

In Silico Weight-of-Evidence Assessment of Drug-Induced Liver Injuries to Translate Preclinical Studies to Humans



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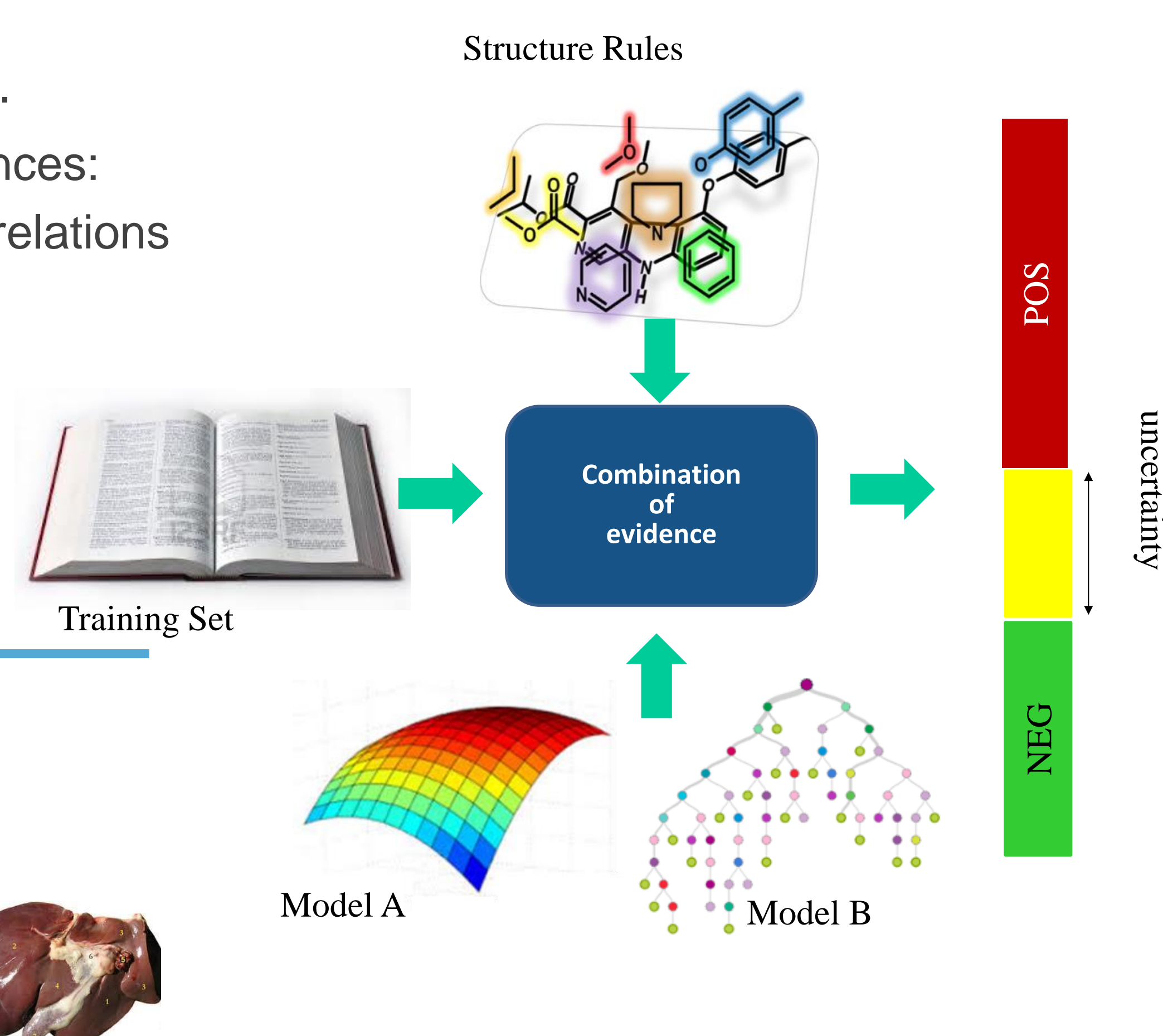
MOTIVATION

- ❖ Drug-induced liver injury (DILI) in humans is an adverse effect whose reliable assessment falls short by current in vivo toxicological studies during drug discovery and development.
- ❖ For cosmetics or industrial chemicals, repeated dose toxicity of target organs is still not replaced by alternative testing methods.
- ❖ A real need exists for a practical and yet reliable alternative.



