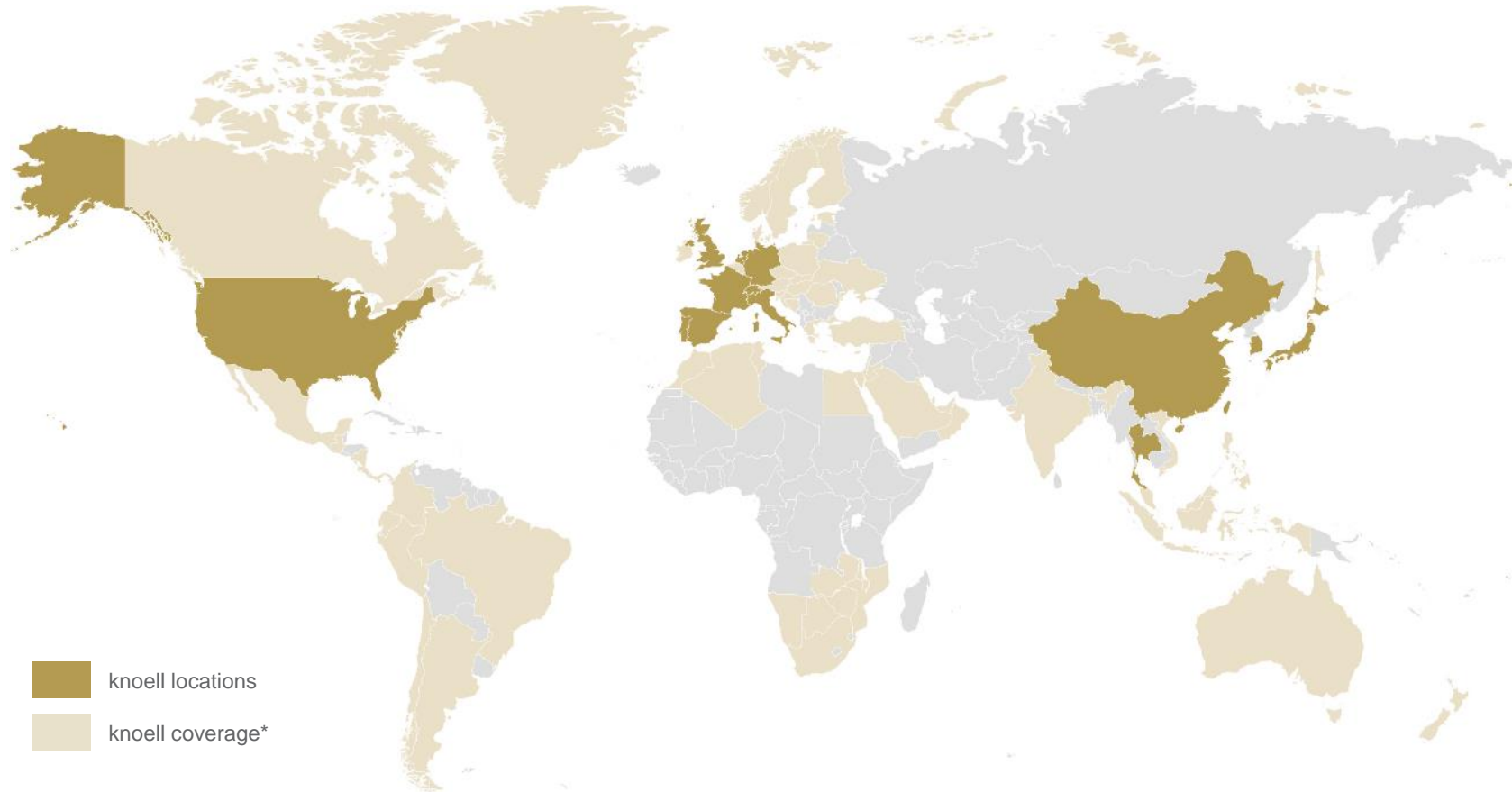


# Utilizzo di risultati QSAR: “lesson learned” e punto di vista del consulente per la preparazione di dossier REACH

13/06/2023, LIFE CONCERT REACH: novità e benefici attesi dall’implementazione degli “*in silico* tools” per le imprese chimiche

