



XVI FORESIGHT TRAINING COURSE Repurposing to cover unmet needs: the current scenario in Europe and the proposed changes to the Pharmaceutical Legislation

In-silico structure-based platforms for drug repurposing

Cosimo D. Altomare Department of Pharmacy – Pharmaceutical Sciences University of Bari Aldo Moro

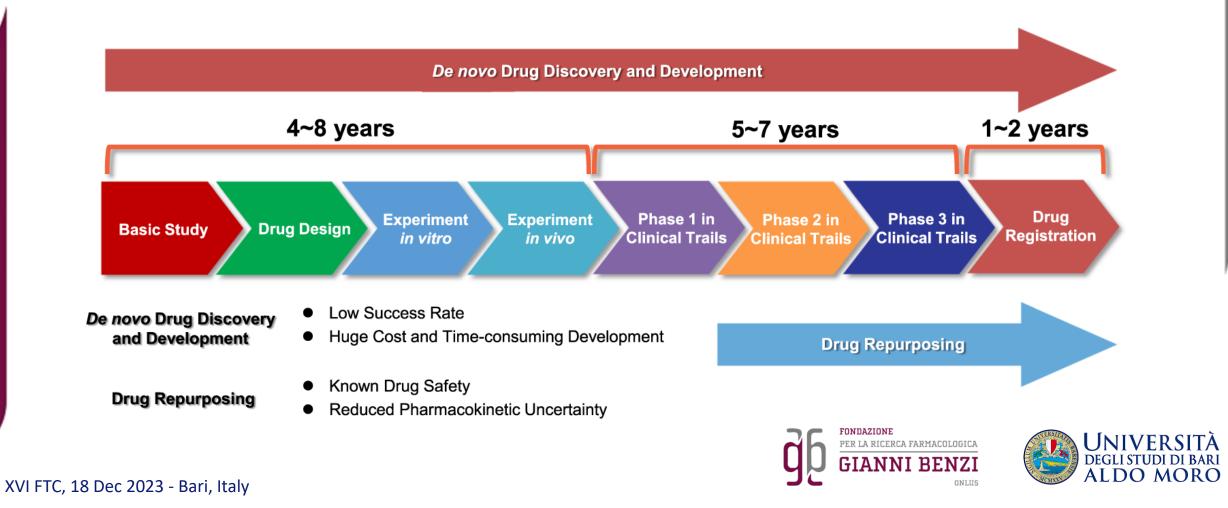


18 Dec 2023 - Bari, Italy

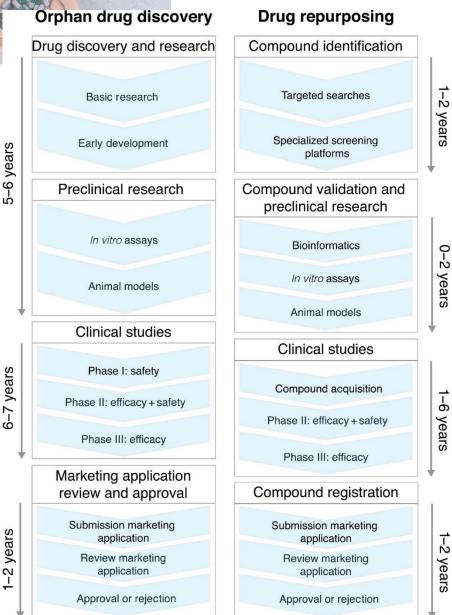


Drug repurposing

Discovering new indications for existing drugs originally developed to treat different diseases



Drug repurposing and orphan drug development



10–15 year process <10% success rate \$2.5 billion

3–12 years reduced risk 30-75% success rate \$300 million

Drug repurposing increase success rates, reduce development costs, shorten time to the market, and therefore reduce the overall development risk compared with traditional drug development

> Drug Repurposing for Rare Diseases. Trends in Pharmacological Sciences, 2021, Vol. 42, No. 4, doi.org/10.1016/j.tips.2021.01.003







Drug repurposing

Historically, drug repurposing has been largely opportunistic and serendipitous.

