



In Silico Tools for Prediction and Mechanistic Interpretation of Systemic and Topical Toxicity

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UNC Chapel Hill, USA
Co-founder, Predictive, LLC*

OUTLINE



- Current NAMs (IMHO: New Alternative Methods) landscape
- Brief summary of current *in silico* approaches to chemical toxicity prediction
- Development of specific *in silico* tools
 - SToPTox for Systemic and Topical Toxicity Prediction
 - PreS/MD for Predicting Sensitization caused by Medical Devices
- Mechanistic interpretation of models
 - Chemical
 - Biological
- Summary and Outlook

NAMs Landscape: Key Directives



17TH CONGRESS
2D SESSION

S. 5002

AN ACT

To allow for alternatives to animal testing for purposes of drug and biological product applications.

1 *Be it enacted by the Senate and House of Representatives of the United States of America in Congress assembled,*

Focus



The OECD calls for urgent mobilisation of national and regional resources to support the validation of new methods for the safety testing of chemicals

» Omics technologies in chemical testing

» NANOMET: Towards tailored safety testing methods for nanomaterials



English EN

Home > Press corner > Commission acts to accelerate phasing out of animal testing

Available languages: English

Press release | 25 July 2023 | Brussels

Commission acts to accelerate phasing out of animal testing in response to a European Citizens' Initiative

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Quote(s)

Today, the Commission is responding to the European Citizens' Initiative (ECI) 'Save Cruelty-free Cosmetics - Commit to a Europe without Animal Testing'. The response provides a comprehensive overview of

Guideline No. 497: Defined Approaches on Skin Sensitisation

A Defined Approach (DA) consists of a selection of information sources (e.g. in silico pre-chemico, in vitro data) used in a specific combination, and resulting data are interpreted data interpretation procedure (DIP) (e.g. a mathematical, rule-based model). DAs use m

04 Jul 2023 | 53 pages | English | Also available in: French

<https://doi.org/10.1787/b92879a4-en> | 9789264903005 (PDF)

Author(s): OECD

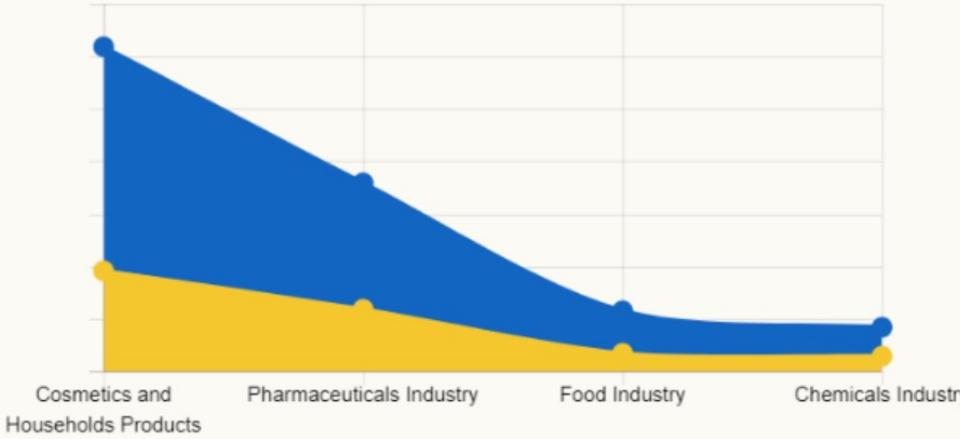
In Vitro Toxicity Testing Services: Market Trends



IN VITRO TOXICITY TESTING MARKET

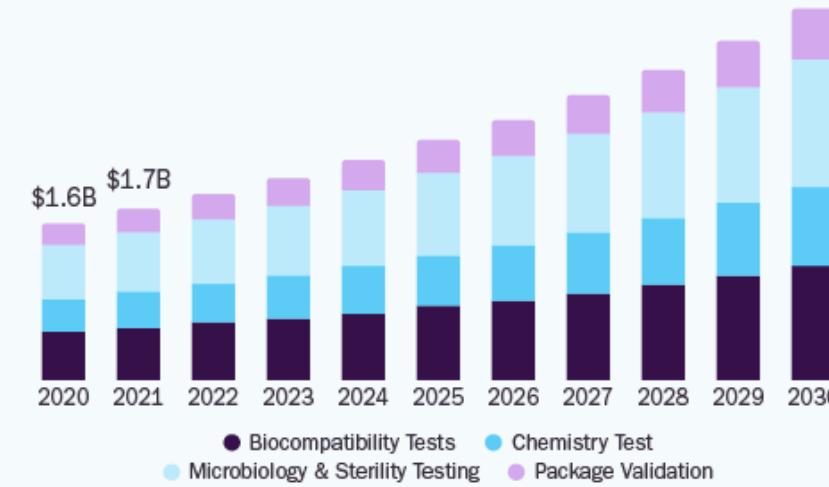
BY END USER

2020 2030



U.S. Medical Device Testing Services Market

size, by service, 2020 - 2030 (USD Billion)



GRAND VIEW RESEARCH

9.0%

U.S. Market CAGR,
2022 - 2030

Source:
www.grandviewresearch.com

Cosmetics and households products segment generated the highest revenue in 2020.

Report Code : A01199 | Source : <https://www.alliedmarketresearch.com/in-vitro-toxicity-testing-market-A01199>

VITRO TOXICITY TESTING MARKET

BY TECHNOLOGY

2020 2030



Cell culture technologies segment generated the highest revenue in 2020.

Report Code : A01199 | Source : <https://www.alliedmarketresearch.com/in-vitro-toxicity-testing-market-A01199>

NAMs Landscape: Tool Development

Web App for Using Defined Approaches to Predict Skin Sensitization Hazard and Potency



Welcome to the DASS App!

The DASS App applies defined approaches on skin sensitization (DASS) that are described in [OECD Guideline No. 497](#) and the U.S. EPA's [Interim Science Policy: Use of Alternative Approaches for Skin Sensitization as a Replacement for Laboratory Animal Testing](#). The defined approaches (DAs) predict skin sensitization hazard (either a sensitizer or non-sensitizer) and potency by integrating data from in vitro assays that represent key events in the [Adverse Outcome Pathway \(AOP\) for Skin Sensitisation Initiated by Covalent Binding to Proteins](#) and in silico hazard predictions.

More details are available in the [User Guide](#).

For more information or to report a problem with the app, please contact NICEATM at ICE-support@niehs.nih.gov.

Step 1: Select the Defined Approaches to Apply

To begin, select the DAs to be implemented. Click on the green information buttons to view a description of the DA and the test methods required to implement the DA.

[Select All](#) | [Deselect All](#)

- 2 out of 3 (2o3)
- Integrated Testing Strategy (ITS)
- Key Event 3/1 (KE 3/1) Sequential Testing Strategy (STS)

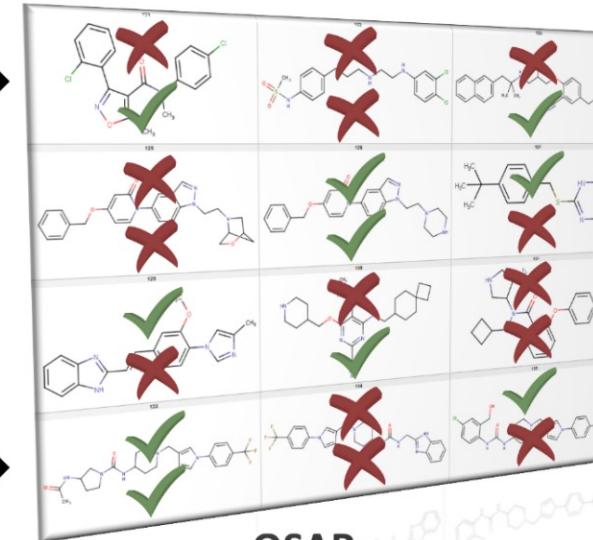
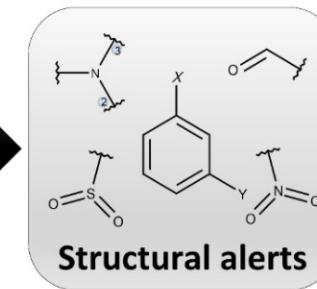
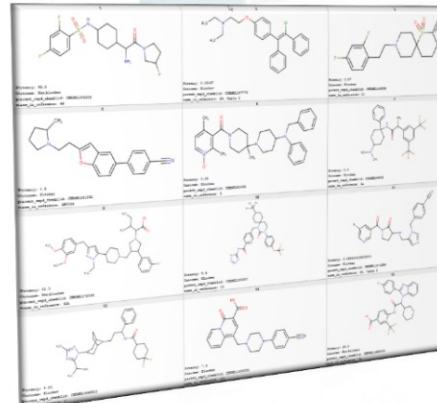
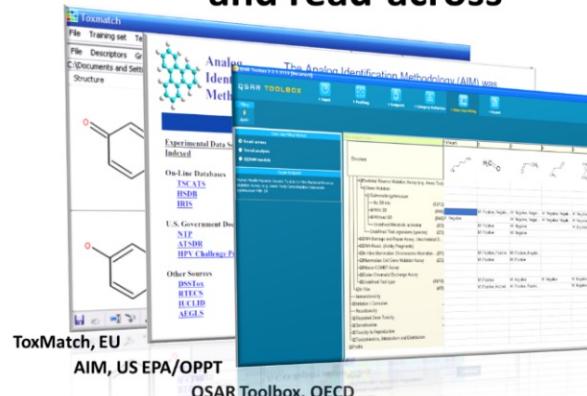
Step 2: Upload Data

<https://ntp.niehs.nih.gov/whatwestudy/niceatm/test-method-evaluations/skin-sens/da/dass-app>

Major cheminformatics approaches to toxicity prediction: Structural alerts vs. Machine Learning (QSAR) methods



Chemical categories and read-across



- ✗ Flagged as possibly toxic
- ✓ Annotated as safe

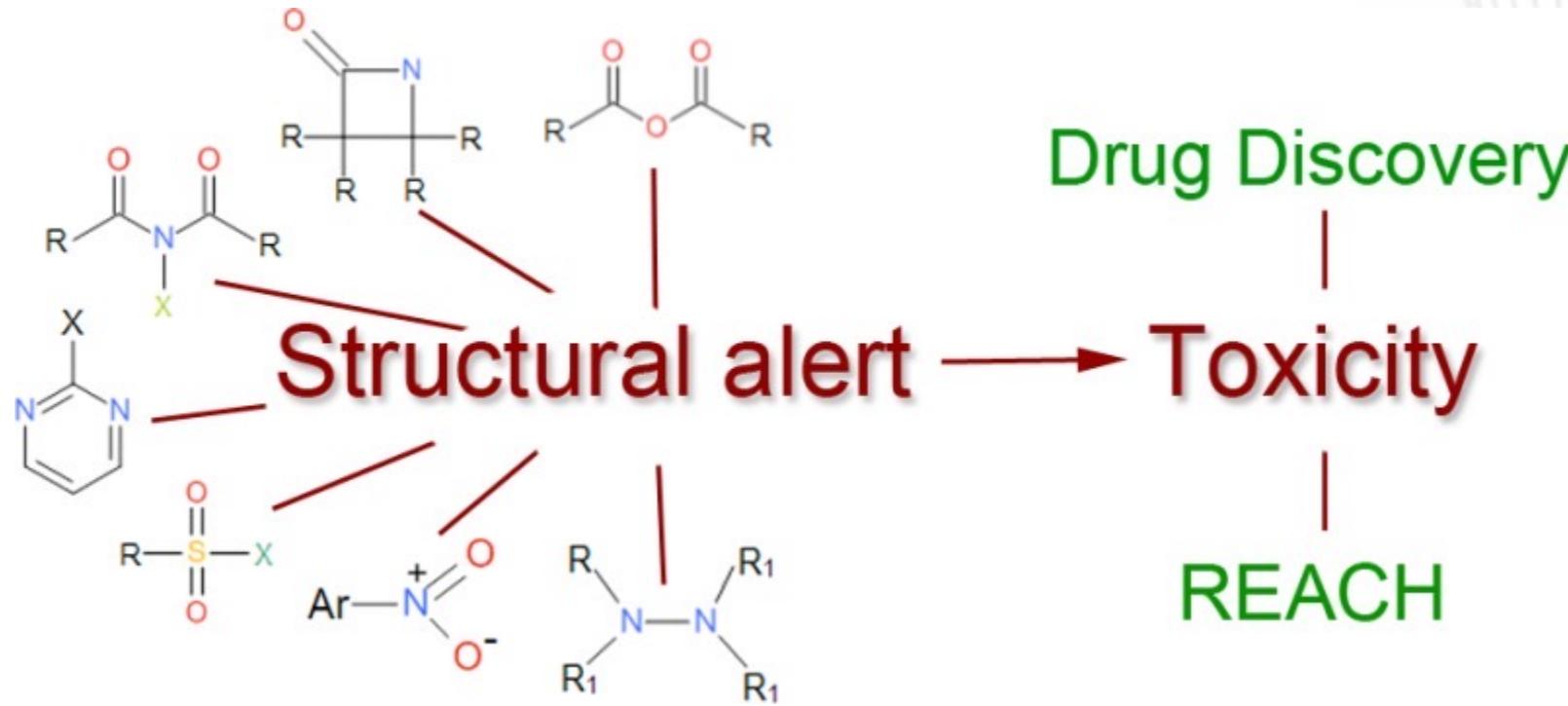
QSAR
model

- ✗ Predicted as toxic
- ✓ Predicted as non-toxic

Read-across: Structural Alerts



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*Structural alerts are “molecular patterns that are associated with particular types of toxicity or ADRs either directly or after undergoing of a metabolic activation in vivo”**

*Image and definition from Sushko et al, J Chem Inf Model. 2012 Aug 27; 52(8): 2310–2316.

Alarms about Alerts: Many alerts cannot distinguish withdrawn vs. marketed drugs



Drug Name	State	QSAR prediction ^{2*}	Toxic hazard classification by Cramer (extension)	Toxic hazard classification by Cramer (original)	Carcinogenicity (genotox and nongenotox) alerts by ISS	DNA alerts for AMES, MN and CA by OASIS v.1.3	In vitro mutagenicity (Ames test) alerts by ISS	In vivo mutagenicity (Micronucleus) alerts by ISS
Amineptine	withdrawn	unsafe	High (Class III)	High (Class III)	No alert found	No alert found	No alert	Alerts
Duract	withdrawn	unsafe	High (Class III)	High (Class III)	No alert found	No alert found	No alert	Alerts
Vioxx	withdrawn	unsafe	High (Class III)	High (Class III)	No alert found	No alert found	No alert	Alerts
Astemizole	withdrawn	unsafe	High (Class III)	High (Class III)	Alerts	No alert found	No alert	Alerts
Cerivastatin	withdrawn	unsafe	High (Class III)	High (Class III)	No alert found	No alert found	No alert	Alerts
Chlormezanone	withdrawn	unsafe	High (Class III)	High (Class III)	Alerts	No alert found	No alert	Alerts
Fenfluramine	withdrawn	unsafe	High (Class III)	High (Class III)	No alert found	No alert found	No alert	No alert
Flosequinan	withdrawn	unsafe	High (Class III)	High (Class III)	Alerts	No alert found	Alerts	Alerts
Glafenine	withdrawn	unsafe	High (Class III)	High (Class III)	Alerts	No alert found	No alert	Alerts
Grepafloxacin	withdrawn	unsafe	High (Class III)	High (Class III)	Alerts	No alert found	No alert	Alerts
Mibefradil	withdrawn	unsafe	High (Class III)	High (Class III)	Alerts	No alert found	No alert	Alerts
Troglitazone	withdrawn	unsafe	High (Class III)	High (Class III)	No alert found	No alert found	No alert	Alerts
Ximelagatran	withdrawn	unsafe	High (Class III)	High (Class III)	No alert found	Alerts	No alert	Alerts
Aspirin	marketed	safe	Low (Class I)	Low (Class I)	No alert found	No alert found	No alert	Alerts
Ibuprofen	marketed	safe	Low (Class I)	Low (Class I)	No alert found	No alert found	No alert	Alerts
Valtrex	marketed	safe	High (Class III)	High (Class III)	No alert found	No alert found	No alert	Alerts
Microzide	marketed	safe	High (Class III)	High (Class III)	Alerts	No alert found	No alert	Alerts
Neurontin	marketed	safe	High (Class III)	High (Class III)	No alert found	No alert found	No alert	Alerts
Enoxaparin	marketed	safe	High (Class III)	High (Class III)	No alert found	No alert found	No alert	Alerts
Lyrica	marketed	safe	Low (Class I)	Low (Class I)	No alert found	No alert found	No alert	Alerts

*Zakharov, Lagunin, Poroikov. Chem. Res. Toxicol., 2012, 25, 2378–2385.