Rodolfo Gonella Diaza, Ph.D.  
*In silico* expert  
knoell Germany GmbH  
qsar@knoell.com

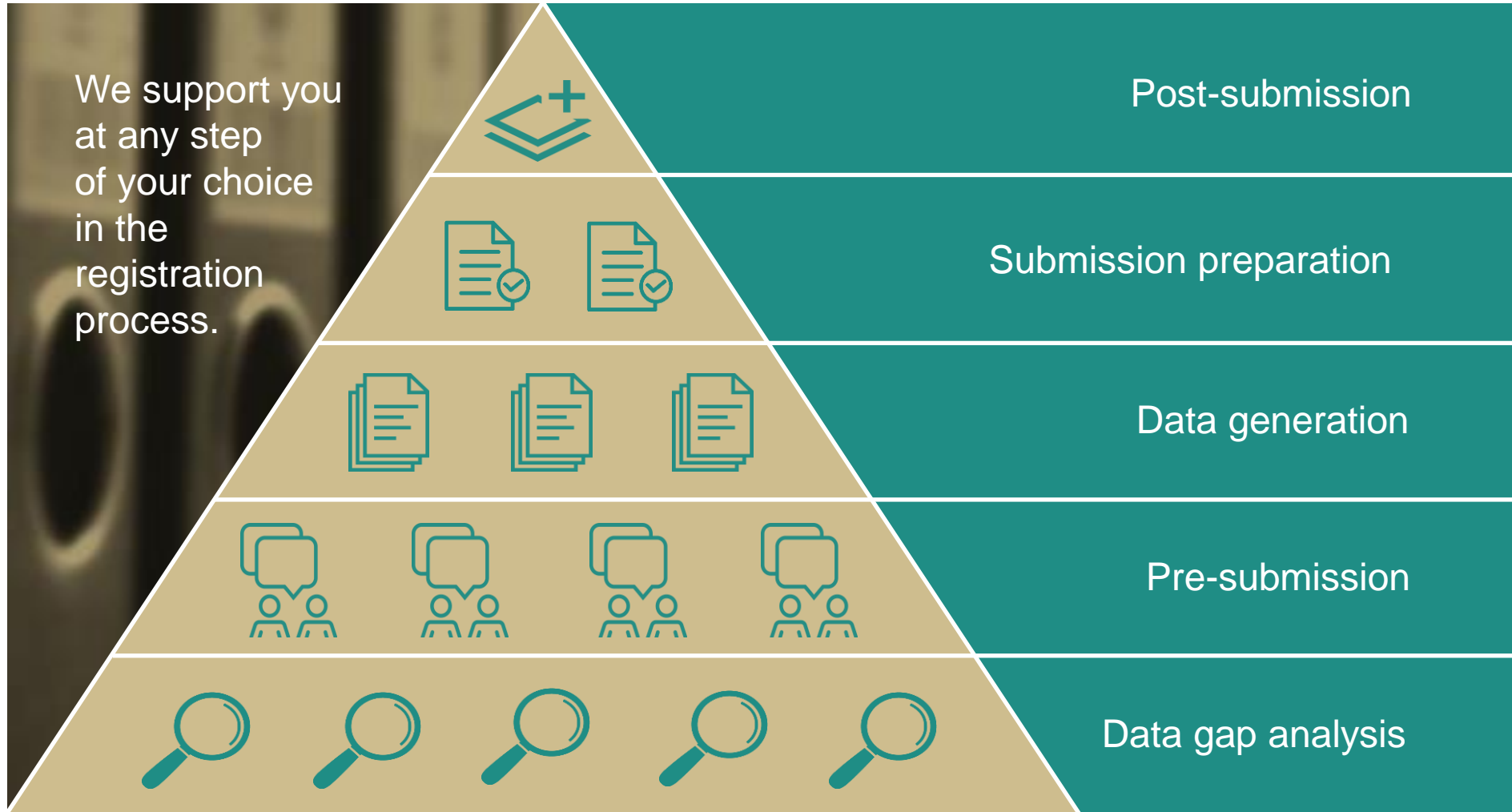


Our experts are located in North America, Europe and Asia with partners worldwide.

