



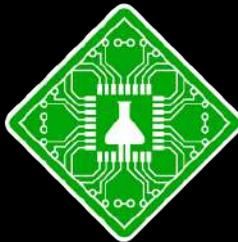
**Insilico  
Medicine**

# Maximizing PTRS: Generative AI and Robotics for End-to-End Drug Discovery and Developme

SCRI SYMPOSIUM, SINGAPORE, JULY, 2024

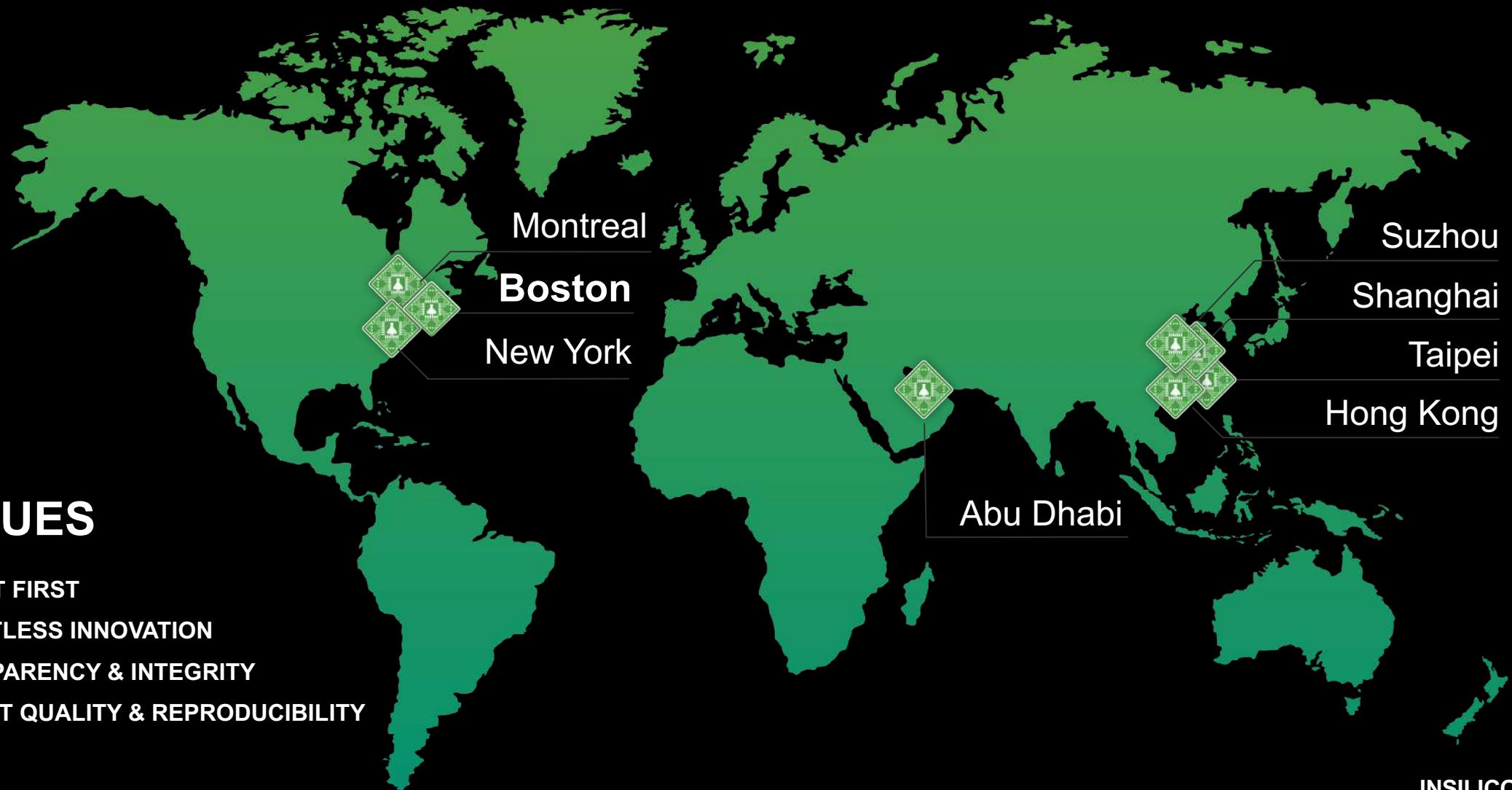


**Alex Zhavoronkov, PhD**  
Founder and CEO  
[alex@insilico.com](mailto:alex@insilico.com)

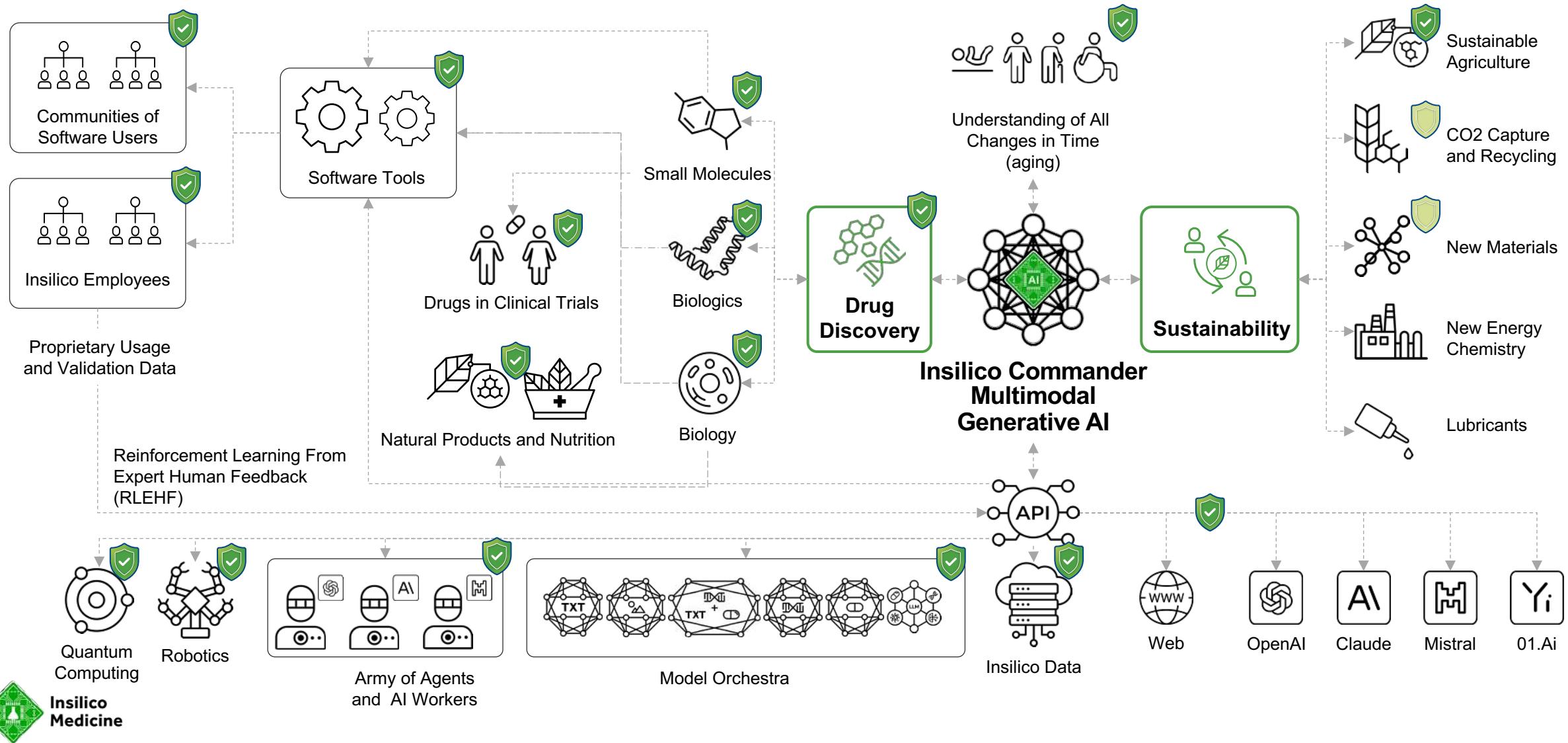


**Insilico  
Medicine**

**A GLOBAL DEEP LEARNING-FIRST CLINICAL-STAGE  
GENERATIVE AI AND ROBOTICS COMPANY ESTABLISHED IN 2014**  
TO EXTEND HEALTHY PRODUCTIVE LONGEVITY FOR EVERYONE



# Insilico Generalist Generative AI Platform For Multimodal Multi-Industry Multi-Domain Learning



# 2024 Most Innovative Biotechnology Company Globally



Insilico  
Medicine

<https://www.fastcompany.com/91034883/biotech-most-innovative-companies-2024>

03-19-2024 | MOST INNOVATIVE COMPANIES 2024

## The most innovative companies in biotech in 2024

Why Insilico Medicine, ElevateBio, Inato, and Exscientia are among Fast Company's Most Innovative Companies in Biotech in 2024.

BIO TECH



### 1. INSILICO MEDICINE

For zooming in on drug-disease targets

### 2. ELEVATEBIO

For catching genetic disorders at the root

### 3. PERSONALIS

For detecting cancers with precision

### 4. EXSCIENTIA

For using AI to personalize cancer treatments

### 5. ROCKET PHARMACEUTICALS

For targeting rare diseases with gene therapy

### 6. GUARDANT HEALTH

For doubling down on cancer detection

### 7. INATO

For bringing clinical trials to local hospitals

### 8. ELUCIDATA

For cleaning up messy biomedical data

### 9. MARAVAI LIFESCIENCES

For improving the safety of immunotherapy

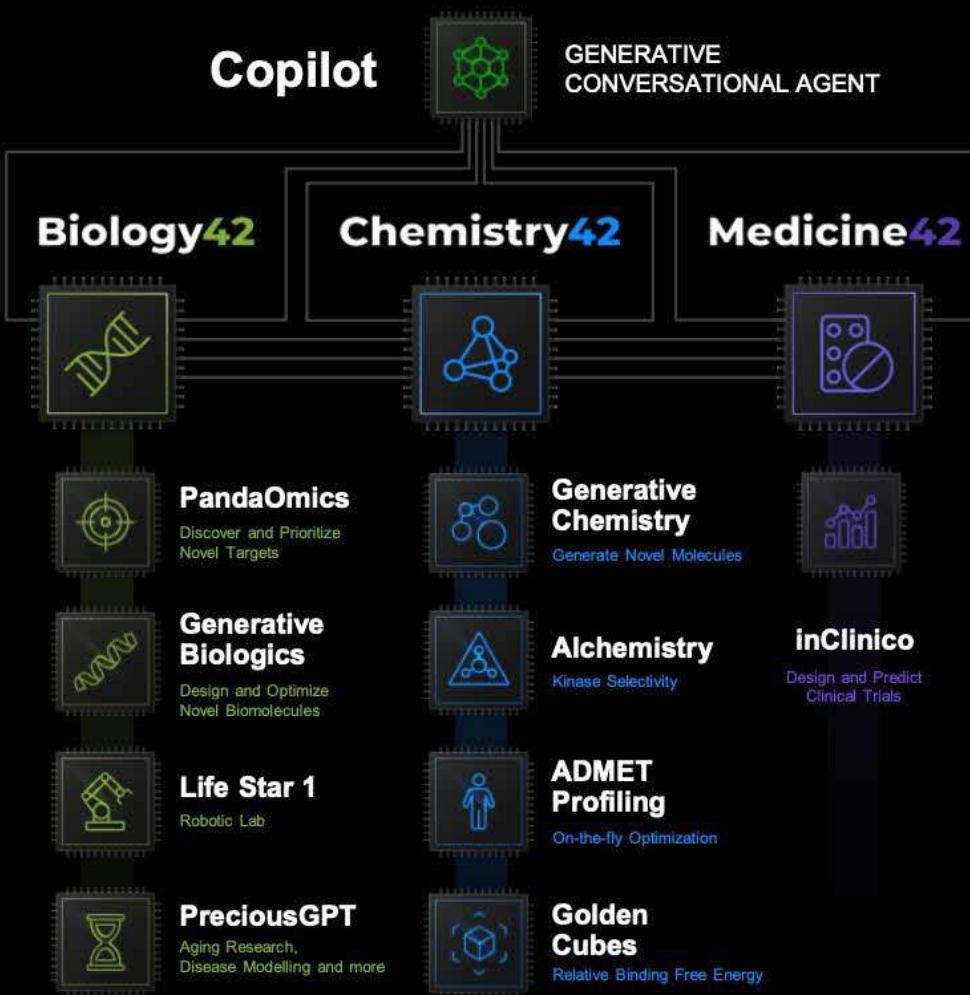
### 10. EMERALD CLOUD LAB

For providing 24/7 lab services in the cloud

# Pharma.AI Platform

# Drug Discovery Pipeline

PLATFORMS



## INDICATION

	TARGET ID	HIT TO LEAD	LEAD OPT.	IND-ENABLING	PHASE I	PHASE II
Idiopathic Pulmonary Fibrosis (IPF)	TNIK				New Zealand	US (FDA)
Idiopathic Pulmonary Fibrosis	TNIK				China	China (NMPA)
Kidney Fibrosis	TNIK					
IPF (Inhalable)	TNIK					
BRCA-mutant cancer	USP1					Out-licensed to Exelixis
Immuno-Oncology	QPCTL					Co-development with Fosun Pharma
Inflammatory Bowel Disease	PHD					Gut-restricted
Anemia of Chronic Kidney Disease	PHD					
MTAP-/ Cancer	MAT2A					IND clearance in US & CN
Mesothelioma, and Solid Tumors	TEAD					
Solid tumors	ENPP1					
ER+/HER2- breast cancer	KAT6					Out-licensed to Menarini
Solid tumors	DGKA					
Solid tumors	CDK12/13					
Solid tumors	FGFR2/3					
Solid tumors	KIF18A					
Solid tumors	WRN					
COVID-19	3CL PRO					

