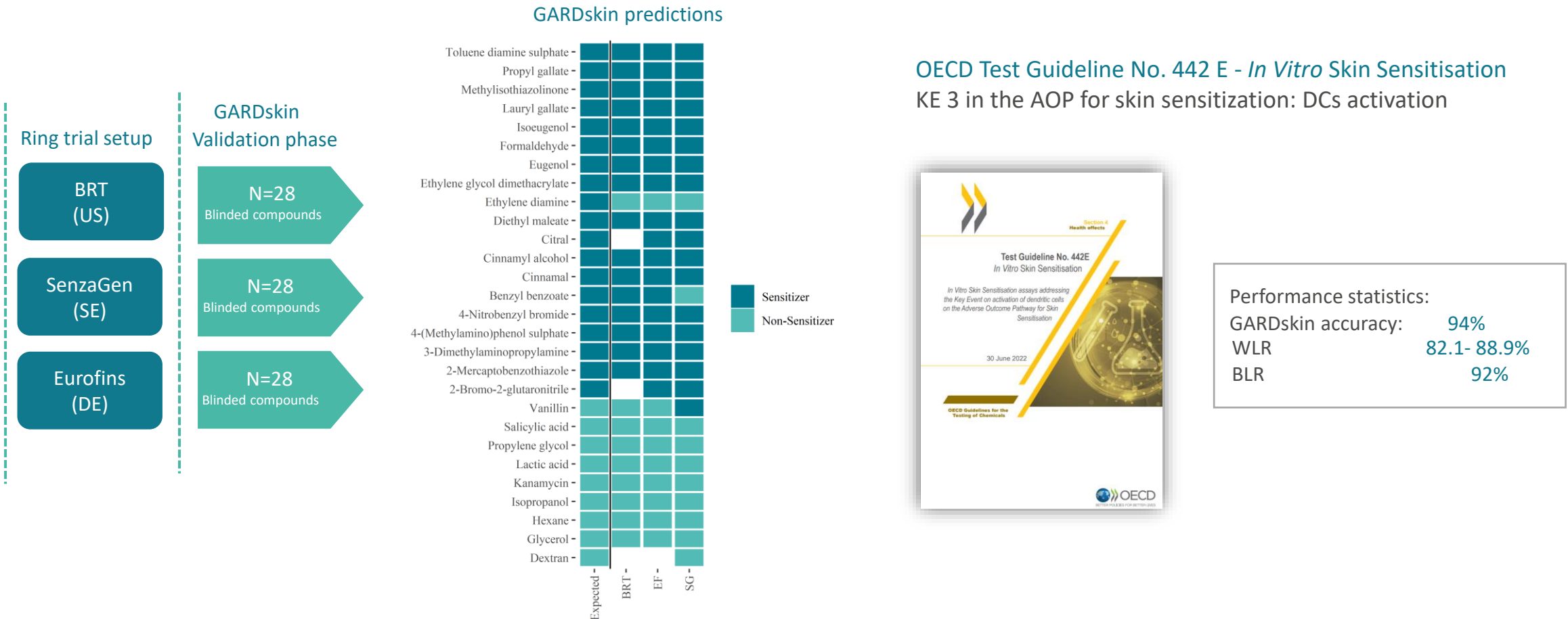
**Prediction model:**

Mean DV  $\geq 0$  : Skin sensitiser (UN GHS category 1)

Mean DV  $< 0$  : Non-sensitiser.

# The OECD approval of GARDskin

Machine learning and omics arrive in the field of regulatory toxicology



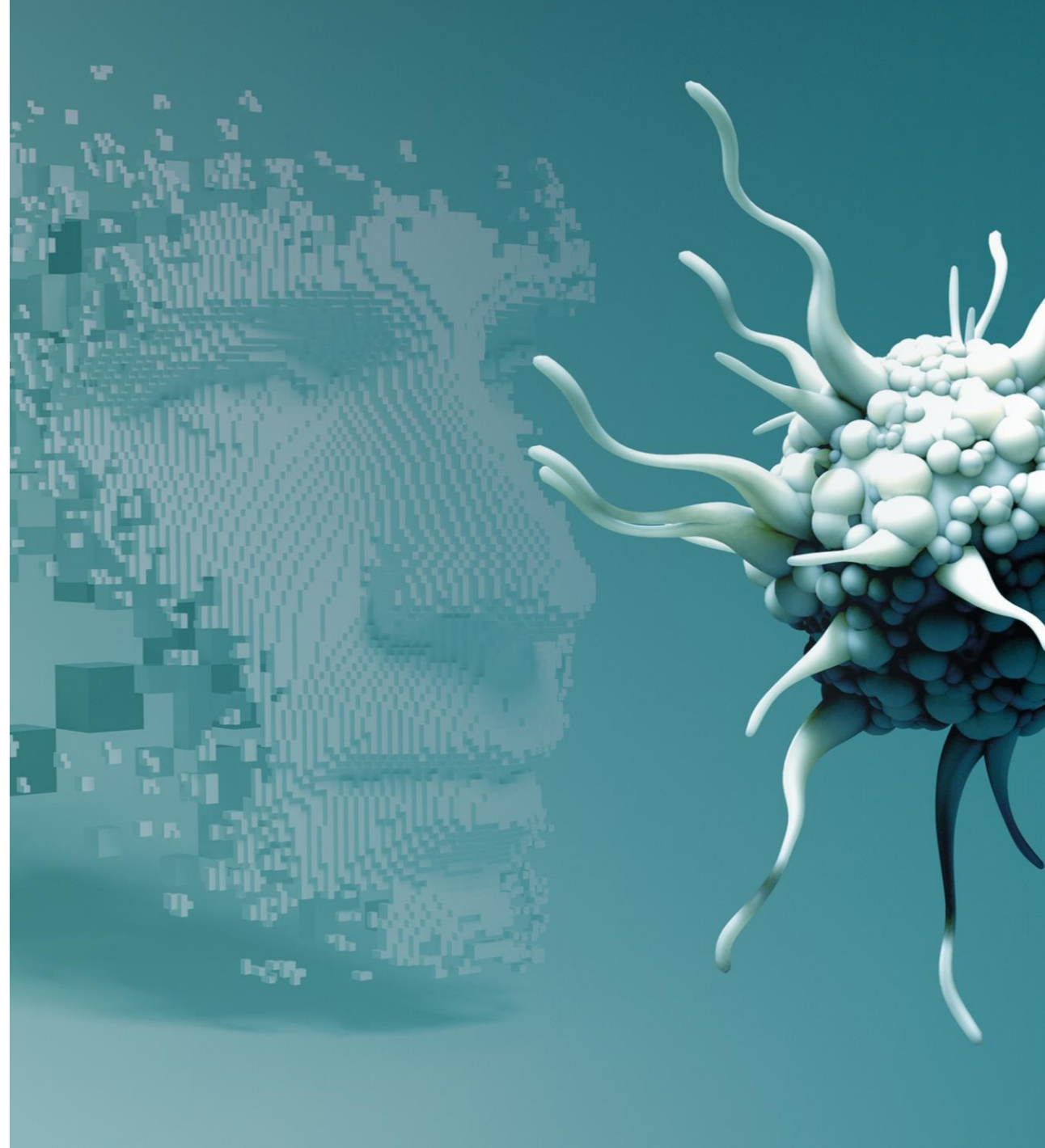
Validation study published in peer-reviewed scientific journal:

GARDskin: Published in Johansson et al. (2019), Validation of the GARD™skin assay for assessment of chemical skin sensitizers - ring trial results of predictive performance and reproducibility. *Toxicological Sciences*.

## GARDskin Dose-Response

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Adaptation of the validated GARDskin protocol to allow for continuous potency predictions



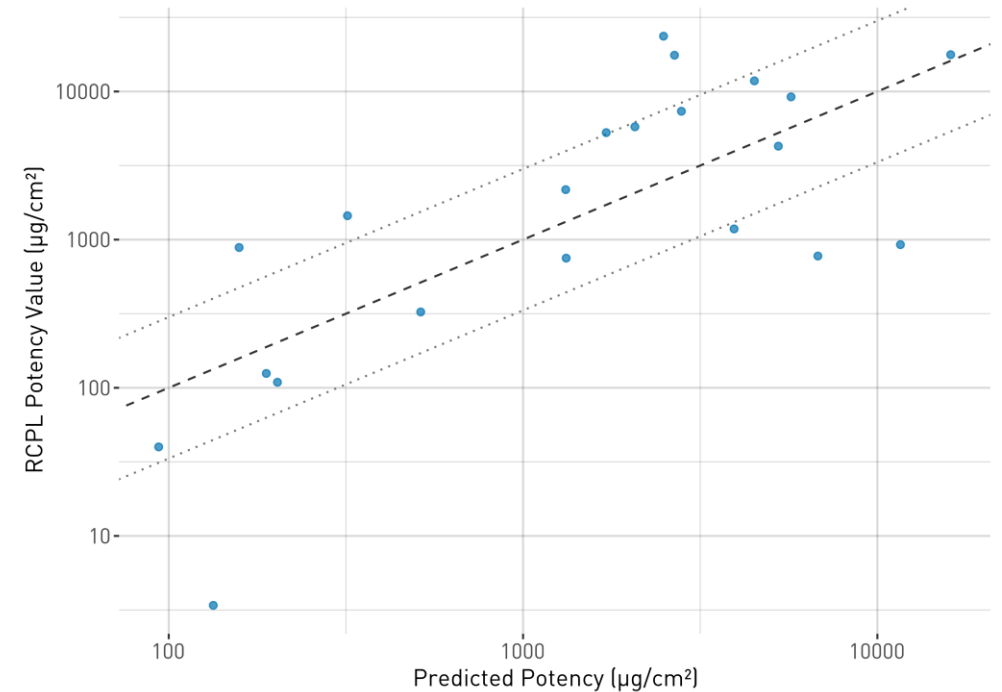


# GARDskin Dose-Response

*In vitro* assessment of skin sensitizing potency

- Based on the validated protocol of GARDskin but produces a quantitative readout on a continuous scale significantly associated with sensitizing potency.
- GARDskin Dose-Response allows for continuous potency predictions in the unit  $\mu\text{g}/\text{cm}^2$ .
- Prediction model and data processing pipeline is fully automated and incorporated into the cloud-based GARD Data Analysis Application (GDAA). No risk for manual errors.