Pushpakom et al. Drug repurposing: progress, challenges and recommendations Nature Reviews Drug Discovery 18, 41–58 **(2019)** Drug name Original New indication Date of Repurposing approach Comments on outcome of repurposing indication used approval Zidovudine was the first anti-HIV drug to be Zidovudine Cancer HIV/AIDS 1987 In vitro screening of compound libraries approved by the FDA Minoxidil Hypertension Hair loss 1988 Retrospective clinical Global sales for minoxidil were analysis (identification of US\$860 million in 2016 (Questale minoxidil hair growth as an adverse sales report 2017; see Related links) effect) Sildenafi Angina Erectile dysfunction 1998 Retrospective clinical Marketed as Viagra, sildenafil became the analysis leading product in the erectile dysfunction drug market, with global sales in 2012 of \$2.05 billion⁸ Thalidomide Morning sickness Erythema nodosum 1998 and Off-label usage and Thalidomide derivatives have achieved 2006 substantial clinical and commercial success leprosum and pharmacological analysis multiple myeloma in multiple myeloma 2000 Celecoxib Pain and Familial Pharmacological analysis The total revenue from Celebrex (Pfizer) at inflammation the end of 2014 was \$2.69 billion (Pfizer 2014 adenomatous financial report; see Related links) polyps Parkinson disease ADHD 2002 Pharmacological analysis Strattera (Eli Lilly) recorded global sales of Atomoxetine \$855 million in 2016 SUL 2004 Pharmacological analysis Approved by the EMA for SUI. The Duloxetine Depression application was withdrawn in the US. Duloxetine is approved for the treatment of depression and chronic pain in the US Rituximab Rheumatoid 2006 Retrospective clinical Global sales of rituximab topped \$7 billion in Various cancers analysis (remission of 2015 (REE 145) arthritis coexisting rheumatoid arthritis in patients with non-Hodgkin lymphoma treated with rituximab¹⁴⁴) 2007 Raloxifene Osteoporosis Breast cancer Retrospective clinical Approved by the FDA for invasive breast cancer. Worldwide sales of \$237 million in analysis 2015 (see Related links) 2010 Fingolimod Transplant MS Pharmacological and First oral disease-modifying therapy to be approved for MS. Global sales for fingolimod structural analysis146 rejection (Gilenya) reached \$3.1 billion in 2017 (see Related links) Analgesia and 2012 Pharmacological analysis Approved in the UK and a number of Dapoxetine Premature depression ejaculation European countries; still awaiting approval in the US. Peak sales are projected to reach \$750 million 2012 Topiramate Epilepsy Obesity Pharmacological analysis Qsymia (Vivus) contains topiramate in combination with phentermine Ketoconazole Fungal infections 2014 Pharmacological analysis Approved by the EMA for Cushing syndrome Cushing syndrome in adults and adolescents above the age of 12 years (see Related links) Colorectal cancer 2015 Analgesia Retrospective clinical and US Preventive Services Task Force released Aspirin pharmacological analysis draft recommendations in September 2015 regarding the use of aspirin to help prevent cardiovascular disease and colorectal cancer⁵²



Genetic association

Genes that are associated with a disease may prove to be potential drug targets

Molecular docking

This is a structure-based computational strategy to predict binding site complementarity between a ligand (for example, a drug) and a therapeutic target (typically a protein)

Signature matching

This involves comparing the 'signature' of a drug characteristics such as its transcriptomic, structural or adverse effect profile with that of another drug or disease phenotype

Binding assays to identify relevant target interactions

Techniques such as affinity chromatography and mass spectrometry can be used to identify novel targets of known drugs

Retrospective clinical analysis

Systematic analysis of EHRs, clinical trial data and postmarketing surveillance data could inform drug repurposing

Novel data sources

Large-scale in vitro drug screens with paired genomic data, EHR-linked large biobanks and self-reported patient data are novel avenues to exploit for drug repurposing

Phenotypic screening

Pathway mapping Network analysis using

genetic, protein or disease data can aid

repurposing targets

identification of

Drug repurposing

> High-throughput phenotypic screening of compounds using in vitro or in vivo disease models can indicate potential for clinical evaluation

> > Computational approaches Experimental approaches

Computational and experimental approaches can also be used to identify repurposing opportunities.