Over 20 additional newly initiated programs in the discovery stage

\*As of May 2024

# Some Internal Benchmarks at Insilico Medicine

# Started Internal Drug Discovery in 2019

- 18 Preclinical Candidates (PCC) Nominated
- 8 Human Clinical Trials
- 2 in Phase II
- Average Time to PCC is 13 Months
- Shortest Time to PCC – 9 Months
- Longest Time to PCC – 18 Months
- In 2022 Nominated 9 PCCs
- Annual Capacity ~ 12 PCCs

# Biology42: Disease Modeling, Target Discovery and Indication Expansion Platform

60+ Target Discovery Philosophies  
25+ AI Models

User Base: Biotechnology Companies, Pharma, Academics (thousands)

# Chemistry42: Generative Chemistry Platform

40+ Generative Models  
500+ Predictive Models

Alchemistry – quantum chemistry platform

User Base: Pharma Companies (10 out of top 20)

RETURN TO ISSUE | < PREV APPLICATION NOTE NEXT >

## PandaOmics: An AI-Driven Platform for Therapeutic Target and Biomarker Discovery

Petrina Kamya, Ivan V. Ozerov, Frank W. Pun, Kyle Tretina, Tatyana Fokina, Shan Chen, Vladimir Naumov, Xi Long, Sha Lin, Mikhail Korzinkin, Daniil Polykovskiy, Alex Aliper, Feng Ren, and Alex Zhavoronkov\*

Cite this: *J. Chem. Inf. Model.* 2024, 64, 10, 3961–3969

Publication Date: February 25, 2024

https://doi.org/10.1021/acs.jcim.3c01119

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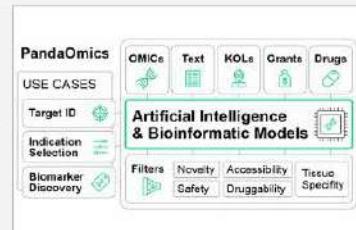
Supporting Info (2) »

SUBJECTS: Biomarkers, Genetics, Mathematical methods, Physiology, Therapeutics

### Abstract

PandaOmics is a cloud-based software platform that applies artificial intelligence and bioinformatics techniques to multimodal omics and biomedical text data for therapeutic target and biomarker discovery. PandaOmics generates novel and repurposed therapeutic target and biomarker hypotheses with the desired properties and is available through licensing or collaboration. Targets and biomarkers generated by the platform were previously validated in both *in vitro* and *in vivo* studies. PandaOmics is a core component of Insilico Medicine's Pharma.ai drug discovery suite, which also includes Chemistry42 for the *de novo* generation of novel small molecules, and inClinico—a data-driven multimodal platform that forecasts a clinical trial's probability of successful transition from phase 2 to phase 3. In this paper, we demonstrate how the PandaOmics platform can efficiently identify novel molecular targets and biomarkers for various diseases.

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## Chemistry42: An AI-Driven Platform for Molecular Design and Optimization

Yuri A. Ivanenkov, Daniil Polykovskiy, Dmitry Bezrukov, Bogdan Zagribelnyy, Vladimir Aladinsky, Petrina Kamya, Alex Aliper, Feng Ren, and Alex Zhavoronkov\*

Cite this: *J. Chem. Inf. Model.* 2023, 63, 3, 696–701

Publication Date: February 2, 2023

https://doi.org/10.1021/acs.jcim.2c01191

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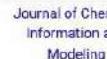
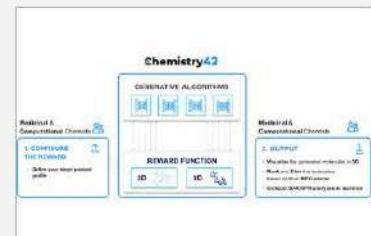
Supporting Info (1) »

SUBJECTS: Drug discovery, Inhibitors, Molecular structure, Molecules, Protein structure

### Abstract

Chemistry42 is a software platform for *de novo* small molecule design and optimization that integrates Artificial Intelligence (AI) techniques with computational and medicinal chemistry methodologies. Chemistry42 efficiently generates novel molecular structures with optimized properties validated in both *in vitro* and *in vivo* studies and is available through licensing or collaboration. Chemistry42 is the core component of Insilico Medicine's **Pharma.ai** drug discovery suite. Pharma.ai also includes PandaOmics for target discovery and multimodal data analysis, and inClinico—a data-driven multimodal forecast of a clinical trial's probability of success (PoS). In this paper, we demonstrate how the platform can be used to efficiently find novel molecular structures against DDR1 and CDK2α.

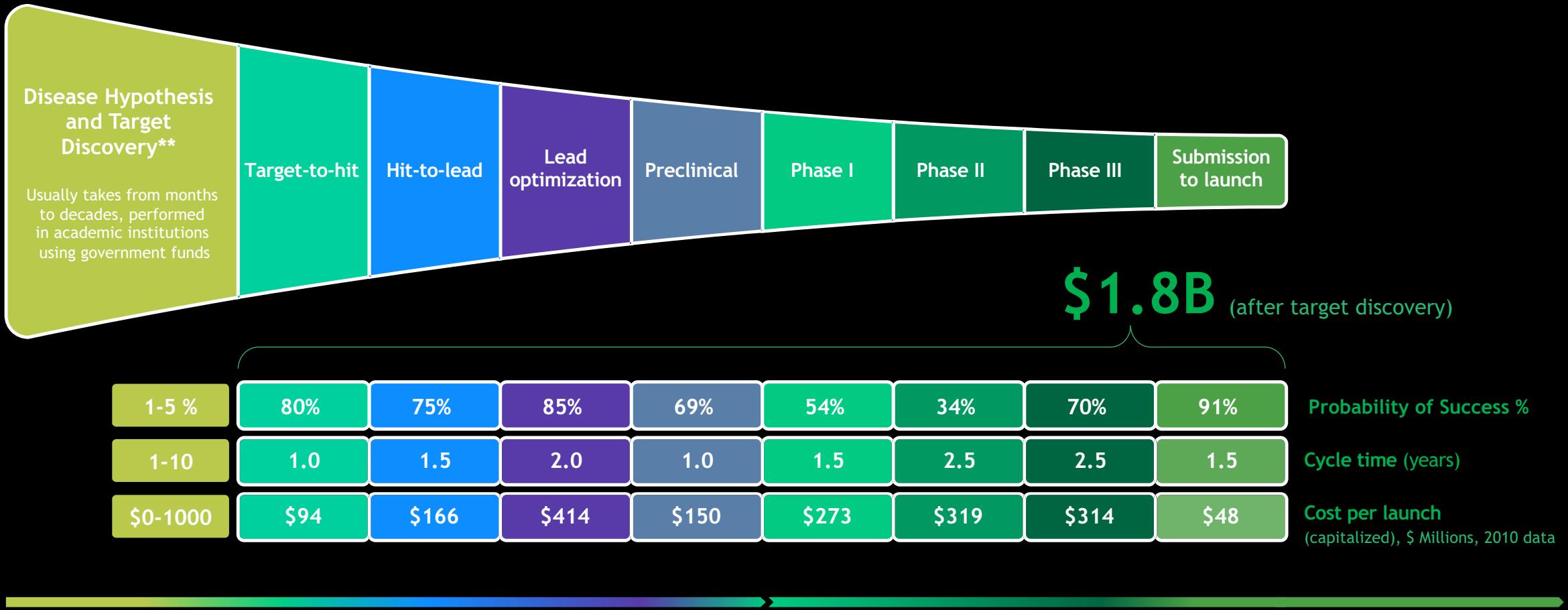
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# Why End-to-End Drug Discovery and Development AI to Increase PTRS?

# Why End-to-End Drug Discovery and Development AI?

- Click to edit Master text styles



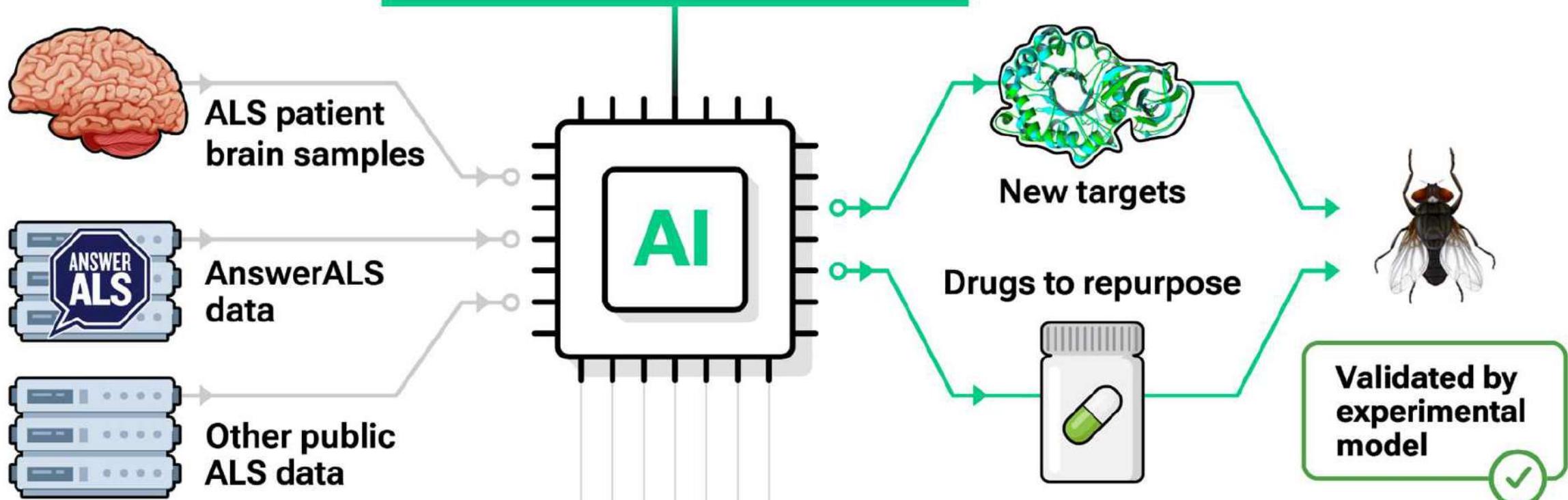
\* Modified from Paul et al, How to improve R&D productivity: the pharmaceutical industry's grand challenge.  
Nature Reviews Drug Discovery , 2010

\*\* Based on interviews with the pharmaceutical industry executives

# What Can Generative AI Do For You Today?

# It Can Discover and Prioritize Protein Targets

# 'panda' Omics



**Frank Pun, PhD**  
Head, Insilico HK



**Merit Cudlowicz, MD**  
Chief of Neurology and Director  
of the Healey & AMG Center  
for ALS at Mass General Hospital  
and Harvard Medical School



**Jeffrey D.  
Rothstein, MD**  
Director, Robert Packard  
Center for ALS Research  
and Answer ALS



**Bai Lu, PhD**  
Professor at Tsinghua  
University and founder  
of 4B Technologies



**Ke Zhang, PhD**  
Professor of  
Neuroscience,  
Mayo Clinic

# ALS.AI

In collaboration with Answer ALS, Johns Hopkins University and Mayo Clinic

## OBJECTIVE

Apply Insilico AI-powered target discovery platform to search for novel targets and repurposed drugs for ALS

## VALUE

Our study exemplifies the full potential of PandaOmics for target discovery with *in vivo* validation



Insilico Medicine

An end-to-end artificial intelligence-driven drug discovery company

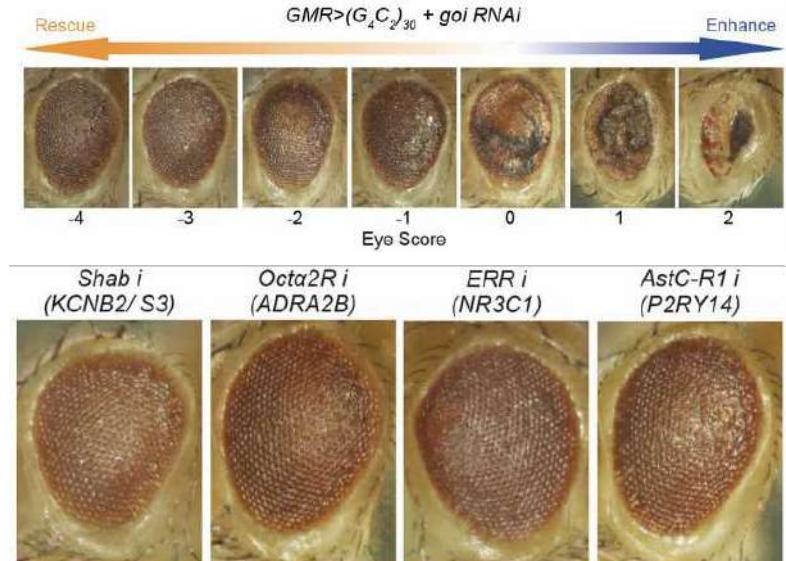


We develop artificial intelligence platforms that utilize deep generative models, reinforcement learning transformer, and other modern machine learning techniques for novel target discovery and generation of novel molecular structures with desired properties. We focus on developing breakthrough solutions for the discovery and development of innovative drugs for cancer, fibrosis, infectious diseases, autoimmune diseases, and age-related diseases.