Spoiler alert: These are the potency predictions for the chemicals in the RCPL-list.

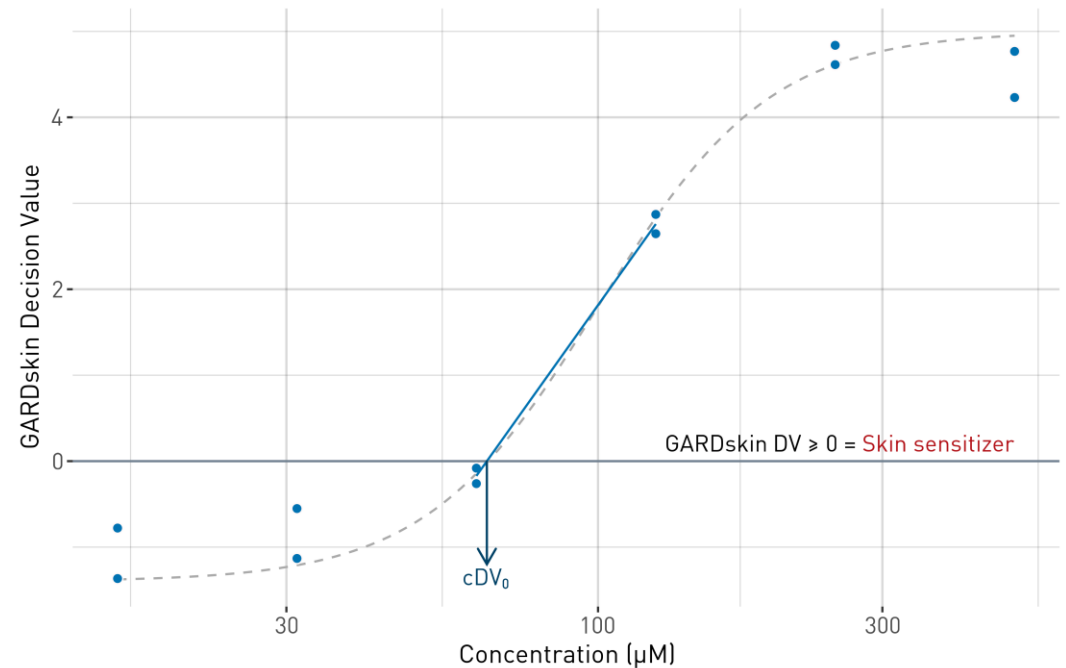


# GARDskin Dose-Response

How does it work in practice

- Perform the GARDskin assay at multiple concentrations.
- Use the standard GARDskin protocol to generate decision values (DVs) for each concentration.
- Visually inspect the dose-response data by plotting decision values versus concentrations.
- Estimate  $cDV_0$ : The lowest concentration expected to induce a positive classification ( $DV \geq 0$ ).

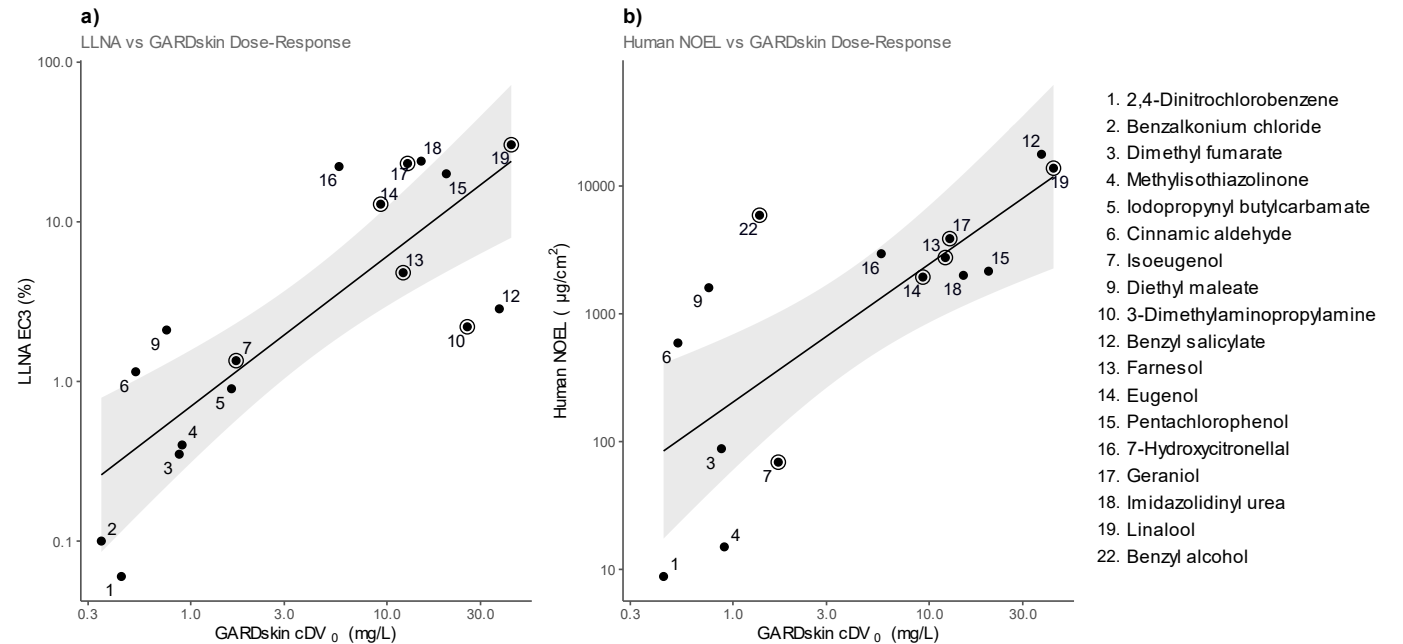
	GARD	LLNA
Response value	DV	SI
Binary threshold	$DV = 0$	$SI = 3$
Readout	$cDV_0$	EC3



# GARDskin Dose-Response

Generated  $cDV_0$  values can be used to inform on skin sensitizing potency

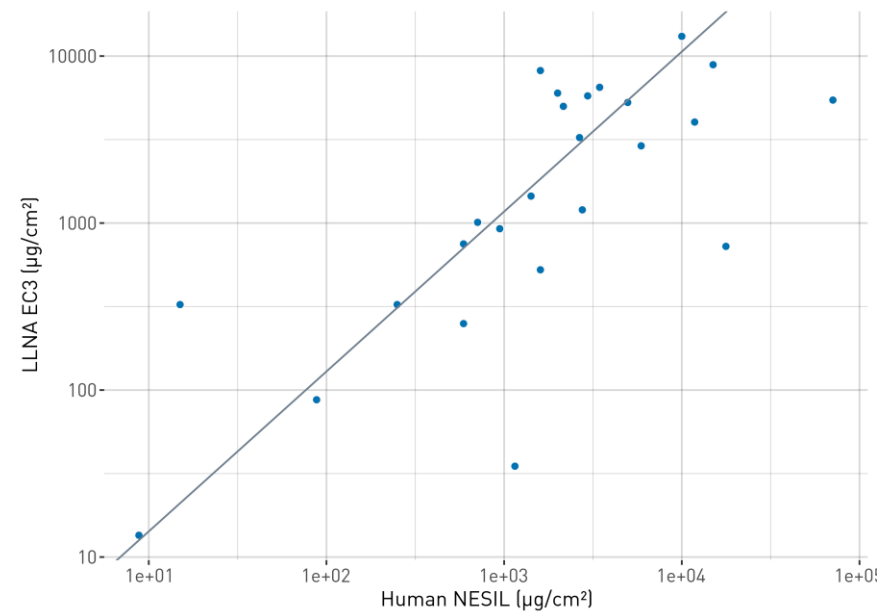
- Experimentally derived  $cDV_0$  values correlate strongly with skin sensitizing potency (LLNA EC3 and human NESIL):
  - Linear correlation:  $0.81$  ( $p = 9.1 \times 10^{-5}$ )
  - Rank correlation:  $0.74$  ( $p = 1.5 \times 10^{-3}$ )



# GARDskin Dose-Response

## Composite potency score

- Should the model predict human NESIL or LLNA EC3?
- It was considered redundant to fit models separately to LLNA EC3 and human NESIL.
- Both references inform on the same phenomenon i.e., skin sensitizing potency, but neither is perfect and associated with measurement errors.
- The composite score was designed to account for main shared variance. Unit is continuous:  $\mu\text{g}/\text{cm}^2$ .

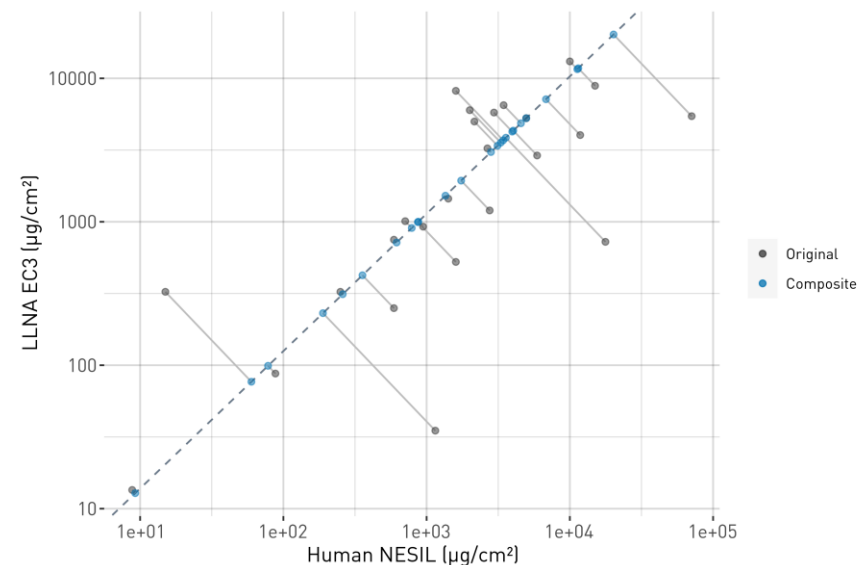


Example	LLNA EC3 ( $\mu\text{g}/\text{cm}^2$ )	Human NESIL ( $\mu\text{g}/\text{cm}^2$ )	Composite ( $\mu\text{g}/\text{cm}^2$ )
DNCB	13.5	8.8	
Cinnamic aldehyde	250	591	
Citral	1450	1420	
...			