Criticism of chemical toxicity alerts



From the journal:
Green Chemistry

Alarms about structural alerts†



Check for updates

Vinicius M. Alves,^{ab} Eugene N. Muratov,^{ac} Stephen J. Capuzzi,^a Regina Politi,^a Yen Low,^d Rodolpho C. Braga,^b Alexey V. Zakharov,^e Alexander Sedykh,^f Elena Mokshyna,^g Sherif Farag,^a Carolina H. Andrade,^b Victor E. Kuz'min,^g Denis Fourches,^h and Alexander Tropsha^{*a}

Chemical Alerts of Toxicity: what are they for, really?

toxtree.sourceforge.net/skinsensiti

AYAK Search Results [Save to Mendeley](#)

Home [Download](#) [P](#) Google™ Cu

Toxtree

Last Published: 2014-06-15

Skin sensitisa

Identification of mechanisms of skin sensitisation

Available since ToxTree 2.1.0. [sensitisation reactivity domain](#) [not predict skin sensitisation p](#)

name is changed to "Skin activity mode of action and do

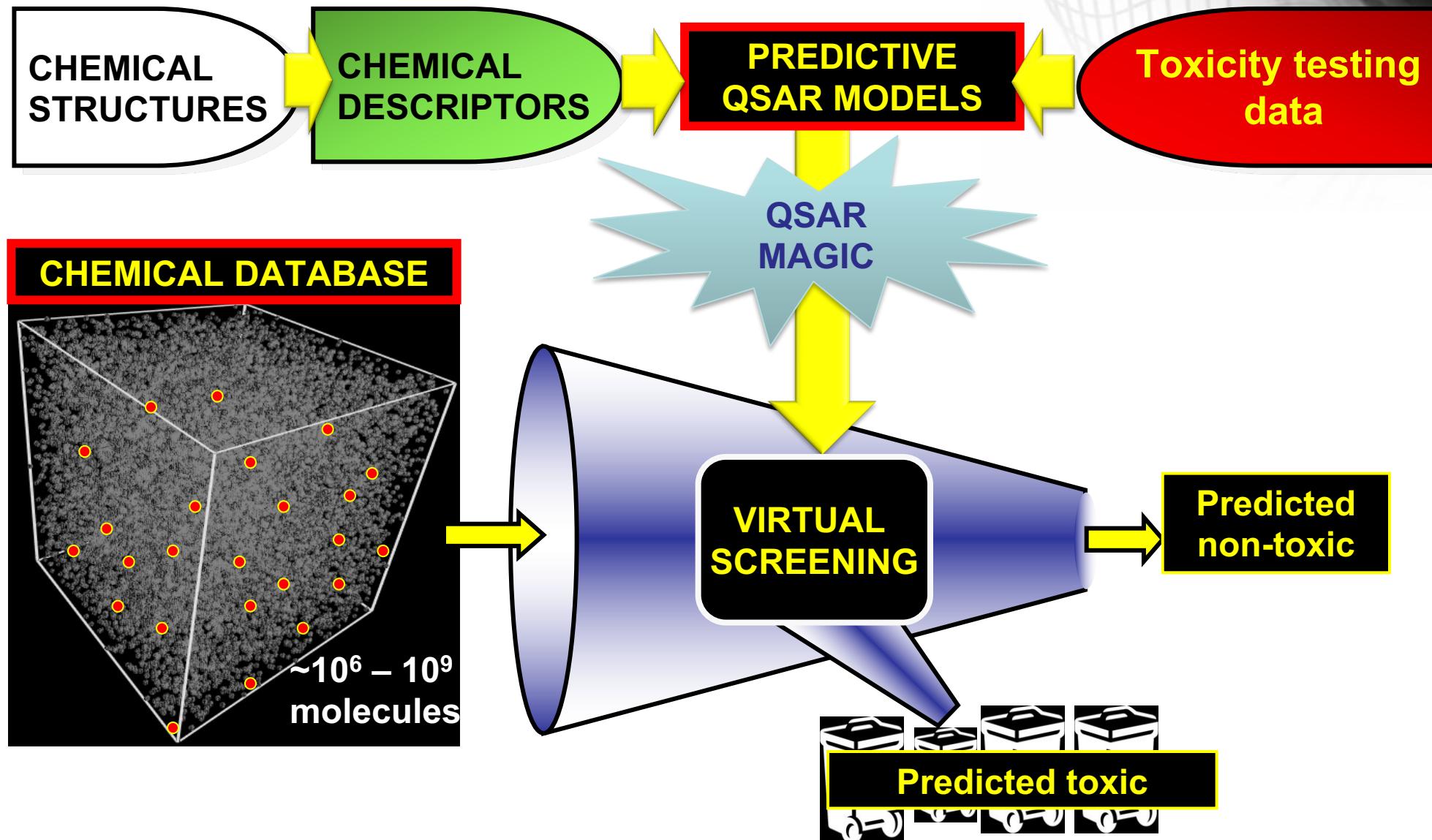
Developed by IdeaConsult Ltd



QSAR-based toxicity prediction



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OECD principles of model validation



To facilitate the consideration of a QSAR model for regulatory purposes, it should be associated with the following information:

- 1) a defined endpoint
- 2) an unambiguous algorithm
- 3) a defined domain of applicability
- 4) appropriate measures of goodness-of-fit, robustness and predictivity ($R^2 > 0.8$; $Q^2 > 0.6$; $Q^2_{ext} > 0.6$)*
- 5) a mechanistic interpretation, if possible

** Model acceptance criteria used in our QSAR studies*

OECD = Organization of Economic Co-operation and Development
<http://www.oecd.org/dataoecd/33/37/37849783.pdf>

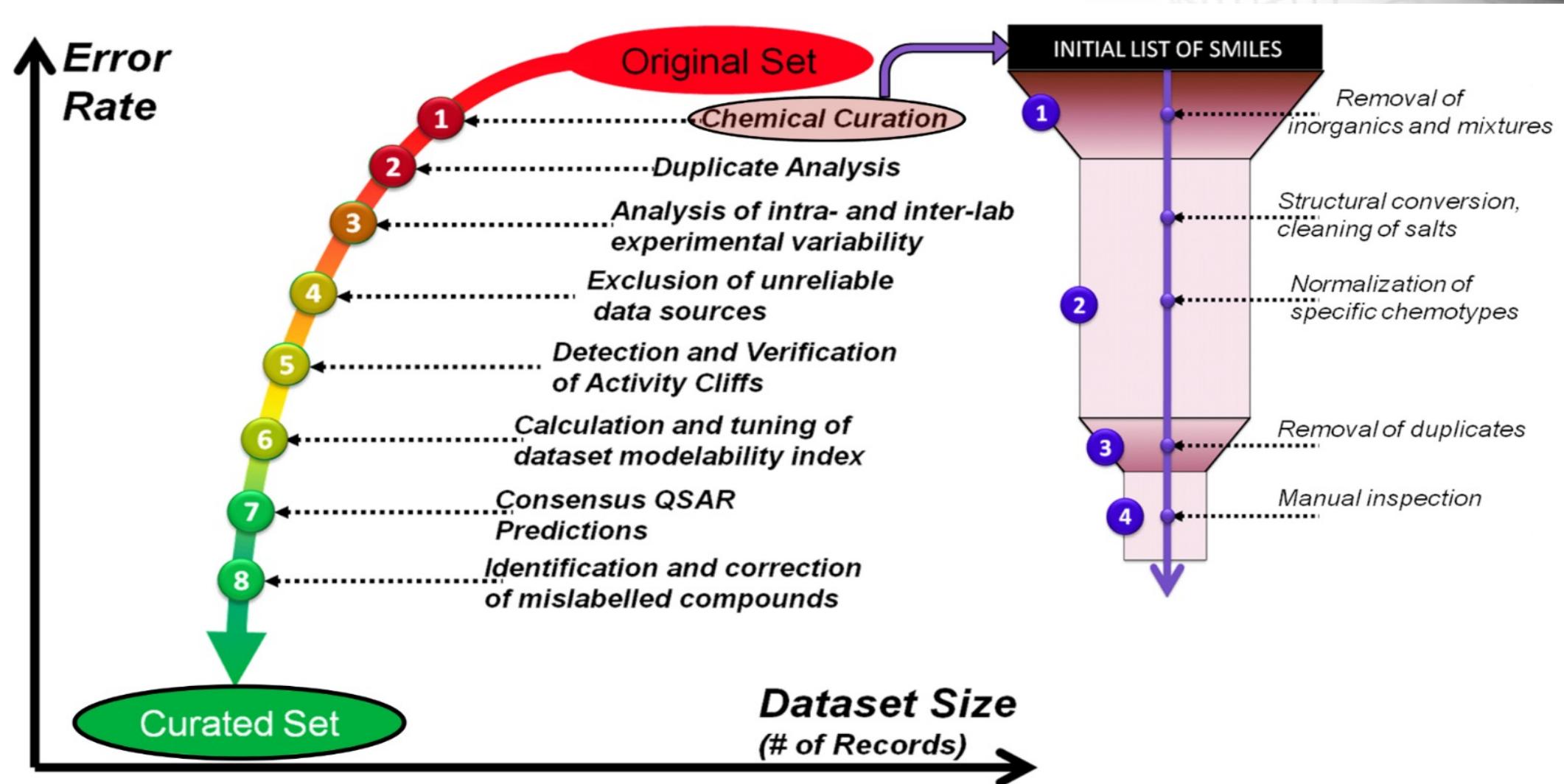
Our key principles of developing and using QSAR models as NAMs

- Data transparency and thorough curation
- Comprehensive model development and internal validation workflow
- Rigorous external validation
- Applicability domain and prediction confidence
- Mechanistic interpretation
 - Chemical functional group
 - Associated toxicity pathways



Comprehensive data curation pipeline

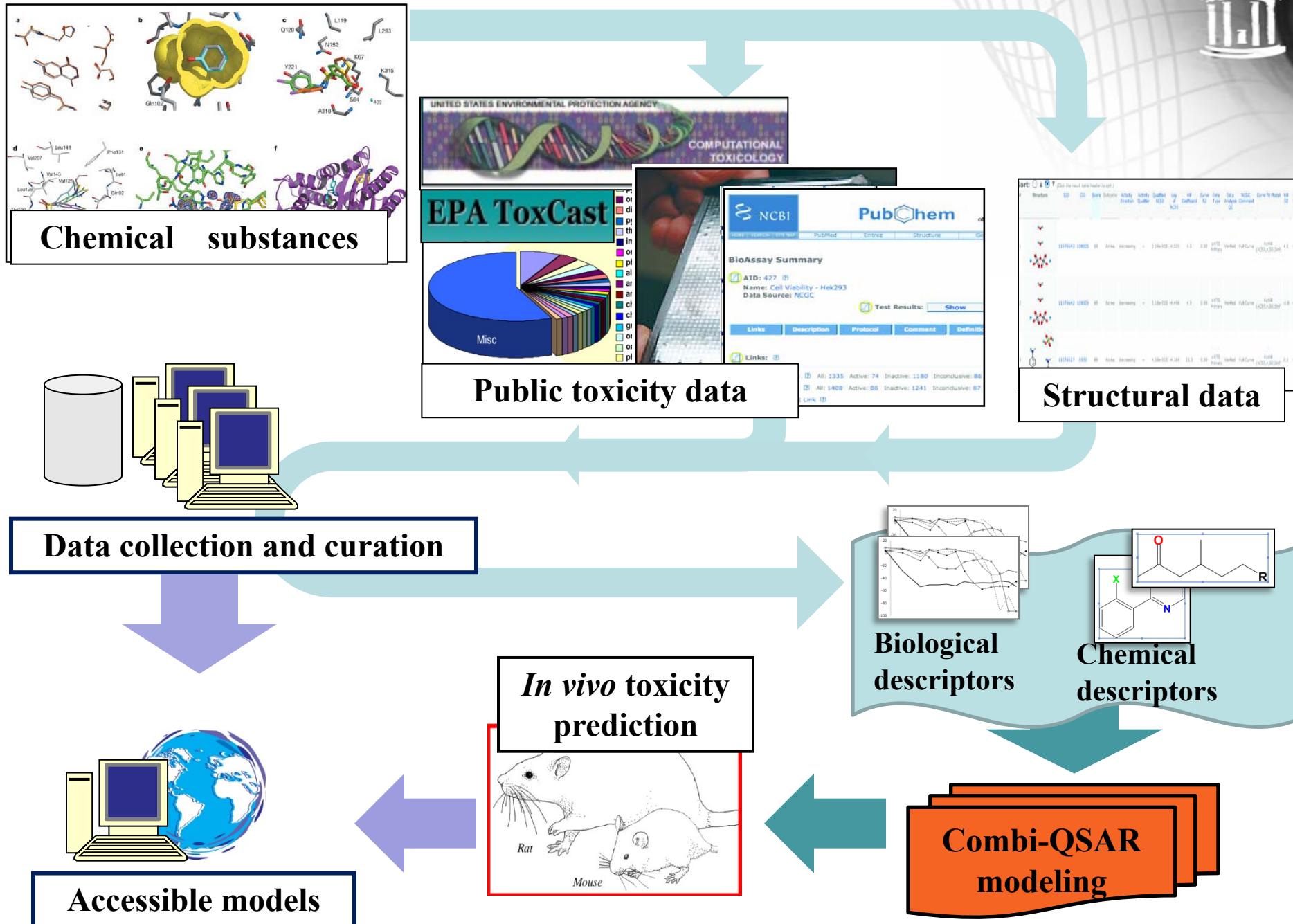
ECHA (OECD Test Guideline No. 406) + Literature; 1639 records



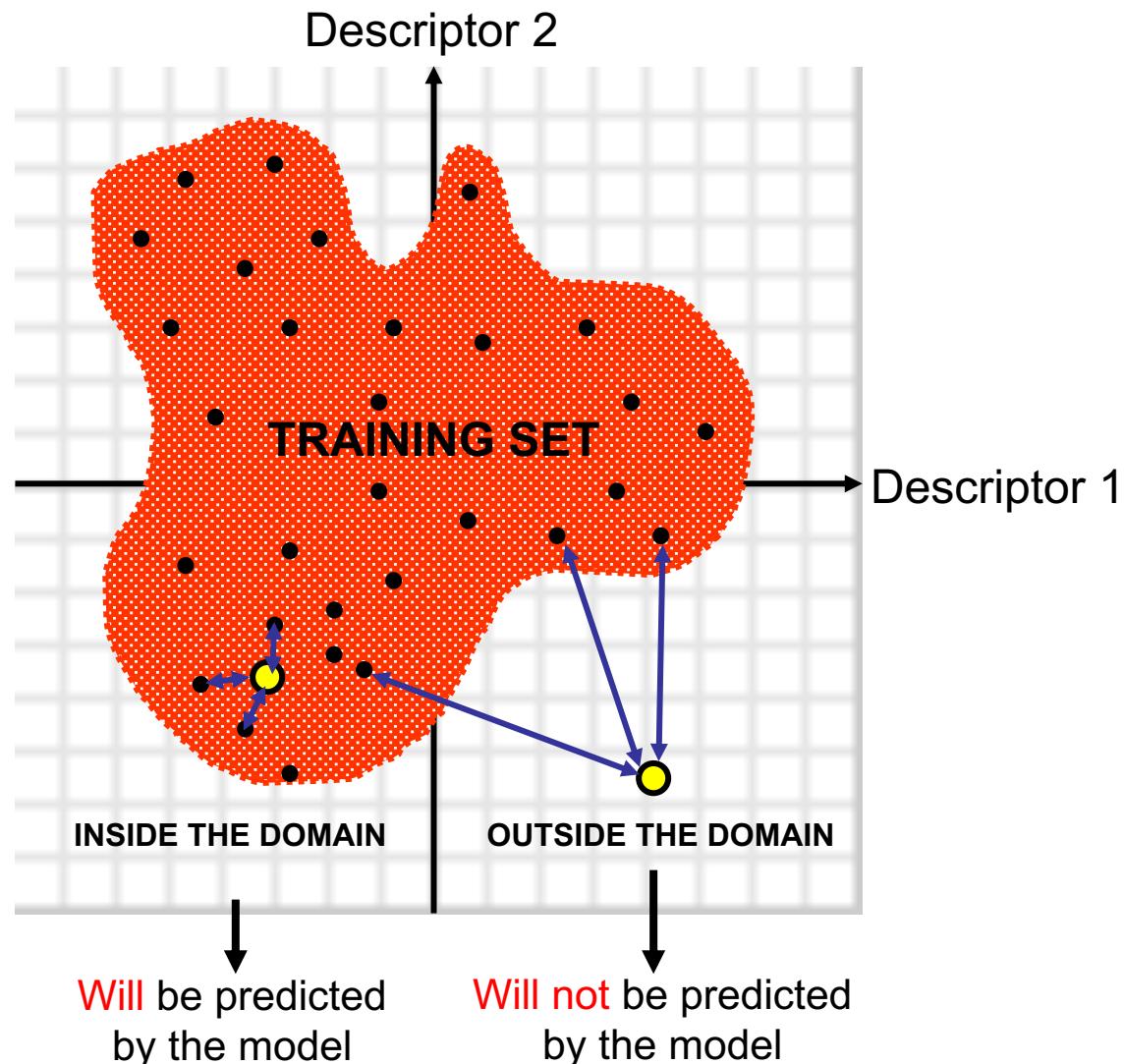
Data Continuum/Modeling workflow



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Applicability domain of QSAR models



For a given model, two parameters are calculated:

- $\langle D_k \rangle$: average euclidian distance between each compound of the training set and its k nearest neighbors in the descriptors space;
- s_k : standard deviation of the distances between each compound of the training set and its k nearest neighbors in the descriptors space.

● = NEW COMPOUND

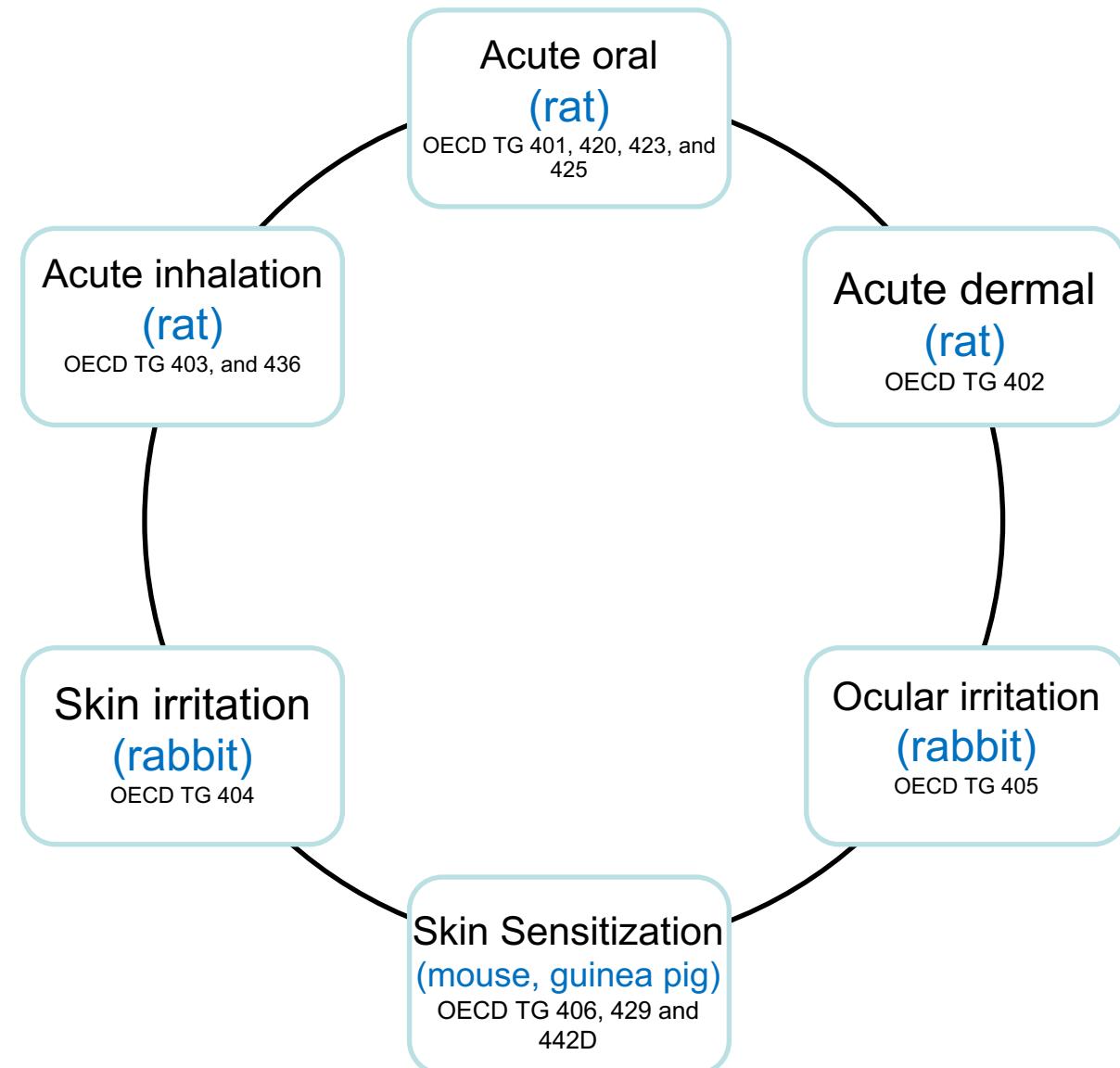
For each test compound i , the distance D_i is calculated as the average of the distances between i and its k nearest neighbors in the training set.