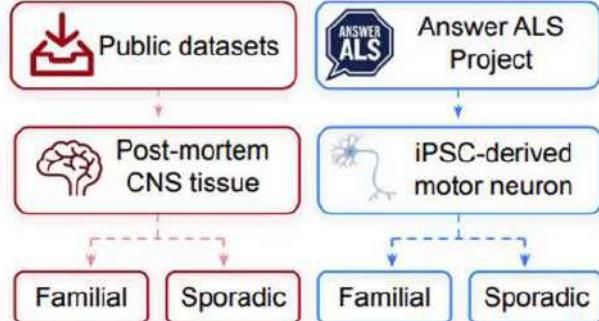
Since 2014, Insilico Medicine has established strategic collaborations with more than 30 pharmaceutical and biotechnology companies and academic research groups in the United States, Europe, China, Japan and other countries and regions, and launched multiple internal R&D pipelines for novel, difficult and previously undruggable targets.

## RESULT

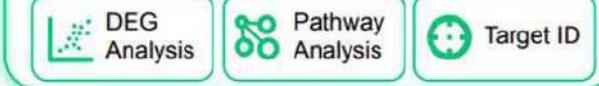
Twenty-eight potential therapeutic targets that participate in a wide range of well-characterized ALS mechanisms were identified. Among the 26 proposed targets screened in the c9ALS *Drosophila* model, we verified 8 unreported genes whose perturbations strongly rescued eye neurodegeneration.



## Amyotrophic lateral sclerosis



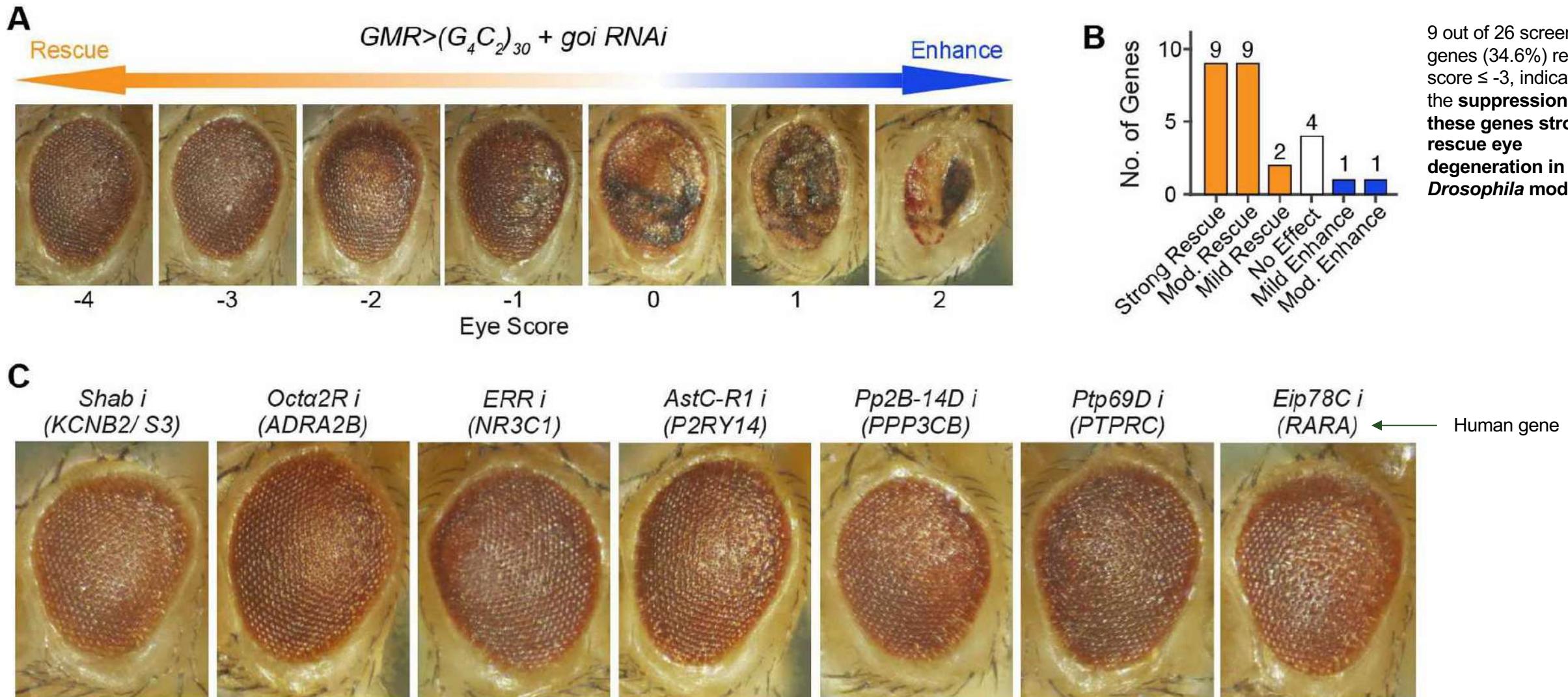
## pandaOmics



Known Targets + Novel Targets

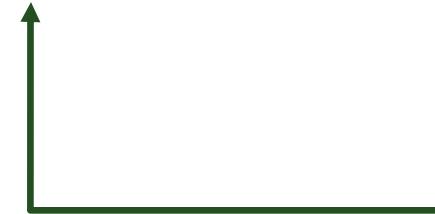


# Loss of 7 unreported fly orthologs, corresponding to 8 genes, strongly rescued ( $G_4C_2$ )<sub>30</sub>- mediated neurodegeneration in a c9ALS *Drosophila* model



# 4B Technologies just enrolled ~64 patients in a clinical trial

## From discovery into patients in <1 year



**Frank Pun, PhD**  
Head, Insilico HK



**Merit Cudlowicz, MD**  
Chief of Neurology and Director  
of the Healey & AMG Center  
for ALS at Mass General Hospital  
and Harvard Medical School



**Jeffrey D.  
Rothstein, MD**  
Director, Robert Packard  
Center for ALS Research  
and Answer ALS



**Bai Lu, PhD**  
Professor at Tsinghua  
University and founder  
of 4B Technologies



**Ke Zhang, PhD**  
Professor of  
Neuroscience,  
Mayo Clinic

**It Can Generate Compounds For  
Targets Without Crystal Structure**

## AI Discovers Target

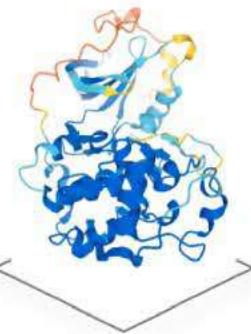
**panda**Omics



Identification of CDK20

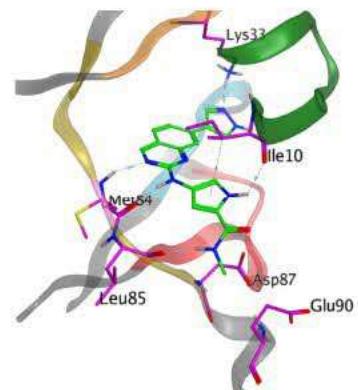
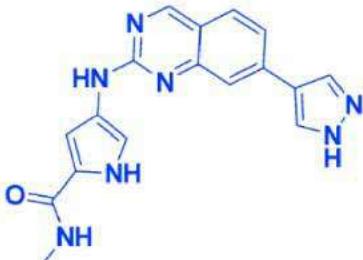
## AI Predicts Crystal

**AlphaFold**

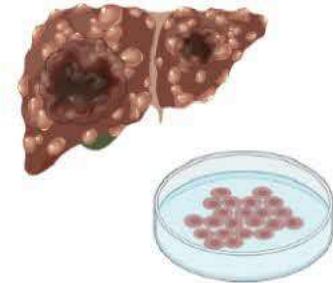


## AI Generates Molecules

**Chemistry42**



## Validation



Issue 5, 2023



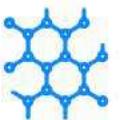
## Chemical Science

AlphaFold accelerates artificial intelligence powered drug discovery: efficient discovery of a novel CDK20 small molecule inhibitor<sup>†</sup>

### 2 rounds of compound generation in Chemistry42



First round generated bioactive compounds  
*SBDD approach*  
**KD (nM) = 7300**



Second round enhanced compound activity  
*Privileged Structure approach*  
**KD (nM) = 180**

Feng Ren, Xiao Ding, Min Zheng, Mikhail Korzinkin, Xin Cai, Wei Zhu, Alexey Mantsyzov, Alex Aliper, Vladimir Aladinskiy, Zhongying Cao, Shanshan Kong, Xi Long, Bonnie Hei Man Liu, Yingtao Liu, Vladimir Naumov, Anastasia Shneyderman, Ivan V. Ozerov, Ju Wang, Frank W. Pun, Daniil Polykovskiy, Chong Sun, Michael Levitt, Alán Aspuru-Guzik and Alex Zhavoronkov



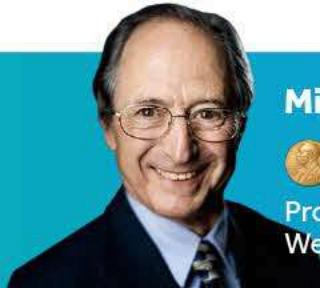
**Alex Zhavoronkov, PhD**

Founder & CEO,  
Insilico Medicine



**Feng Ren, PhD**

Co-CEO & CSO,  
Insilico Medicine



**Michael Levitt, PhD**

2013 Nobel Laureate  
in Chemistry  
Professor, Stanford University,  
Weizmann University



**Alán Aspuru-Guzik, PhD**

Professor and Director,  
University of Toronto,  
Former professor,  
Harvard University

**It Can Generate Compounds With  
The Desired Properties for a Broad  
Range of Targets**

## Review article

<https://doi.org/10.1038/s42256-024-00843-5>

# Machine learning-aided generative molecular design

Received: 19 July 2023

Accepted: 24 April 2024

Published online: 18 June 2024

Yuanqi Du<sup>1,10</sup> , Arian R. Jamasb<sup>2,3,9,10</sup>  Jeff Guo<sup>4,5,10</sup> Tianfan Fu<sup>6</sup> , Charles Harris<sup>3</sup>  Yingheng Wang<sup>1</sup> Chenru Duan<sup>7</sup> , Pietro Liò<sup>3</sup>  Philippe Schwaller<sup>4,5</sup> Tom L. Blundell<sup>8</sup> 

Machine learning has provided a means to accelerate early-stage drug discovery by combining molecule generation and filtering steps in a single architecture that leverages the experience and design preferences of medicinal chemists. However, designing machine learning models that can achieve this on the fly to the satisfaction of medicinal chemists remains a challenge owing to the enormous search space. Researchers have addressed de novo design of molecules by decomposing the problem into a series of tasks determined by design criteria. Here we provide a comprehensive overview of the current state of the art in molecular design using machine learning models as well as important design decisions, such as the choice of molecular representations, generative methods and optimization strategies. Subsequently, we present a collection of practical applications in which the reviewed methodologies have been experimentally validated, encompassing both academic and industrial efforts. Finally, we draw attention to the theoretical, computational and empirical challenges in deploying generative machine learning and highlight future opportunities to better align such approaches to achieve realistic drug discovery end points.