# GARDskin Dose-Response

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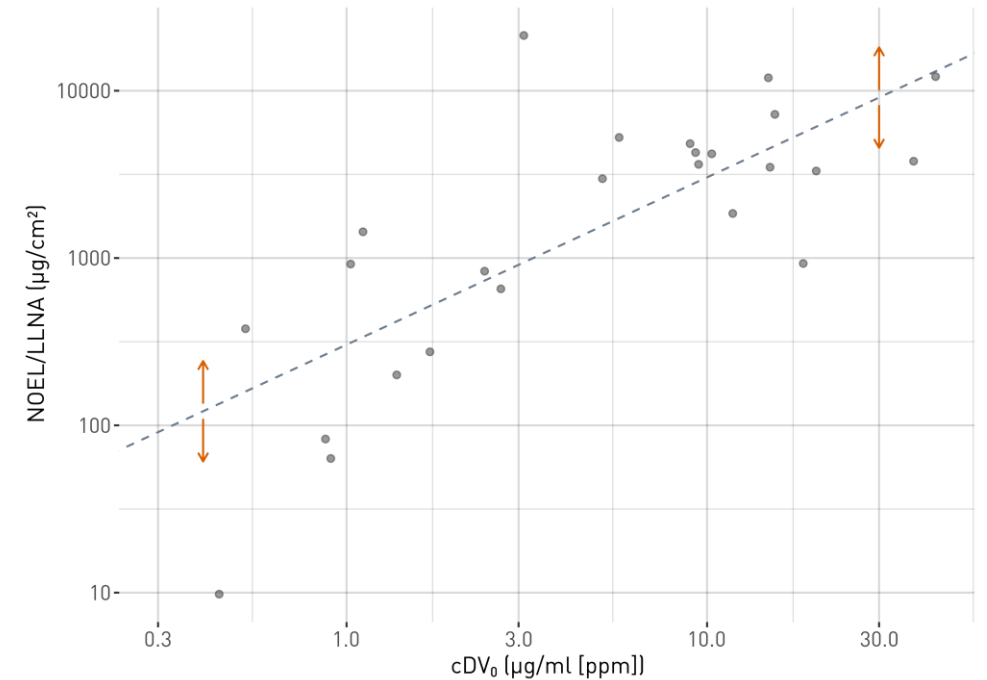
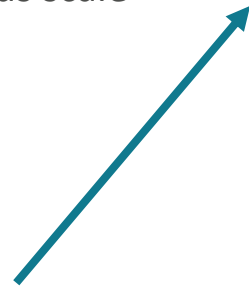
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DNCB	13.5	8.8	9.8
Cinnamic aldehyde	250	591	378
Citral	1450	1420	1440
...	...	...	...

# GARDskin Dose-Response

Quantitative assessment of skin sensitizing potency

- The correlation between  $cDV_0$  and potency is described by a linear regression model.
- The regression model is simple and only contains 1 parameter:
  - Prediction in  $\mu\text{g}/\text{cm}^2 = cDV_0$  in  $\mu\text{g}/\text{ml} \times \theta$
- The model can be used to predict potency on a continuous scale for test materials of unknown sensitizing potential.

Composite score created from LLNA EC3 and Human NESIL



# GARDskin Dose-Response

## How to derive continuous potency predictions

### Step 1: Dose-Response testing.

- Generation of a dose response curve by plotting DV vs concentration.
- Identification of a  $cDV_0$  value using linear interpolation.

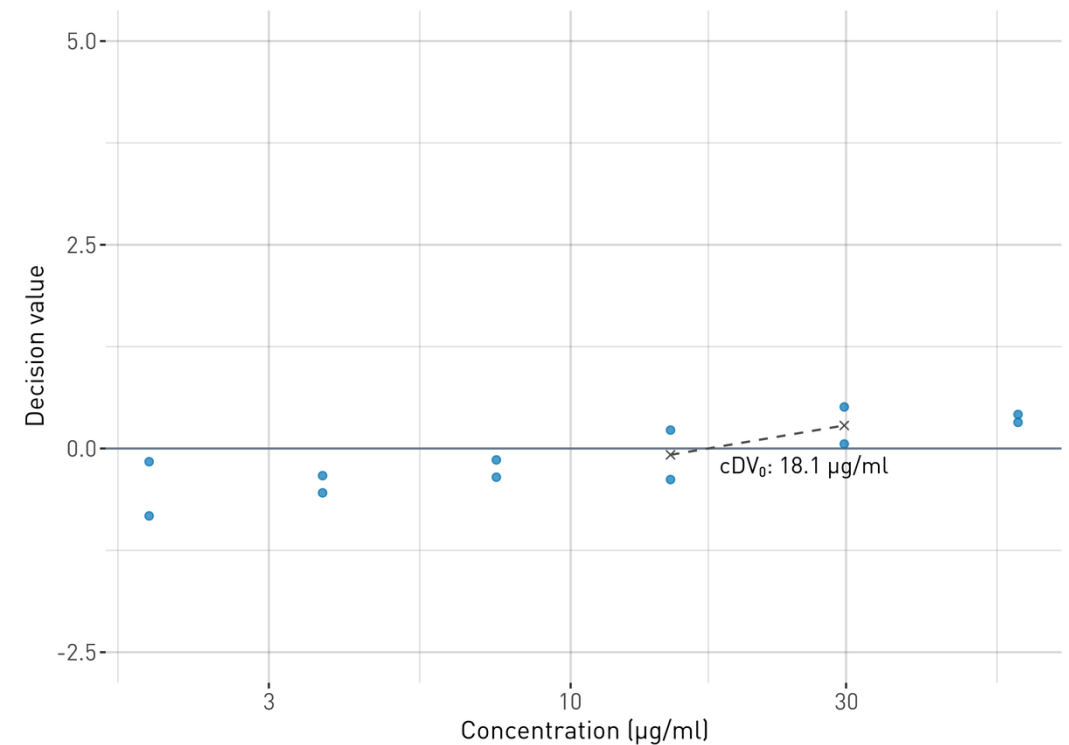
### Step 2: Continuous potency predictions.

- Correlation between  $cDV_0$  and potency is described by a linear regression model.
- The  $cDV_0$  value is used as input into the regression model to derive a potency prediction in the unit  $\mu\text{g}/\text{cm}^2$  (LLNA EC3/Human NESIL)

### Step 3: Provide an estimate of uncertainty in predictions

- A 95% confidence interval for the predicted NESIL value is calculated to provide an estimate of uncertainty in prediction.

Test Item: Benzyl Cinnamate



# GARDskin Dose-Response

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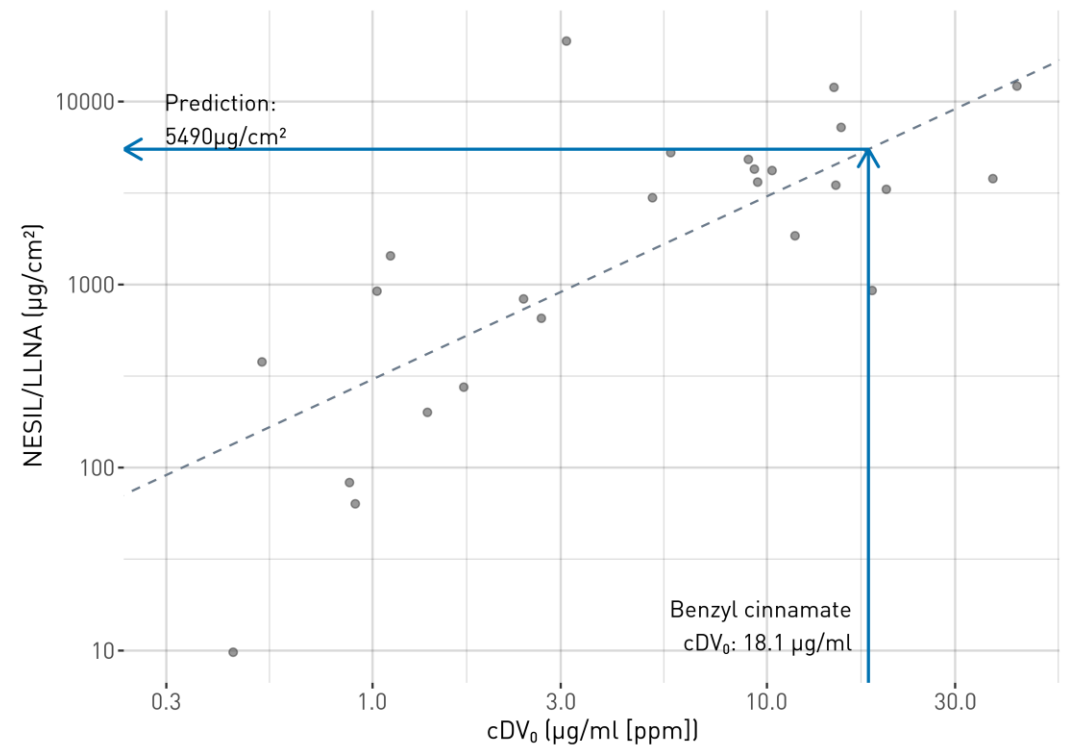
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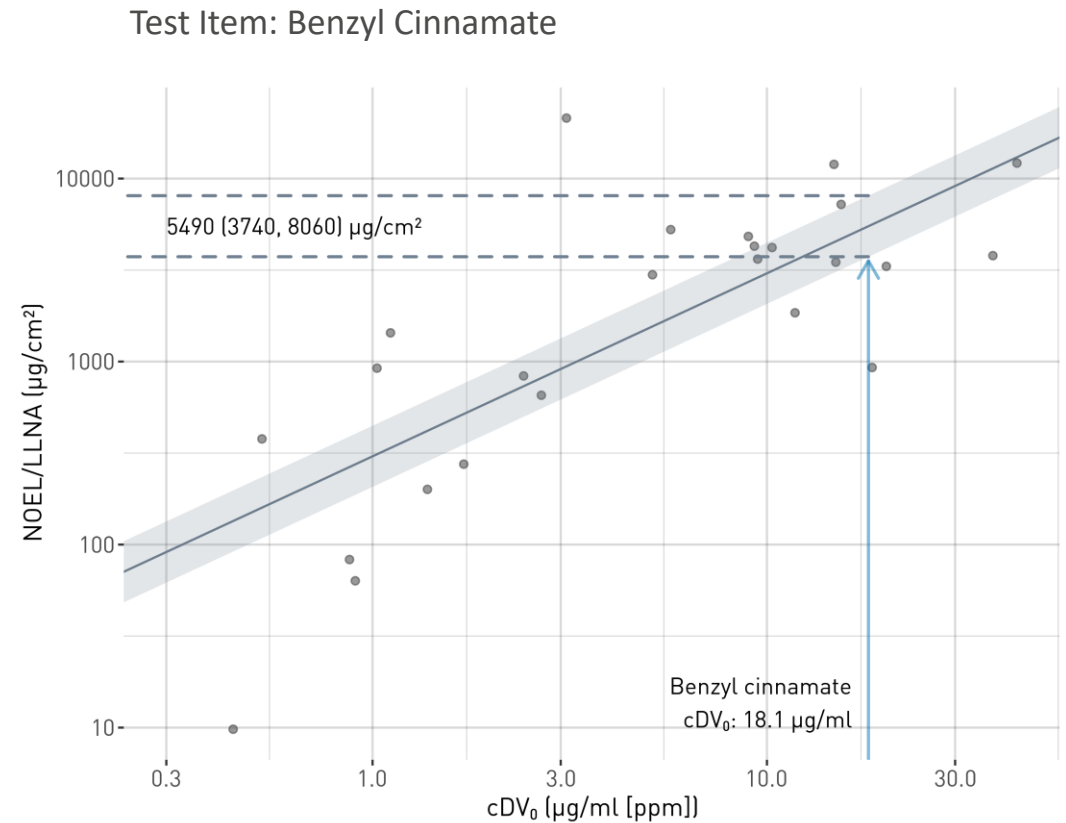
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# GARDskin Dose-Response