WEIGHT-OF-EVIDENCE IN SILICO APPROACHES

- ❖ QSAR (Quantitative Structure Activity Relationship) has not yet been demonstrated to be satisfactory for predictions of target organ effects.
- ❖ Multiple *in silico* approaches are employed to leverage various evidences:
 - Structural knowledge – rule-based for positive and negative correlations
 - QSAR method based on partial logistic regression
 - Decision forest partitioning method
- ❖ Decision Theory is applied to combine evidence sources to obtain a weight-of-evidence prediction with estimated uncertainty

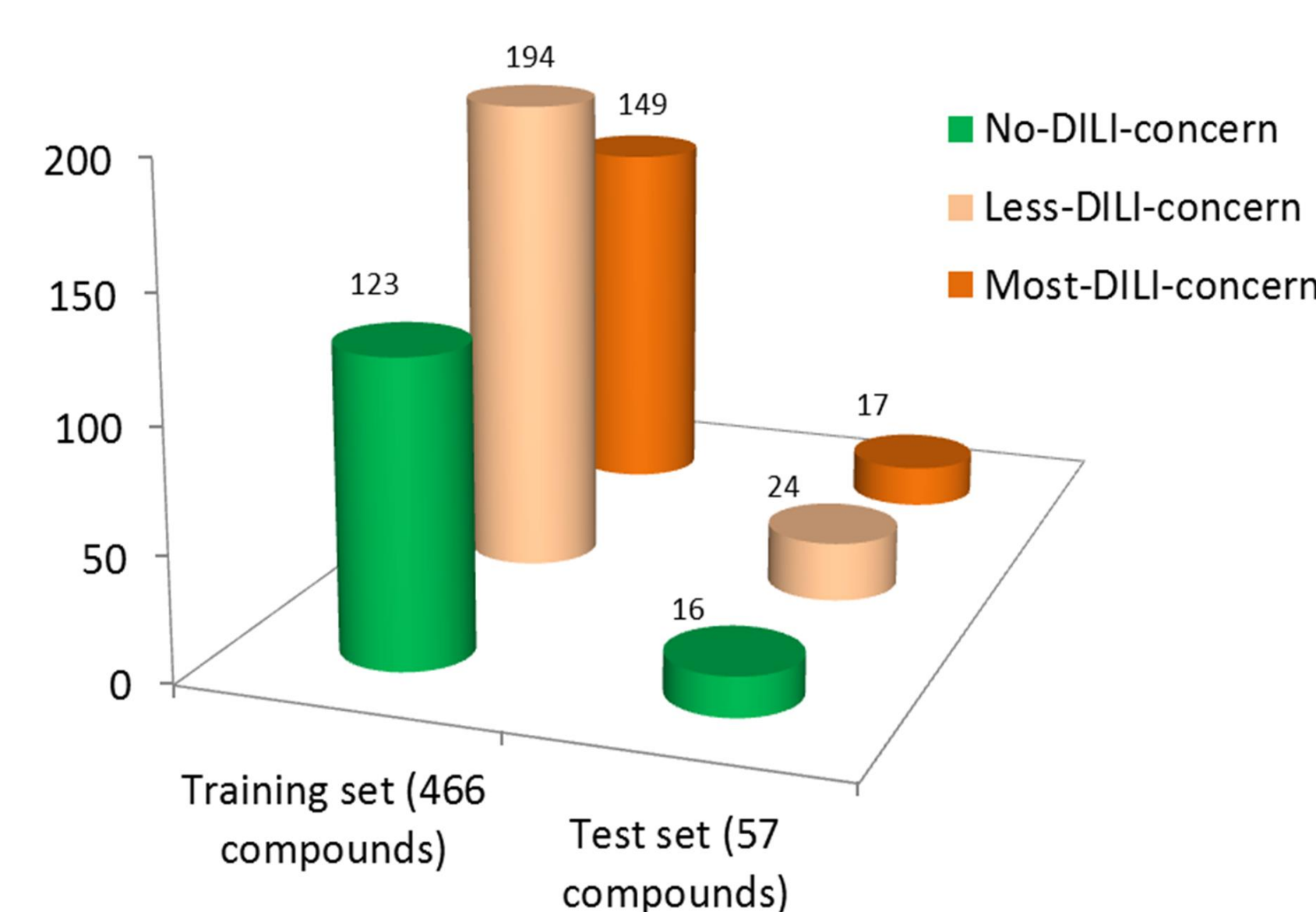


MAMMALIAN DILI DATASET

- ❖ The eTOX project¹ compiled over 1800 Active Pharmaceutical Ingredients (APIs) with detailed pre-clinical toxicity data
- ❖ Training set:
 - 600 structures with treatment-related findings
 - 308 structures with no liver findings
- ❖ Ontology approach: findings descriptions linked to diseases were grouped to score the liver toxicity.
 - over 400 descriptions (liver enzyme, organ weight changes, fatty degenerations, pigmentation, vacuolization, inflammation, necrosis, etc.) were mapped into categories of steatosis, hepatitis, fibrosis/cirrhosis, etc..

HUMAN DILI DATASET

- ❖ US FDA NCTR provides a liver toxicity knowledgebase.