If a country is not covered by your interest, please contact us. We can make many things possible and are continuously expanding.

\* service coverage can vary per country due to resources and expertise

# Full-service or individual solutions







01

*In silico* methods for  
regulatory purposes

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REACH: practical examples of  
(Q)SAR data generation and  
evaluation

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REACH: Documenting (Q)SAR  
results in IUCLID for dossier  
preparation

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# In silico methods for regulatory purposes



worldwide registration



LIFE17 GIE/IT/000461

## Results Gateway

The "gateway" reports all the predictive software available in the four platforms relative to REACH endpoints.

### REACH ENDPOINTS

7. PHYSICOCHEMICAL PROPERTIES

30 models or datasets

8. TOXICOLOGICAL INFORMATION

165 models or datasets

9. ECOTOXICOLOGICAL INFORMATION

74 models or datasets

### OUT-OF REACH ENDPOINTS

+ ENDOCRINE ACTIVITY MODELS

58 models or datasets

More than 30 REACH endpoints addressed by:









- 291 statistical and knowledge-based (Q)SAR models;
- 35 sets of experimental data.

The (Q)SAR models can be used within other regulatory frameworks.

In addition, 58 models for evaluation of potential endocrine activity.

# In silico methods for regulatory purposes

All VEGA AND ToxRead DANISH QSAR DATABASE AMBIT OCHEM

End Point	Model	Type	Dataset size	Training set size	Test set size	Cross-validation procedure	Platform	Remarks
BCF	BCF (L/kg wet-wt) (EPI)	continuous					DanishQSARDatabase	
Log BCF	Log BCF (L/kg wet-wt) (EPI)	continuous					DanishQSARDatabase	
Whole Body Primary Biotransformation Fish Half-Life	Whole Body Primary Biotransformation Fish Half-Life (days) (EPI)	continuous					DanishQSARDatabase	
BCF Arnot-Gobas (upper trophic) Including Biotransformation	BCF Arnot-Gobas (upper trophic) Including Biotransformation (L/kg wet-wt) (EPI)	continuous					DanishQSARDatabase	
BCF Arnot-Gobas (upper trophic) Zero Biotransformation	BCF Arnot-Gobas (upper trophic) Zero Biotransformation (L/kg wet-wt) (EPI)	continuous					DanishQSARDatabase	
BAF Arnot-Gobas (upper trophic) Including Biotransformation	BAF Arnot-Gobas (upper trophic) Including Biotransformation (L/kg wet-wt) (EPI)	continuous					DanishQSARDatabase	
BAF Arnot-Gobas (upper trophic) Zero Biotransformation	BAF Arnot-Gobas (upper trophic) Zero Biotransformation (L/kg wet-wt) (EPI)	continuous					DanishQSARDatabase	
Bioaccumulation in								

For each endpoint, **multiple models are available**

Examples:

- 12 models for bioconcentration factor (BCF)
- 8 models for octanol/water partition coefficient (log Kow)
- 24 bacterial mutagenicity (Ames test) models

Endpoints selected as case studies for practical examples  
Next section of this presentation

# *In silico* methods for regulatory purposes

With all these models available, questions can arise:

**Q1: Which model(s)** should I use?

**Q2: Do regulators** indicate reliable models?

**Q3: Which data** can be generated and for **which purpose**?



# *In silico* methods for regulatory purposes

Q1: Which model(s) should I use?

Q2: Do regulators indicate reliable models?

- **A priori selection is generally not possible**
  - Indeed, **regulators don't/can't give clear indications**
  - However, **experience in using the models and information from** developers (e.g., which substances compose the training set) **might suggest** which model could give more reliable results for certain type of substances (e.g., industrial chemicals, active substances, etc.)
- Selection can be based on:
  - Information on **compliance** of the target molecule **with the applicability domain of the model**
  - **Comparison with similar molecules** with available experimental results
- It is generally required to **use multiple and different models** for evaluating the same endpoint

Expert analysis of the results and supporting information is needed

Tools in LIFE CONCERT REACH gateway provide the required information

(next section)

# *In silico* methods for regulatory purposes

Q3: **Which data** can be generated and for **which purpose**?



