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AI Predictive Tools and Animal-Free Drug Discovery

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Executive Summary

The 2026 AAPS National Biotechnology Conference (NBC 2026) in San Diego was previewed in pre-conference announcements as centered on a paradigm shift in pharmaceutical research: the integration of artificial intelligence (AI)-driven predictive tools with animal-free testing methods to accelerate and humanize drug discovery. Opening and closing plenaries, led by Thomas Hartung, M.D., Ph.D. (Johns Hopkins University) and Lingle Wang, Ph.D. (Schrödinger, Inc.), framed the meeting around these themes (www.biopharminternational.com) (www.aaps.org). AAPS announced that Hartung would deliver the opening plenary and a keynote titled “New Approach Methods – From Ugly Ducklings to Beautiful Swans,” on *New Approach Methods* (NAMs) – a framing consistent with the program’s emphasis on computational models, organoids and organ-on-chip systems (www.aaps.org). Likewise, AAPS announced that Wang would conclude the conference by examining how computational modeling can optimize drug discovery – a theme that bears on how teams prioritize lead candidates and reduce experimental burden. Overall, the pre-conference announcements frame AI and human-relevant models as key to **safer, faster, and more efficient drug development** (www.biopharminternational.com) (www.aaps.org).

This report provides an in-depth analysis of these developments. We begin by contextualizing the historical reliance on animal models and the ethical/scientific drivers prompting new methodologies. We then examine **AI-driven predictive tools** – including machine learning algorithms, generative chemistry platforms, and *in silico* simulations – which are revolutionizing target identification, lead optimization, and toxicity prediction (www.biopharminternational.com) (academic.oup.com). Case studies from industry (e.g. Insilico Medicine’s AI-designed fibrosis drug (www.eurekalert.org) and Amazon’s Bio Discovery platform for biotherapeutics

(www.techradar.com)) illustrate how AI is being applied to candidate design and the navigation of vast chemical spaces. We compare these tools to traditional screening methods, showing that modern *in silico* models sometimes rival or exceed animal assays in predictive accuracy (academic.oup.com).

Next, we explore **animal-free testing strategies**, often termed NAMs (New Approach Methodologies) by regulators (www.fda.gov). This includes advanced *in vitro* systems such as organoids (miniaturized organ models), organs-on-chips (microfluidic devices mimicking human tissues), and 3D cell cultures, as well as holistic computational models. Regulatory momentum is strong: the US FDA announced plans in 2025 to phase out mandatory animal testing for many biologics (www.axios.com), and the European Commission adopted a roadmap towards phasing out animal testing for chemical safety assessments on 1 June 2026 (single-market-economy.ec.europa.eu). These changes reflect empirical realities – e.g., organ-on-chip liver models have demonstrated the potential to cut pharmaceutical costs by billions annually (www.axios.com) – and ethical imperatives (3Rs) that disfavor less-predictive animal models (academic.oup.com) (www.nature.com). We review the scientific foundations of organoid and microphysiological systems, citing the US Government Accountability Office on their human relevance and current limitations (www.gao.gov). Tables compare traditional animal assays with emerging alternatives, highlighting enhanced human predictivity and reduced time/cost for NAMs (albeit with ongoing validation challenges).

Throughout, we integrate perspectives from academia, industry, and regulatory bodies. For example, NIH and FDA partnerships on microphysiological systems, international efforts by EURL/ECVAM in Europe (publications.jrc.ec.europa.eu), and commentary from thought-leaders (Donald Ingber on continued conservatism in toxicology (www.axios.com)) illustrate a broad consensus and remaining debates. We also present detailed data where available: for instance, the Insilico trial reported positive topline Phase IIa results for an AI-driven IPF candidate (www.eurekalert.org), and a recent review reports that, with sufficient data, predictive models for hepatotoxicity and cardiotoxicity have approached or even surpassed traditional animal-based assays, with performance varying by model and endpoint (academic.oup.com).

Finally, we discuss the implications for the future of biopharma: AI-enabled *in vitro* paradigms promise a “digital & human-centric” workflow that could reduce reliance on animal use (medx.it.com) (www.axios.com). Challenges remain (data quality, interpretability, regulatory acceptance, and technical hurdles in complex in vitro systems), but the trajectory is clear. The NBC 2026 program, as announced, positions AI-driven predictive tools and animal-free methods as central to next-generation R&D. Our conclusion emphasizes that these innovations offer safer, smarter drug discovery aligned with both ethical values and scientific rigor, charting a path toward more effective therapies delivered to patients faster (www.biopharminternational.com) (www.aaps.org).

Introduction and Background

Traditional drug discovery has long depended on a sequence of empirical animal studies – from target validation in rodent models to toxicity testing in multiple species – and extensive trial-and-error chemistry. This paradigm, however, is costly, slow, and often of limited predictive value. Studies estimate that bringing a new drug to market costs upward of $1–2 billion and takes over a decade (medx.it.com), with more than 90% of candidates failing in clinical trials, often due to unexpected toxicity or lack of efficacy. Much of this waste is attributed to poor human relevance of animal models: species differences create uncertainties when animal

results are extrapolated to humans (academic.oup.com). Furthermore, ethical concerns and public pressure have intensified around animal use: each year tens of millions of vertebrate animals are used worldwide in experiments, sparking urgent calls to **reduce, refine, and replace** (=3Rs) animal testing whenever possible.