- ❖ 1036 drugs administered to humans have been classified in terms of their DILI risk based on FDA drug labels, called DILIRank, after verification for causality^{2,3,4}
- ❖ A subset of 769 drugs with verified DILIRank were identified.^{3,4}
- ❖ A data set of 523 orally administered drugs. Ambiguous DILI classifications were not used.
- ❖ DILI descriptions: serum enzyme elevations, no jaundice/jaundice, with/without hospitalizations, other severe symptoms, hepatic failure, liver transplant, etc..



STRUCTURAL RULES AND QSAR MODELS

- ❖ Structural rules derived from ToxPrint chemotypes⁶ (<https://chemotyper.org/>)
- ❖ Data sources of knowledgebase
 - Human drug structure set of 769 (originally from FDA NCTR LiverTox Knowledgebase)
 - Mammalian API dataset of 908 from eTOXsys¹
- ❖ Potency-aware rules by correlating with LO(A)EL
- ❖ QSAR models: ordinal partial logistic regression
 - Structural features: ToxPrint chemotypes⁶
 - Quantum mechanical properties: HOMO/LUMO, heat of formation; physicochemical properties: logP, logS, TPSA, HBA, dipole moment, shape descriptors, etc.
- ❖ Decision theory approach based on Dempster-Shafer theory used to combine multiple results to arrive at a weight-of-evidence outcome with associated estimation of uncertainty.⁷