The new compound will be predicted by the model, only if :

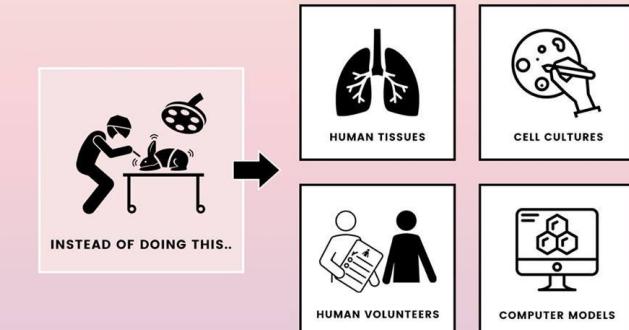
$$D_i \leq \langle D_k \rangle + Z \times s_k$$

with Z , an empirical parameter (0.5 by default)

The “six-pack” battery of acute toxicity tests



Alternatives to Animal Testing



ETHICAL ELEPHANT . COM

SToPTox - web-based predictor of Systemic and Topical Toxicity

- The largest curated “6-pack” dataset in public domain
- Models developed and validated in compliance with OECD guidelines
- Comprehensive computational platform that can be used as an alternative to 6-pack regulatory animal assays (current cost ca. 10K/compound/assay).
- Implemented as Web Portal, <http://stoptoxt.mml.unc.edu>
- Commercial version available from Predictive, LLC



The screenshot shows the SToPTox web portal. At the top, there is a header with the UNC logo, the MML logo, and the text "ESELMAN SCHOOL OF PHARMACY". Below the header, the URL <https://stoptoxt.mml.unc.edu> is displayed in a browser bar. The main content area features the SToPTox logo (a red octagon with a white dog head inside) and the text "SToPTox" in large bold letters, followed by a subtitle: "a machine learning app to predict the battery of acute toxicity test classically known as "6-pack". Below this, there is a section titled "App characteristics" with a detailed description of the tool's purpose and history. To the right of this text is a "Enter SMILES" input field and a "Draw molecule or load a file" section with a chemical editor interface. The editor includes a text input field, a toolbar with various chemical symbols and functions, and a vertical element list on the left containing elements like C, N, O, S, F, Cl, Br, I, P, and X.

SToPTox

a machine learning app to predict the battery of acute toxicity test classically known as "6-pack".

App characteristics

The SToPTox app is a fast, reliable, and user-friendly tool available as an alternative method for assessing the potential of chemicals to cause acute toxicity. The acute toxicity tests are used to identify hazard potentials resulting from short exposure times. The battery of in vivo assays commonly known as "6 pack" assays are required by many regulatory agencies to evaluate several aspects of acute toxicity in humans, including acute oral toxicity, acute dermal toxicity, acute inhalation toxicity, skin irritation and corrosion, eye irritation and corrosion, and skin sensitization. The indiscriminate use of animals in laboratory tests have been a public and political concern. Despite some progress in developing alternative methods for assessing the toxicity potential of chemical substances, there are few in vitro tests developed to address all "6-pack" endpoints. Machine Learning (ML) models provide a rapid screening approach and contribute valuable information for the assessment of chemical toxicity. The app provides easy and

Enter SMILES

Draw molecule or load a file

SMILES input field

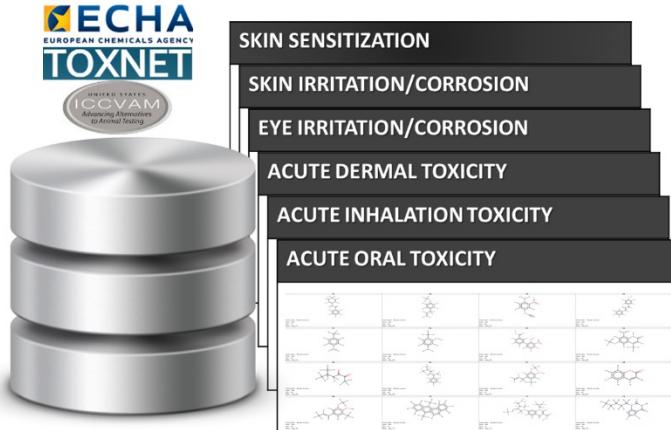
Chemical editor toolbar

Element list: C, N, O, S, F, Cl, Br, I, P, X

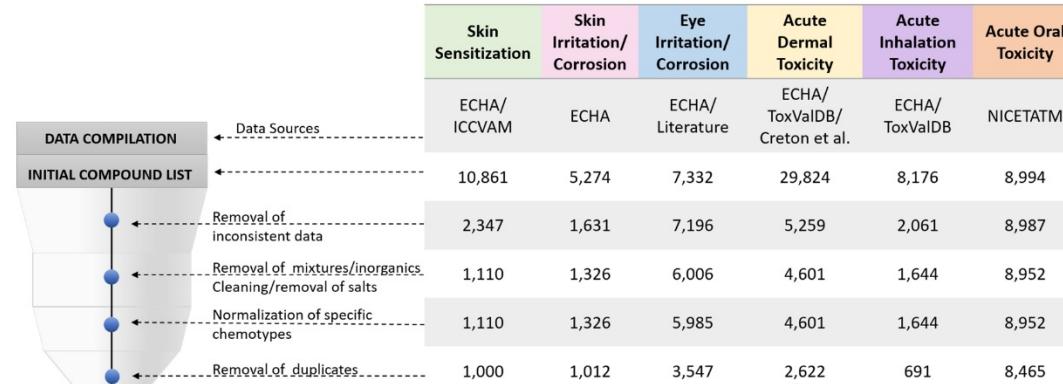
General workflow for SToxTox



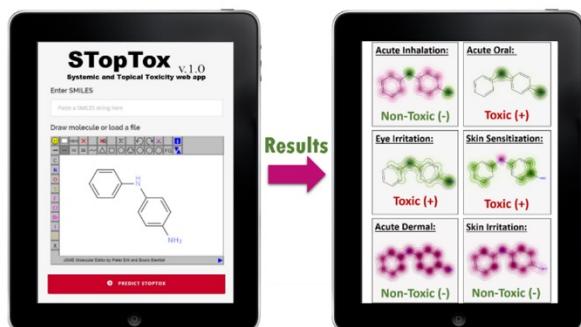
Data Retrieval



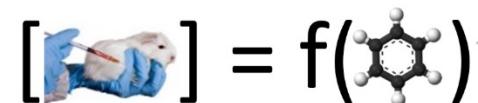
Data Curation



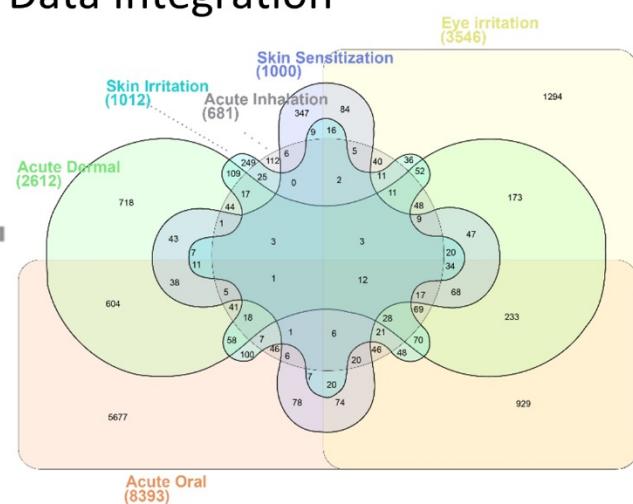
SToTox Server



QSAR modeling



Data Integration

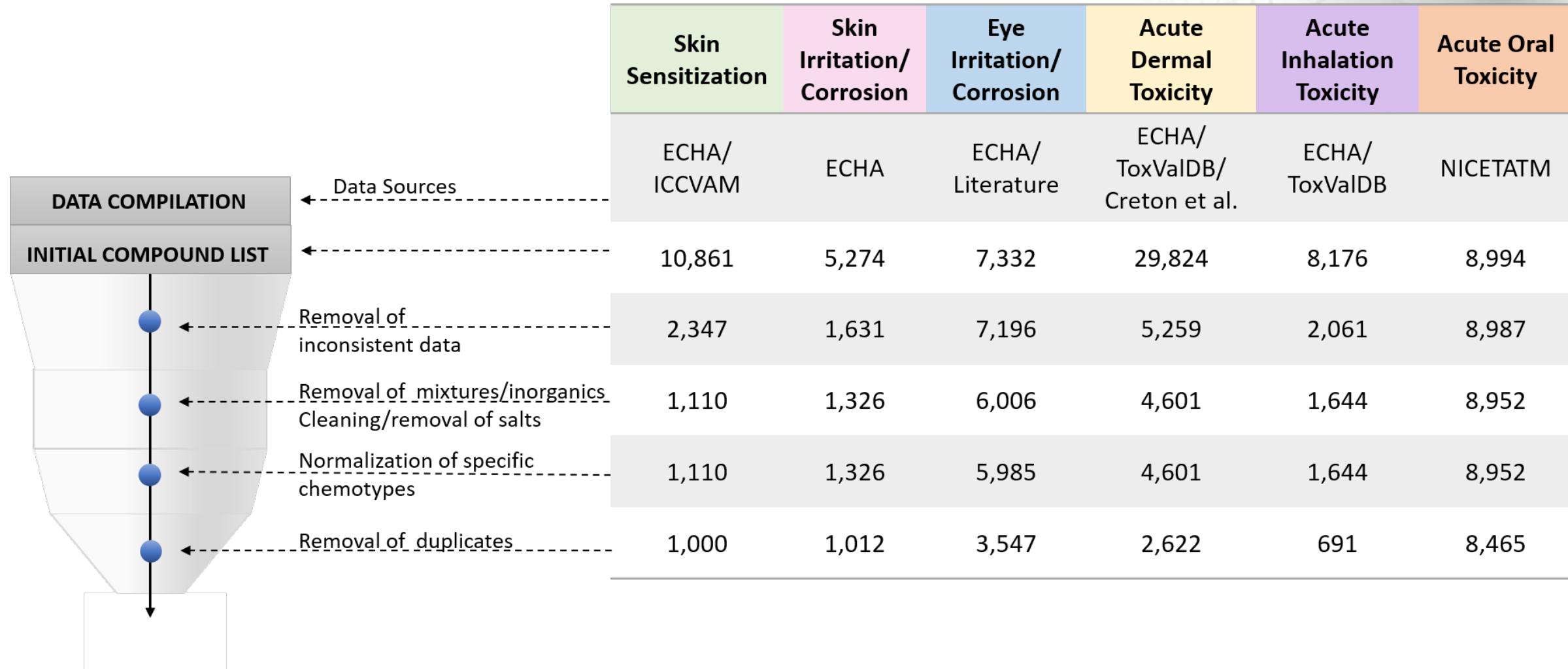


Datasets for endpoints to develop SToxTox

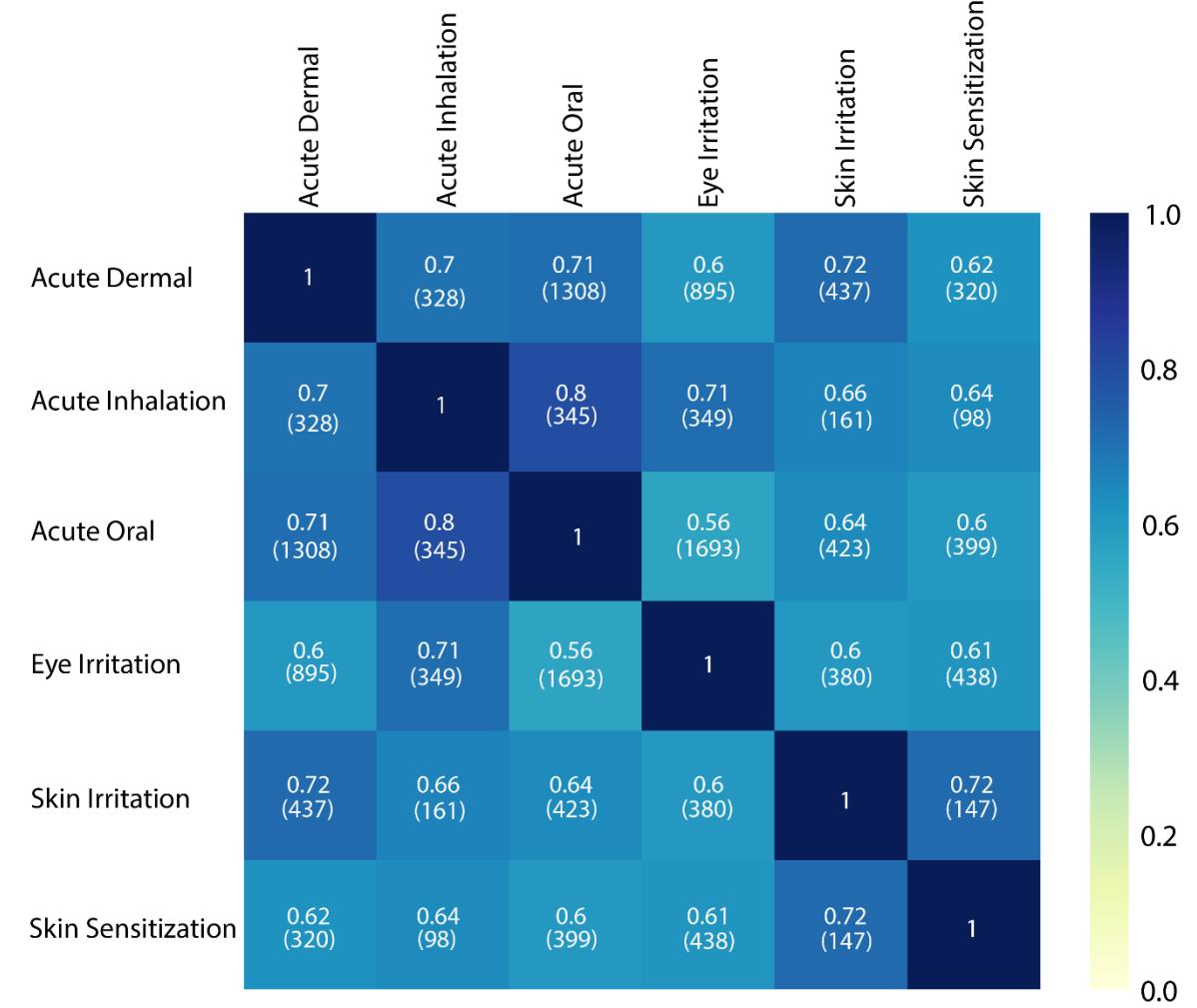
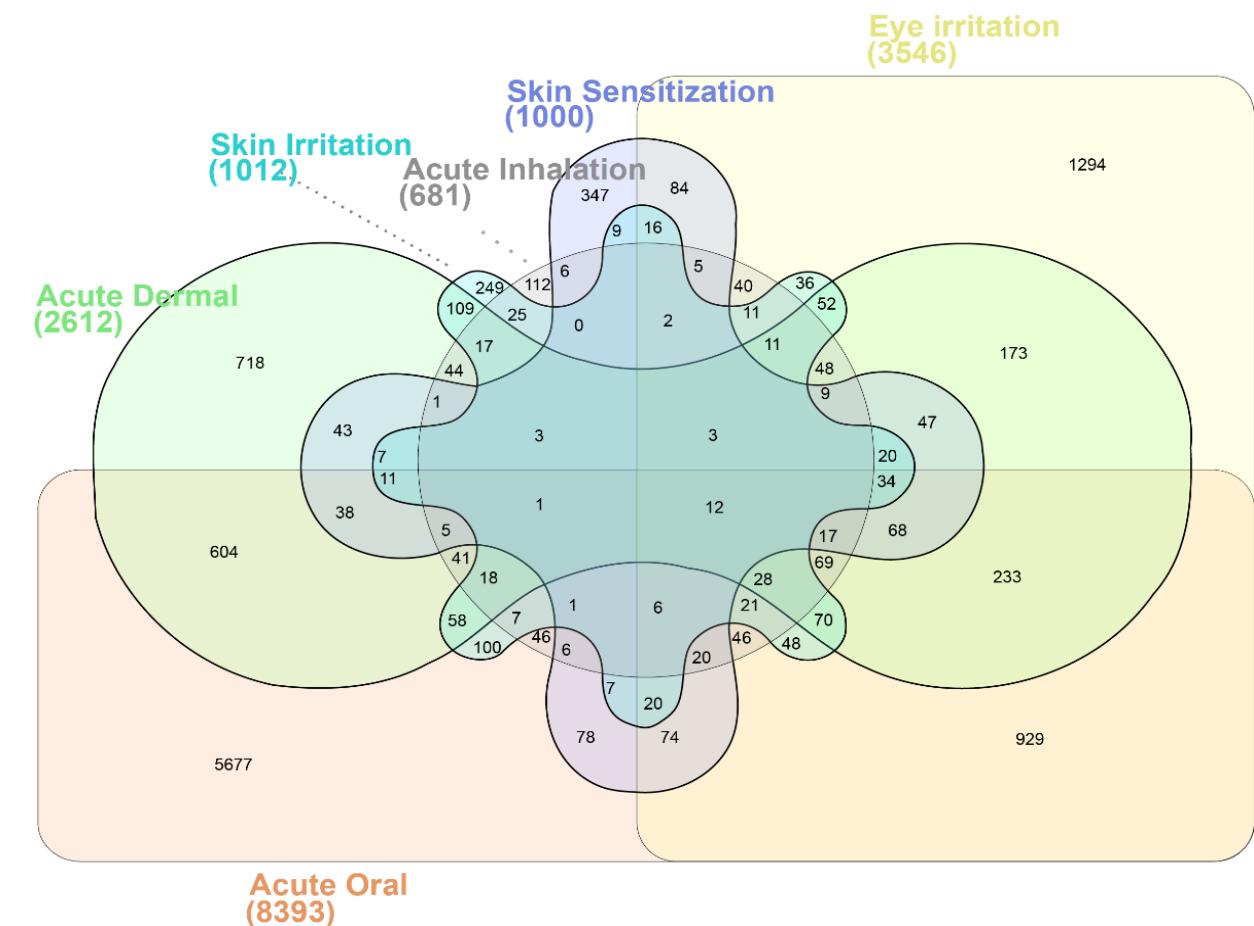