Both approaches are increasingly being used synergistically

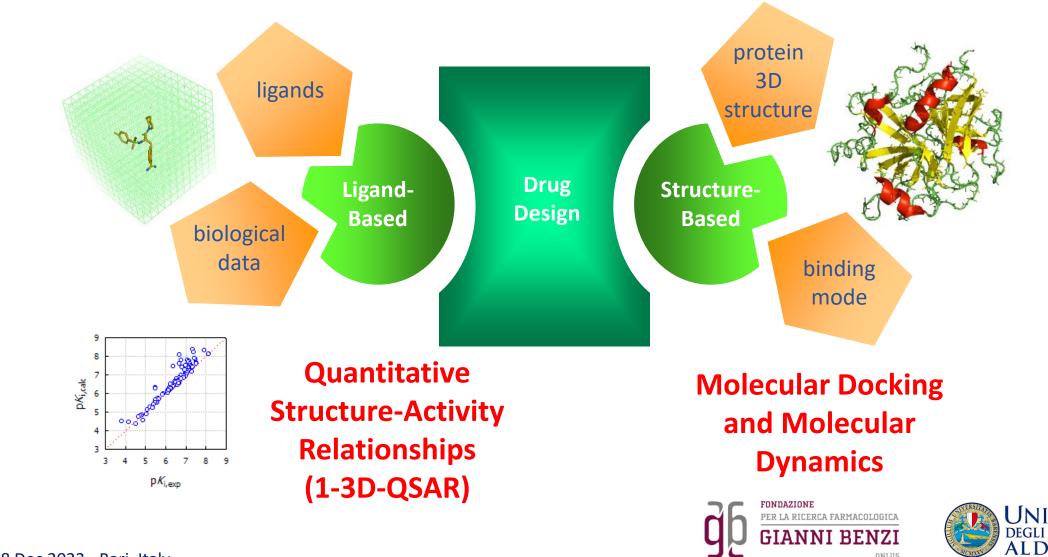




Nature Reviews | Drug Discovery

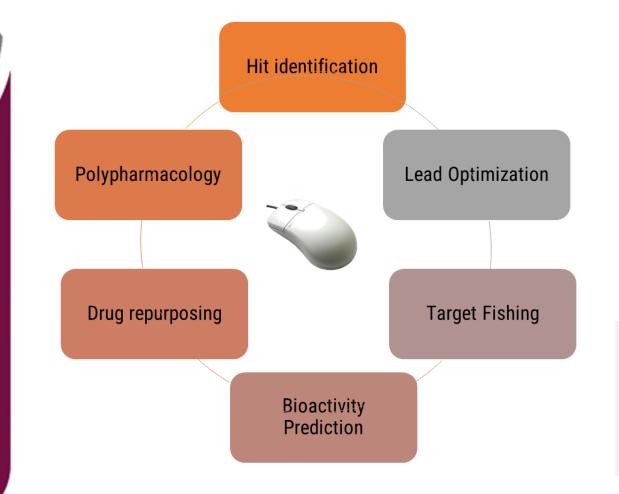
In-silico Drug Discovery/Repurposing

A knowledge-based inventive process





How in silico methods can be useful in drug discovery?



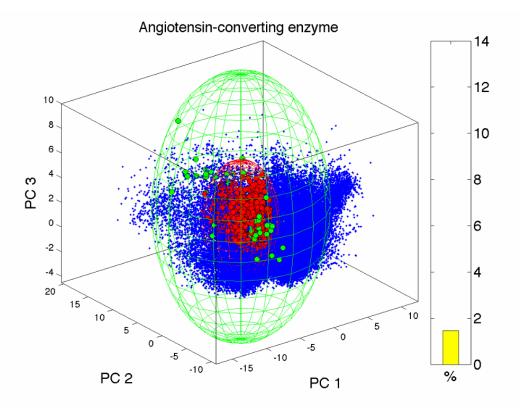
- ✓ Hit identification to identify compounds able to interact with confirmed activity against a biological target
- Lead Optimization improve potency, reduce off-target activities, and physiochemical/metabolic properties
- Target Fishing: identify potential target proteins that are likely to bind to a given small molecule
- Bioactivity Prediction: prediction of bioactivity values for a set of potential target proteins.
- Polypharmacology: interaction of drug molecules with multiple targets.
- Drug repurposing: discovering new uses for existing drugs originally developed to treat a different disease or condition.







Navigating from chemical to biology and medicine spaces



The continuum of the chemical space and the discrete areas of chemical space that are occupied by target and off-target compounds







Platforms for biological activity/ADMETox prediction

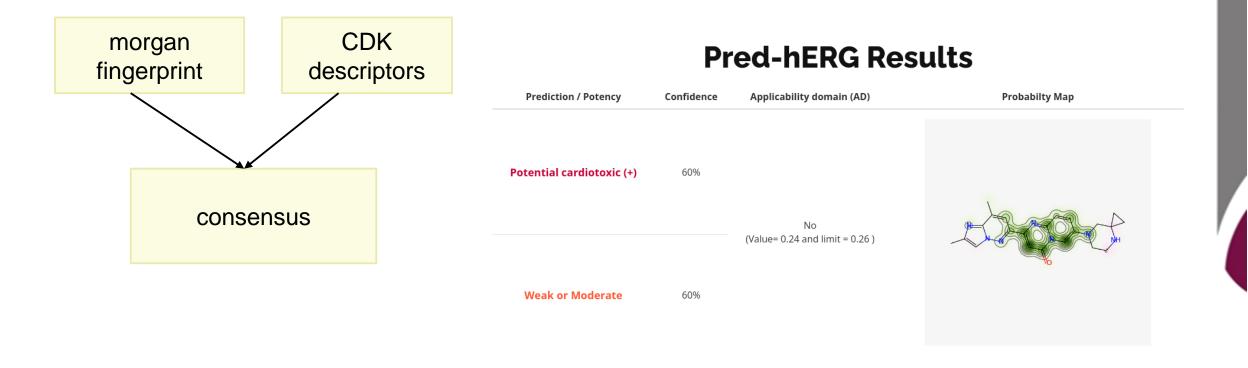
- Pred-herg : <u>http://predherg.labmol.com.br/predict</u>
- Venompred : <u>http://www.mmvsl.it/wp/venompred/</u>
- SwissADME : <u>http://www.swissadme.ch/index.php</u>