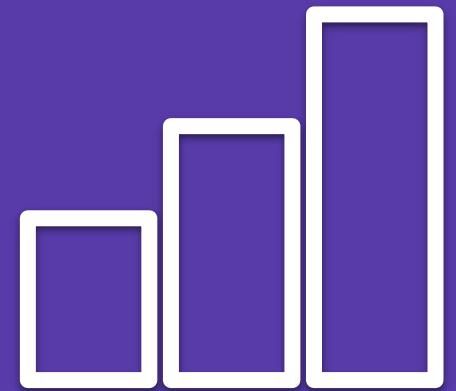
Table 4 | Experimentally validated small-molecule generative design case studies

Model	Input	Output	Design task	Target	Hit rate	Outcome	Publication year
<b>Distribution learning</b>							
LSTM RNN <sup>146</sup>	SMILES	SMILES	De novo	RXR	4/5 (80%)	nM agonist	2018
LSTM RNN <sup>147</sup>	SMILES	SMILES	De novo	RXR	2/4 (50%)	μM agonist	2018
GraphGMVAE <sup>148</sup>	Graph	SMILES	Scaffold hopping	JAK1	7/7 (100%)	nM inhibitor	2021
LSTM RNN <sup>149</sup>	SMILES	SMILES	De novo	LXR	17/25 (68%)	μM agonist	2021
LSTM RNN <sup>150</sup>	SMILES	SMILES	De novo	ROR $\gamma$	3/3 (100%)	μM agonist	2021
LSTM RNN <sup>151</sup>	SMILES	SMILES	De novo	FLT3	1/1(100%)	μM inhibitor	2022
GGNN GNN <sup>151</sup>	Graph	Graph	Fragment linking	CDK8	9/43 (21%)	nM inhibitor	2022
GRU RNN <sup>152</sup>	SMILES	SMILES	De novo	Bacteria	0/1 (0%) <sup>a</sup>	μM inhibitor	2022
BIRNN encoder-decoder <sup>153</sup>	SMILES	SMILES	De novo	DDR1	2/2 (100%)	nM inhibitor	2021
GRU RNN <sup>154</sup>	SMILES	SMILES	Reaction-based de novo	MERTK	15/17 (88%)	μM inhibitor	2022
LSTM RNN <sup>155</sup>	SMILES	SMILES	De novo	PI3K $\gamma$	3/18 (17%)	nM inhibitor	2023
Transformer <sup>156</sup>	SMILES	SMILES	Fragment linking	TBK1	1/1(100%)	nM inhibitor	2023
VAE and transformer <sup>157</sup>	SMILES	SMILES	Fragment hopping/linking	CDK2	17/23 (74%) <sup>f</sup>	nM inhibitor (MC) <sup>b</sup>	2023
LSTM RNN <sup>158</sup>	SMILES	SMILES	De novo	Nurr1 $\gamma$	2/6 (33%)	nM inhibitor	2023
Graph-transformer-LSTM RNN <sup>159</sup>	Graph	SMILES	De novo	PPAR $\gamma$	2/2 (100%)	μM agonist	2023
<b>Goal-oriented</b>							
DNC <sup>160</sup>	SMILES	SMILES	De novo	Kinases	0 <sup>a</sup>	μM inhibitor	2018
AAE (conditional) <sup>160</sup>	SMILES	SMILES	De novo	JAK3	1/1(100%)	μM inhibitor	2018
VAE <sup>161</sup>	SMILES	SMILES	De novo	DDR1	4/6 (67%)	nM inhibitor <sup>b</sup>	2019
LSTM RNN <sup>162</sup>	SMILES	SMILES	De novo ligand based	DDR1	4/6 (67%)	nM inhibitor	2021
Stack-GRU RNN <sup>163</sup>	SMILES	SMILES	De novo	EGFR	4/15 (27%)	nM inhibitor	2022
LSTM RNN (conditional) <sup>167</sup>	SMILES	SMILES	De novo	RIPK1	4/8 (50%)	nM inhibitor <sup>b</sup>	2022
Chemistry42 <sup>168</sup>	Mixed	Mixed	De novo structure based	CDK20	6/13 (46%) <sup>a</sup>	nM inhibitor	2023
Chemistry42 <sup>169</sup>	Mixed	Mixed	De novo structure based	CDK8	1/1(100%)	nM inhibitor <sup>b</sup>	2023
Chemistry42 <sup>170</sup>	Mixed	Mixed	De novo structure based (R-group)	SIK2	6/6 (100%)	nM inhibitor	2023
VAE <sup>165</sup>	SMILES	SMILES	De novo structure based	KOR	2/5 (40%)	μM antagonist	2023
Chemistry42 <sup>166</sup>	Mixed	Mixed	De novo structure based	PHD enzymes	1/1(100%)	nM inhibitor <sup>b</sup>	2024
GRU RNN-transformer <sup>165</sup>	SMILES	SMILES	De novo activity model	NLRP3	0 <sup>a</sup>	nM inhibitor <sup>b</sup>	2024
Transformer-VAE (conditional) <sup>166</sup>	Geometry-SMILES	SMILES	De novo	Tuberculosis ClpP	1/6 (17%) <sup>a</sup>	μM inhibitor	2024
QC-LSTM RNN-Chemistry42 <sup>167</sup>	SMILES	SMILES	De novo structure based	KRAS	1/12 (8%) <sup>a</sup>	μM inhibitor	2024
Graph transformer <sup>168</sup>	Graph	Graph	De novo activity model	MGLL	1/3 (33%) <sup>a</sup>	μM inhibitor	2024
Chemistry42 <sup>169</sup>	Mixed	Mixed	Fragment linking	Pol $\theta$	4/6 (67%)	μM inhibitor <sup>b</sup>	2024
Chemistry42 <sup>171</sup>	Mixed	Mixed	De novo structure based	TNIK	Unknown <sup>f</sup>	nM inhibitor <sup>b</sup>	2024
Attention-convolution layers <sup>172</sup>	Substructure vector	SMILES	Scaffold based	Factor Xa	Unknown <sup>a</sup>	μM inhibitor	2024
Flow (conditional) <sup>171</sup>	Geometry	Geometry	De novo	HAT1 and YTHDC1	0/2 and 0/3 (0%) <sup>a</sup>	Both μM inhibitor <sup>a</sup>	2024
Activity model (MCTS) <sup>173</sup>	Variable	Variable	Reaction based	Bacteria	6/58 (10%)	μg inhibitor <sup>b</sup>	2024
Chemistry42 <sup>172</sup>	Mixed	Mixed	De novo structure based	KIF18A	Unknown <sup>a</sup>	nM inhibitor <sup>b</sup>	2024
Diffusion (conditional) <sup>173</sup>	Geometry	Geometry	Lead optimization	CDK2	7/7 (100%)	nM inhibitor (MC)	2024

**It Can Predict Outcomes of Some  
Clinical Trials and Help With Go-No-  
Go Decisions and Clinical Trial  
Design**



**Multi-modal artificial intelligence  
platform for predicting and  
optimizing clinical trial  
outcomes**



# Platform capabilities



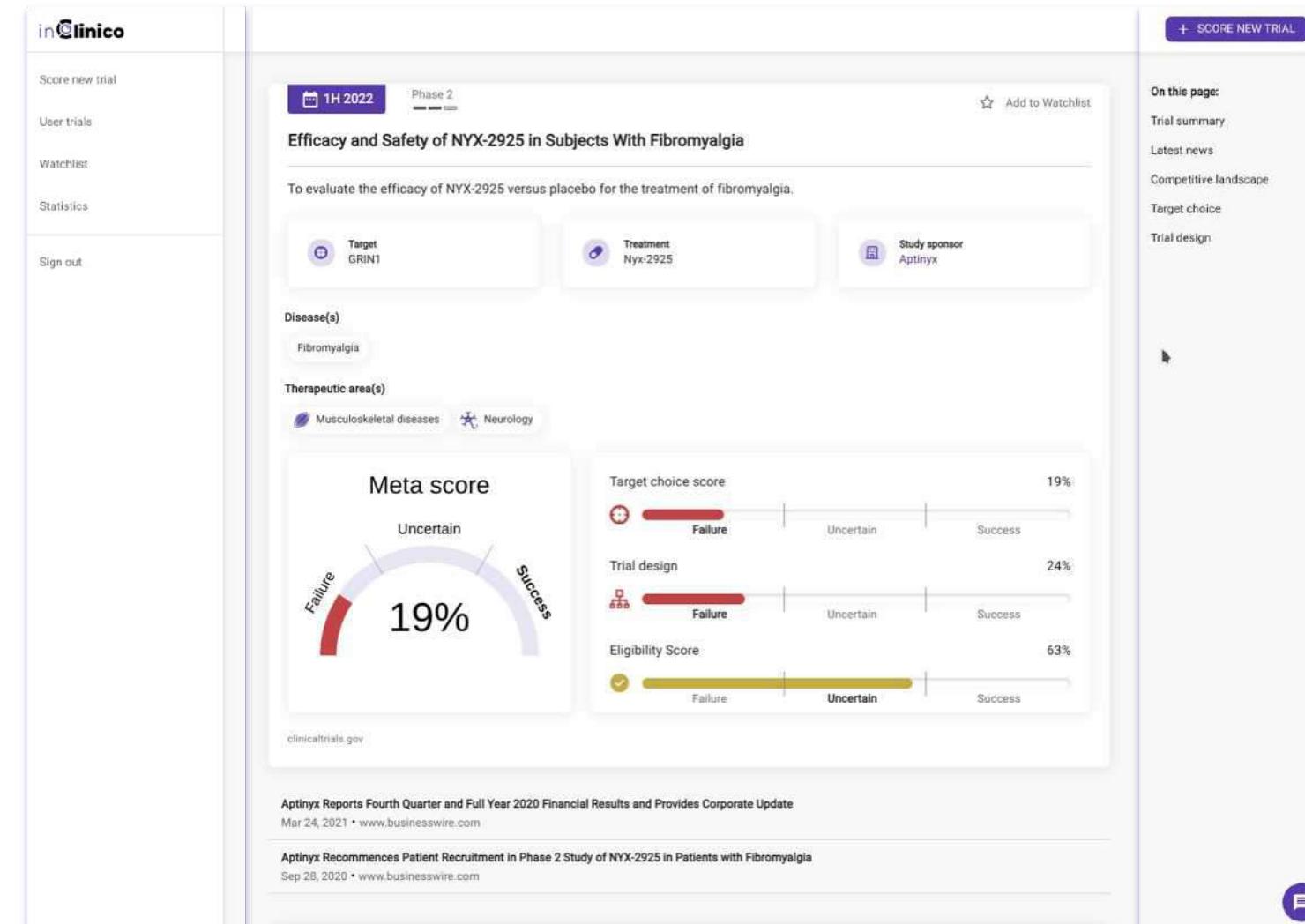
**Get data-driven forecasts** of clinical trial outcomes



**Explore and analyze clinical landscape** for the given disease, therapeutic area

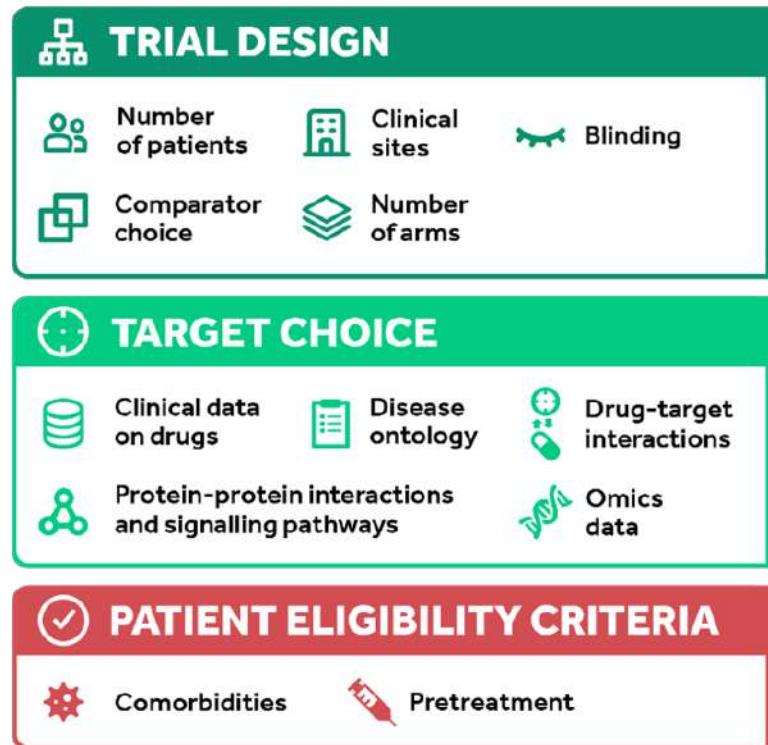


**Score your trials**, prioritize programs in early stages and optimize trial designs to improve probability of success



\*Validated for Phase 2 clinical trials

# Platform – approach



The **InClinico** platform scoring methods rely on the state-of-the-art ML models for multimodal assessment of clinical trial probability of success (PoS)

**Comprehensive dataset**  
with extensive mappings on  
**multiple data sources**

**150k**  
trials

**41k**  
drugs

**22k**  
conditions

# Validation



Insilico models have been extensively **back tested**

We were able to correctly predict **more than 80%** of phase 2  $\Rightarrow$  phase 3 transitions from 2018 to 2021