Endpoint	Assay type	# Chemicals before/after curation
Skin Sensitization	LLNA,	11,648 / 1,000
	DPRA,	194 / 194
	KeratinoSens,	190 / 190
	h-CLAT,	160 / 160
	human data	302 / 138
Skin irritation/corrosion	Draize test	5,274 / 1012
Eye irritation/corrosion	Draize test	6,387 / 3,547
Acute dermal	Acute dermal toxicity test	29,824 / 2,622
Acute inhalation	Acute inhalation toxicity test	8,176 / 681
Acute oral	Acute oral toxicity test	8,994 / 8,795

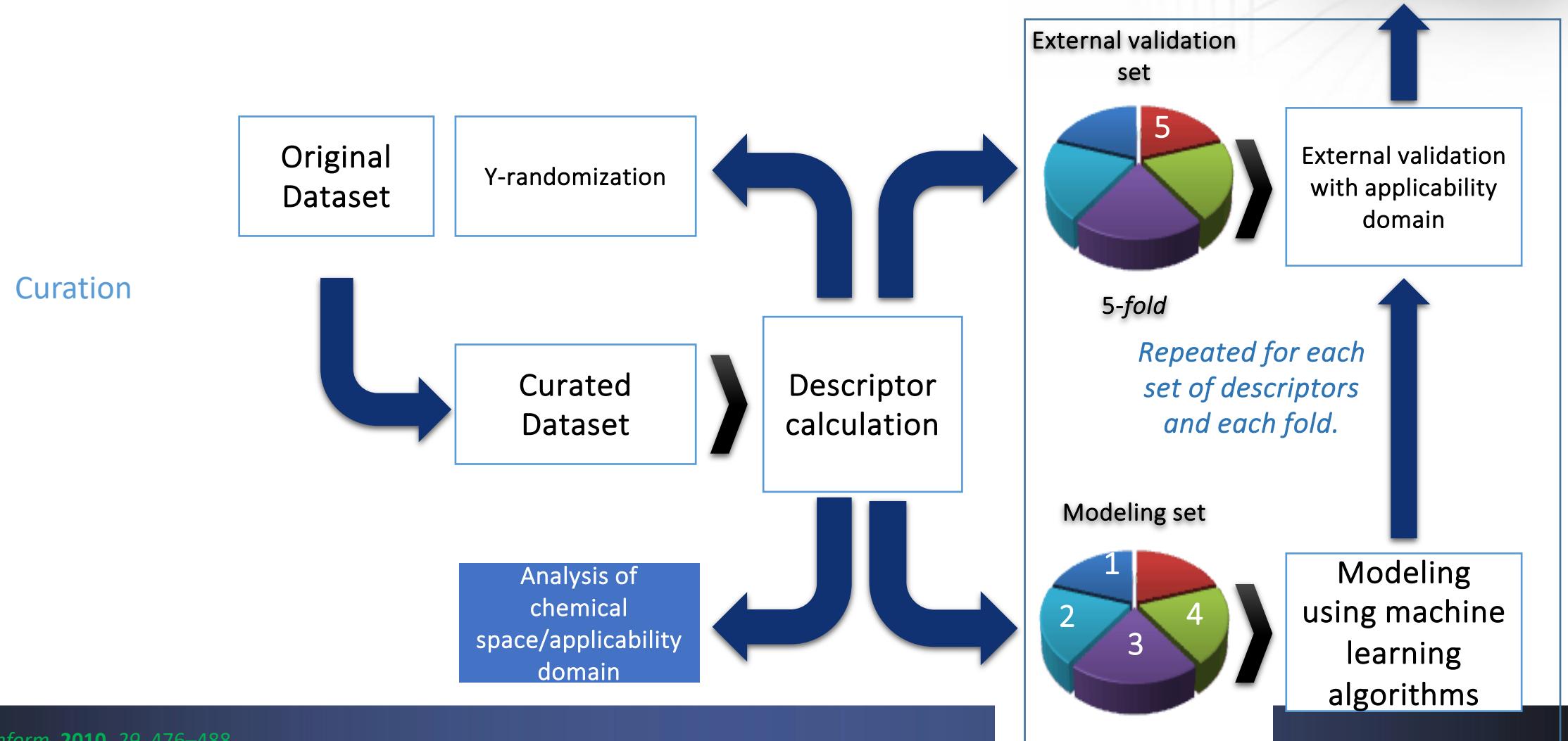
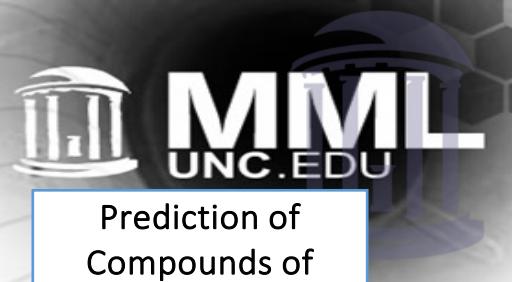
Data Curation



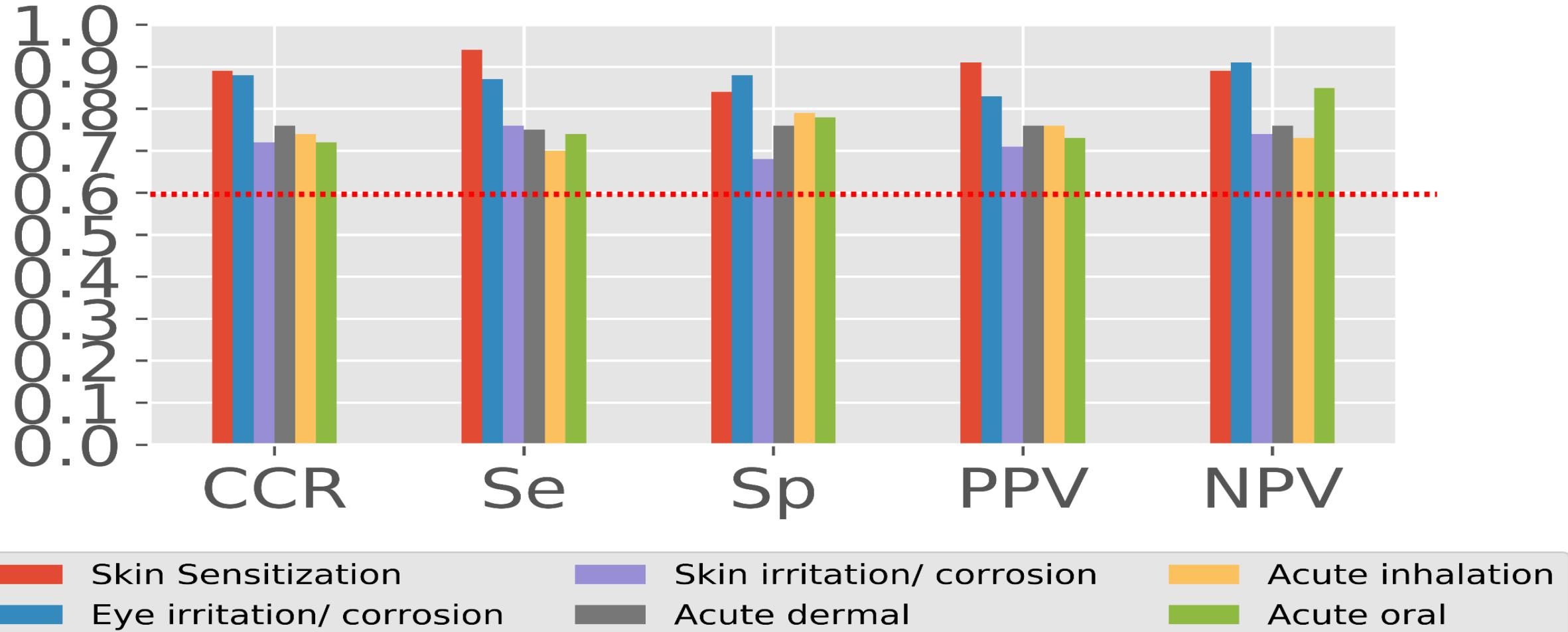
Cross-endpoint analysis of accessible data



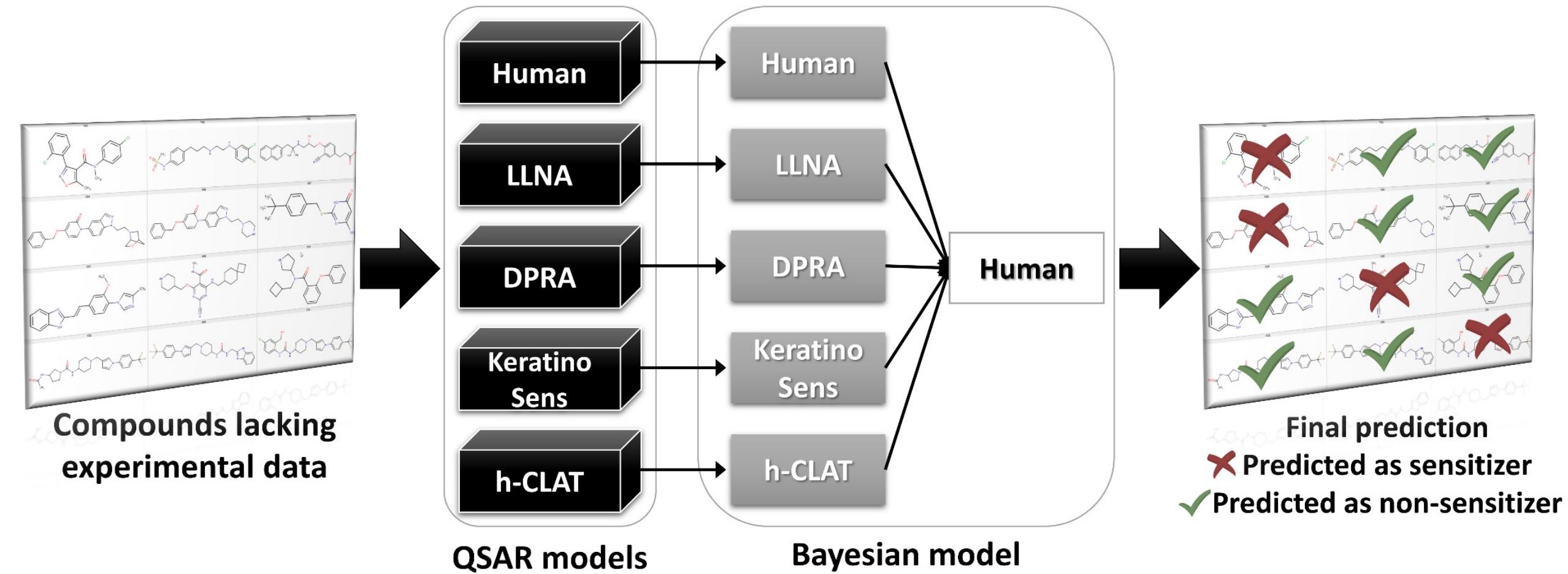
QSAR model development and validation workflow



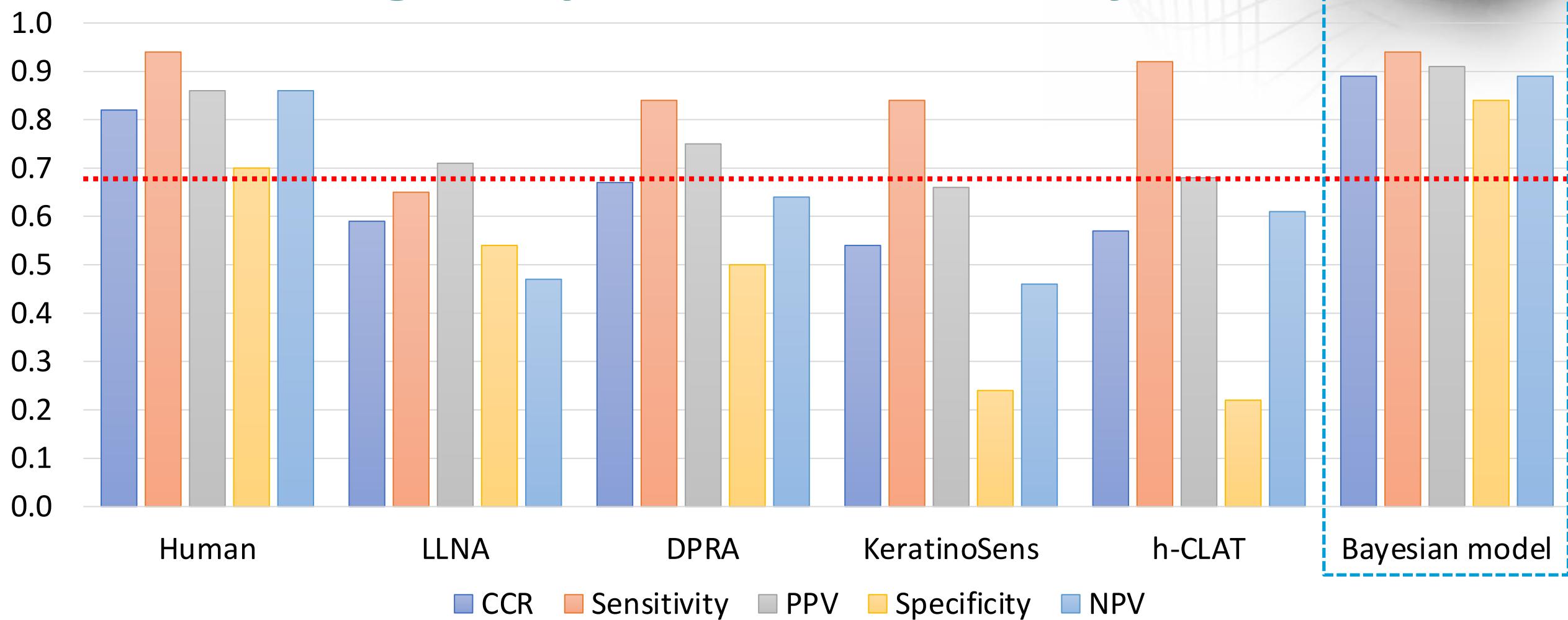
Statistical characteristics of QSAR models



Consensus modeling with Bayesian approach



Bayesian model for skin sensitization shows the highest prediction accuracy



External validation accuracy of SToxTox prediction (OECD DASS-me-too program)



External set of 40 chemicals; **apparent** accuracy of 97.5% (39/40)

BUT: The answer is known for 36
chemicals
(they are already in the training set)!

Real External set of 4 chemicals; accuracy of 75% (3/4)

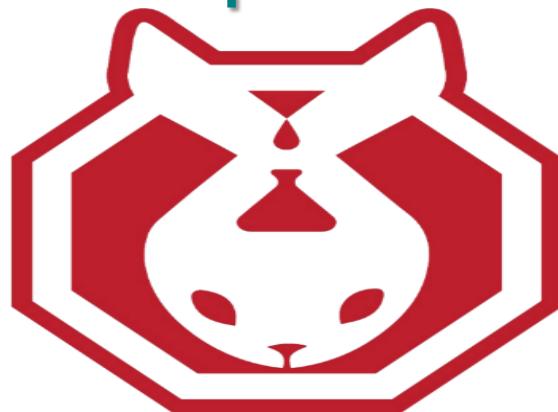
Vol. 130, No. 2 | Research

STopTox: An *in Silico* Alternative to Animal Testing for Acute Systemic and Topical Toxicity

Joyce V.B. Borba, Vinicius M. Alves, Rodolpho C. Braga, Daniel R. Korn, Kirsten Overdahl, Arthur C. Silva, Steven U.S. Hall, Erik Overdahl, Nicole Kleinstreuer, Judy Strickland, David Allen, Carolina Horta Andrade, Eugene N. Muratov  and Alexander Tropsha 

Published: 22 February 2022 | CID: 027012 | <https://doi.org/10.1289/EHP9341> | Cited by: 18

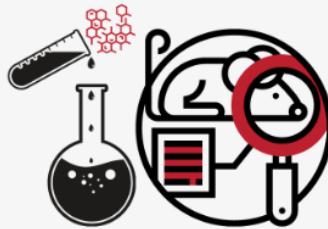
Pilot SToxTox Web-App: <https://stoptox.mml.unc.edu/>



SToTTox

a machine learning app to predict the battery of acute toxicity test classically known as "6-pack".

LARGE DATA COLLECTION



SToTTox was developed based on the largest publicly available data for the "6-pack" animal assays.

CURATED DATA



The collected data was carefully analyzed and curated to guarantee high quality models.

MACHINE LEARNING



QSAR models were developed using powerful machine learning algorithms.

RELIABLE PREDICTIONS



We follow the best practices for model development and validation for regulatory purposes recommended by OECD.