Cross-sector collaboration to evaluate reproducibility and performance

## Background

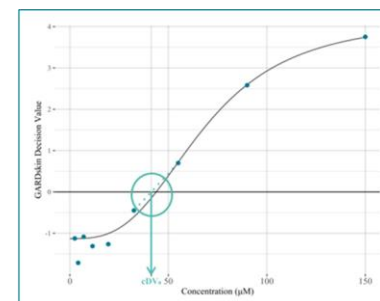
- Collaboration SenzaGen, IFF and RIFM
- Pre-validation exercise to evaluate reproducibility and performance of the GARDskin Dose-Response assay.

## Methods

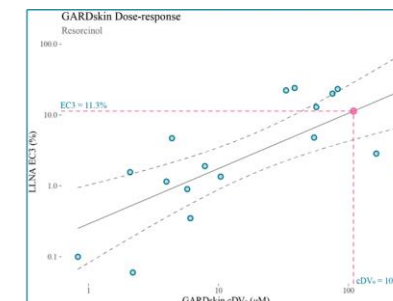
- Materials were tested in blinded studies according to GARDskin Dose-Response protocols.
- The identified  $cDV_0$  values were used to predict potency (LLNA EC3/Human NESIL).
- Following decoding of sample IDs, results were compared to available reference data, mainly from the comprehensive database available at RIFM.



**Step 1**  
Perform cellular stimulations  
(6 x conc).



**Step 2**  
Generate a dose-response  
curve and identify  $cDV_0$ .



**Step 3**  
Predict EC3/NESIL using the  
established regression  
models.



# GARDskin Dose-Response

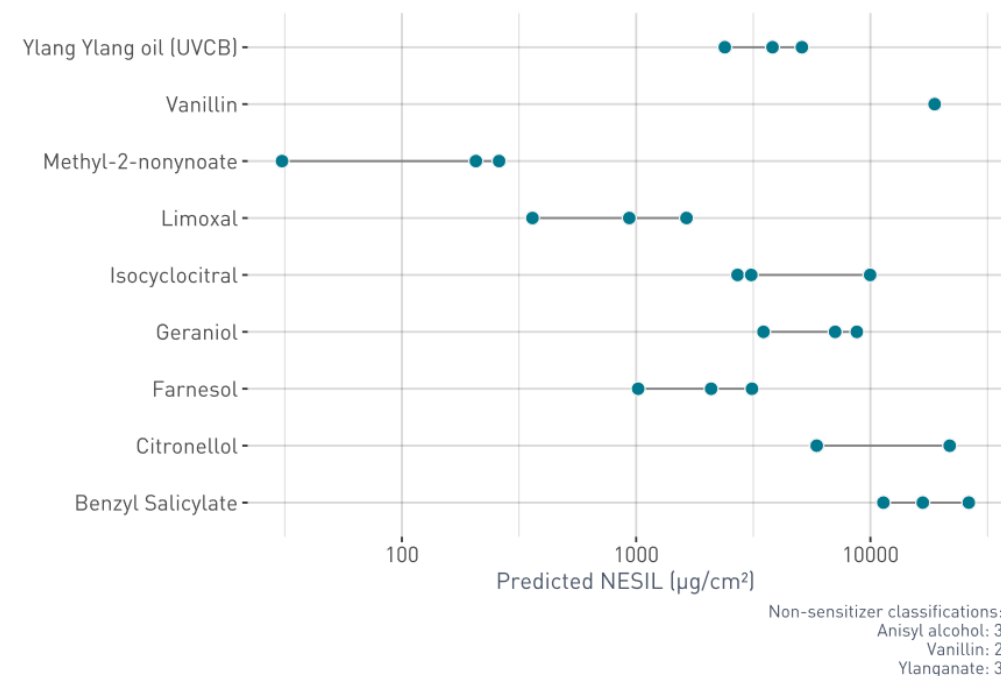
Cross-sector collaboration to evaluate reproducibility and performance

## Results

- Repeated measurements of 11 materials in three independent runs (blinded).
- The predicted potency values from GARDskin Dose-Response were reproducible between experiments with a typical variation of 1.8-fold-changes.\*

## Conclusions

- Gold standard LLNA: Typical variation observed from multiple runs is 2.4-fold-changes.#
- GARDskin Dose-Response provides reproducible continuous potency predictions.



\*Based on residual standard deviations.

#Calculated from the Cosmetic Europe database published in Hoffmann et al. (2018)



# GARDskin Dose-Response

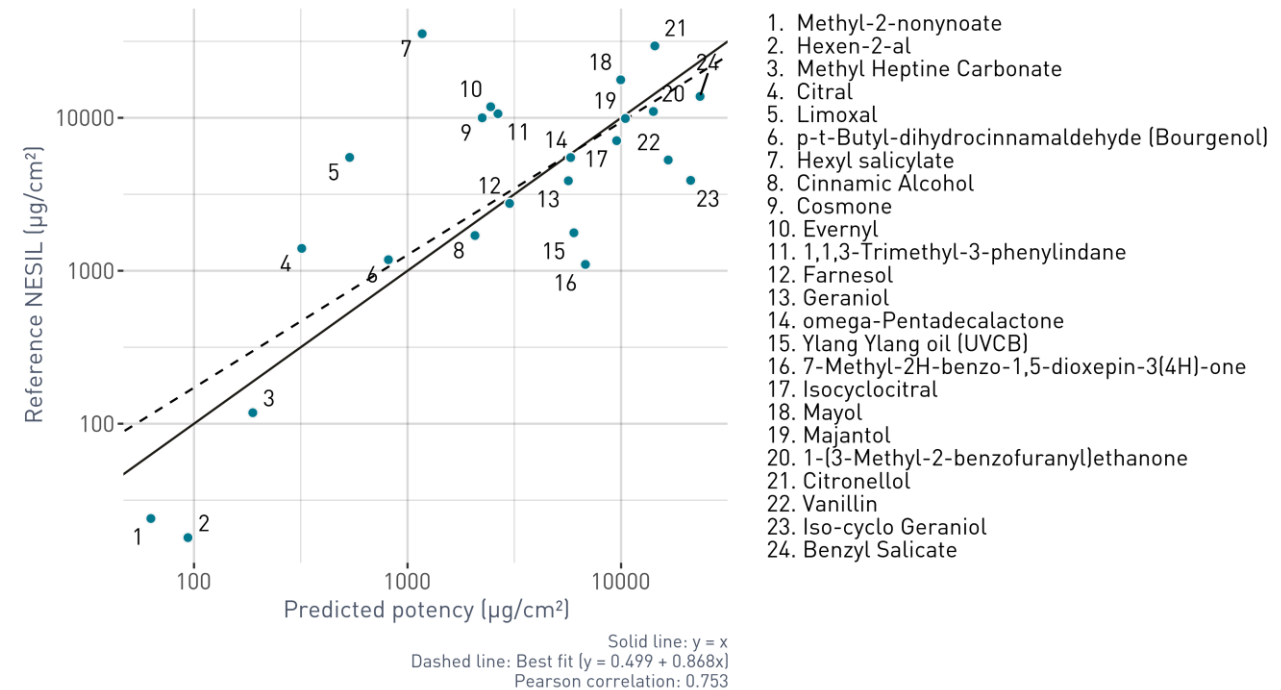
Cross-sector collaboration to evaluate reproducibility and performance

## Results

- GARDskin Dose-Response data available for a total of 24 fragrance materials.
- The GARDskin Dose-Response predicted potency values correlated well with Human NESIL values ( $r=0.75$ ).