Training data

Validation data

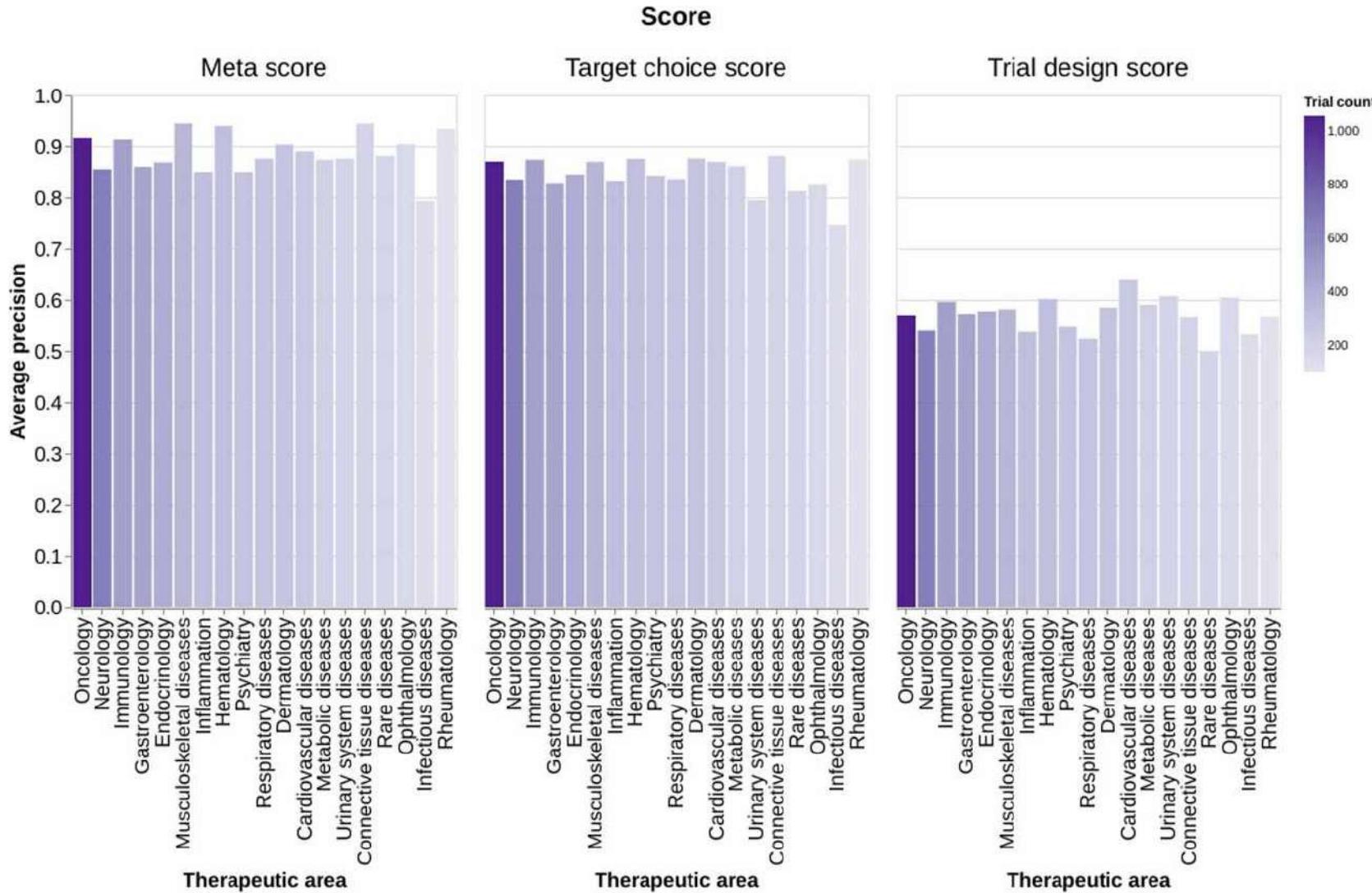
1995

2017

2018

2021

# Quasi-Prospective Validation



**Meta score ROC AUC**

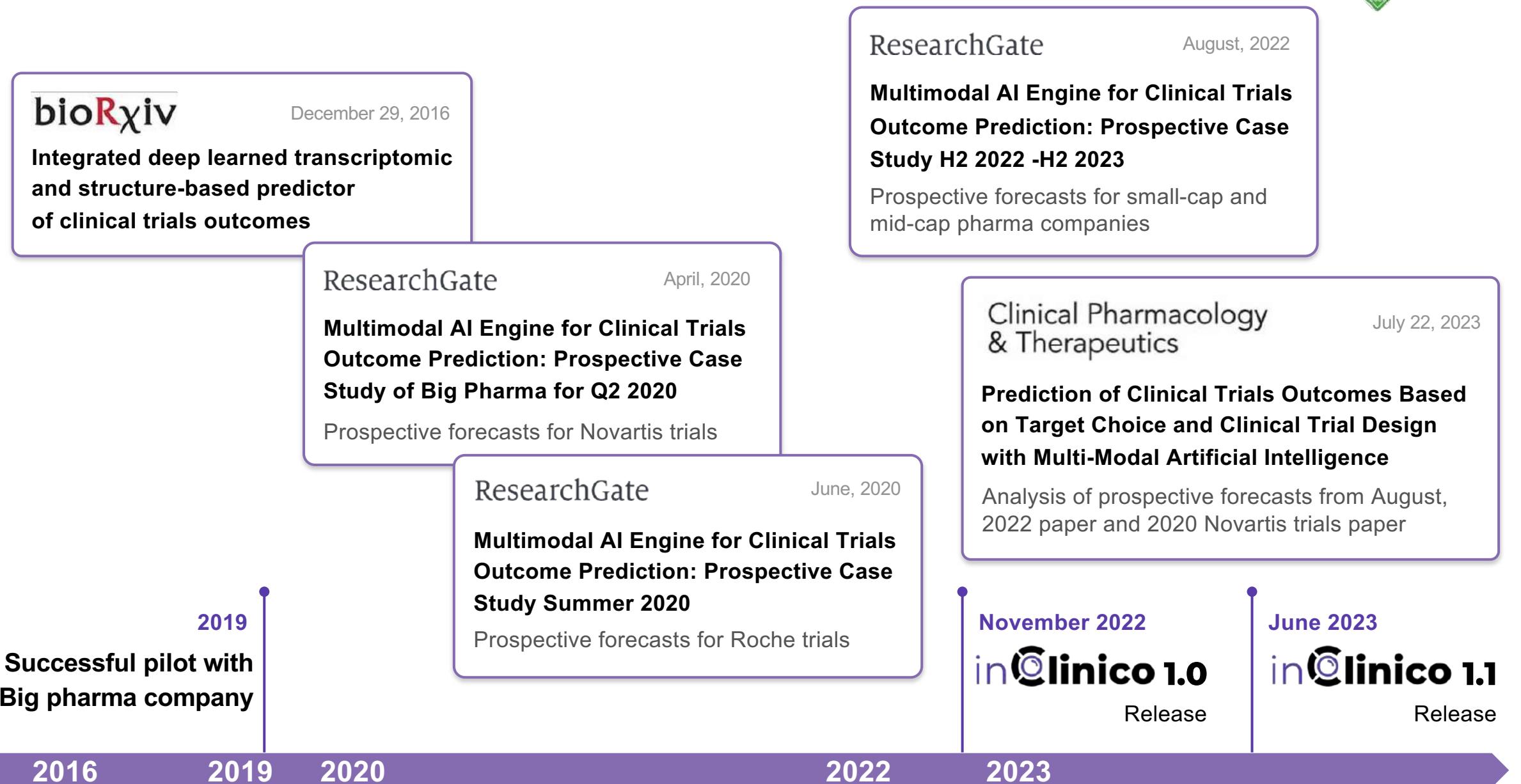
**88%**

# Quasi-Prospective Validation – First-in-class drugs



	ROC AUC		Average precision	
	Overall	First-in-class	Overall	First-in-class
<b>Meta score</b>	0.882	0.724	0.879	0.731
<b>Target choice score</b>	0.841	0.697	0.841	0.701
<b>Trial design score</b>	0.582	0.591	0.545	0.581

# Publications



# Clinical Pharmacology & Therapeutics

Review | **Open Access** |

## Prediction of Clinical Trials Outcomes Based on Target Choice and Clinical Trial Design with Multi-modal Artificial Intelligence

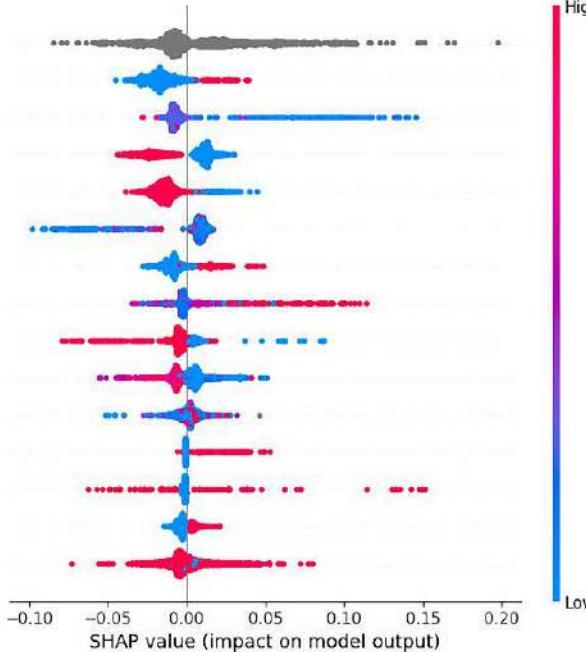
Alex Aliper, Roman Kudrin, Daniil Polykovskiy, Petrina Kamya, Elena Tutubalina, Shan Chen, Feng Ren, Alex Zhavoronkov

First published: 22 July 2023 | <https://doi.org/10.1002/cpt.3008> | Citations: 2

SECTIONS

PDF TOOLS SHARE

Combined influence of therapeutic area  
Other type of funder  
Minimal age of patients  
Tolerability  
Safety  
Anticipated enrollment  
Number of sponsors  
Number of arms  
United States  
Maximal age of patients  
Primary endpoint time frame  
Italy  
Japan  
No masking  
Sum of 38 other features



**Figure 2** The features that impacted the probability of phase II clinical trial success the most as per SHAP values.<sup>31,32</sup> Full list of features and the descriptions are summarized in **Table S2**. SHAP, Shapley Additive Explanations.

**Table 3** Prediction performance metrics for quasi-prospective validation dataset for the whole dataset of clinical trials and for clinical trials with first-in-class drugs

	ROC AUC		Average precision	
	Overall	First-in-class	Overall	First-in-class
Meta score	0.882	0.724	0.879	0.731
Target choice score	0.841	0.697	0.841	0.701
Trial design score	0.582	0.591	0.545	0.581

Abbreviations: AUC, area under the curve; ROC, receiver operating characteristic.

The following criteria were used simultaneously to determine if the phase II trial was successful (**Table 3**):

- Statistical and clinical significance of efficacy and safety end points;
- Company decision to transition drug program to phase III;
- Momentary increase of company's stock price in response to clinical trial results.

The results of trials listed in **Table 4** are summarized in **Table S3**. It is important to note that the "success" cutoff for the inClinico meta score differs from 0.5 and is 0.48 instead. The threshold was

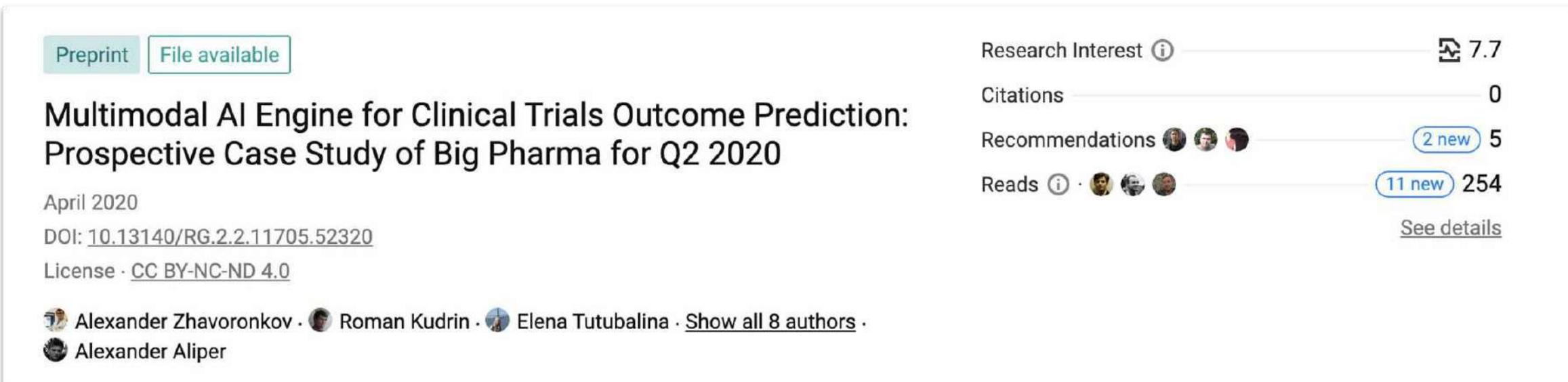
selected by choosing the threshold which corresponded to the maximum of F1 score on a quasi-prospective validation set.

**Case study—NYX-2925 for fibromyalgia** conducted by Aptinyx. We used SHAP values to measure the impact of the trial design features to gain insights about the predictions. We provide SHAP values for the NYX-2925 phase II clinical trial in fibromyalgia (NCT04147858) in **Figure 4**. The main features influencing the probability of the NYX-2925 trial success are anticipated enrollment, primary type of funder, number of sponsors, tolerability, musculoskeletal system disease, safety, minimal age of patients, and location (USA). The NYX-2925 phase II clinical trial was a randomized, double-blind, placebo-controlled study designed to evaluate the efficacy and safety of NYX-2925 in fibromyalgia. Fibromyalgia is a musculoskeletal system disease characterized by chronic widespread pain.<sup>35</sup> The indication of this trial, along with the absence of a tolerability measurement and several numbers of sponsors, improved the forecast probability of success. Other trial design characteristics negatively impact the probability of trial success. The expected enrollment for the NYX-2925 study was substantial for the phase II trial design (300 participants), which could increase the study duration and result in increased cost and resource utilization or failure to recruit the required number of patients. However, Aptinyx was able to enroll the necessary number of participants in the allotted time.