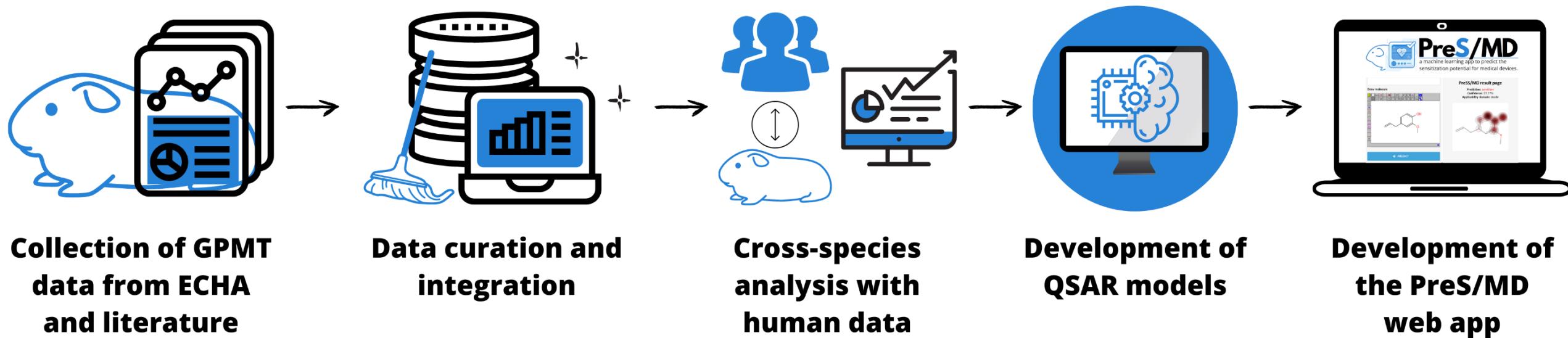
USER FRIENDLY



Models predictivity are assured by high quality curated data and proper external validation.

Commercial version: please visit <https://www.predictive-llc.com/>

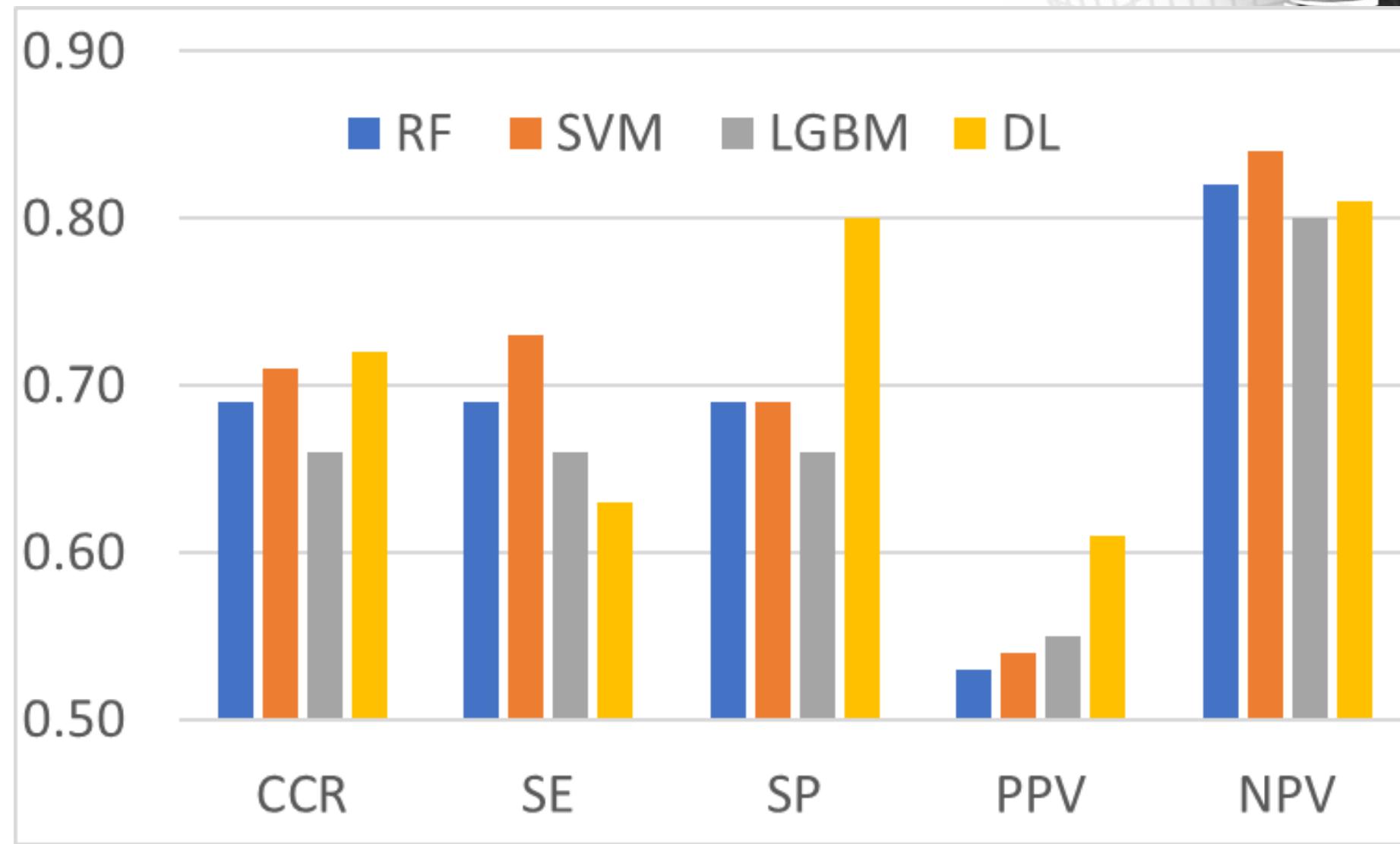
Predictor of Sensitization for Medical Devices (PreS/MD): Study design



Relevance of GPMT assay: comparison with human patch assay data for skin sensitization

GPMT	Human		Total
	Sensitizer	Non-Sensitizer	
Sensitizer	46	14	60
Non-sensitizer	8	41	49
Total	54	55	109

Model accuracy



Experimental results and predictions for external set compounds

Ingredient	GPMT	PreS/MD
Abietic Acid	Sensitizer	Sensitizer
Ethanol	Sensitizer	Non-sensitizer
Eugenol	Sensitizer	Sensitizer
Geraniol	Non-sensitizer	Non-sensitizer
Methylparaben	Non-sensitizer	Non-sensitizer
Sulfanilic Acid	Sensitizer	Sensitizer
1,2-Dibromo-2,4-dicyanobutane	Non-sensitizer	Sensitizer
2-Methyl-3(2H)-isothiazolone	Sensitizer	Sensitizer
4,5-Dichloro-2-methyl-4-isothiazolin-3-one	Non-sensitizer	Sensitizer

Planned enhancements of PreS/md → PredTox/MD



Computational Software covering skin sensitization, irritation, and cytotoxicity endpoints.

Software	Endpoint			Computational Approach				Version	
	Skin Sensitization	Irritation	Cytotoxicity	QSAR	Structural Alerts	Read-Across	Bayesian	Free (Web)	Proprietary
PredTox/MD	✓	✓	✓	✓	✗	✓	✓	✓	✓
TIMES-SS	✓	✓	✗	✓	✓	✗	✗	✗	✓
TOPKAT	✓	✓	✗	✓	✗	✗	✗	✓	✓
ACD/ Percepta	✓	✓	✗	✓	✗	✗	✗	✗	✓
CASE Ultra	✓	✓	✗	✓	✓	✗	✗	✗	✓
DEREK NEXUS	✓	✓	✗	✗	✓	✗	✗	✗	✓
REACHAcross (RASAR)	✓	✓	✗	✓	✗	✓	✗	✗	✓
Danish QSAR database	✓	✓	✗	✓	✓	✗	✗	✓	✗
ToxTree	✓	✓	✗	✗	✓	✗	✗	✓	✗
OECD QSAR Toolbox	✓	✓	✓	✓	✗	✓	✗	✓	✗
VEGA	✓	✗	✗	✗	✗	✓	✗	✓	✗
Pred-Skin	✓	✗	✗	✓	✗	✗	✓	✓	✗

“Best Published Paper Advancing the Science of Risk Assessment Award” at the 2023 Society of Toxicology (SOT) annual meeting.



PreS/MD: Predictor of Chemical Substances

Vinicius M. Alves,* Joyce V. B. B. ,
Nicole Kleinstreuer ,[†] Kevin ,
and Eugene N. Muratov *,¹

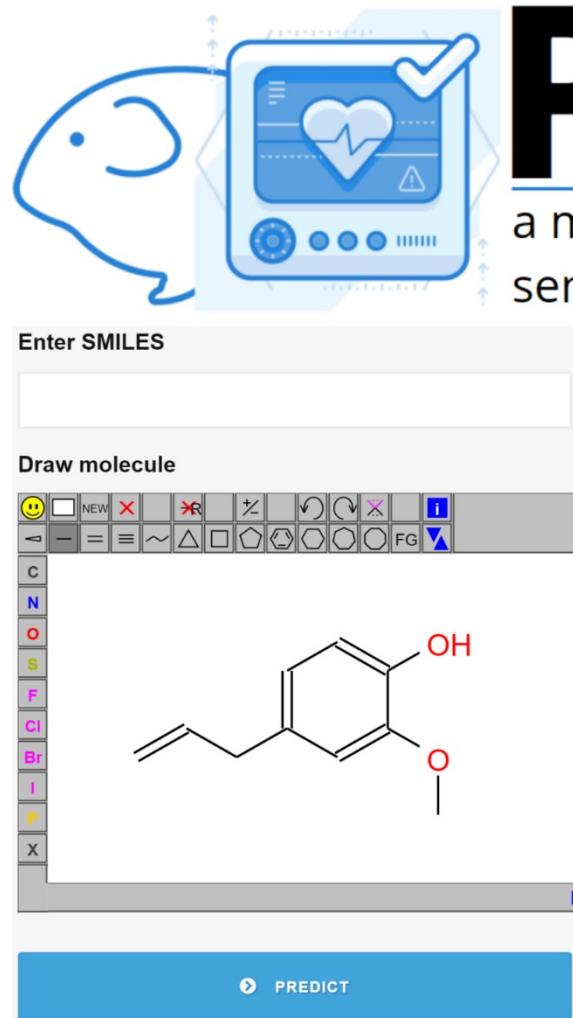


Pilot PRES/MD WEB-app: <https://pressmd.mml.unc.edu/>



PreS/MD

a machine learning app to predict the sensitization potential for medical devices.

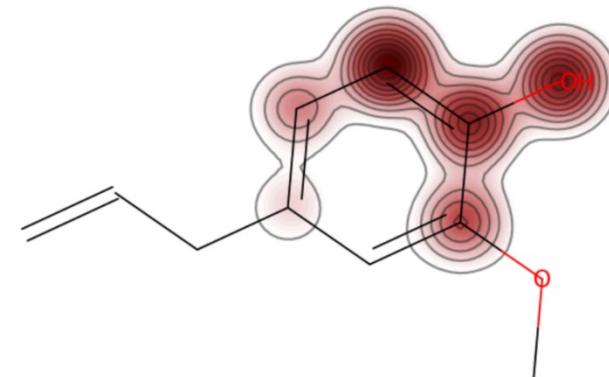


PreS/MD result page

Prediction: sensitize

Confidence: 97.77%

Applicability domain: inside

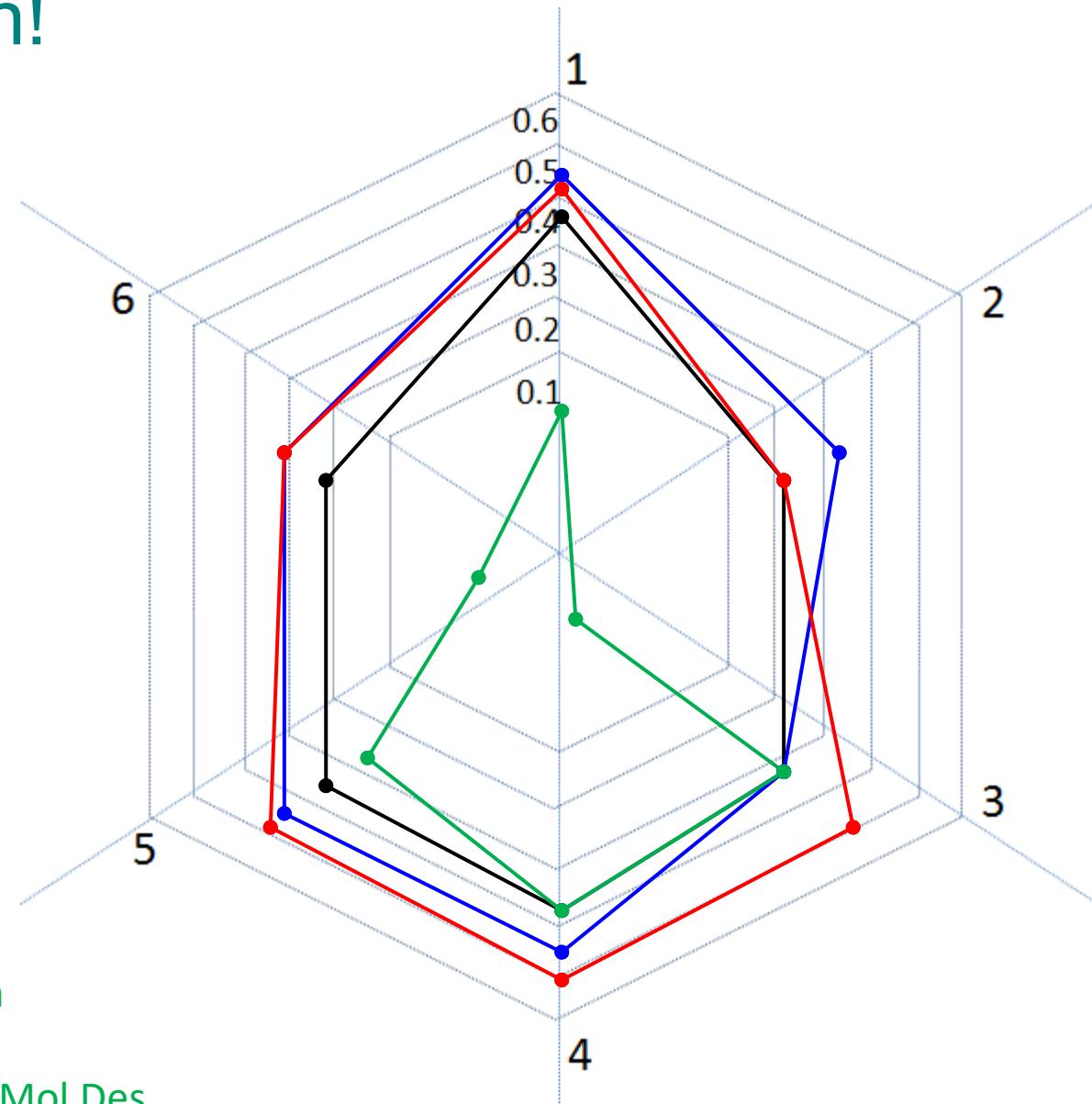


Commercial version: please visit <https://www.predictive-llc.com/>

Model interpretation: Chemical fragments don't act in isolation!

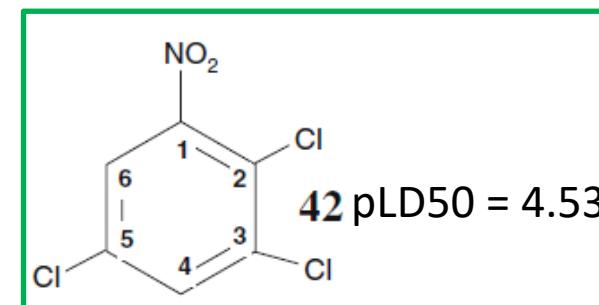
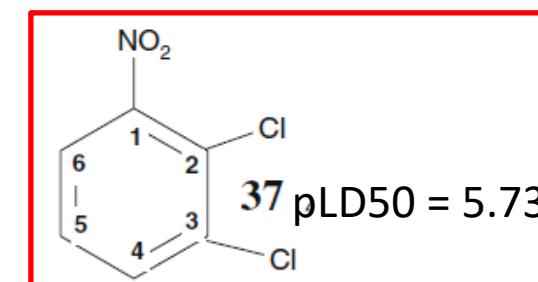
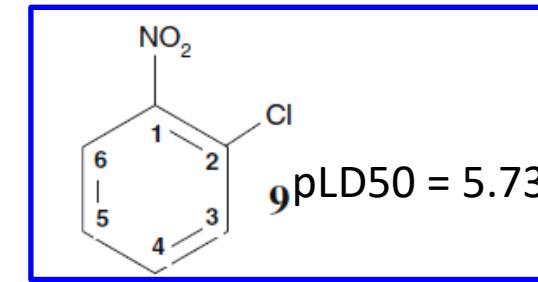
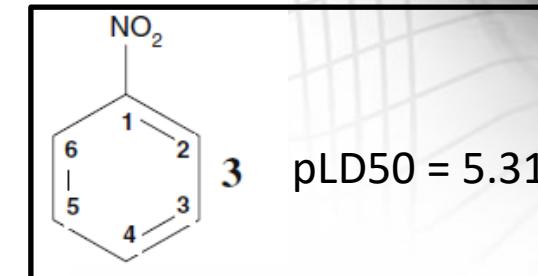


MML
UNC.EDU

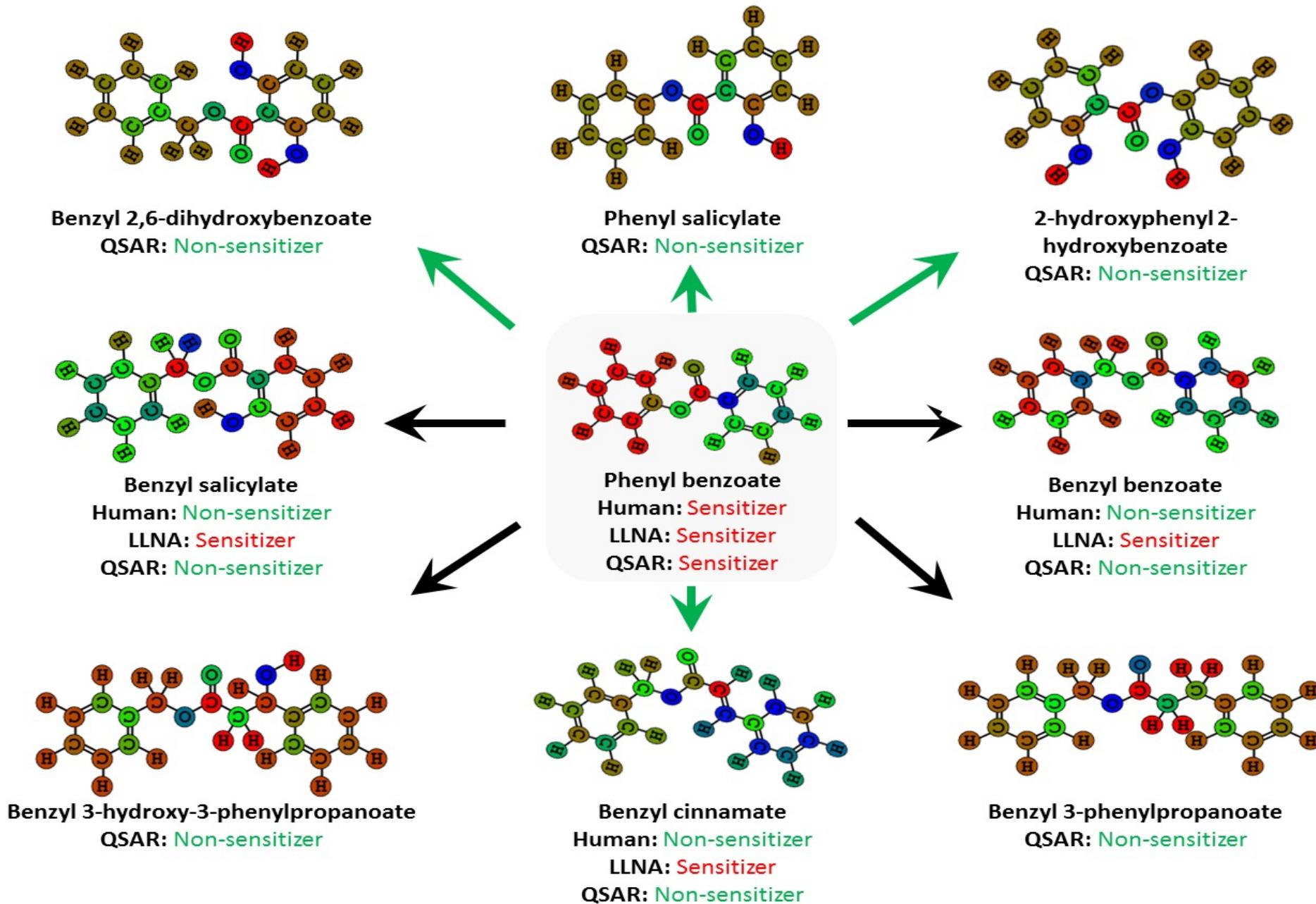


Modified from
Kuz'min et al.