Pred-hERG: platform for cardiotoxicity prediction







VenomPred : platform for toxicity prediction

fingerprint based:

- 1. Morgan
- 2. RDKit
- 3. Pharm2D
- 4. PubChem
- 5. LINGO

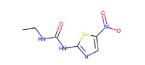
ML models:

- 1. Random Forest
- 2. Support Vector Machine
- 3. K Nearest Neighbour
- 4. MultiLayer Perceptron

VenomPred



VenomPred is a Machine Learning based platform for qualitative prediction of *mutagenicity, carcinogenicity, hepatotoxicity* and *estrogenicity* of chemicals.



Name	Entry_1
SMILES	CCNC(=0)NC1=NC=C(S1)[N+](=0)[O-]





Molecular Modeling & Virtual Screening Laboratory





Probability

37 %

7 %



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SwissADME

A website for computing descriptors and predicting ADME parameters, druglikeness of small molecules to support drug discovery

eliglustat			
👥 🛛 🖓 🏈			Water Solubility
	LIPO	Log S (ESOL) 🔞	-4.03
	\sim	Solubility	3.74e-02 mg/ml ; 9.25e-05 mol/l
сн, о	REX SIZE	Class 🔞	Moderately soluble
	Lundoh Carlos	Log S (Ali) 📀	-4.87
Ĥ		Solubility	5.43e-03 mg/ml ; 1.34e-05 mol/l
ĺ.		Class 📀	Moderately soluble
		Log S (SILICOS-IT) 🔞	-5.54
	•	Solubility	1.18e-03 mg/ml ; 2.91e-06 mol/l
	INSOLU	Class 🔞	Moderately soluble
000000000000000000000000000000000000000	NICAAUVICAAU		Pharmacokinetics
SMILES (c1ccc2c(c1)OCC	N[C@@H]([C@@H] 202)0)CN1CCCC1	GI absorption 🤨	High
Př	hysicochemical Properties	BBB permeant 📀	Yes
Formula	C23H36N2O4	P-gp substrate 🔞	No
Molecular weight	404.54 g/mol	CYP1A2 inhibitor 🗐	No
Num. heavy atoms	29	CYP2C19 inhibitor 8	No
Num. arom. heavy atoms	6	CYP2C9 inhibitor 🔞	No
Fraction Csp3	0.70	CYP2D6 inhibitor 📀	Yes
Num. rotatable bonds	12	CYP3A4 inhibitor @	No
Num. H-bond acceptors	5		-6.15 cm/s
Num. H-bond donors	2	Log K _p (skin permeation) 🤨	
Molar Refractivity	118.44 71.03 Ų	Lininalii 🙆	Druglikeness
TPSA 🔞		Lipinski 📀	Yes; 0 violation
Les B (1000) 0	Lipophilicity	Ghose 📀	Yes
Log P _{o/w} (iLOGP) 📀	4.20	Veber 🔞	No; 1 violation: Rotors>10
Log P _{o/w} (XLOGP3) 📀	3.69	Egan 🐵	Yes
Log P _{o/w} (WLOGP) 📀	2.73	Muegge 🤨	Yes
Log P _{o/w} (MLOGP) 📀	1.86	Bioavailability Score 🔞	0.55
Log P _{o/w} (SILICOS-IT) 📀	4.40		Medicinal Chemistry
Consensus Log Poly 0	3.38	PAINS 📀	0 alert
		Brenk 🔞	0 alert
		Leadlikeness 📀	No; 3 violations: MW>350, Rotors>7, XLOGP3>3.5
		Synthetic accessibility 📀	4.24

ALERTS MedChem

- PAINS: Pan-assay interference compounds. i.e., chemical compounds that often give false positive results in high-throughput screens. PAINS tend to react nonspecifically with numerous biological targets rather than specifically affecting one desired target.
- <u>Brenk</u>: hint to toxicity, but also poor stability or dying properties