# Prospective Validation – 2020 paper



Predict      Publish      Wait      Compare      Improve the Predictor



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Published forecasts for 40 ongoing clinical trials  
**19 predicted to succeed, 21 to fail**

# Prospective Validation — Comparison of inClinico's forecasts with actual trial outcomes



## Clinical Pharmacology & Therapeutics

Review | Open Access |

### Prediction of Clinical Trials Outcomes Based on Target Choice and Clinical Trial Design with Multi-Modal Artificial Intelligence

Alex Aliper, Roman Kudrin, Daniil Polykovskiy, Petrina Kamya, Elena Tutubalina, Shan Chen, Feng Ren, Alex Zhavoronkov

First published: 22 July 2023 | <https://doi.org/10.1002/cpt.3008>

# Prospective Validation

Analysis is [published](#)  
in Clinical Pharmacology  
& Therapeutics

**11 out of 14**  
outcomes (79%)  
**Predicted correctly**

**First-in-class drug  
for a rare disease**

NCT ID	Company Ticker	Drug	inClinico Meta-score	Readout Date	Predicted Outcome	Outcome	Stock price, 10.08.2022	Stock price, Report date
NCT04456998	GOSS	Seralutinib	0.42	Q4 2022	Failure	Failure*	13.62	2.36 (-83%)
NCT04257929	HRMY	Pitolisant	0.27	H2 2022	Failure	Success	52.44	59.26 (12%)
NCT04030026	TRVI	Nalbuphine	0.37	Q3 2022	Failure	Failure*	4.26	2.45 (-42%)
NCT04147858	APTX	NYX-2925	0.09	Q3 2022	Failure	Failure	0.69	0.41 (-40%)
NCT04148391	APTX	NYX-458	0.35	Q1 2023	Failure	Failure	0.69	0.19 (-72%)
NCT04519658	AZN	Atuliflapon	0.57	H2 2022	Failure	Failure	-	-
NCT05137002	CINC	Baxdrostat	0.49	H2 2022	Success	Failure	33.35	14.11 (-58%)
NCT03818256	CORT	Miricorilant	0.42	Q4 2022	Failure	Failure	27.7	21.38 (-22%)
NCT04524403	CORT	Miricorilant	0.42	Q4 2022	Failure	Failure	27.7	21.38 (-22%)
NCT05193409	BNOX	BNC210	0.56	Q4 2022	Success	Failure	6.32	5.89 (-7%)
NCT04265651	BBIO	Infigratinib	0.59	Q1 2023	Success	Success	11.99	18.55 (+55%)
NCT04112199	BIVI	Terlipressin	0.5	Q1 2023	Success	Success	2.05	9.2 (+349%)
NCT04109313	NVS	Remibrutinib	0.77	Q3 2022	Success	Success	-	-
NCT03896152	NVS	LNP029	0.79	Q2 2021	Success	Success	-	-

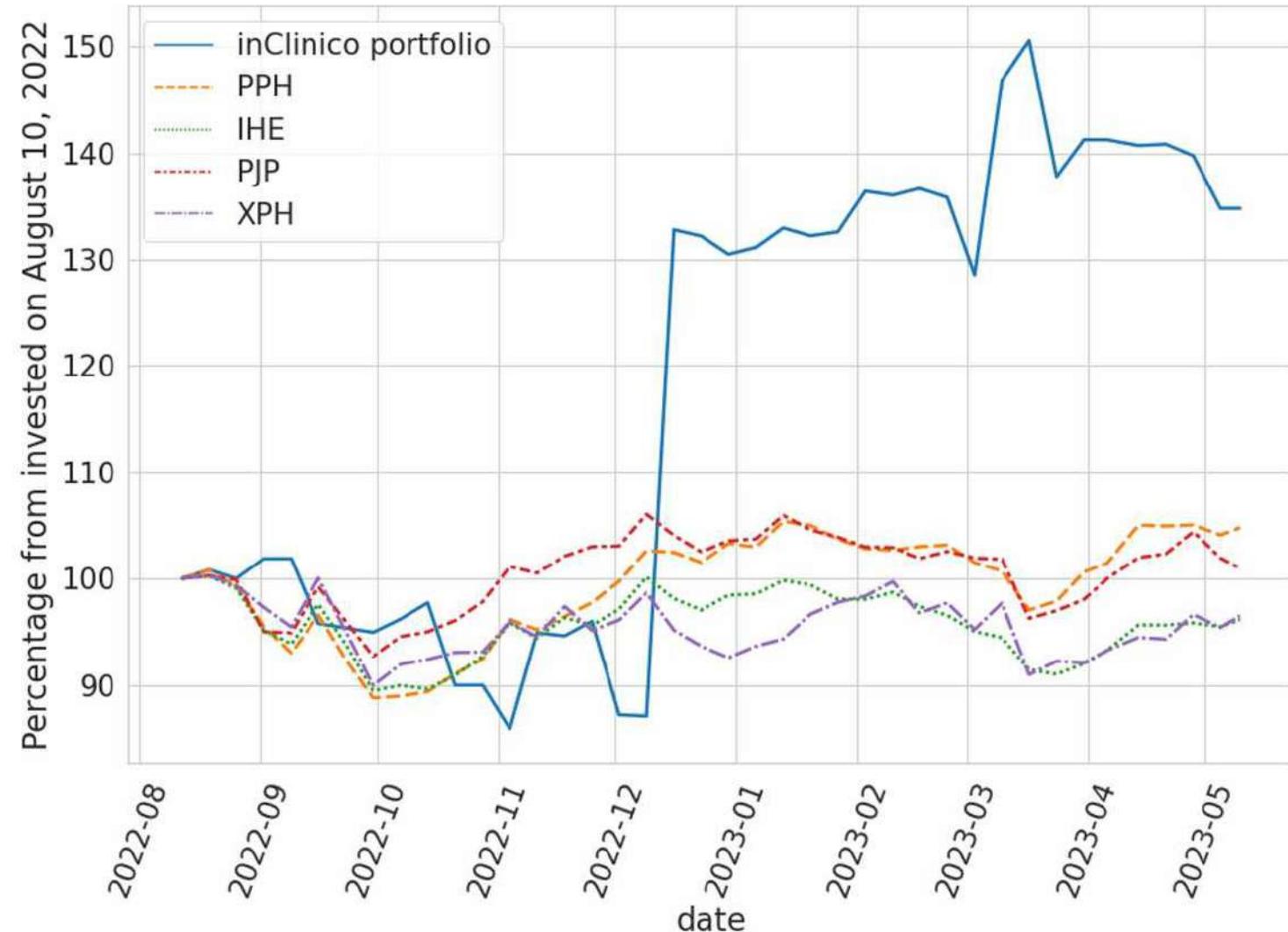
\* Gossamer Bio's and Trevi Therapeutics's clinical readouts were statistically significant and presented as positive, the "Failure" assumption is based on the investment community reception

# Prospective Validation



9-month Mid- & Small-cap CBOE option-based portfolio time-weighted return (TWR) – **35%**

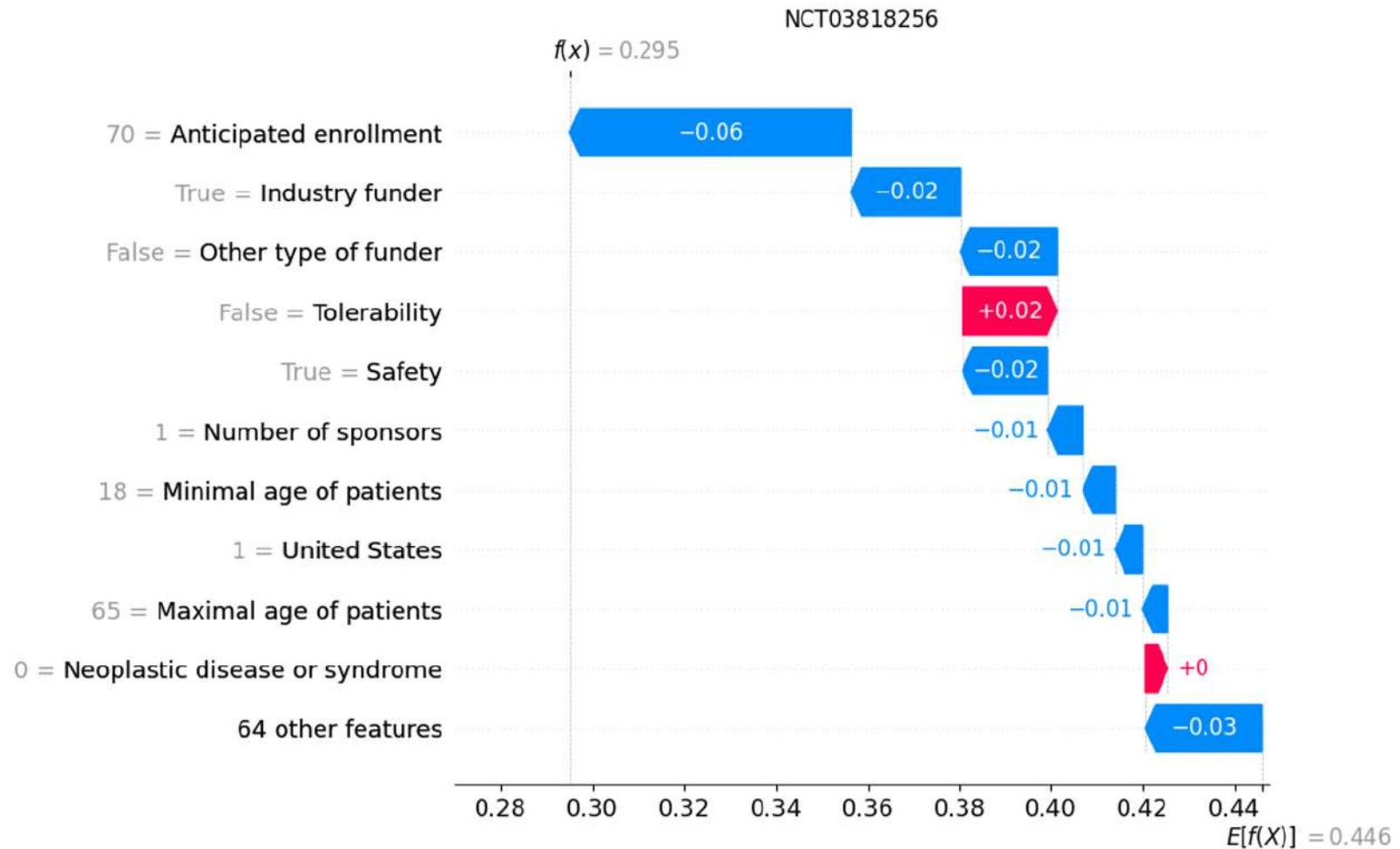
PPH - VanEck Pharmaceutical ETF  
IHE - iShares US Pharmaceuticals ETF  
PJP - Invesco Dynamic Pharmaceuticals ETF  
XPH - SPDR S&P Pharmaceuticals ETF



# De-black-boxing Impact of Clinical Trial Design Features on the Forecast



<b>Condition</b>	Anti-psychotic-induced weight gain
<b>Target(s)</b>	NR3C1, NR3C2
<b>Organization</b>	Corcept
<b>NCT ID</b>	NCT03818256
<b>Phase</b>	2
<b>Readout date</b>	December 8, 2022
<b>Stock price change</b>	<b>-22%</b>
<b>Trial design score</b>	<b>0.295</b>
<b>Actual outcome</b>	<b>Failure</b>



# Common Use Cases



## From Pharma's point of view



Identify the red flags of current and ongoing trials to make corrections before the first patient is enrolled



Identify what went wrong with past trials



Prioritize clinical and preclinical programs



Keep track of the competition



## From an Investor's point of view



Identify what companies or projects are likely to be successful



Correctly adjust NPV for risk and value to generate greater returns

## Start your clinical trial search

**FILTER**

Search clinical trials

**EXPORT**

Rows per page: 10

1-10 of 150833

Study title	Probability of Success	Score modalities			Phase	ID	Readout expected		Disease	Therapeutic Area
		Target choice	Trial design	Patient Eligibility			Start	End		
☆ <a href="#"><sup>89</sup>Zr-Df-IAB22M2C PET/CT in Patients With Selected Solid Malignancies or Hodgkin's Lymphoma</a>	18%	19%	24%	56%	Phase 1	NCT03107663	2018-08-16	2018-08-16	Hodgkins lymphoma	Hematology Infectious diseases Oncology
☆ <a href="#"><sup>89</sup>Zr-Df-IAB22M2C (CD8 PET Tracer) for PET/CT in Patients With Metastatic Solid Tumors</a>	18%	19%	30%	55%	Phase 2	NCT03802123	2022-12-01	2022-12-01	Metastatic malignant neoplasm	Oncology
☆ <a href="#">Sofosbuvir/Simeprevir/Daclatasvir/Ribavirin and HCV Genotype 4-infected Egyptian Experienced Participants</a>	73%	-	55%	69%	Phase 1/2	NCT04387539	2017-10-31	2017-10-31	Chronic hepatitis c virus infection	Endocrine system diseases Infectious diseases Gastroenterology ...
☆ <a href="#">A Dose-finding Study to Assess the Efficacy and Safety of CD-008-0045 in Patients With Generalized Anxiety Disorder</a>	47%	-	42%	69%	Phase 2	NCT04524975	2019-11-01	2019-11-01	Generalized anxiety disorder	Neurology Psychiatry
☆ <a href="#">5 in Dementia Clinical Trials</a>	58%	41%	45%	71%	Phase 2/3	NCT05592678	2027-11-01	2027-11-01	Dementia Mental deterioration Alzheimer disease	Neurology Psychiatry
☆ <a href="#">γδT Cells Immunotherapy in Patients With Relapsed or Refractory Non-Hodgkin's Lymphoma</a>	50%	-	54%	55%	Phase 1	NCT04028440	2022-03-31	2022-03-31	Chronic lymphocytic leukemia Non-hodgkins lymphoma	Hematology Musculoskeletal disorders Oncology Immunology

# Can We Use AI to Discover a Novel Target, Generate Compounds With Desired Properties, and Predict PTRS For A Commercial Clinical Program?