## Conclusions

- GARDskin Dose-Response provides reproducible and accurate potency predictions with high correlation to human NESIL values.



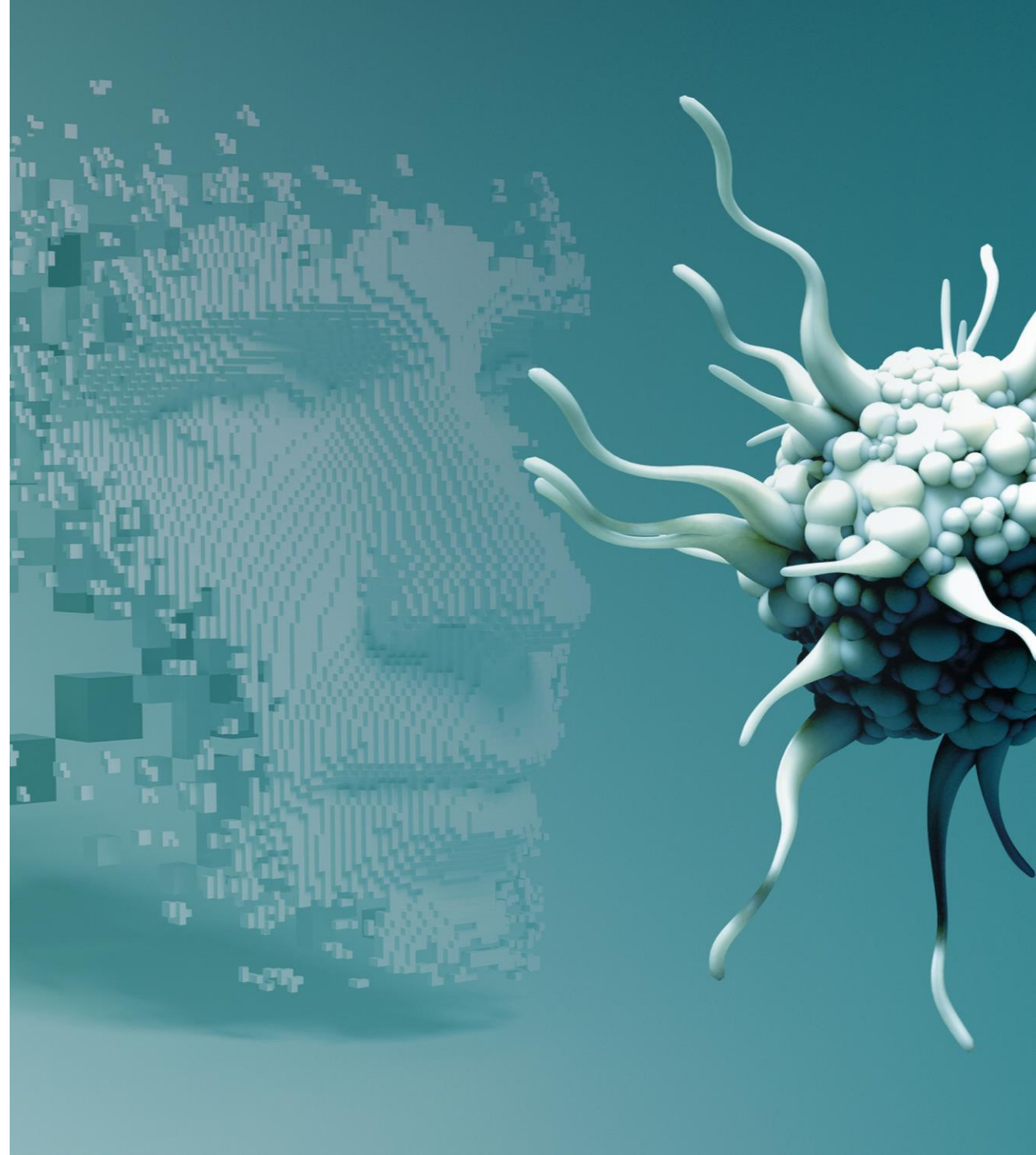
Data have been collected for an extended dataset ( $n=100$ ). Manuscript is being prepared together with RIFM and IFF.



## GARDskin Dose-Response

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Evaluation based on Reference Chemical Potency List (RCPL)

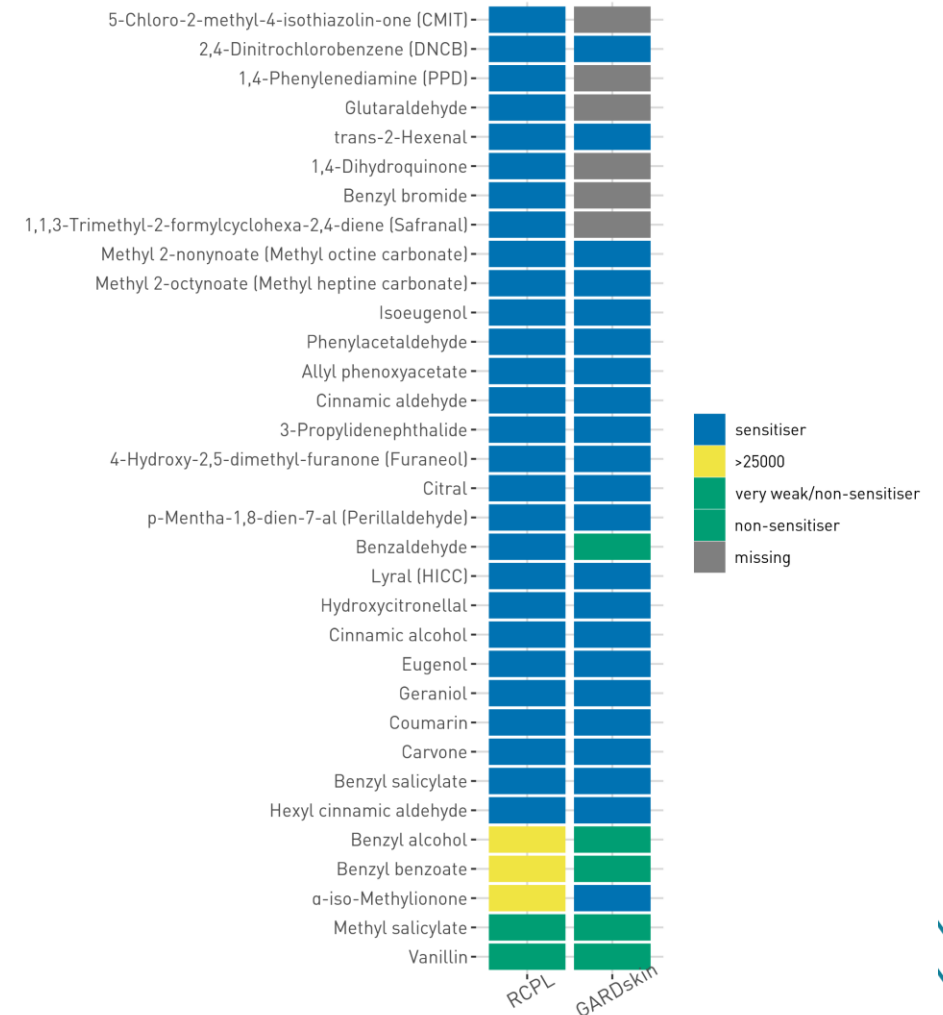


# Reference Chemical Potency List

## Binary outcomes and data coverage in GARDskin Dose-Response

- Data available for 27/33 materials in the RCPL list. High integrity of data, most obtained in blinded studies.
- 21/22 Sensitizers were correctly classified.
- 2/2 Non-Sensitizers were correctly classified.
- 1/3 Very weak sensitizers (<25,000) was classified as a sensitizer.

Overall, the binary classifications were consistent with the expected reference categories.

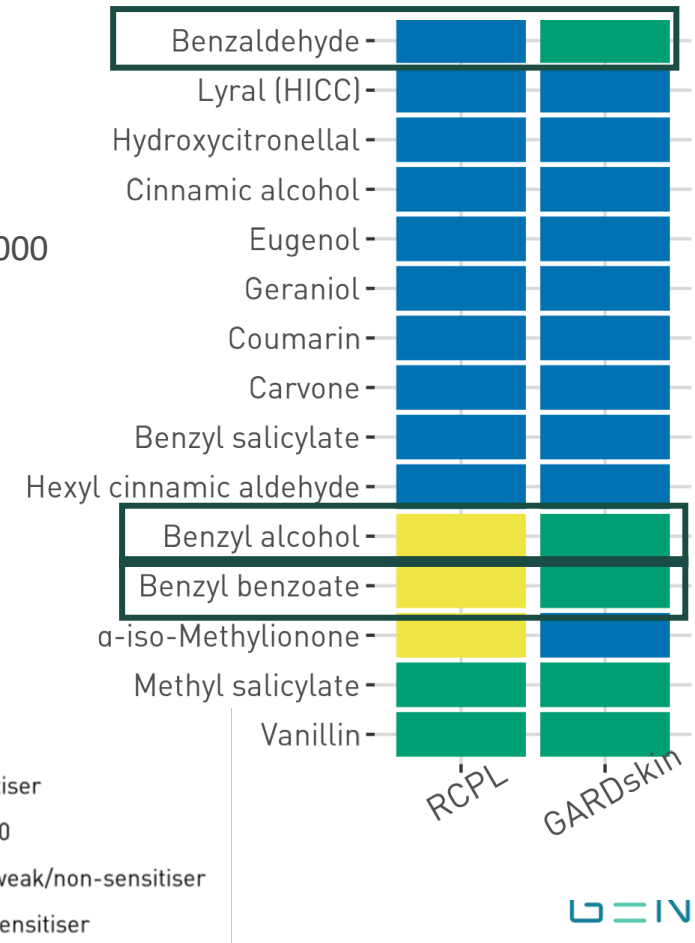


# Reference Chemical Potency List

## Binary outcomes and data coverage in GARDskin Dose-Response

- The binary disagreement consisted of 3 chemicals: benzyl benzoate, benzyl alcohol and benzaldehyde.
- Benzyl benzoate** has been assayed in GARDskin at multiple instances. Borderline chemical. Negative in DASS.
- Benzyl alcohol** has positive instances in the GARDskin assay but appears to be more stably classified as a non-sensitizer.
- Benzaldehyde** has consistently been classified as a non-sensitizer in the GARDskin assay.
  - LLNA is negative at 25% ( $>6250 \mu\text{g}/\text{cm}^2$ ).
  - DPRA is negative. KeratinoSens & h-CLAT is positive.