Prometheus Lab

PLATO POLYPHARMACOLOGY PLATFORM PREDICTION



TIRESIA

TOXICOLOGY INTELLIGENCE AND REGULATORY EVALUATIONS FOR SCIENTIFIC AND INDUSTRY APPLICATIONS





CANNABINOID ITERATIVE REVALUATION FOR CLASSIFICATION AND EXPLAINABILITY





TIRESIA IMPROVED BY STRUCTURE-BASED EXPLAINABILITY

<< JUST SUBMITTED>>







Plato

<u>Polypharmacology pLAT</u>form for predicti<u>O</u>n

A ligand-based polypharmacology web drug discovery predictive platform designed for two-fold main objectives

a) target fishing

Target	score	reliable
Integrin alpha-IIb/beta-3:Homo sapiens	13.00	yes
Nicotinate phosphoribosyltransferase:Homo sapiens	13.00	yes
Cyclooxygenase-1:Bos taurus	13.00	yes
Gamma-glutamyltranspeptidase 1:Homo sapiens	13.00	yes
Cyclooxygenase-2:Homo sapiens	13.00	yes
Cyclooxygenase-1:Ovis aries	13.00	yes
Cyclooxygenase-2:Ovis aries	13.00	yes
Cyclooxygenase-1:Homo sapiens	13.00	yes
Complement factor D:Homo sapiens	8.66	yes
Complement factor D:Rattus norvegicus	8.66	yes
Carbonic anhydrase IX:Homo sapiens	7.54	yes

b) quantitative activity profiling

IC50	EC50	Ki	Kd	σ_P
6.57µM		1.78µM	$33.1 \mu \mathrm{M}$	1.5: IC50
$758 \mathrm{nM}$	330nM	6.17µM	$172 \mathrm{nM}$	1.5: IC50
		$0.39 \mathrm{nM}$		1.5: Ki
1.90µM		12.5µM		1.5: IC50
1.13µM				1.5: IC50
5.50µM		49.2µM	$266 \mathrm{nM}$	1.5: IC50
231nM	33.1nM	$192 \mathrm{nM}$	4.96nM	1.6: IC50
	6.57μM 758nM 1.90μM 1.13μM 5.50μM	6.57µМ 758nМ 330nМ 1.90µМ 1.13µМ 5.50µМ	6.57µМ 330nM 6.17µМ 758nM 330nM 6.17µМ 0.39nM 1.90µМ с. 12.5µМ 1.13µМ с. 12.5µМ	6.57µM 1.78µM 3.3.1µM 758nM 330nM 6.17µM 172nM 0.39nM 172nM 1.90µM 12.5µM 1.5 1.13µM 1.5 5.50µM 1.5 49.2µM 2.66nM







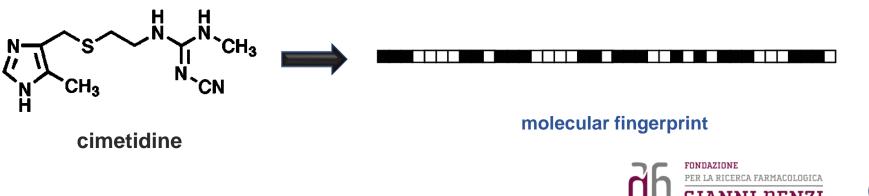
PLATO predictions



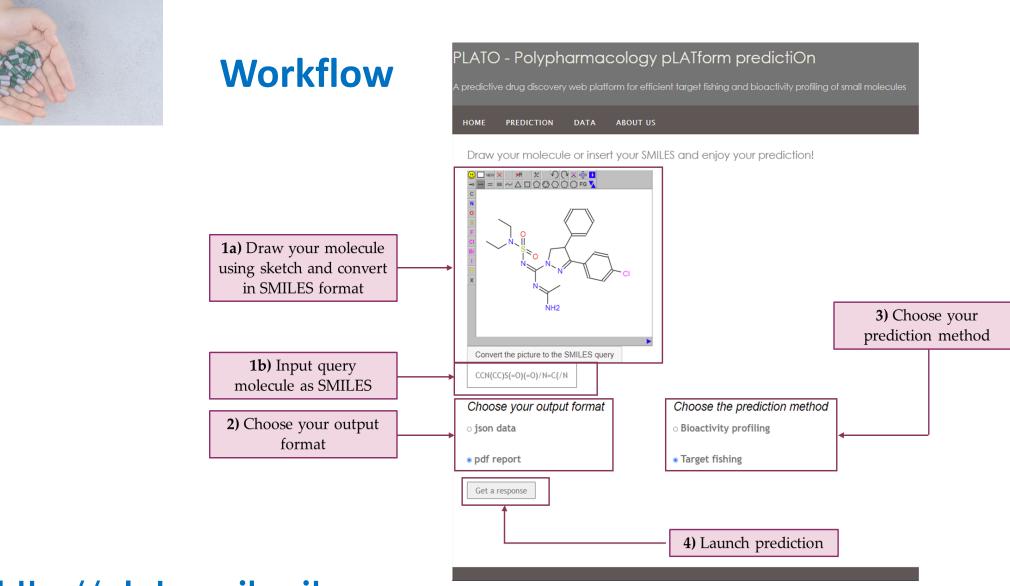
Based the similarity principle, through a reverse ligand-based screening, a large collection of experimentally active chemicals on > 6000 protein targets implementing two just optimized multifingerprint similarity-based algorithms, which have been recently published.