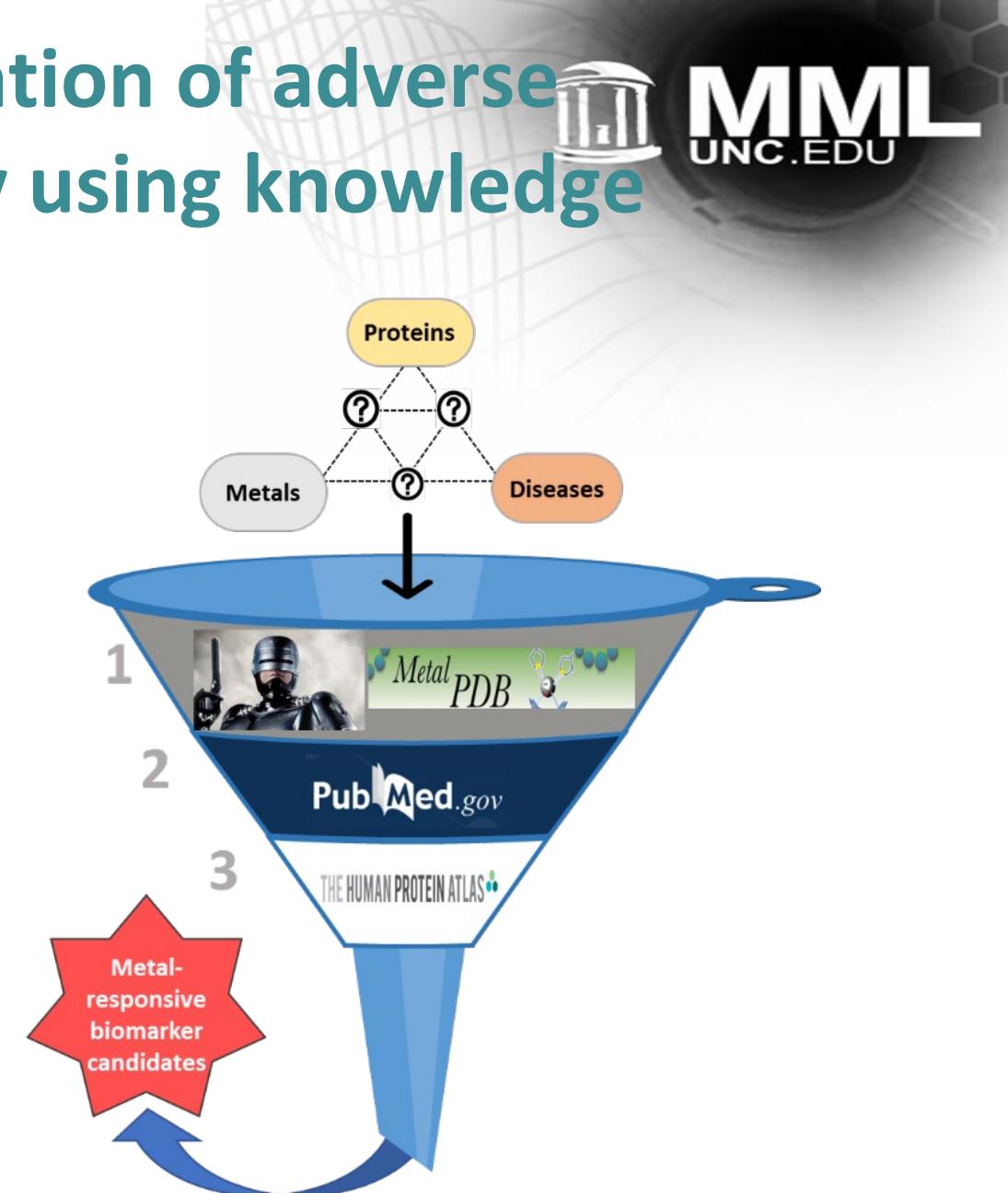
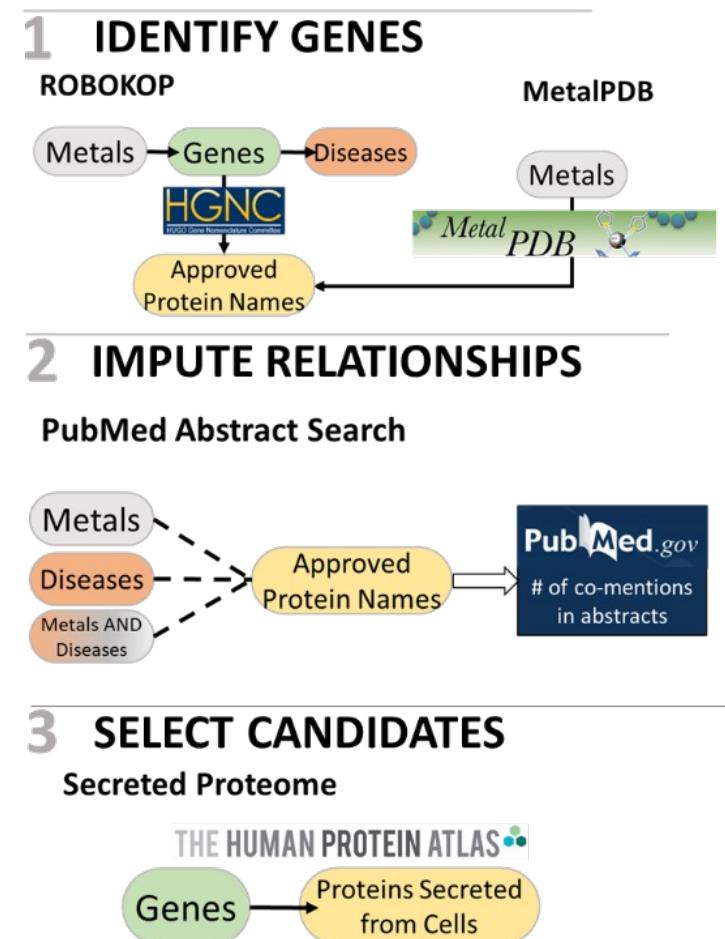
J Comp Aided Mol Des
2008, 22, 747–759



Model-driven Structure optimization



Computational metallomics: Elucidation of adverse outcome pathways of metal toxicity using knowledge graph mining



Metal Leaching from Implants Causes Toxicity

- Mechanical forces and corrosion release metal particles
- Adverse local tissue reaction (ALTR) -Severe inflammation, tissue necrosis, and pseudotumor formation at site of implant [1]
- Neuropathic pain disorders, hypersensitization/allergic responses, and cardiomyopathy among other reported adverse events [1,2]

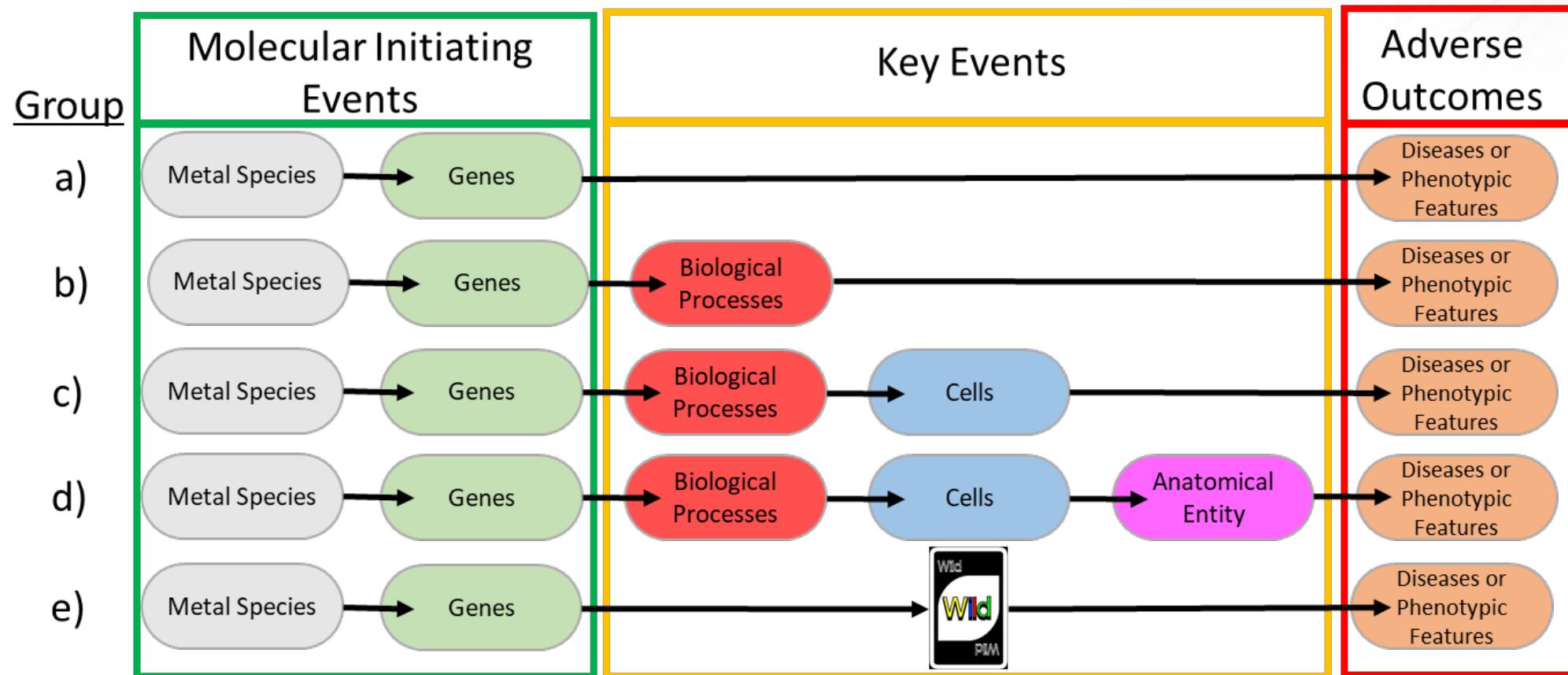


Photo: Anastasia Floyd. Case Study Early Failure of a Modular Hip Implant. Univ. of Calif. Berkeley. 2015.

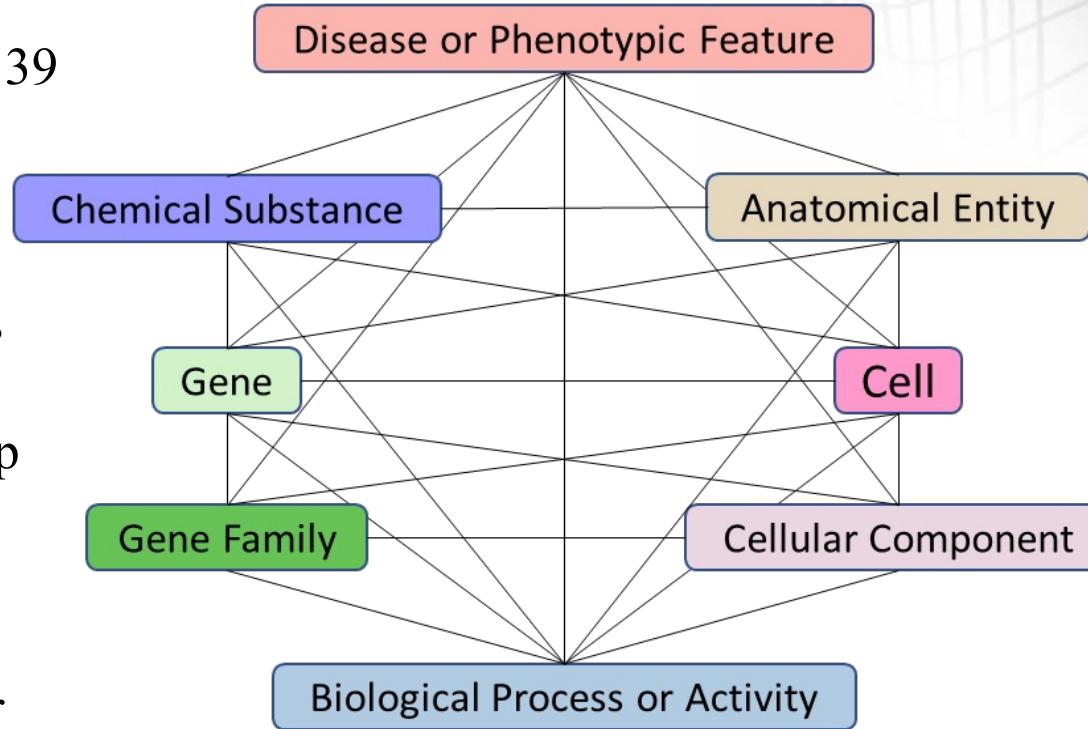
[1] U.S. Food and Drug Administration Center for Devices and Radiological Health. *Biological Responses to Metal Implants*. www.fda.gov/media/131150/download (2019).

[2] Eliaz, N. Corrosion of Metallic Biomaterials: A Review. *Materials (Basel)*. 12, (2019).

Adverse Outcome Pathway (AOP) Models can help explain Toxicity and identify disease biomarkers



- ~9M nodes and ~130M edges drawn from 39 biomedical data sources and bio/chemical-ontologies
- Nodes represent biomedical entities; edges provide predicates, publications, and quantitative data that explain the relationship between connected nodes
- Leverages Biolink Model (<https://biolink.github.io/biolink-model/>) for semantic harmonization and standardization of node and edge types



Funders

U24ES035214

OT3TR002020

OT2TR003430

UL1TR002489

UL1TR002489-03S4

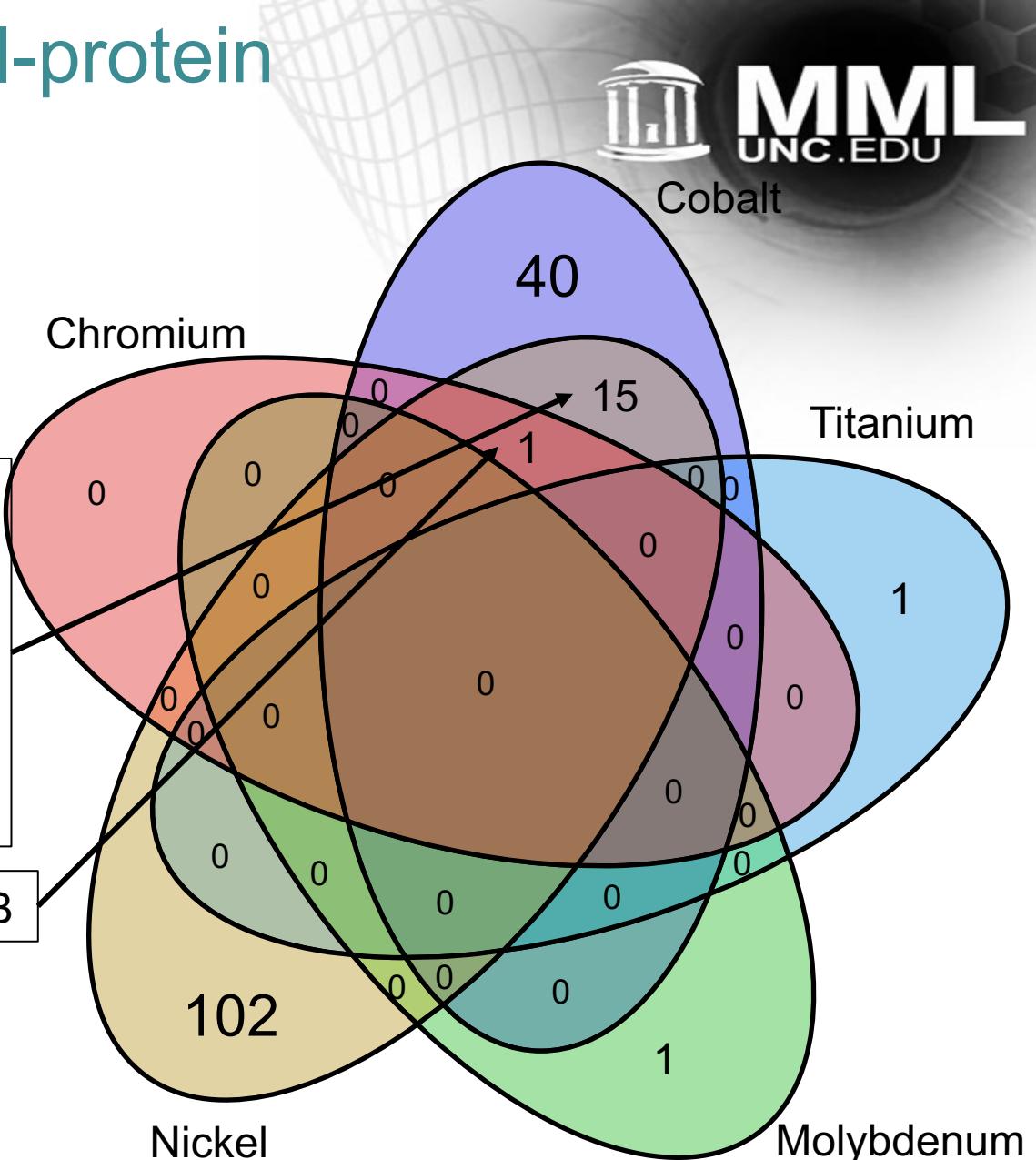
Structure-based Knowledge of Metal-protein Interactions from MetalPDB