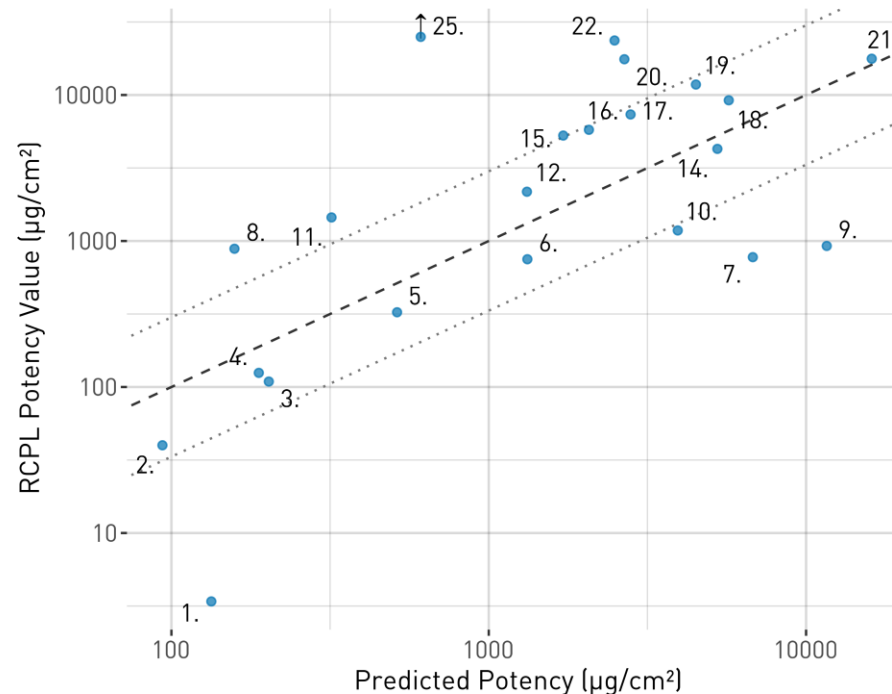
RCPL Potency Value:  $>25,000$



# Reference Chemical Potency List

GARDskin Dose-Response's prediction of potency values

- GARDskin Dose-Response data available for a total of 22 compounds.
  - Pearson correlation: 0.74 ( $p = 0.000136$ )
- >35% (8/22) of predictions are within 2-fold changes.
- >50% (12/22) of predictions are within 3-fold changes
- Only 3 materials with fold-change > 10



- 27. Vanillin
- 26. Methyl salicylate
- 25.  $\alpha$ -iso-Methylionone
- 24. Benzyl benzoate
- 23. Benzyl alcohol
- 22. Hexyl cinnamic aldehyde
- 21. Benzyl salicylate
- 20. Carvone
- 19. Coumarin
- 18. Geraniol
- 17. Eugenol
- 16. Cinnamic alcohol
- 15. Hydroxycitronellal
- 14. Lyral (HICC)
- 13. Benzaldehyde
- 12. p-Mentha-1,8-dien-7-al (Perillaldehyde)
- 11. Citral
- 10. 4-Hydroxy-2,5-dimethyl-furanone (Furaneol)
- 9. 3-Propylideneephthalide
- 8. Cinnamic aldehyde
- 7. Allyl phenoxyacetate
- 6. Phenylacetaldehyde
- 5. Isoeugenol
- 4. Methyl 2-octynoate (Methyl heptene carbonate)
- 3. Methyl 2-nonynoate (Methyl octine carbonate)
- 2. trans-2-Hexenal
- 1. 2,4-Dinitrochlorobenzene (DNCB)

Dashed line:  $y = x$   
Dotted lines: 3 Fold difference  
Green labels: Classified as non-sensitizers



# Reference Chemical Potency List

GARDskin Dose-Response's prediction of potency values

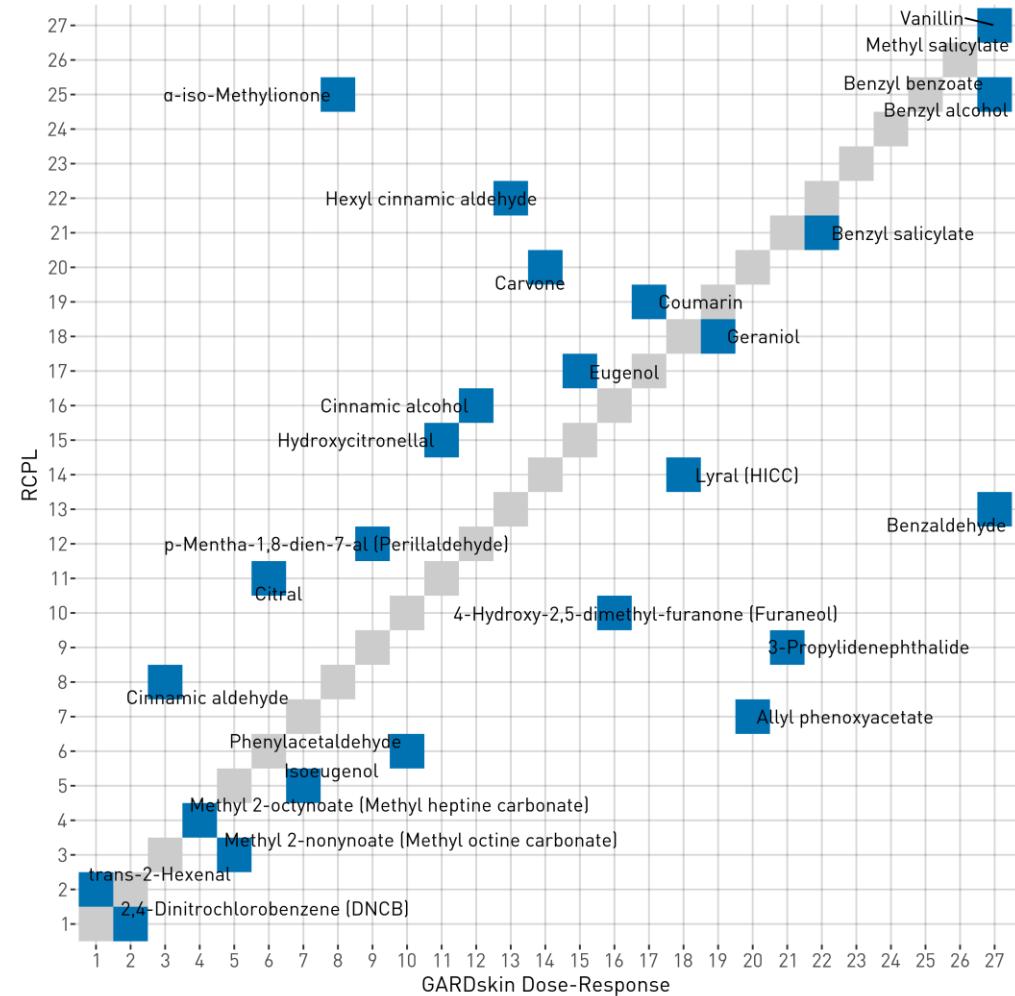
- Considering the entire dataset 44% (12/27) were either correct or within 2-fold change.
  - **Green:** 44% Correct or < 2-fold changes
  - **Yellow:** 70% < 5-fold-changes
  - **Orange:** 89% <10-fold-changes
  - **Red:** 11% > 10-fold-changes

Chemical	CAS	PV	Predicted
5-Chloro-2-methyl-4-isothiazolin-one (CMIT)	26172-55-4	2.3	NA
<b>2,4-Dinitrochlorobenzene (DNCB)</b>	<b>97-00-7</b>	<b>3.4</b>	<b>133.6</b>
1,4-Phenylenediamine (PPD)	106-50-3	3.9	NA
Glutaraldehyde	111-30-8	20.0	NA
<b>trans-2-Hexenal</b>	<b>6728-26-3</b>	<b>39.9</b>	<b>93.67</b>
1,4-Dihydroquinone	123-31-9	47.5	NA
Benzyl bromide	100-39-0	50.0	NA
1,1,3-Trimethyl-2-formylcyclohexa-2,4-diene (Safranal)	116-26-7	106	NA
<b>Methyl 2-nonynoate (Methyl octine carbonate)</b>	<b>111-80-8</b>	<b>109</b>	<b>202.7</b>
<b>Methyl 2-octynoate (Methyl heptine carbonate)</b>	<b>111-12-6</b>	<b>125</b>	<b>188.5</b>
<b>Isoeugenol</b>	<b>97-54-1</b>	<b>325</b>	<b>514.2</b>
<b>Phenylacetaldehyde</b>	<b>122-78-1</b>	<b>750</b>	<b>1323</b>
<b>Allyl phenoxyacetate</b>	<b>7493-74-5</b>	<b>775</b>	<b>6793</b>
<b>Cinnamic aldehyde</b>	<b>104-55-2</b>	<b>885</b>	<b>158.0</b>
<b>3-Propylidene-phthalide</b>	<b>17369-59-4</b>	<b>925</b>	<b>11620</b>
<b>4-Hydroxy-2,5-dimethyl-furanone (Furaneol)</b>	<b>3658-77-3</b>	<b>1181</b>	<b>3941</b>
<b>Citral</b>	<b>5392-40-5</b>	<b>1450</b>	<b>319.5</b>
<b>p-Mentha-1,8-dien-7-al (Perillaldehyde)</b>	<b>2111-75-3</b>	<b>2175</b>	<b>1319</b>
<b>Benzaldehyde</b>	<b>100-52-7</b>	<b>4094</b>	<b>NS</b>
<b>Lyrar (HICC)</b>	<b>31906-04-4</b>	<b>4275</b>	<b>5254</b>
<b>Hydroxycitronellal</b>	<b>107-75-5</b>	<b>5275</b>	<b>1717</b>
<b>Cinnamic alcohol</b>	<b>104-54-1</b>	<b>5775</b>	<b>2068</b>
<b>Eugenol</b>	<b>97-53-0</b>	<b>7357</b>	<b>2798</b>
<b>Geraniol</b>	<b>106-24-1</b>	<b>9197</b>	<b>5706</b>
<b>Coumarin</b>	<b>91-64-5</b>	<b>11792</b>	<b>4496</b>
<b>Carvone</b>	<b>6485-40-1</b>	<b>17573</b>	<b>2675</b>
<b>Benzyl salicylate</b>	<b>118-58-1</b>	<b>17715</b>	<b>16100</b>
<b>Hexyl cinnamic aldehyde</b>	<b>101-86-0</b>	<b>23620</b>	<b>2491</b>
<b>Benzyl alcohol</b>	<b>100-51-6</b>	<b>&gt;25000</b>	<b>NS</b>
<b>Benzyl benzoate</b>	<b>120-51-4</b>	<b>&gt;25000</b>	<b>NS</b>
<b>α-iso-Methylionone</b>	<b>127-51-5</b>	<b>&gt;25000</b>	<b>610.4</b>
<b>Methyl salicylate</b>	<b>119-36-8</b>	<b>non-sensitiser</b>	<b>NS</b>
<b>Vanillin</b>	<b>121-33-5</b>	<b>non-sensitiser</b>	<b>NS</b>