## REACH Regulation (EC) No 1907/2006

Results from (Q)SAR model predictions can be used for:

- Experimental data replacement (e.g., physico-chemical and environmental fate properties)
- Supporting (eco)toxicological data (e.g., weight of evidence (WoE))
- Impurities evaluation
- Supporting read-across strategies
- Screening and prioritization
- Testing strategies definition

# *In silico* methods for regulatory purposes



worldwide registration



**Q3: Which data** can be generated and for **which purpose?**

*In silico* methods are increasingly used in several other regulatory frameworks

## **Impurities (eco)toxicological assessment**

(when no experimental data available or for testing strategy)



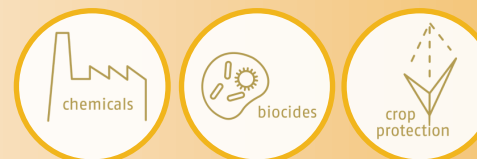
## **Grouping strategies**

(for read-across)



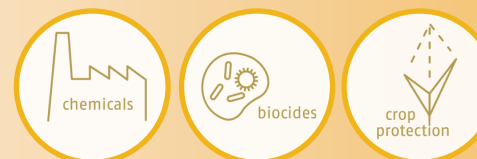
## **Metabolites or residues prediction or assessment**

(when no experimental data available or for testing strategy)



## **Endocrine Disruption assessment**

(**WoE** with experimental evidence)



## **Non-intentionally added substances (NIAS) assessment**

(when no experimental data available or for testing strategy)



# *In silico* methods for regulatory purposes

## Take home messages

- *In silico* models are **increasingly accepted** within several EU regulations
- CONCERT REACH gateway: **>300 models** for **30 REACH endpoints** and **potential endocrine activity** evaluation
- Regulators do not provide recommendation about the models to use, ***a priori* decision is not possible**
- For each endpoint, **multiple models should be used**
- Results from *in silico* models can **support, replace** or **fine tune experimental testing**

01

*In silico* methods for  
regulatory purposes

02

**REACH: practical examples of  
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evaluation**

03

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results in IUCLID for dossier  
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# *In silico* models: practical examples of using models in the gateway



LIFE17 GIE/IT/000461

Four case studies have been presented during two web-seminars

17 May **VEGA CAESAR** model + **Danish QSAR database consensus** model for *in vitro* gene mutation in bacteria

2023 **VERA automated read-across** and application on **carcinogenicity**

31 May **3 VEGA models** (Meylan/KOWWIN, ALogP and MLogP) for **octanol/water partition coefficient**

2023 **VEGA CAESAR** model + **OCHEM Gramatica & Papa** model for **bioconcentration factor**

**Aim:** showing applications of **different models** from **different platforms** from the CONCERT REACH network

- **8 (Q)SAR** models from **3 platforms**, covering **3 REACH endpoints**
- 1 novel **automated read-across** tool (VERA), applied on a **4<sup>th</sup> endpoint**

For (Q)SAR models, **preparation of IUCLID entries for REACH dossier** is demonstrated, according to ECHA's Practical guide - How to use and report (Q)SARs



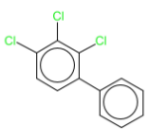
**Recordings and slides will be available on CONCERT REACH website**

<https://www.life-concertreach.eu/>

# VEGA: Example of critical evaluation of the automated Applicability Domain (AD) / reliability evaluation

## 3.1 Applicability Domain:

### Similar Compounds, with Predicted and Experimental Values



Prediction: ● Reliability: ★★★

Prediction is NON-Mutagenic, but the result shows some critical aspects, which require to be checked:

- some similar molecules found in the training set have experimental values that disagree with the predicted value

Compound: Molecule 0  
 Compound SMILES: c1ccc(cc1)c2ccc(c(c2Cl)Cl)Cl  
 Experimental value: -  
 Predicted Mutagen activity: NON-Mutagenic  
 Structural Alerts: -  
 Reliability: The predicted compound could be out of the Applicability Domain of the model  
 Remarks: none

**Global AD Index**  
 AD index = 0.801  
 Explanation: The predicted compound could be out of the Applicability Domain of the model.