FINGERPRINTS

bit string or feature set representations of molecular structure and properties







http://plato.uniba.it







SCAN ME

DevTox is the study of adverse effects on the development of the organism:

- Abnormal Growth
- Any Alteration which interferes with Homeostasis

IRESIA

Structural or Functional Alteration



TIRESIA: An eXplainable Artificial Intelligence Platform for Predicting Developmental Toxicity

Maria Vittoria Togo, Fabrizio Mastrolorito, Fulvio Ciriaco, Daniela Trisciuzzi, Anna Rita Tondo, Nicola Gambacorta, Loredana Bellantuono, Alfonso Monaco, Francesco Leonetti, Roberto Bellotti, Cosimo Damiano Altomare, Nicola Amoroso* , and Orazio Nicolotti*

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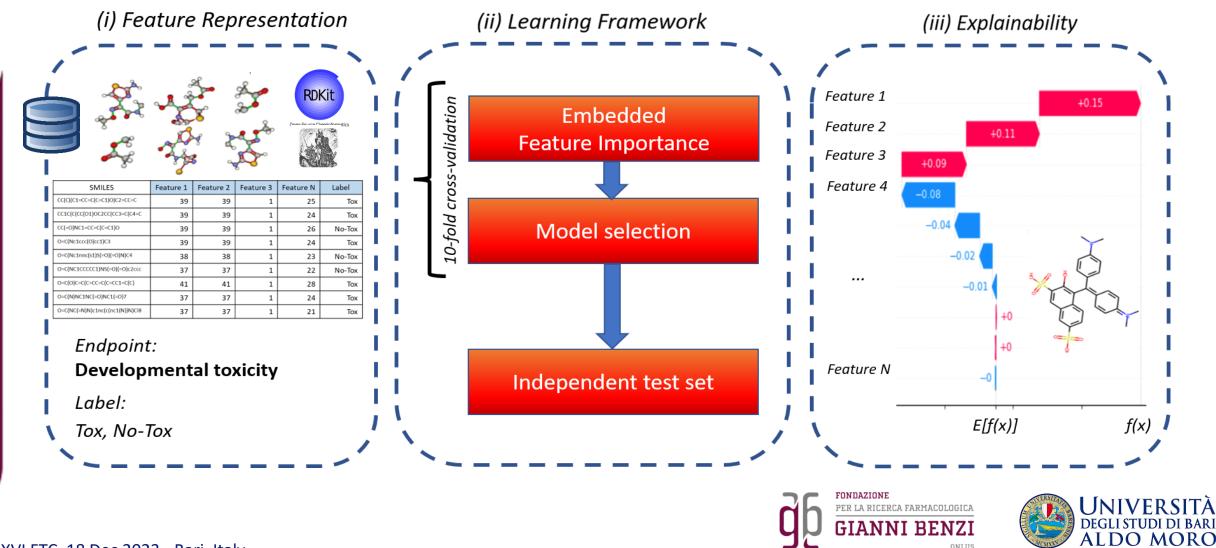








XAI framework for DevTox





Case study: ELIGUSTAT

A ceramide glucosyltransferase inhibitor as first line oral therapy for adults with Gaucher disease type 1 (a rare genetic disorder)