- Known metal-protein structures mined from MetalPDB*
- 56 cobalt, 1 chromium, 1 molybdenum, 118 nickel, and 1 titanium PDB entries

ARG1, B2M, BF, BFD, BRCA1, CA2, CDABP0092, CFB, HDCMA22P, JMJD3, JMJD5, KDM6B, KDM8, KIAA0346, RNF53

POLB



ROBOKOP was used to mine metal-gene interactions and generate hypothetical Adverse Outcome Pathways

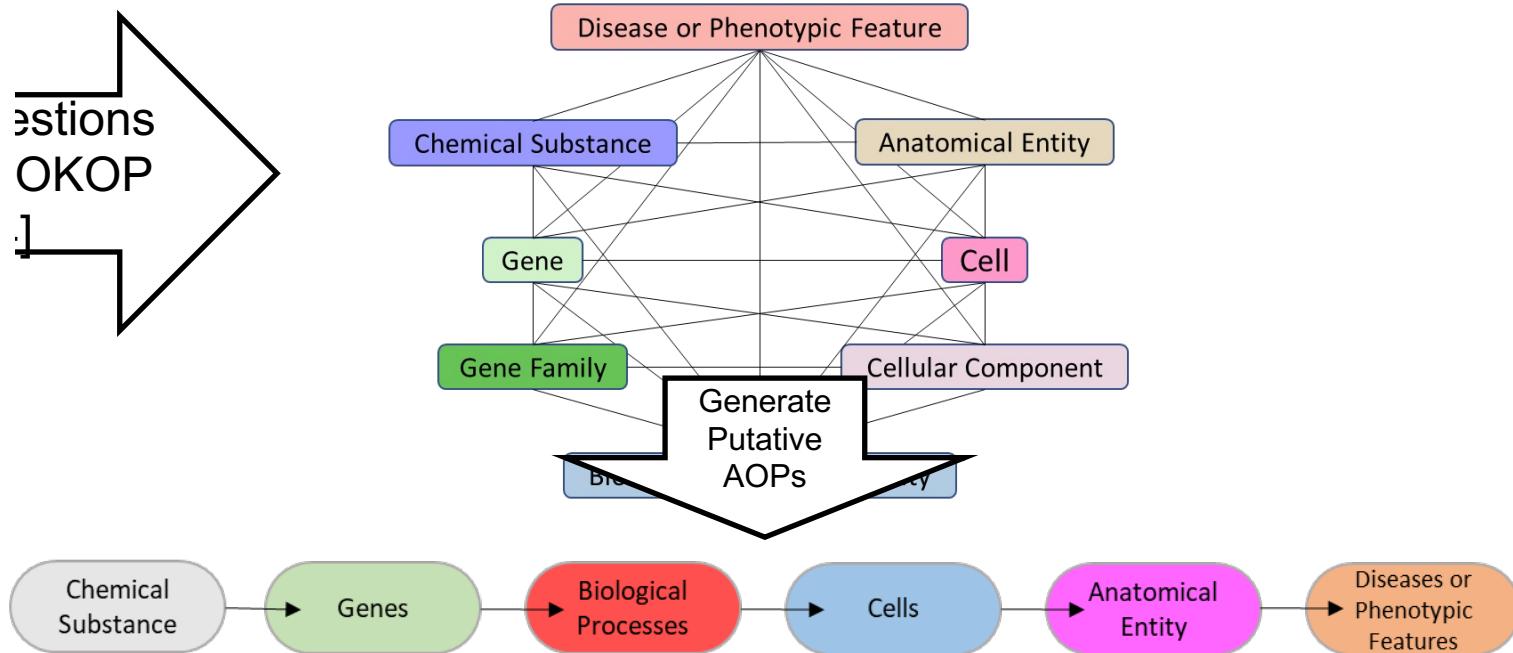
*Taken from [1]

Metal Species	"chemical entity" ROBOKOP Terms	"disease or phenotypic feature" ROBOKOP Terms
Titanium	titanium atom	Innate Immune Response, Nlrp3 Inflammasome Complex, Periprosthetic Osteolysis
Cobalt	cobalt atom, cobalt cation, cobalt(1+), cobalt(2+), cobalt(3+)	Innate Immune Response, Nlrp3 Inflammasome Complex, Periprosthetic Osteolysis, cardiomyopathy, heart failure, dyspnea, palpitations, chest tightness, Neurotoxicity Syndromes, Demyelinating Polyneuropathy, Cognitive Impairment, Tinnitus, Fibromyalgia, Chronic Fatigue, Hypothyroidism, Prostate Cancer, Melanoma (Disease)
Nickel	nickel atom, nickel ion, nickel cation, nickel(1+), nickel(2+), nickel(3+)	Innate Immune Response, Nlrp3 Inflammasome Complex, Periprosthetic Osteolysis, Prostate Cancer, Metal Allergy, Allergic Contact Dermatitis, Localized Skin Lesion, Squamous Cell Carcinoma, Anaplastic Large Cell Lymphoma
Chromium	chromium atom, chromium ion, chromium cation, chromium(2+), chromium(3+), chromium(4+), chromium(5+), chromium(6+)	Melanoma (Disease), Anaplastic Large Cell Lymphoma
Molybdenum	molybdenum atom, molybdenum cation, molybdenum(4+), molybdenum(5+), molybdenum(6+)	Anaplastic Large Cell Lymphoma

ROBOKOP

Robokop

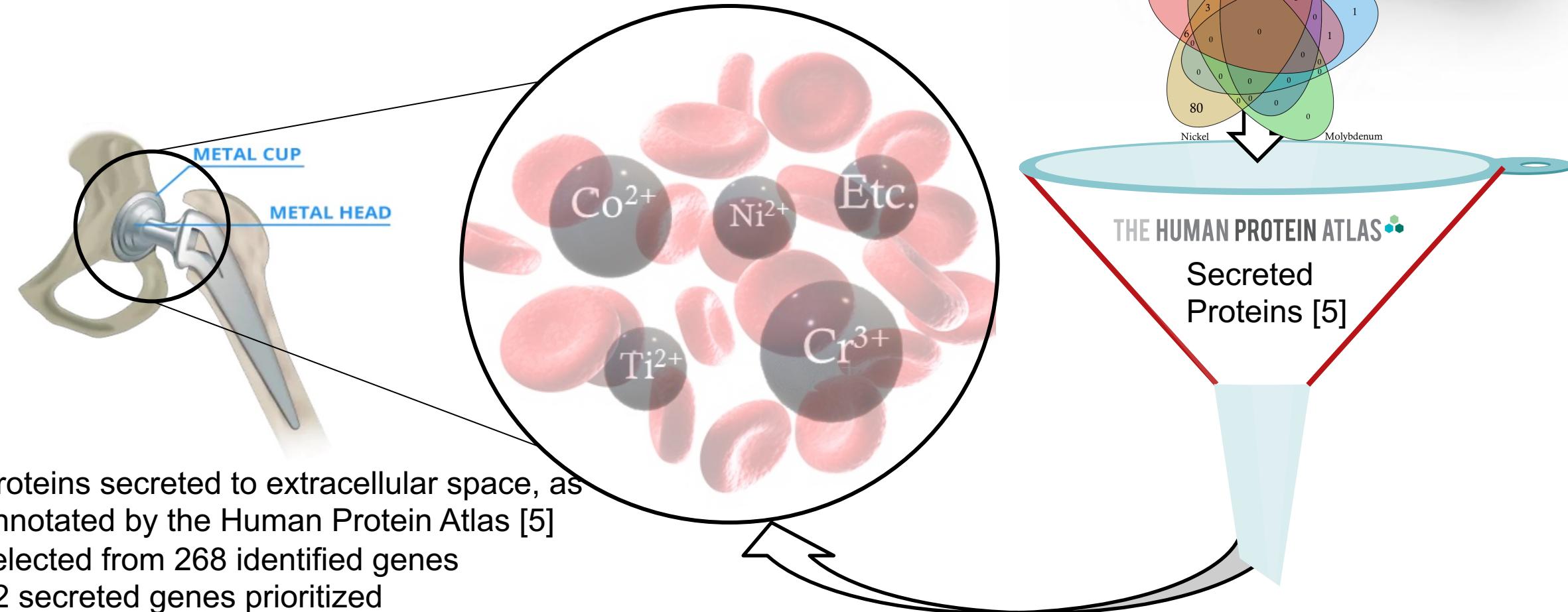
Reasoning Over Biomedical Objects linked in Knowledge Oriented Pathways



[1] U.S. Food and Drug Administration Center for Devices and Radiological Health. *Biological Responses to Metal Implants*. www.fda.gov/media/131150/download (2019).

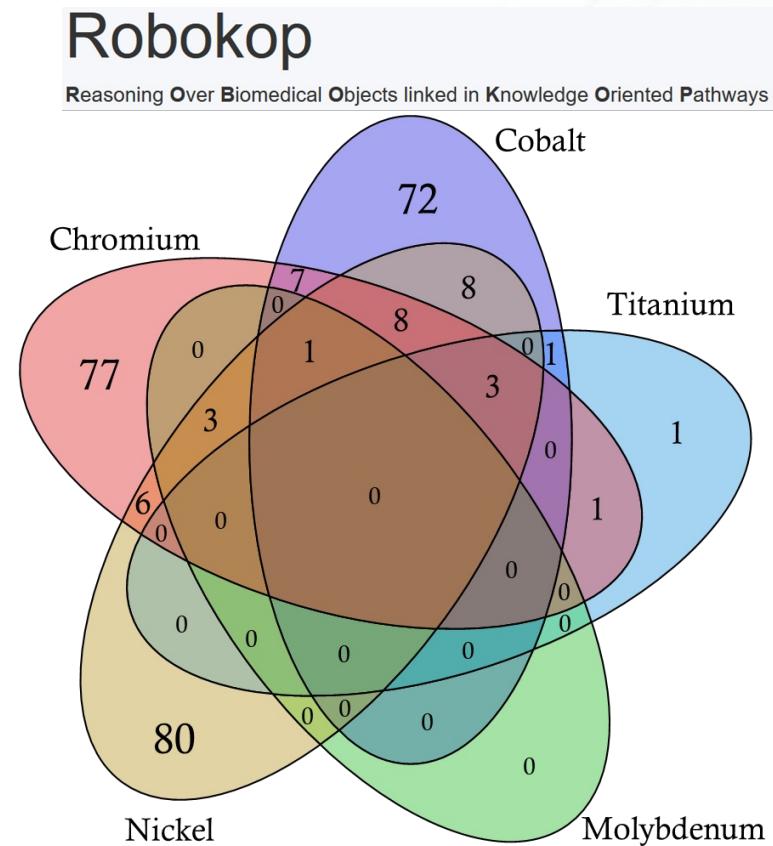
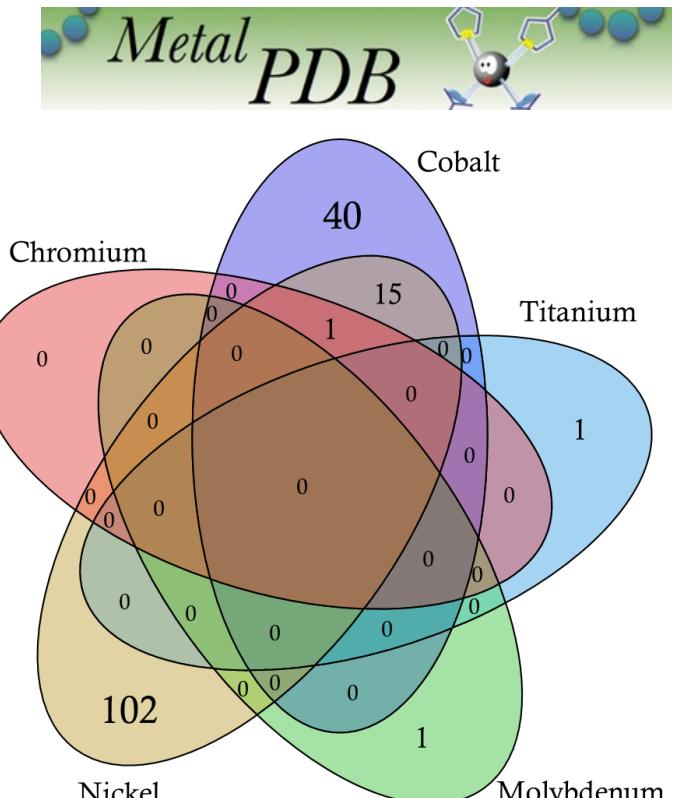
[4] Morton, K. et al. ROBOKOP: an abstraction layer and user interface for knowledge graphs to support question answering. *Bioinformatics* **35**, 5382–5384 (2019).

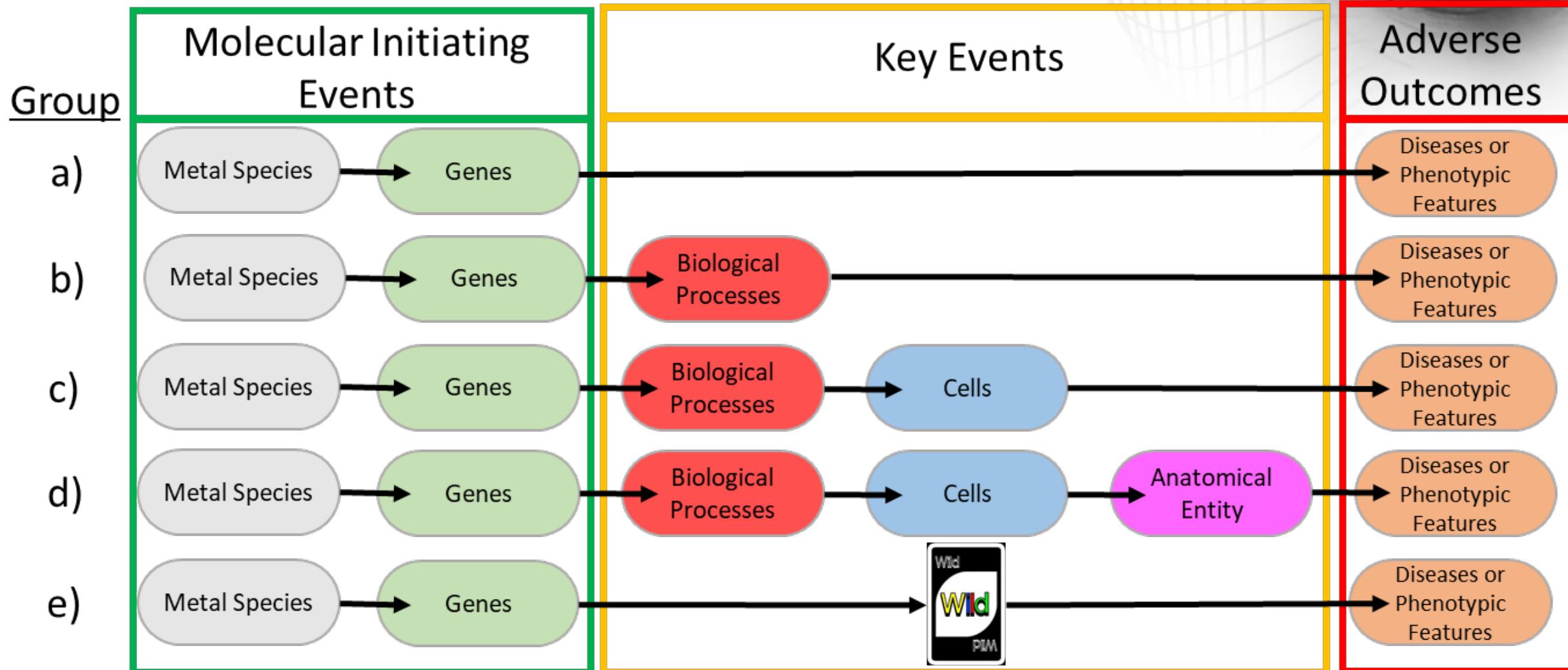
Hypothetical AOPs prioritized if they contain a secreted protein



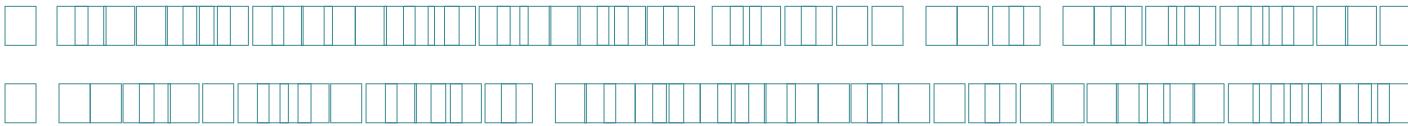
[5] M. U. et al. Proteomics. Tissue-based map of the human proteome. *Science* **347**, (2015).