**Similar molecules with known experimental value**  
 Similarity index = 0.889  
 Explanation: Strongly similar compounds with known experimental value in the training set have been ...

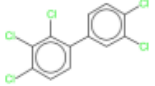
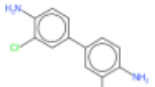
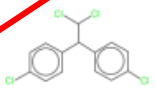
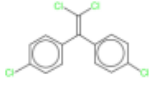
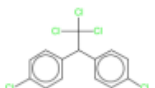
**Accuracy of prediction for similar molecules**  
 Accuracy index = 1  
 Explanation: Accuracy of prediction for similar molecules found in the training set is good..

**Concordance for similar molecules**  
 Concordance index = 0.521  
 Explanation: some similar molecules found in the training set have experimental values that disagree with the predicted value..

**Atom Centered Fragments similarity check**  
 ACF index = 1  
 Explanation: all atom centered fragment of the compound have been found in the compounds of the training set..

Two most similar molecules considered

Affected by one molecule, with a different alerts profile

	<p><b>Compound #1</b>                      CAS: N.A.                      Dataset id:441 (Training Set)                      SMILES: <chem>c1cc(c(cc1c2ccc(c(c2Cl)Cl)Cl)Cl)Cl</chem>                      Similarity: 0.925                      Experimental value : NON-Mutagenic                      Predicted value : NON-Mutagenic</p>
	<p><b>Compound #2</b>                      CAS: 91-94-1                      Dataset id:458 (Training Set)                      SMILES: <chem>Nc1ccc(cc1Cl)c2ccc(N)c(c2)Cl</chem>                      Similarity: 0.86                      Experimental value : Mutagenic                      Predicted value : Mutagenic</p> <p>Alerts (not found also in the target): SA28 Primary aromatic amine, hydroxyl amine and its derived esters (with restrictions)</p>
	<p><b>Compound #3</b>                      CAS: 72-54-8                      Dataset id:473 (Training Set)                      SMILES: <chem>c1cc(ccc1C(c2ccc(cc2)Cl)C(Cl)Cl)Cl</chem>                      Similarity: 0.828                      Experimental value : NON-Mutagenic                      Predicted value : Mutagenic</p> <p>Alerts (not found also in the target): SA8 Aliphatic halogens</p>
	<p><b>Compound #4</b>                      CAS: 72-55-9                      Dataset id:176 (Training Set)                      SMILES: <chem>c1cc(ccc1C(c2ccc(cc2)Cl)=C(Cl)Cl)Cl</chem>                      Similarity: 0.815                      Experimental value : NON-Mutagenic                      Predicted value : NON-Mutagenic</p>
	<p><b>Compound #5</b>                      CAS: 50-29-3                      Dataset id:751 (Training Set)                      SMILES: <chem>c1cc(ccc1C(c2ccc(cc2)Cl)C(Cl)Cl)Cl</chem>                      Similarity: 0.813                      Experimental value : NON-Mutagenic                      Predicted value : NON-Mutagenic</p>

A higher reliability could be assigned to the negative prediction, also considering that all other similar molecules (mostly with the same "no alerts" profile) are experimentally negative

# Danish (Q)SAR Database: results for *in vitro* gene mutation in bacteria



LIFE17 GIE/IT/000461

## *In vitro* Genotoxicity - Bacterial Reverse Mutation Test (Ames test)

	Exp	Battery	CASE Ultra	Leadscope	SciQSAR
Ames test in <i>S. typhimurium</i> ( <i>in vitro</i> )		NEG_IN	NEG_IN	NEG_IN	NEG_IN
*Direct Acting Mutagens (without S9)	N/A	NEG_IN	NEG_IN	NEG_IN	NEG_IN
*Base-Pair Ames Mutagens	N/A	NEG_IN	NEG_IN	NEG_IN	NEG_OUT
*Frameshift Ames Mutagens	N/A	NEG_IN	NEG_IN	NEG_IN	NEG_OUT
*Potent Ames Mutagens, Reversions $\geq$ 10 Times Controls	N/A	POS_IN	POS_OUT	POS_IN	POS_IN

### DTU-developed models

\* The four models (Direct Acting mutagens (without S9), Base-Pair Ames Mutagens, Frameshift Ames Mutagens, Potent Ames Mutagens) should not be used to determine if substances are Ames mutagens, but can be used for indication of mechanism or potency for cases where the main Ames model (Ames test in *S. typhimurium* (*in vitro*)) is POS\_IN.