CHEMOTYPES DIFFERENTIATING SPECIES

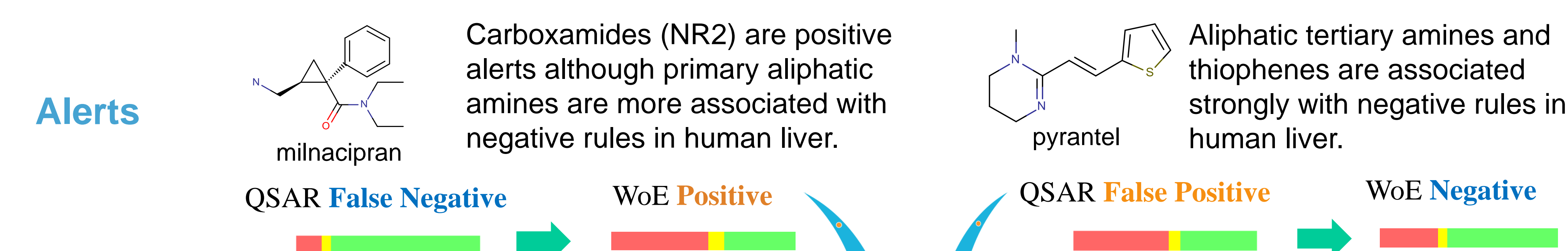
Chemotypes	Z-scores Human DILI (523)	Z-scores Mammal DILI (506)
Halide any	3.57 (152)	12.8 (264)
Halide aromatic	3.14 (122)	3.25 (223)
Halide alkyl	0.72 (33)	2.21 (66)
Carboxylic acid	3.10 (108)	0.57 (72)
Amine tertiary	-3.75 (156)	2.30 (191)
Amine aromatic primary	1.95 (28)	0.48 (26)
Amine alicyclic	-2.51 (108)	2.70 (159)
Furan	2.20 (13)	-1.00 (15)
Imidazole / Benzimidazole	2.18 (36)	-1.20 (34)
Nitro	1.96 (17)	-1.25 (10)
Piperazine	1.43 (27)	4.23 (59)
Pyrimidine	1.42 (27)	2.03 (54)
Benzyl alcohol	-4.29 (23)	1.78 (13)

$$z_c = \frac{\bar{y}_c - \bar{y}}{\sqrt{\frac{n_c}{n_c} S^2}} = \frac{\bar{y}_c - \bar{y}}{S}$$

Number in () represents frequency of each class.

- Chemotypes differentiating humans and mammals (especially rodent), and routes of administration (oral vs. injection) have been identified.

RESULTS



Training and cross validation performance for ordinal (3-level) classification QSAR models

DILI Concern	Global 1 N = 295			Global 2 N = 294			Alcohol N = 149		
	0	1	2	0	1	2	0	1	2
none (0)	106	15	2	105	15	3	48	5	1
less (1)	22	48	27	26	42	29	6	30	18
most (2)	13	35	27	10	28	36	3	20	18

WoE predictions for test set

DILI Concern	WoE prediction on test set (N = 57)		
	0	1	2
none (0)	12	4	0
less (1)	4	11	9
most (2)	3	10	4

diagonal-plus-one concordance = 95%

SUMMARY

FUTURE

- ❖ A liver knowledgebase prediction system has been developed. and is available from ChemTunes•ToxGPS and eTOXsys
 - Structural rule-base system based on ontology-driven mechanistic data mining and chemoinformatics
 - Structural alerts for specific phenotypes, e.g., steatosis, hepatitis, steatohepatitis, and fibrosis
- ❖ Weight of evidence-based approach used to systematically combine different information.
- ❖ Next steps: systematic validation and extension of this knowledgebase and approach to cosmetics and industrial chemicals.



REFERENCES

(1) eTOXsys products at <http://etoxsys.com/>, eTOXsys sampler at <https://etoxsys.eu/etoxsys.v3-demo-bk/dashboard/>. (2) Willyard C. *Nature Medicine*, 22(5), 450-451, 2016. (3) Chen M et al. *Toxicol Sci* 136(1), 242-249, 2013. (4) Thakkar S, Chen M, Fang H, Liu Z, Roberts R, Tong W. *Expert Review of Gastroenterology & Hepatology*, 12:1, 31-38, 2017. "The Liver Toxicity Knowledge Base (LKTb) and drug-induced liver injury (DILI) classification for assessment of human liver injury". (5) Steger-Hartmann T, Pognan F. *Pharmazeutische Medizin*, Jahrgang 19, Heft 1, März, 2017. (6) Yang C et al. *Journal of Chemical Information and Modeling*, 55(3), 510-528, 2015. (7) Rathman J, Yang C, Zhou H. *Computational Toxicology*, in press, 2018. "Dempster-Shafer theory for combining *in silico* evidence and estimating uncertainty in chemical risk assessment"