# Reference Chemical Potency List

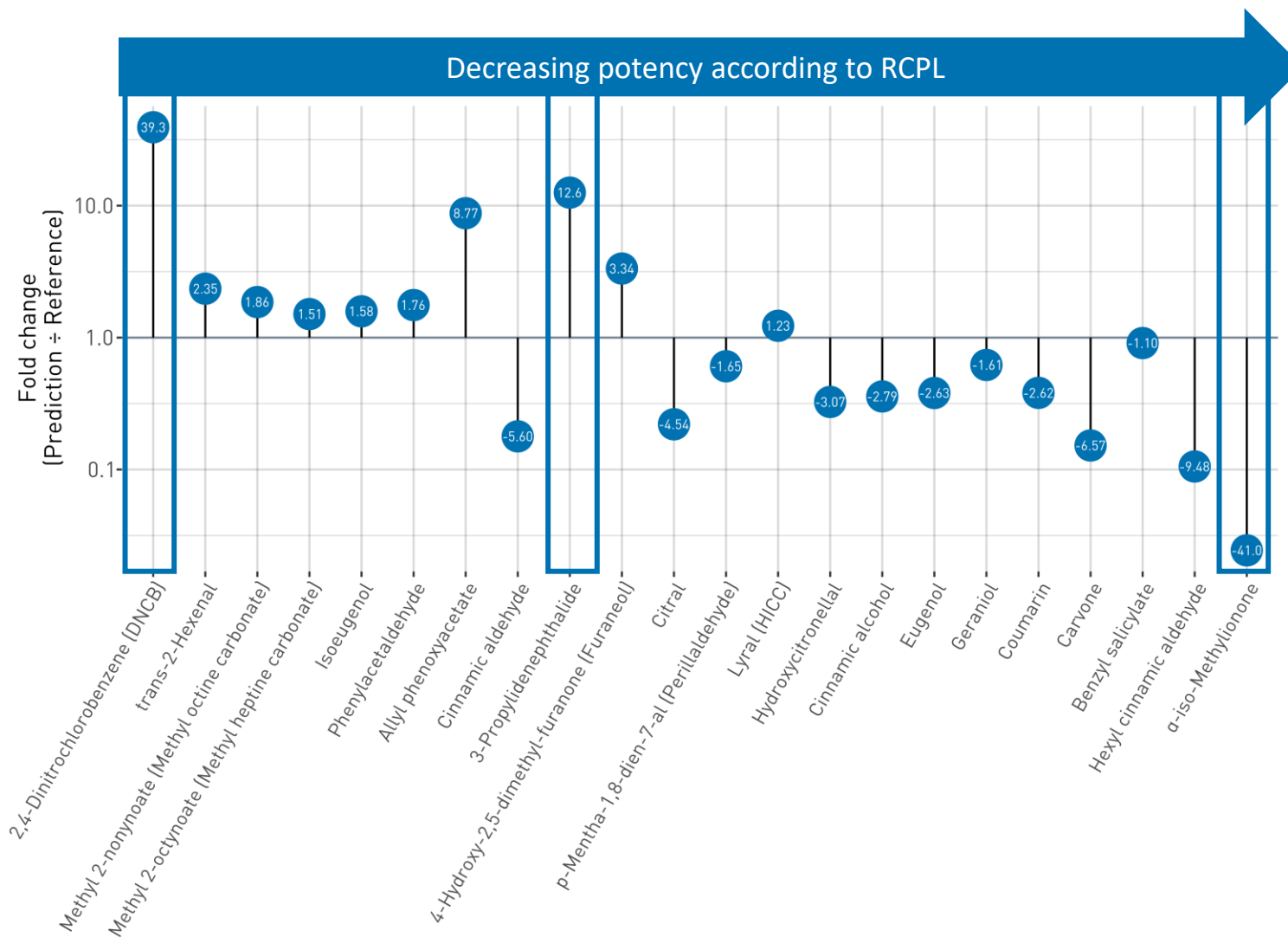
GARDskin Dose-Response's prediction of potency values

- The rank-correlation provides a measure of the similarity of the ranking between GARDskin Dose-response and RCPL-list:
  - Rank correlation: 0.69 (p = 0.000071)



# Reference Chemical Potency List

GARDskin Dose-Response's prediction of potency values



Unsigned fold-changes (errors)

- Geometric mean: 3.72
- Median: 2.71

# Reference Chemical Potency List

Largest discrepancies (FC > 10):  $\alpha$ -isomethylionone

Potency overpredicted with at least 41.0-fold changes

Predicted: 610  $\mu\text{g}/\text{cm}^2$  (moderate)

Expected: >25,000  $\mu\text{g}/\text{cm}^2$

Reference data

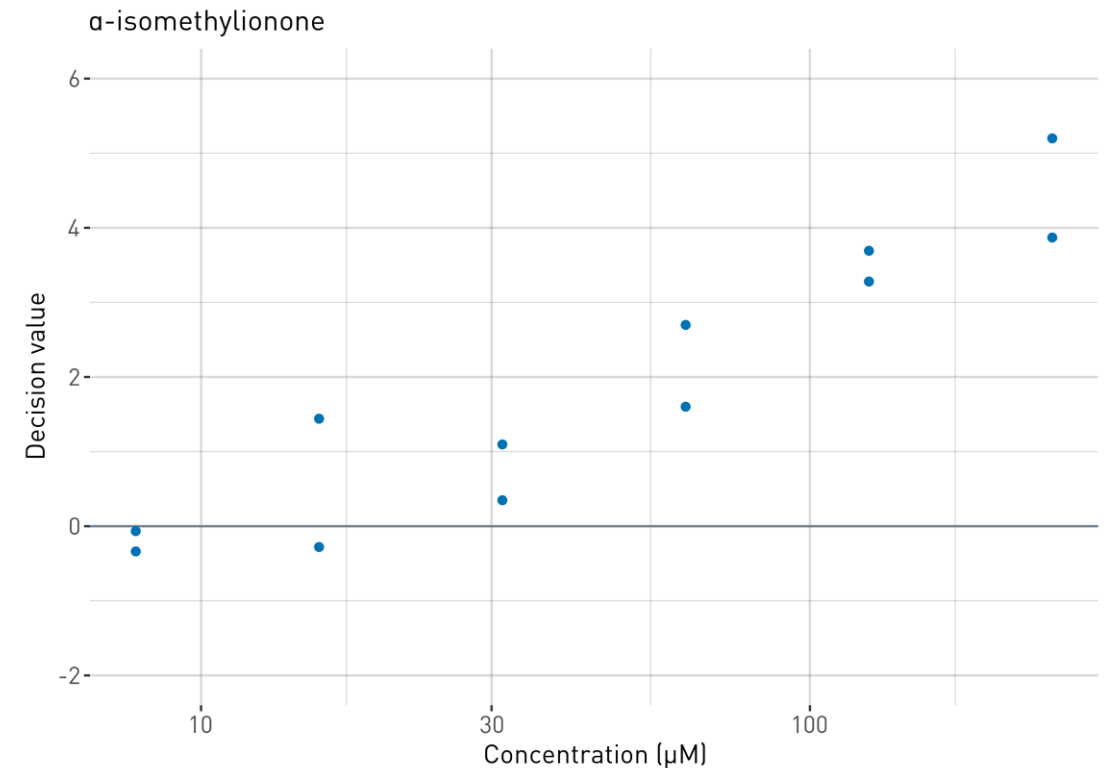
Predicted Michael acceptor but no observed protein reactivity.

Positive in LLNA with EC3 of 5450  $\mu\text{g}/\text{cm}^2$  (21.8%).