3 models + battery (consensus) for Ames test and for the four further endpoints to be considered only if the outcome for Ames is Positive and in domain (POS\_IN)

The target molecule was evaluated as **compliant with AD of all Ames models**, which generated **consistent negative predictions**.  
The other four models should not be considered.

Within LIFE CONCERT REACH, results from the four VEGA models and the Consensus model have been integrated

	VEGA	Mut. / Non-mut. scores	Used models
Mutagenicity consensus	NEG	0.23 / 0.25	4

Mutagenicity (Ames) consensus model version 1.0.2 contained in VEGA version 1.1.4 with calculation core version 1.2.4

Prediction: POS = Mutagenic, NEG = Non-mutagenic.

### VEGA

ISS	CAESAR	SarPy	KNN
<u>NEG_Mod</u>	NEG_Low	<u>NEG_Low</u>	<u>POS_Good</u>

Four individual models in mutagenicity consensus model version 1.0.2 contained in VEGA version 1.1.4 with calculation core version 1.2.4

Prediction: POS = Mutagenic, NEG = Non-mutagenic, SUSP.POS = Suspected mutagenic, POSS.NEG = Possible Non-mutagenic, Exp = experimental value, Good = Good reliability, Mod = Moderate reliability, Low = Low reliability.

Structural alerts identified by two endpoint-specific profilers present in the OECD QSAR Toolbox

### DNA alerts for AMES by OASIS, alerts in:

- parent only No alert found

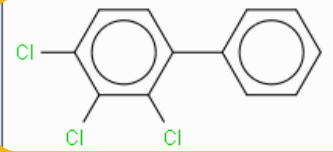

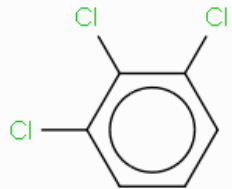

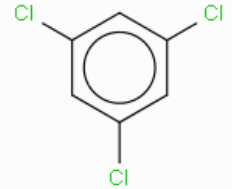

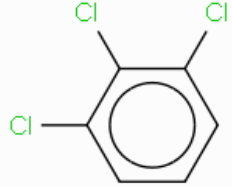

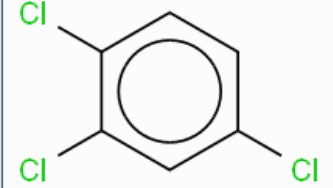

### *In vitro* mutagenicity (Ames test) alerts by ISS, alerts in:

- parent only No alert found

### OECD QSAR Toolbox v.4.2 profilers

Profiler predictions are supporting information to be used together with the relevant QSAR predictions

# Danish (Q)SAR Database: identification of similar molecules

Structure	Id	Similarity	Bacterial Reve... Experimental	Bacterial Reve... Battery	+
	XXXXX-XX-X 	1.0		NEG_IN	
	XXXXX-XX-X 	0.784	NEG	NEG_IN	
	XXX-XX-X 	0.784	NEG	NEG_IN	
	XX-XX-X 	0.784	NEG	NEG_IN	
	XXX-XX-X 	0.784	NEG	NEG_IN	

## Target molecule

## Supporting similar molecules

- **Not automatically** provided
- **Manual** stepwise approach
- Danish (Q)SAR Database **can be searched** for molecules, based on available **experimental data, (Q)SAR predictions, structural alerts**, etc., for the endpoint of interest

### Our case:

- Search for experimentally **positive and negative** molecules for Ames;
- Target molecule has no Alerts for DNA binding or *in vitro* gene mutation in bacteria; **similar molecules can be selected with the same** “no alerts” **profile**.