PLATO

Target	IC50	EC50	Ki	Kd	σ_P
Ceramide glucosyltransferase:Homo sapiens	48.6nM				1.1: IC50
Protein kinase C delta:Homo sapiens	$138 \mathrm{nM}$	$121 \mathrm{nM}$	$357 \mathrm{nM}$	$421 \mathrm{nM}$	2: Ki
Sigma-1 receptor:Cavia porcellus	$191 \mathrm{nM}$		$53.8 \mathrm{nM}$	$2.90 \mathrm{nM}$	2: Ki
Renin:Homo sapiens	24.0nM		$53.7 \mathrm{nM}$	23.6nM	2.1: IC50
NADH-ubiquinone oxidoreductase chain 1:Bos aurus	1.90µM				2.1: IC50
Mu opioid receptor:Homo sapiens	222 nM	$94.9 \mathrm{nM}$	$39.2 \mathrm{nM}$	$0.79 \mathrm{nM}$	2.1: Ki
Delta opioid receptor:Homo sapiens	$60.2 \mathrm{nM}$	$39.3 \mathrm{nM}$	104 nM	$24.9 \mathrm{nM}$	2.1: Ki
Kappa opioid receptor:Homo sapiens	482 nM	$34.2 \mathrm{nM}$	$34.9 \mathrm{nM}$	$1.67 \mathrm{nM}$	2.1: Ki
Peroxisome proliferator-activated receptor gamma:Homo sapiens	$229 \mathrm{nM}$	331nM	$132 \mathrm{nM}$	$172 \mathrm{nM}$	2.2: Ki
Protein kinase C epsilon:Homo sapiens	$395 \mathrm{nM}$	$11.3 \mu M$	$42.5 \mathrm{nM}$	106 nM	2.2: Ki
Protein kinase C gamma:Homo sapiens	486 nM		$743 \mathrm{nM}$	$0.47 \mathrm{nM}$	2.2: Ki
Protein kinase C beta:Homo sapiens	$160 \mathrm{nM}$	$0.56 \mathrm{nM}$	$50.1 \mathrm{nM}$	372 nM	2.2: Ki
Protein kinase C theta:Homo sapiens	$23.9 \mathrm{nM}$	$6.20 \mu M$	$140 \mathrm{nM}$	$252 \mathrm{nM}$	2.2: Ki
Protein kinase C eta:Homo sapiens	$61.1 \mathrm{nM}$		$32.8 \mathrm{nM}$	$67.9 \mathrm{nM}$	2.2: Ki
Protein kinase C alpha:Homo sapiens	206 nM		110 nM	497 nM	2.2: Ki
Peroxisome proliferator-activated receptor al- pha:Homo sapiens	$627 \mathrm{nM}$	$387 \mathrm{nM}$	$320 \mathrm{nM}$	331nM	2.2: EC50
Dopamine D2 receptor:Homo sapiens	137 nM	$38.2 \mathrm{nM}$	$142 \mathrm{nM}$	$61.3 \mathrm{nM}$	2.3: Ki
Serotonin 1a (5-HT1a) receptor:Rattus norvegicus	$37.0 \mathrm{nM}$	229 nM	$39.0 \mathrm{nM}$	$0.59 \mathrm{nM}$	2.3: Ki
Dopamine D3 receptor:Homo sapiens	$105 \mathrm{nM}$	$11.0 \mathrm{nM}$	$26.6 \mathrm{nM}$	$9.75 \mathrm{nM}$	2.3: Ki
Serotonin 7 (5-HT7) receptor:Rattus norvegicus	$1.20 \mu M$		$68.2 \mathrm{nM}$		2.3: Ki
Cannabinoid CB2 receptor:Homo sapiens	277nM	48.4nM	79.0nM	13.2nM	2.3: Ki
FUNDAZIUNE		VERSIT			

GIANNI

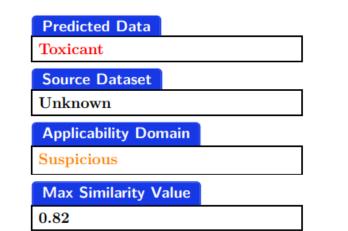


palpitations: advertized collateral effect

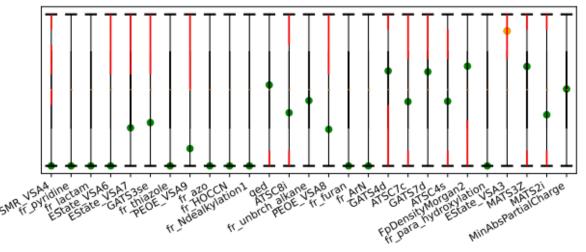
main target: pharmacological effect

recognized collateral effects for eliglustat are also: analgesia, sedation, low blood pressure, itching, nausea and constipation due to reduced intestinal mobility



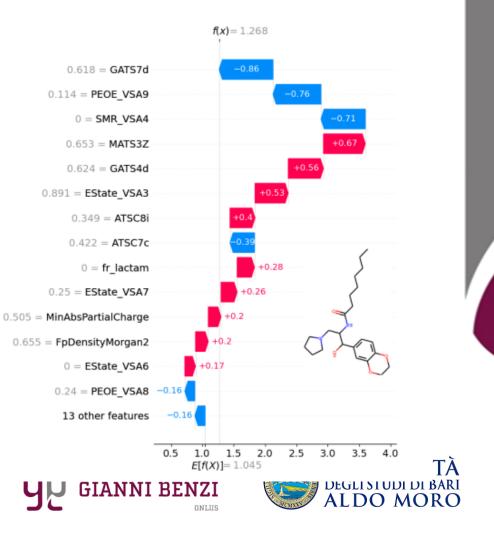






Eligustat on TIRESIA

Explainability



Prediction Toxicant (score=0.72)