# A small-molecule TNIK inhibitor targets fibrosis in preclinical and clinical models

Received: 26 June 2023

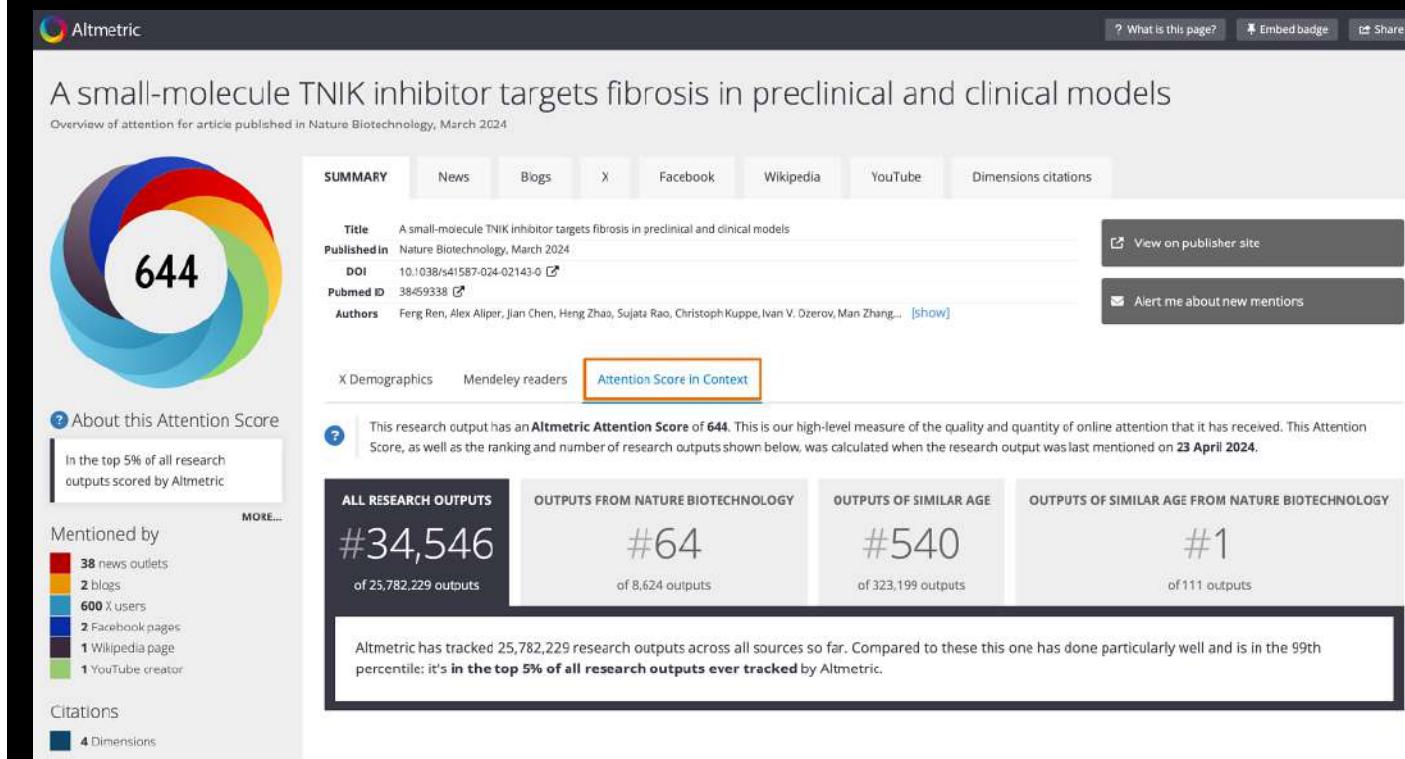
Accepted: 16 January 2024

Published online: 08 March 2024

Check for updates

Feng Ren<sup>1,2</sup>, Alex Aliper<sup>2,3</sup>, Jian Chen<sup>4</sup>, Heng Zhao<sup>1</sup>, Sujata Rao<sup>5</sup>, Christoph Kuppe<sup>6,7</sup>, Ivan V. Ozerov<sup>3</sup>, Man Zhang<sup>1</sup>, Klaus Witte<sup>3</sup>, Chris Kruse<sup>3</sup>, Vladimir Aladinskiy<sup>2</sup>, Yan Ivanenkov<sup>3</sup>, Daniil Polykovskiy<sup>8</sup>, Yanyun Fu<sup>1</sup>, Eugene Babin<sup>2</sup>, Junwen Qiao<sup>1</sup>, Xing Liang<sup>1</sup>, Zhenzhen Mou<sup>1</sup>, Hui Wang<sup>1</sup>, Frank W. Pun<sup>3</sup>, Pedro Torres Ayuso<sup>9</sup>, Alexander Vevierskiy<sup>2</sup>, Dandan Song<sup>4</sup>, Sang Liu<sup>1</sup>, Bei Zhang<sup>1</sup>, Vladimir Naumov<sup>3</sup>, Xiaoqiang Ding<sup>10</sup>, Andrey Kukharenko<sup>3</sup>, Evgeny Izumchenko<sup>11</sup> & Alex Zhavoronkov<sup>12,3,5,8</sup>

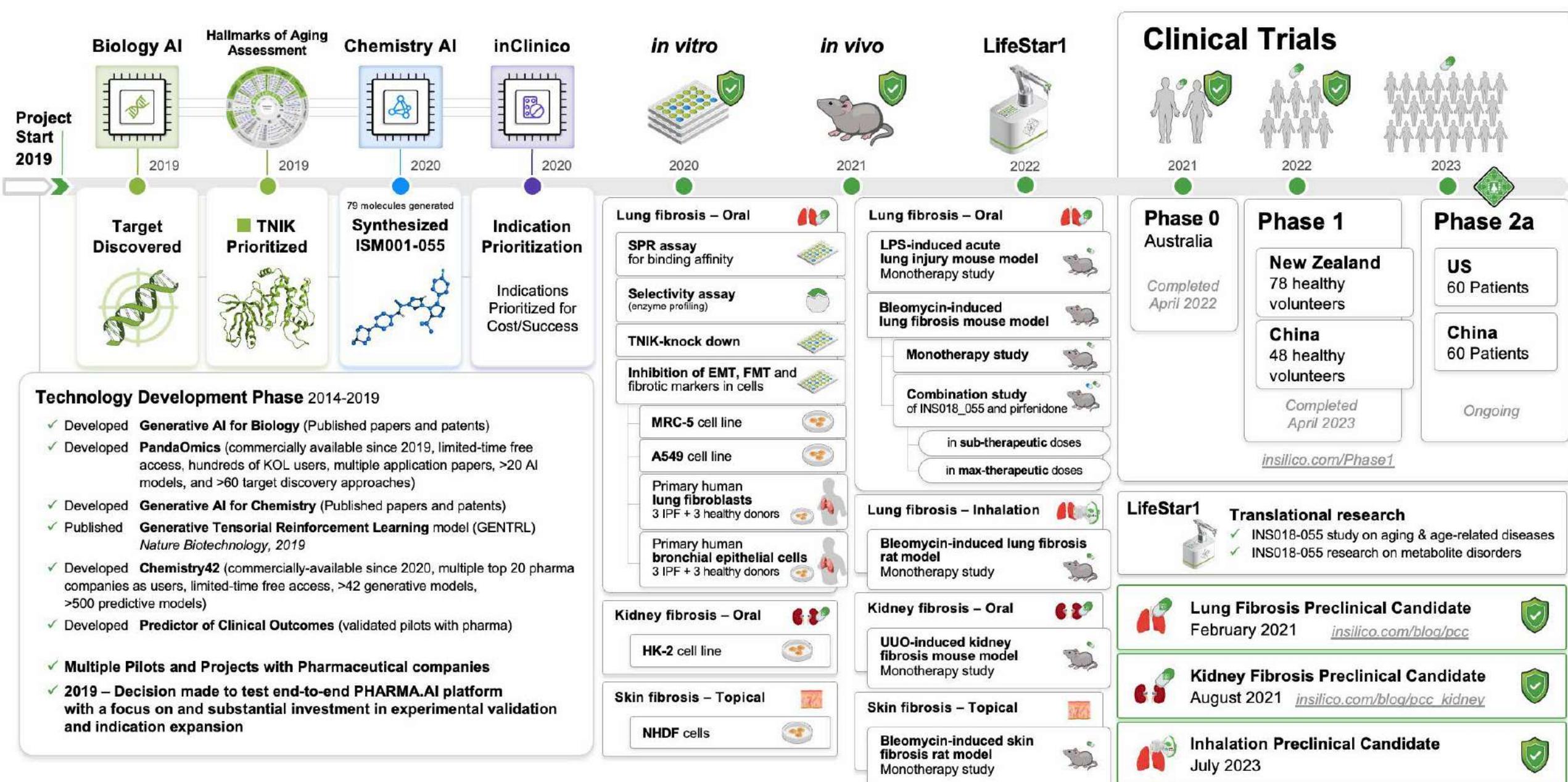
Idiopathic pulmonary fibrosis (IPF) is an aggressive interstitial lung disease with a high mortality rate. Putative drug targets in IPF have failed to translate into effective therapies at the clinical level. We identify TRAF2- and NCK-interacting kinase (TNIK) as an anti-fibrotic target using a predictive artificial intelligence (AI) approach. Using AI-driven methodology, we generated INS018\_055, a small-molecule TNIK inhibitor, which exhibits desirable drug-like properties and anti-fibrotic activity across different organs *in vivo* through oral, inhaled or topical administration. INS018\_055 possesses anti-inflammatory effects in addition to its anti-fibrotic profile, validated in multiple *in vivo* studies. Its safety and tolerability as well as pharmacokinetics were validated in a randomized, double-blinded, placebo-controlled phase I clinical trial (NCT05154240) involving 78 healthy participants. A separate phase I trial in China, CTR20221542, also demonstrated comparable safety and pharmacokinetic profiles. This work was completed in roughly 18 months from target discovery to preclinical candidate nomination and demonstrates the capabilities of our generative AI-driven drug-discovery pipeline.