# OChem: results and AD for bioconcentration factor

**Online chemical database**  
with modeling environment

Home Database Models

Model profile X Apply a model X

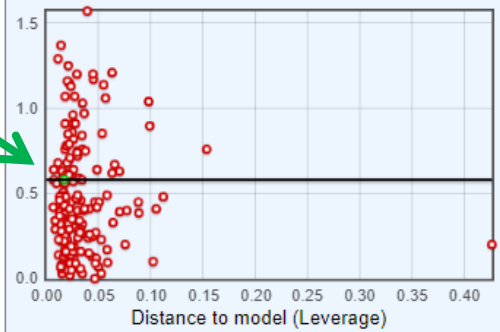
OChem predictor - results  
Here you can browse the predictions for your compounds and export them in a variety of formats

Export results in a file (Excel, CSV or SDF)

Advanced applicability domain charts

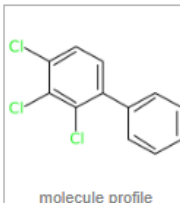
**BCF tutorial**

Applicability domain for model *BCF tutorial* for property *BCF*



The applicability domain chart allow to estimate the expected prediction accuracy. The green dots indicate the predicted compounds, where its X-position is its "distance to model" and its Y-position is the expected prediction accuracy (for classification models) or the expected RMSE (for regression models).

Sorting none Ascending  
1 - 1 of 1



molecule profile

BCF (BCF tutorial) = 4.1 Log unit ± 1.14 (Leverage = 0.02, estimated RMSE = 0.58) **CACHED**

95% confidence interval

Target chemical compliant with the AD of the model

Compound predicted as bioaccumulative (LogBCF > 3.3)

"Distance to model" value

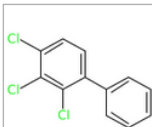


# OCHEM: similar molecules as supporting information

## Prediction neighbors explorer

The training set compounds nearest to the selected prediction

### The predicted compound



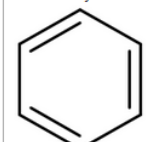
molecule profile

BCF (BCF tutorial) = 4.1 Log unit  $\pm$  1.14 (Leverage = 0.02, estimated RMSE = 0.58) CACHED

### Nearest training set neighbours

Similarity measure: Structural similarity

Similarity: 1.00



molecule profile

● BCF = 0.64 (in Log unit)  
Predicted value: 1.10 (in Log unit)  
Leverage: 0.03

Gramatica, P. Papa, E.  
An Update of the BCF QSAR Model Based on Theoretical Molecu...

QSAR Comb. Sci. 2005; 24 (8) 953-960

Benzene, 71-43-2  
MoleculeID: M663937

[\[open in browser\]](#) [\[prediction neighbors\]](#)

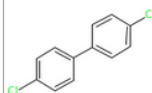
Dataset = Train

itetko / published

Experimental and predicted data, leverage and similarity of the most similar compounds

Sources

Similarity: 1.00



molecule profile

● BCF = 3.28 (in Log unit)  
Predicted value: 3.87 (in Log unit)  
Leverage: 0.02

Gramatica, P. Papa, E.  
An Update of the BCF QSAR Model Based on Theoretical Molecu...

QSAR Comb. Sci. 2005; 24 (8) 953-960

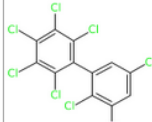
4,4'-Dichlorobiphenyl, 2050-88-2  
MoleculeID: M13799

[\[open in browser\]](#) [\[prediction neighbors\]](#)

Dataset = Train

itetko / published

Similarity: 1.00



molecule profile

● BCF = 5.88 (in Log unit)  
Predicted value: 4.92 (in Log unit)  
Leverage: 0.03

Gramatica, P. Papa, E.  
An Update of the BCF QSAR Model Based on Theoretical Molecu...