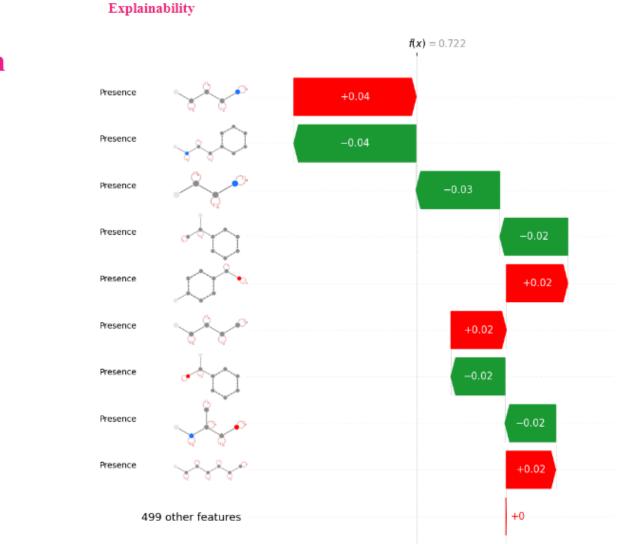
Eligustat on TISBE

FONDAZIONE

PER LA RICERCA FARMACOLOGICA

GIANNI BENZI

ONLUS



0.70

0.72

0.68

0.74

0.76

E[f(X)] = 0.754

0.78

UNIVERSITÀ degli studi di bari ALDO MORO

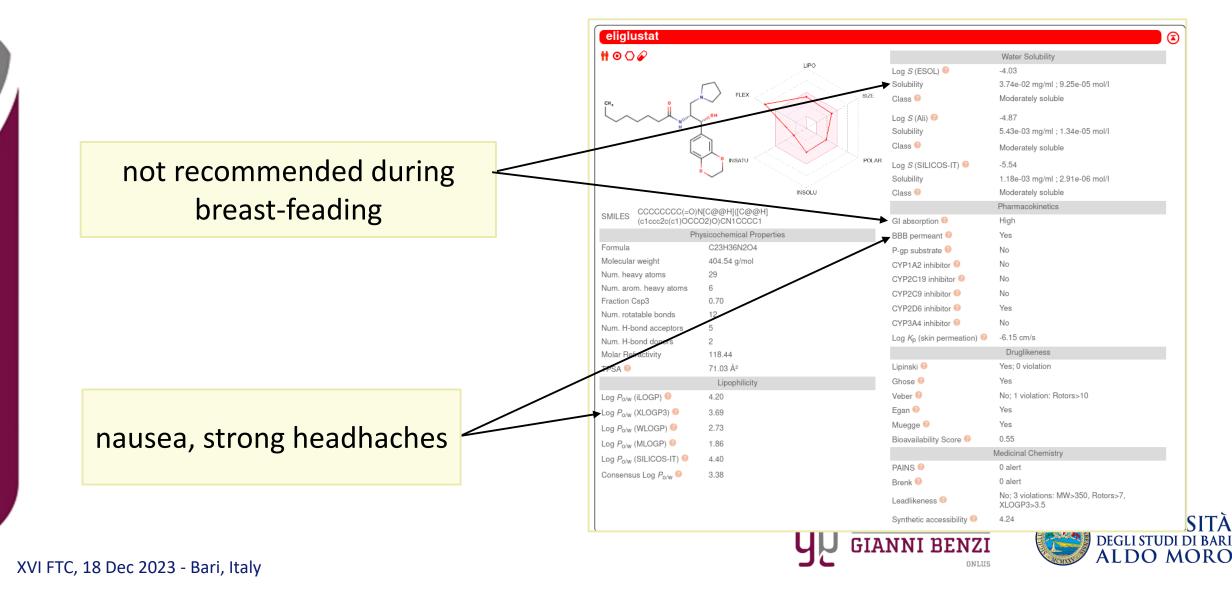
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Already in Dataset

False



SwissADME

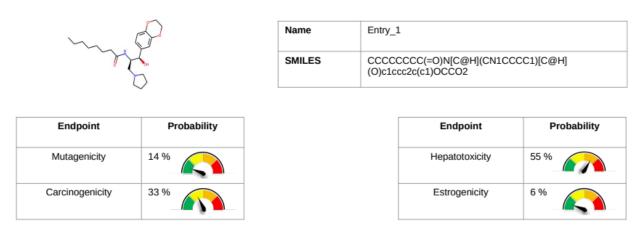




VenomPred



VenomPred is a Machine Learning based platform for qualitative prediction of *mutagenicity, carcinogenicity, hepatotoxicity* and *estrogenicity* of chemicals.



The main article describing the web service and its underlying methodologies is: VenomPred: A Machine Learning Based Platform for Molecular Toxicity Predictions. Int. J. Mol. Sci. 2022, 23, 2105



Pred-hERG Results

Prediction / Potency	Confidence	Applicability domain (AD)	Probabilty Map
Non-cardiotoxic (-)	50%	Yes Maluar 0.27 and limit = 0.26 \	and a second
Not applicable	Not applicable	(Value= 0.27 and limit = 0.26)	A







Take-home message

- Better integrative platforms for data analysis
- Greater access to data from industry-sponsored phase 2b-4 clinical trials
- Newer safety liabilities of repurposed drugs should be studied
- Funding opportunities for drug repurposing in general, but especially for rare diseases







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Thanks for the attention