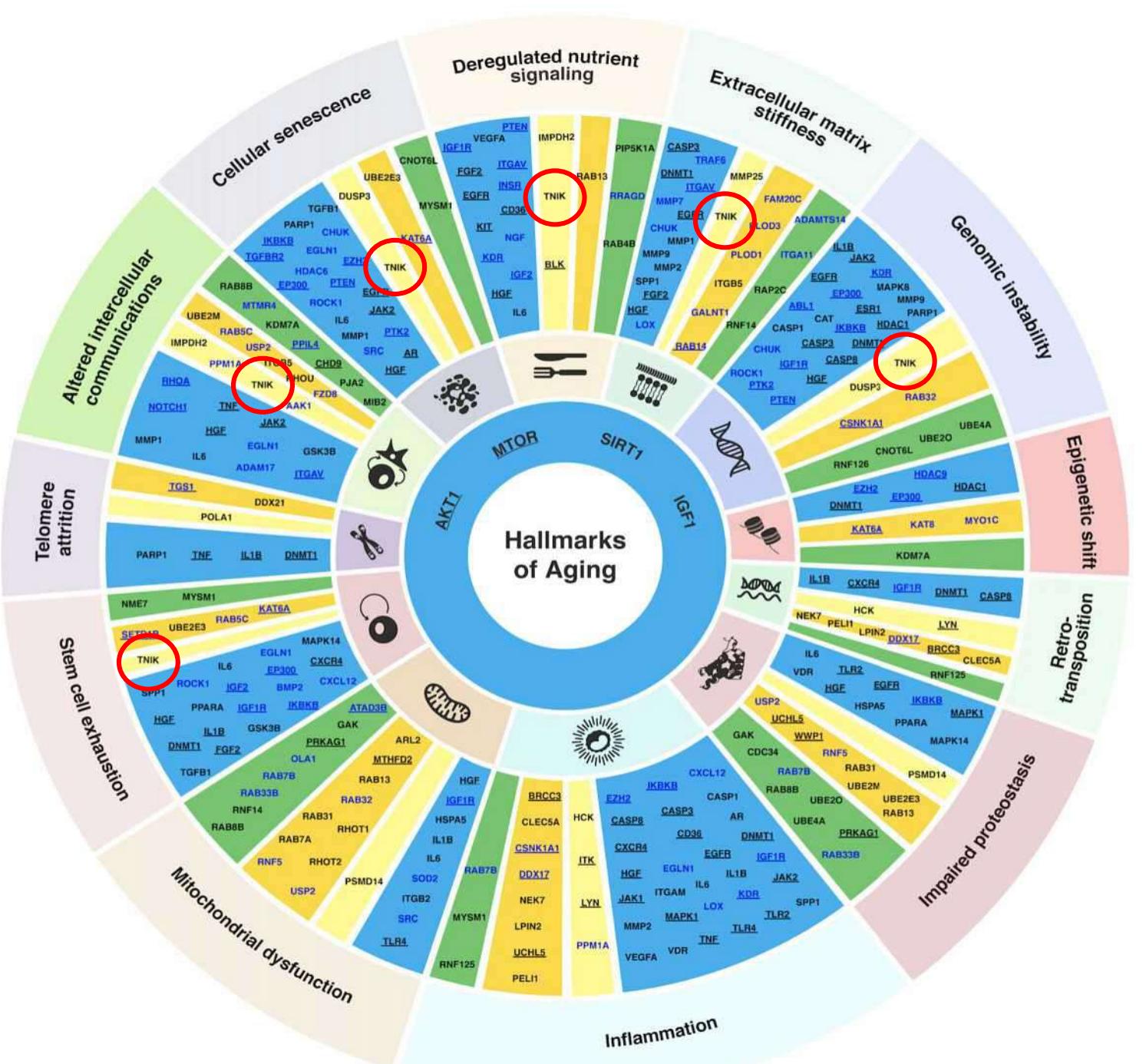


Ren, F., Aliper, A., Chen, J. *et al.* A small-molecule TNIK inhibitor targets fibrosis in preclinical and clinical models. *Nat Biotechnol* (2024). <https://doi.org/10.1038/s41587-024-02143-0>  
Published: March 8, 2024  
<https://www.nature.com/articles/s41587-024-02143-0>

# TNIK Discovery and Development Paper – Nature Biotechnology 2024

Documentary materials are available at [insilico.com/docuthon](https://insilico.com/docuthon)



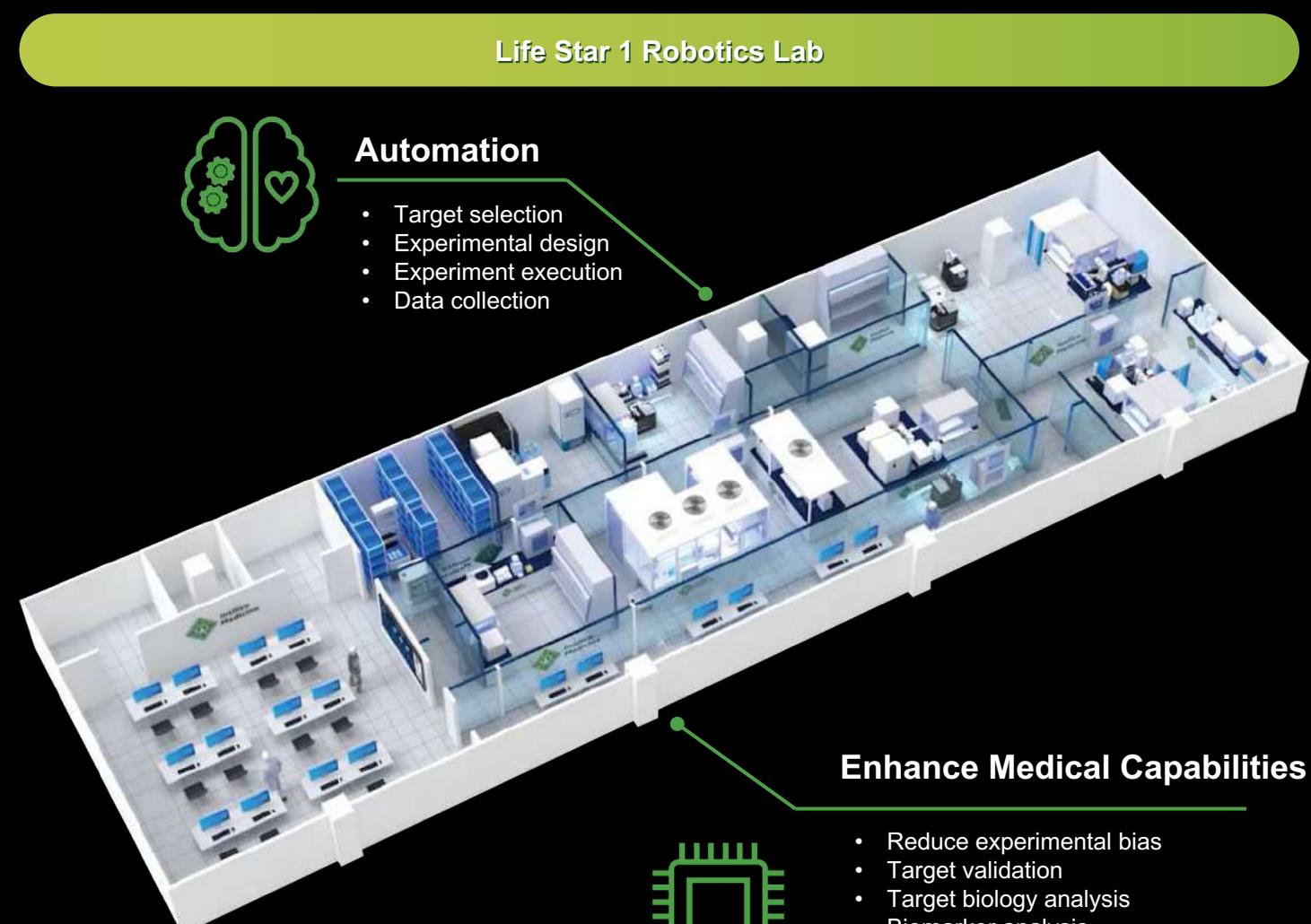


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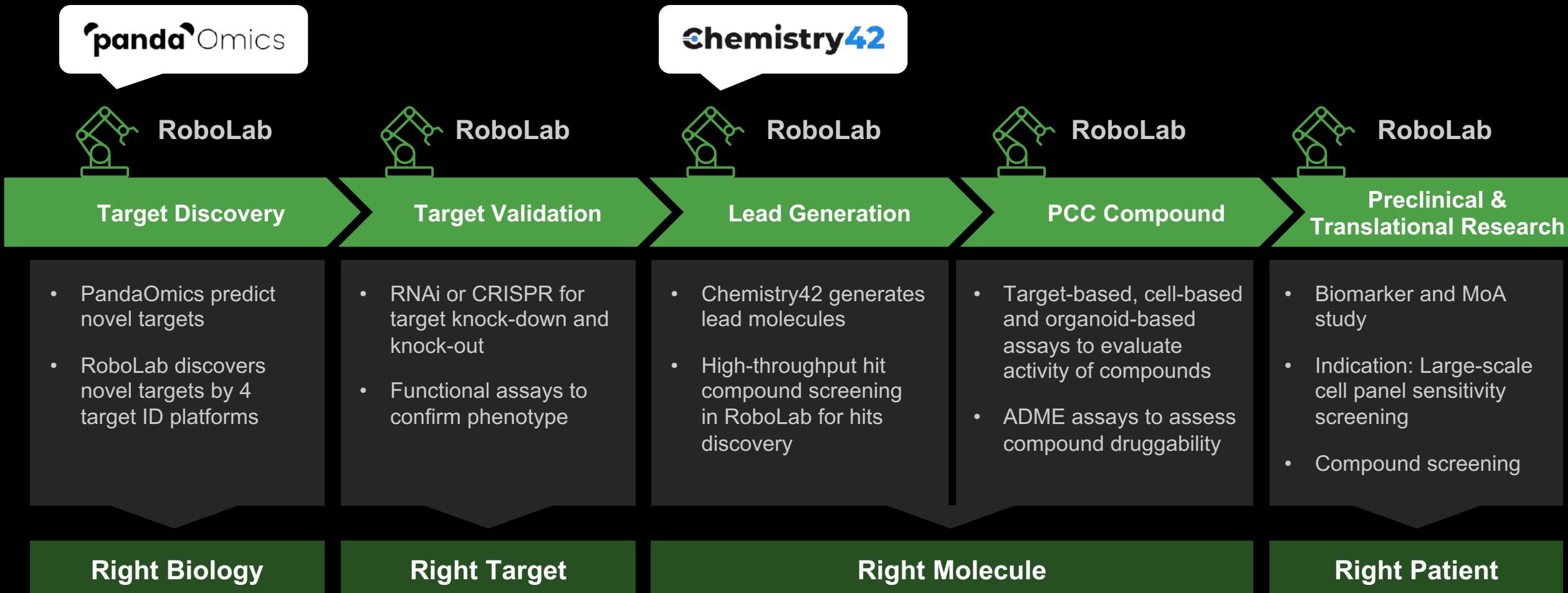
# Next-gen Robotics Lab Expanding Research Capabilities

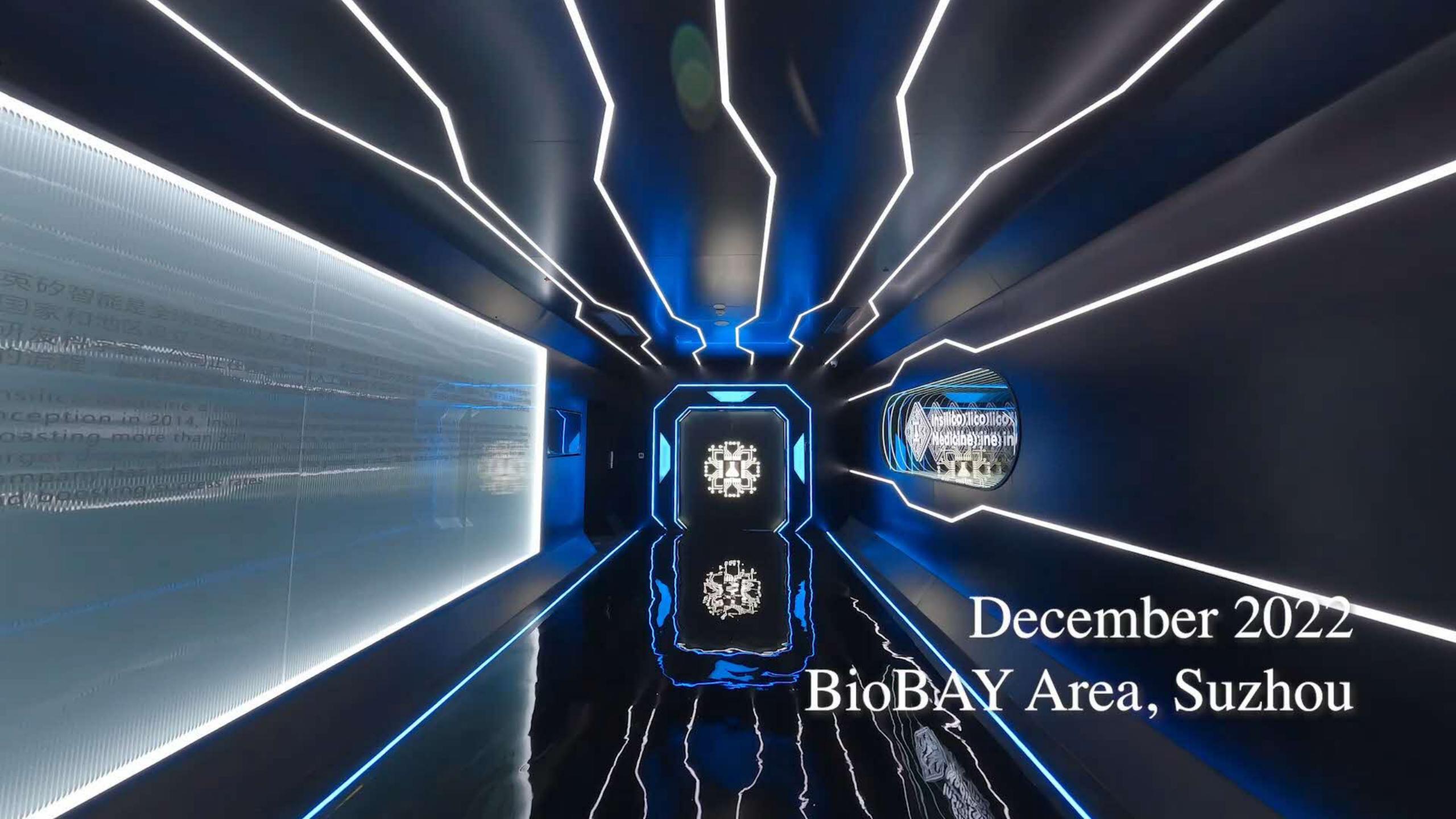


Life Star 1 Robotics Lab



# AI-driven Robotic Lab Has the Potential to Accelerate Early Stage Drug Discovery Process





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