QSAR Comb. Sci. 2005; 24 (8) 953-960

68194-17-2, 2,2',3,3',4,5,5',6-OCTACHLOROBIPHENYL  
MoleculeID: M44945

[\[open in browser\]](#) [\[prediction neighbors\]](#)

Dataset = Train

itetko / published

Two compounds from the training set:

- are similar to the target
- are moderately well predicted
- have experimental values in line with target prediction ( $\log\text{BCF} = 4.1 \pm 1.14$ )

## Take home messages

- The *in silico* tools integrated in the gateway **provide information for expert evaluation** of the generated results and associated reliability:
  - VEGA, OCHEM and Danish QSAR database: **automated applicability domain** evaluation;
  - VEGA and OCHEM: **automated** extraction of **similar molecules**;
  - Danish QSAR database: non-automated but **“customizable” similar molecules** identification.
- For more information: **recording and slides of the case studies will be published** on the LIFE CONCERT REACH project website.

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# (Q)SAR results in IUCLID

VEGA outcome reported according to ECHA Practical guide “How to use and report (Q)SARs” Version 3.1 – July 2016

**Administrative data** None None

**Endpoint** <sup>i</sup> ^ <sup>?</sup> ^  
in vitro gene mutation study in bacteria

**Type of information**  
(Q)SAR

**Adequacy of study**  
None

Robust study summary

Used for classification

Used for SDS

**Study period**  
None

**Reliability**  
None

**Rationale for reliability incl. deficiencies**  
None

Weight of evidence OR supporting study

According to ECHA Practical guide “it should normally be a maximum of 2”  
IUCLID includes several possibilities for explaining the assigned reliability.

Appropriate rationale should be chosen considering both VEGA AD and reliability evaluation and expert assessment

# (Q)SAR results in IUCLID

## Justification for type of information

### 1. SOFTWARE

### 2. MODEL (incl. version number)

### 3. SMILES OR OTHER IDENTIFIERS USED AS INPUT FOR THE MODEL

### 4. SCIENTIFIC VALIDITY OF THE (Q)SAR MODEL

[[Explain how the model fulfils the OECD principles for (Q)SAR model validation. Consider attaching the QMRF and/or QPRF or providing a link]

- Defined endpoint:
- Unambiguous algorithm:
- Defined domain of applicability:
- Appropriate measures of goodness-of-fit and robustness and predictivity:
- Mechanistic interpretation:

### 5. APPLICABILITY DOMAIN

[Explain how the substance falls within the applicability domain of the model]

- Descriptor domain:
- Structural domain:
- Mechanistic domain:
- Similarity with analogues in the training set:
- Other considerations (as appropriate):

### 6. ADEQUACY OF THE RESULT

[Explain how the prediction fits the purpose of classification and labelling and/or risk assessment]

VEGA v1.2.3

Mutagenicity ISS Model (version 1.0.3)

c1ccc(cc1)c2ccc(c(c2Cl)Cl)Cl

(QMRF) can be attached and referenced here

VEGA report can be attached and used as reference. However, if expert assessment is performed, it can be described here.

procedure used to identify similar molecules in Danish QSAR database can be explained here


Expert assessment is needed



# (Q)SAR results in IUCLID

## Test material

### Test material information

 2,3,4-Trichlorobiphenyl | 2,3,4-trichlorobiphenyl | 1,2,3-trichloro-4-phenylbenzene | 55702-46-0

### Additional test material information

None

### Specific details on test material used for the study

SMILES: c1ccc(cc1)c2ccc(c(c2Cl)Cl)Cl

### Specific details on test material used for the study (confidential)

None

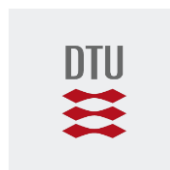
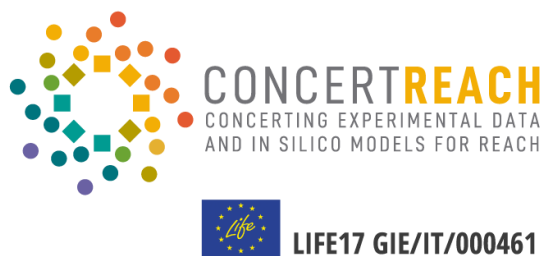
Test material must reflect the evaluated structure

If multiple constituents are assessed for one substance, the Practical Guide suggest to prepare separate entries

## Acknowledgement:

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# CREDITS



# Utilizzo di risultati QSAR: “lesson learned” e punto di vista del consulente per la preparazione di dossier REACH