177 metal-interacting proteins identified by metalPDB,
268 identified by ROBOKOP

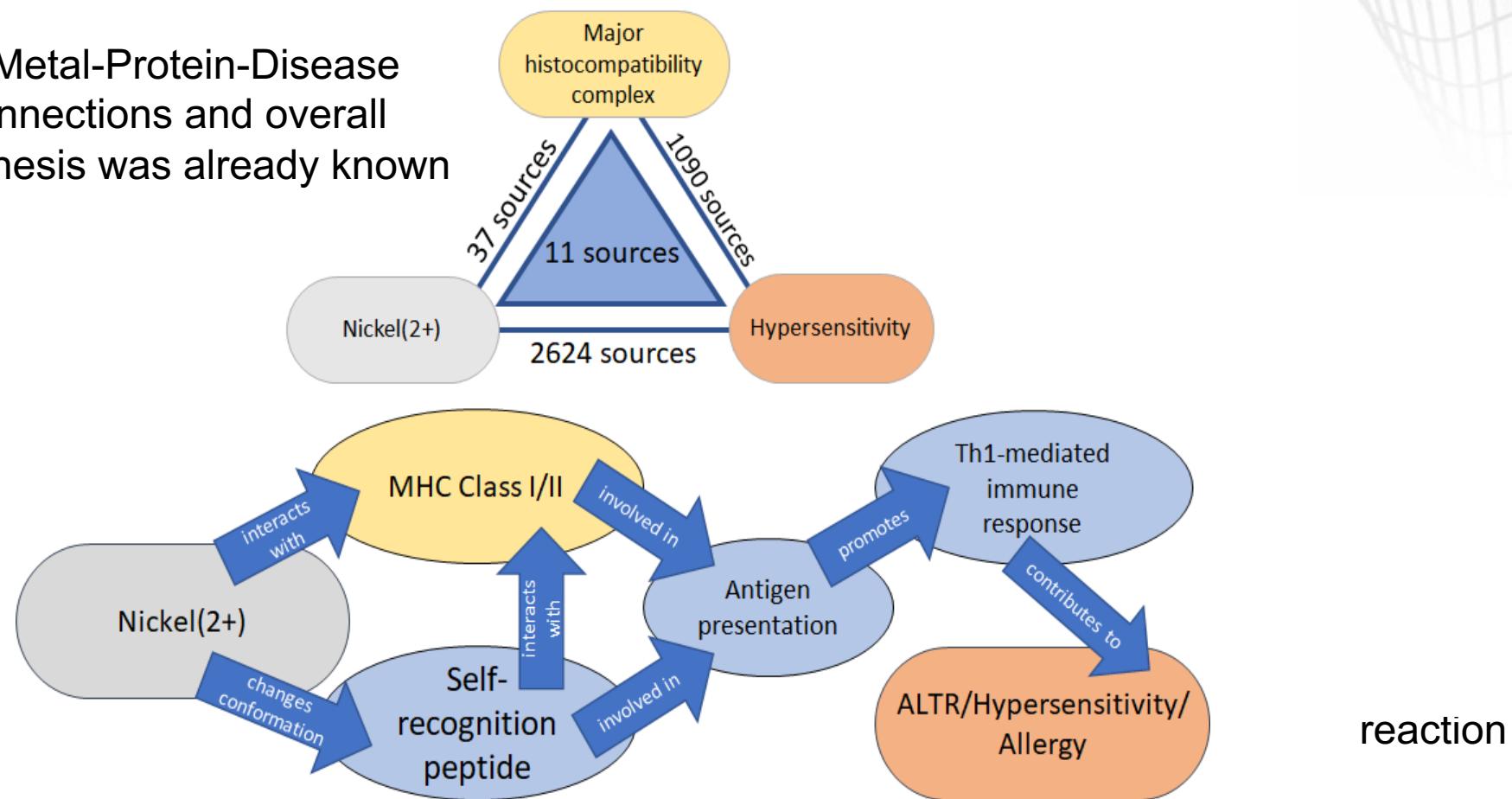




Edwards, S. W., et al. (2016). Adverse Outcome Pathways-Organizing Toxicological Information to Improve Decision Making. *The Journal of pharmacology and experimental therapeutics*, 356(1), 170–181. <https://doi.org/10.1124/jpet.115.228239>
 U.S. National Toxicology Program. Adverse Outcome Pathways. <https://ntp.niehs.nih.gov/whatwestudy/niceatm/comptox/ct-aop/aop.html>



(i) Metal-Protein-Disease connections and overall hypothesis was already known



Fisher, A. A. Allergic dermatitis presumably due to metallic foreign bodies containing nickel or cobalt. *Cutis* **19**, (1977).

Cramers, M. & Lucht, U. Metal Sensitivity in Patients Treated for Tibial Fractures with Plates of Stainless Steel. <http://dx.doi.org/10.3109/17453677708988763> **48**, 245–249 (2009).

Baskett, D. A., Briatico-Vangosa, G., Kaestner, W., Lally, C. & Bontinck, W. J. Nickel, cobalt and chromium in consumer products: a role in allergic contact dermatitis? *Contact Dermatitis* **28**, 15–25 (1993).

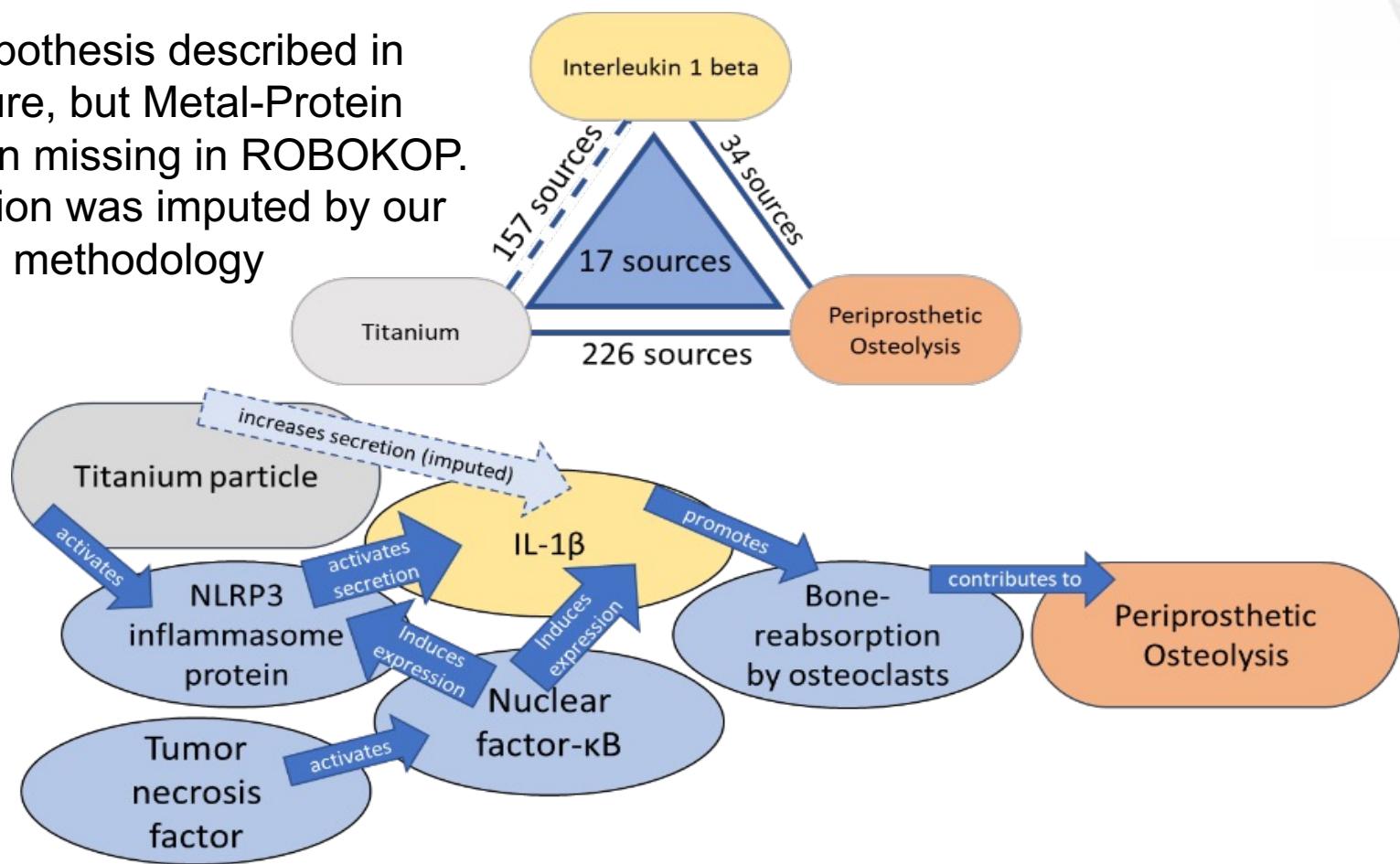
Hallab, N. J., Caicedo, M., Finnegan, A. & Jacobs, J. J. Th1 type lymphocyte reactivity to metals in patients with total hip arthroplasty. *J. Orthop. Surg. Res.* **3**, 6 (2008).

Wang, Y. & Dai, S. Structural basis of metal hypersensitivity. *Immunol. Res.* **55**, 83–90 (2013).

Driller, R. *et al.* Metal-triggered conformational reorientation of a self-peptide bound to a disease-associated HLA-B*27 subtype. *J. Biol. Chem.* **294**, 13269–13279 (2019).

Kilb, B. K. J. *et al.* Frank Stinchfield Award: Identification of the At-risk Genotype for Development of Pseudotumors Around Metal-on-metal THAs. in *Clinical Orthopaedics and Related Research* vol. 476 230–241 (Lippincott Williams and Wilkins, 2018).

(ii) Hypothesis described in literature, but Metal-Protein connection missing in ROBOKOP. Connection was imputed by our methodology



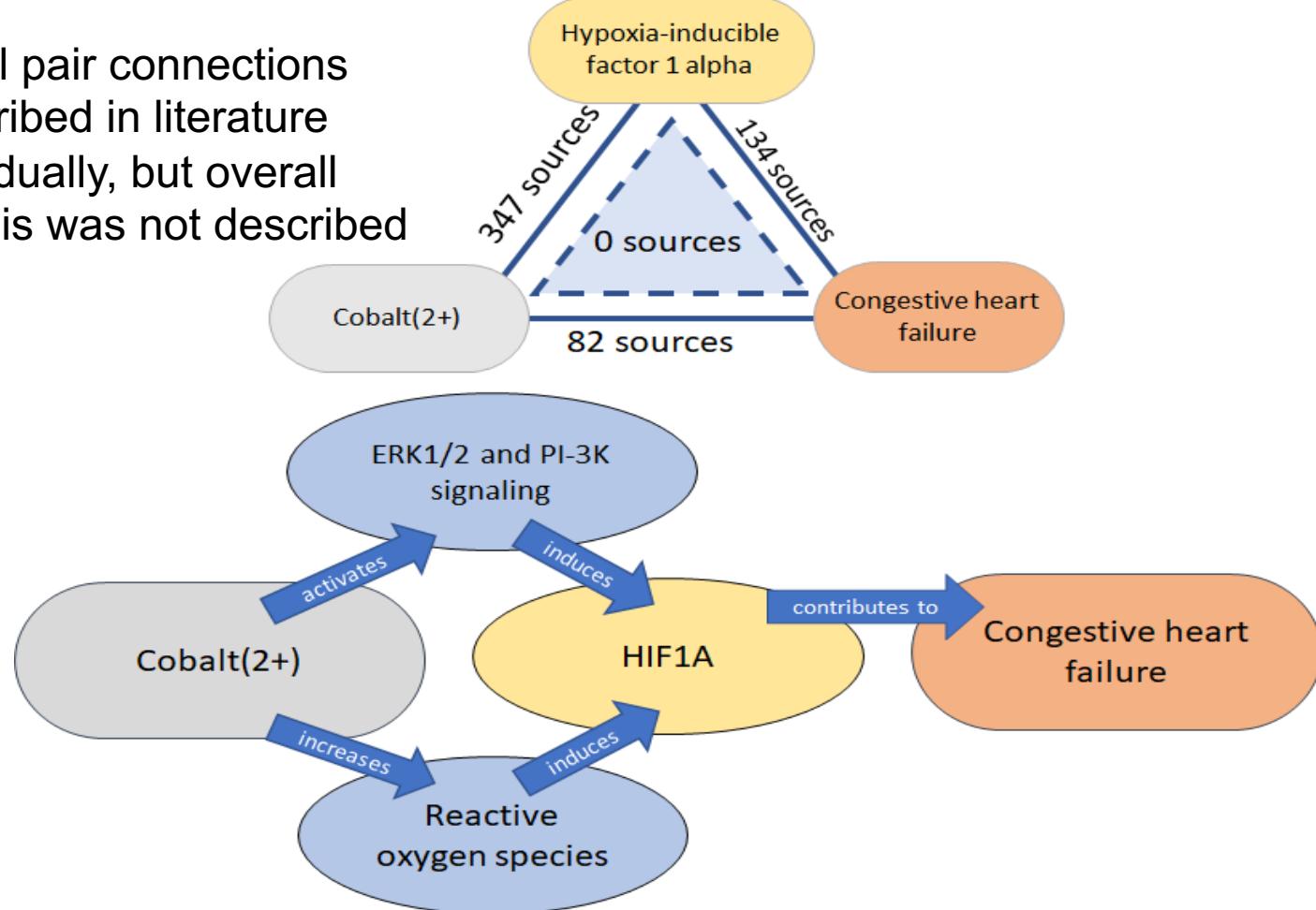
E, J. et al. Tumor necrosis factor primes and metal particles activate the NLRP3 inflammasome in human primary macrophages. *Acta Biomater.* **108**, 347–357 (2020).

Pierre, C. A. S. et al. Periprosthetic Osteolysis: Characterizing the innate immune response to titanium wear-particles. *J. Orthop. Res.* **28**, 1418 (2010).

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Y, H., H, H. & G, N. Mechanism and Regulation of NLRP3 Inflammasome Activation. *Trends Biochem. Sci.* **41**, 1012–1021 (2016).

(iii) All pair connections described in literature individually, but overall hypothesis was not described



A, T. et al. Cobalt induces hypoxia-inducible factor-1alpha (HIF-1alpha) in HeLa cells by an iron-independent, but ROS-, PI-3K- and MAPK-dependent mechanism. *Free Radic. Res.* **40**, 847–856 (2006).

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Summary

- 177 structure-based and 268 knowledge-based metal-interacting proteins uncovered
- 2170 unique metal-protein-disease triples mined from AOPs generated via ROBOKOP
- 72 secreted proteins prioritized for further review
- Cases studies demonstrated the utility of our workflow for accelerating hypothesis generation and literature review.
- Hypothetical AOPs can be used as the motivation for research into biomarkers of metal implant-related toxicity.

Questions that should be Addressed to Support the Acceptability of a QSAR model

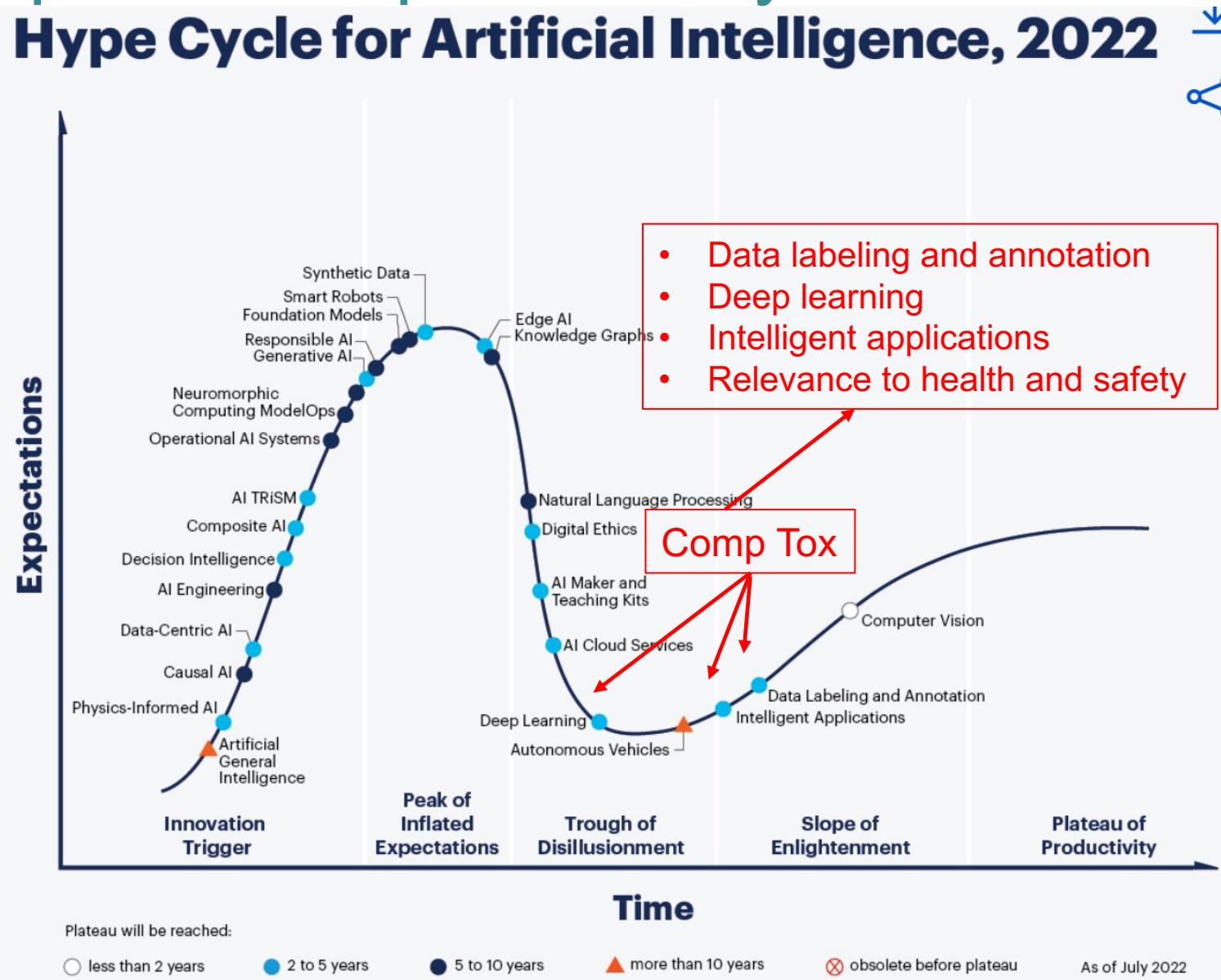
- Compliance with OECD principles of model validation
- Descriptor values can be reproduced?
 - Values provided or their calculation described
- Model definition can be confirmed?
 - Modeling algorithm described explicitly
- External validation set independent of model?
 - External set has no overlaps with training set compounds
 - Descriptors filtered and selected based on training set only
 - Models tuned on training set only
- Model is available and can be tested independently?

Conclusions and Outlook

- Rapid accumulation of large biomolecular datasets :
 - Strong need for both chemical and biological data curation
- Novel approaches towards integration of inherent chemical properties with additional data streams
 - improve the outcome of structure – *in vitro* – *in vivo* extrapolation
- Interpretation of significant chemical and biological descriptors emerging from externally validated models
 - inform the selection or design of effective and safe chemicals
- Critical challenge: via integration of short-term assays and computational data modeling, achieve accuracy of *in vivo* toxicity acceptable for regulatory decision making
 - Minimize animal-based toxicity assessment
- Tool and data sharing
 - Commercial and public web portals

AI and CompTox: are we reaching the “plateau of productivity”*?

Hype Cycle for Artificial Intelligence, 2022



<https://www.gartner.com/en/articles/what-s-new-in-artificial-intelligence-from-the-2022-gartner-hype-cycle>

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