Negative in DPRA & KeratinoSens;

Positive in h-CLAT (ITS score of 2) & U-Sens

Positive in Derek & OECD TB



Only a single experiment available: Some uncertainty in the replicate measurement for the second lowest concentration  $\rightarrow$  may shift the prediction towards a higher concentration

# Reference Chemical Potency List

Largest discrepancies (FC > 10): DNCB

Potency underpredicted with 39.3-fold changes

Predicted: 134  $\mu\text{g}/\text{cm}^2$  (moderate)

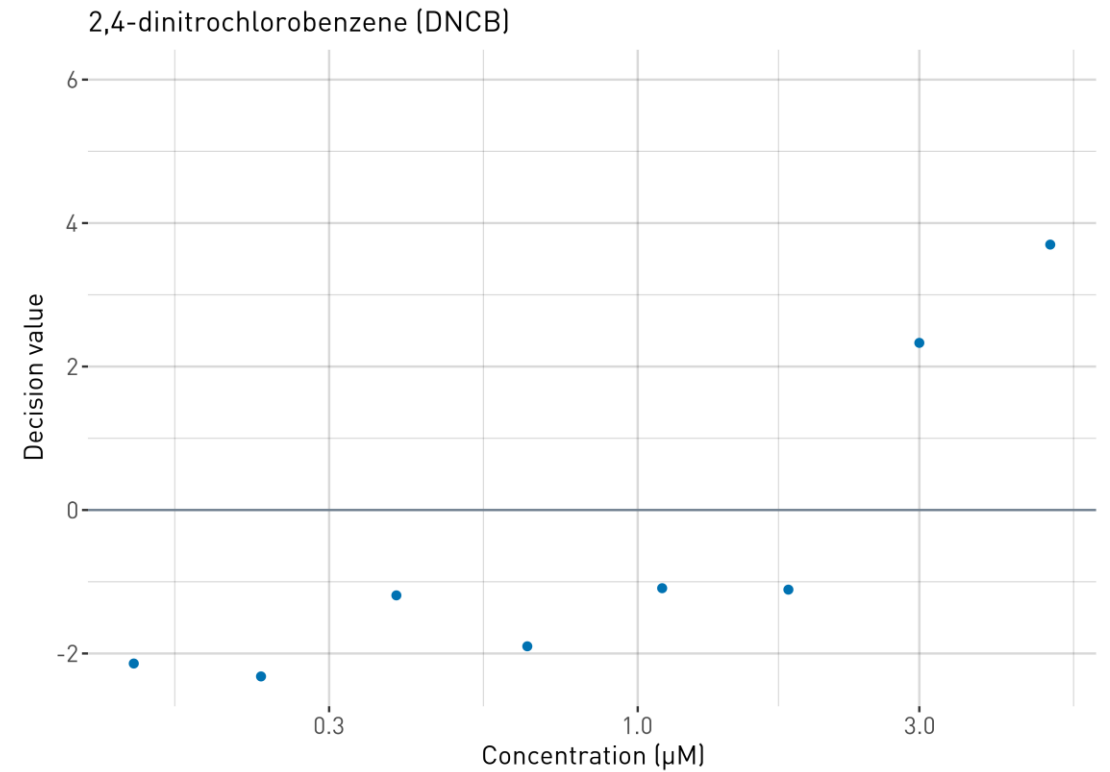
Expected: 3.4  $\mu\text{g}/\text{cm}^2$

Reference data

Positive in LLNA with EC3 of 13.5  $\mu\text{g}/\text{cm}^2$  (0.054%).

Positive in DPRA, KeratinoSens, and h-CLAT.

Positive in Derek & OECD TB



# Reference Chemical Potency List

Largest discrepancies (FC > 10): 3-propylenephtalide

Potency underpredicted with 12.6-fold changes

Predicted: 11 600  $\mu\text{g}/\text{cm}^2$  (very weak)

Expected: 925  $\mu\text{g}/\text{cm}^2$

Clear dose-response pattern in GARDskin Dose-Response.

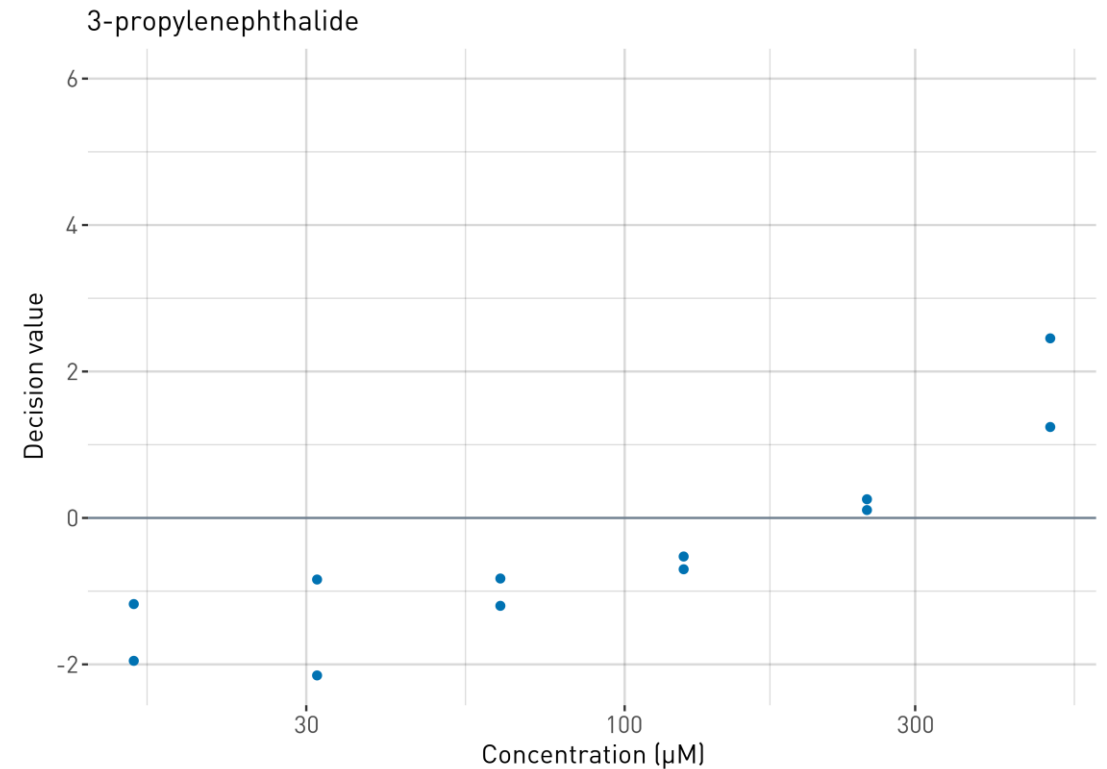
Reference data

LLNA and NESIL values very similar.

Human LOEL (HMT): 2760  $\mu\text{g}/\text{cm}^2$ .

Positive in h-CLAT (ITS score of 2) and DPRA (ITS score of 1);

Negative in KeratinoSens.



# Summary & conclusions



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- Continuous potency predictions from the GARDskin Dose-Response assay correlated well with PVs for chemicals in the RCPL list (pearson correlation: 0.74).
- The average misprediction from GARDskin Dose-Response was 3.7-fold (geometric mean) and 44% of predictions were either correct or within 2-fold changes from reference value.
- Overall, very similar potency rankings with GARDskin Dose-Response and RCPL potency list (spearman: 0.69)
- Balanced predictions across the potency interval, no systematic bias for under- or over-predictions.
- Mispredictions appears not to be attributable to a certain chemical reactivity domains or to indirect acting haptens.

Thank you for  
listening!



# Prediction table

Chemical	CAS	RCPL ( $\mu\text{g}/\text{cm}^2$ )	GSDR ( $\mu\text{g}/\text{cm}^2$ )	FC	Log <sub>2</sub> FC
5-Chloro-2-methyl-4-isothiazolin-one (CMIT)	26172-55-4	2.3	-	-	-
2,4-Dinitrochlorobenzene (DNCB)	97-00-7	3.4	134	39.3	5.3
1,4-Phenylenediamine (PPD)	106-50-3	3.9	-	-	-
Glutaraldehyde	111-30-8	20	-	-	-
trans-2-Hexenal	6728-26-3	39.9	93.7	2.35	1.23
1,4-Dihydroquinone	123-31-9	47.5	-	-	-
Benzyl bromide	100-39-0	50	-	-	-
1,1,3-Trimethyl-2-formylcyclohexa-2,4-diene (Safranal)	116-26-7	106	-	-	-
Methyl 2-nonynoate (Methyl octine carbonate)	111-80-8	109	203	1.86	0.895
Methyl 2-octynoate (Methyl heptine carbonate)	111-12-6	125	189	1.51	0.593
Isoeugenol	97-54-1	325	514	1.58	0.662
Phenylacetaldehyde	122-78-1	750	1320	1.76	0.819
Allyl phenoxyacetate	7493-74-5	775	6790	8.77	3.13
Cinnamic aldehyde	104-55-2	885	158	0.179	-2.49
3-Propylideneephthalide	17369-59-4	925	11600	12.6	3.65
4-Hydroxy-2,5-dimethyl-furanone (Furaneol)	3658-77-3	1181	3940	3.34	1.74
Citral	5392-40-5	1450	319	0.22	-2.18



# Prediction table

Chemical	CAS	RCPL ( $\mu\text{g}/\text{cm}^2$ )	GSDR ( $\mu\text{g}/\text{cm}^2$ )	FC	Log <sub>2</sub> FC
p-Mentha-1,8-dien-7-al (Perillaldehyde)	2111-75-3	2175	1320	0.607	-0.721
Benzaldehyde	100-52-7	4094	NS	-	-
Lyr al (HICC)	31906-04-4	4275	5250	1.23	0.297
Hydroxycitronellal	107-75-5	5275	1720	0.325	-1.62
Cinnamic alcohol	104-54-1	5775	2070	0.358	-1.48
Eugenol	97-53-0	7357	2800	0.38	-1.39
Geraniol	106-24-1	9197	5710	0.62	-0.689
Coumarin	91-64-5	11792	4500	0.381	-1.39
Carvone	6485-40-1	17573	2680	0.152	-2.72
Benzyl salicylate	118-58-1	17715	16100	0.909	-0.138
Hexyl cinnamic aldehyde	101-86-0	23620	2490	0.105	-3.25
Benzyl alcohol	100-51-6	>25000	NS	-	-
Benzyl benzoate	120-51-4	>25000	NS	-	-
$\alpha$ -iso-Methylionone	127-51-5	>25000	610	0.0244	-5.36
Methyl salicylate	119-36-8	very weak/non-sensitiser	NS	-	-
Vanillin	121-33-5	very weak/non-sensitiser	NS	-	-