In response, the pharmaceutical community has seen a "transformative shift" toward **data-driven and human-relevant methods** (www.aaps.org). Computational approaches – billions of data points and molecules analyzed by AI – and advanced *in vitro* models (organoids, micro-physiological systems) are emerging as credible alternatives to animal work. This trend is backed by regulatory initiatives: in 2025 the U.S. FDA unveiled a roadmap to phase out animal testing for monoclonal antibodies and similar biologics, favoring "human-relevant" assays and modeling (www.axios.com) (www.fda.gov). Likewise, the European Commission adopted a roadmap towards phasing out animal testing for chemical safety assessments on 1 June 2026 (single-market-economy.ec.europa.eu). These policy changes reflect technological maturation: recent advancements in machine learning, organ-on-chip engineering, high-content imaging, and multi-omics have dramatically improved the predictivity of non-animal methods (academic.oup.com) (www.nature.com).

Terminology: Throughout this report we use "AI-driven predictive tools" to refer to any computational or automated approach (including machine learning, deep learning, data mining, and physics-based simulation) applied to drug discovery problems such as target identification, lead optimization, ADMET prediction, or clinical trial simulation. "Animal-free testing" encompasses New Approach Methods (NAMs) – experimental systems that omit live animal use – including human cell-based assays, organoids, organs-on-chips (microphysiological systems, MPS), and full *in silico* screening strategies (www.fda.gov) (www.aaps.org). These areas often intersect; for instance, AI can analyze data from human *in vitro* models, and computational models can simulate organ responses (www.aaps.org) (academic.oup.com). NBC 2026 explicitly focused on the convergence of these domains: the opening plenary announced that AI and NAMs "advance predictive toxicology and human-relevant models to improve drug safety and translational research" (www.biopharminternational.com), and the program included sessions on computational discovery, organoid culture, and regulatory science.

Historical context: Early in the 21st century, increases in available biological data and computing power spurred the development of quantitative structure–activity relationship (QSAR) models and virtual screening tools, but these were often limited by data scarcity and simple algorithms. In the last decade, however, breakthroughs in deep learning, cloud computing, and microfabrication have accelerated progress. Key milestones include DeepMind's AlphaFold (2020) – which predicted atomic-level protein structures for basically any gene (colab.ws) – enabling structure-based drug design at scale, and the maturation of organoid technology (miniaturized 3D tissues derived from stem cells) that can replicate human organ function in vitro. Simultaneously, high-throughput genomic and imaging assays have generated large training datasets for AI, while NIH and other agencies have championed collaborative initiatives like Tox21 (high-throughput toxicity screening of 10,000 compounds). Conferences like NBC 2026 are now convening cross-disciplinary experts precisely to share these advances and translate them to practice.

AI-Driven Predictive Tools in Drug Discovery

Machine Learning and Data Integration

Artificial intelligence (AI) and machine learning (ML) have already begun to transform key stages of drug R&D. In target identification, for example, AI tools like Insilico's **PandaOmics** analyze gene expression, literature, and pathway data to prioritize disease-related targets that might be missed by human review. AI also excels in **virtual screening**: deep neural networks and graph-based models can rapidly sift through enormous chemical libraries (tens to hundreds of millions of structures) to select those most likely to bind a given target or have desirable properties. In one notable demonstration, Amazon's AWS Bio Discovery platform leveraged 40+ specialized AI models to filter 300,000 novel antibody candidates down to the top results for laboratory testing in just weeks (compared to an estimated year with traditional methods) (www.techradar.com). The platform's integrated **"lab in the loop"** approach – where cloud-based design tools connect directly to synthesis labs – exemplifies how automation is streamlining end-to-end discovery (www.techradar.com).

Once leads are proposed, **generative chemistry** uses AI to create novel compounds. Generative adversarial networks (GANs), variational autoencoders, and reinforcement learning have been trained on known bioactive molecules to propose new structures optimized for a target's binding pocket and drug-like properties. Insilico Medicine, a clinical-stage biotech, has utilized such approaches to design INS018_055, a first-in-class small molecule for idiopathic pulmonary fibrosis. Impressively, INS018_055 (also called ISM001-055) was developed utilizing generative AI, and Insilico reported positive topline Phase IIa results in November 2024 (www.eurekalert.org). Dr. Zuojun Xu (Peking Union Medical College), the investigator of INS018_055's trial, commented that "AI…is already playing a crucial role in…drug discovery," underscoring that these tools are now delivering tangible **clinical candidates** (www.eurekalert.org).

Parallel to chemistry, AI enhances **ADMET and toxicity prediction**. Traditional ADMET (Absorption, Distribution, Metabolism, Excretion, Toxicity) testing relied on animal studies and in vitro assays with limited throughput. Modern AI-based models train on vast public and proprietary datasets (often millions of data points) to predict, for example, a molecule's likelihood of causing liver or cardiac toxicity. According to a recent review, under ideal conditions AI models for hepatotoxicity and cardiotoxicity "have approached or even surpassed" the predictive performance of animal assays (academic.oup.com). Advanced architectures like **graph neural networks (GNNs)** automatically encode molecular structure and functional groups, learning complex relationships between structure and activity (academic.oup.com). Transformers and multimodal deep learners even integrate chemical, genomic, and phenotypic data, creating end-to-end pipelines for toxicology prediction (academic.oup.com). Reported performance varies by endpoint, dataset and model, so benchmark figures should be compared model by model. For companies, this means that many late-stage failures (which typically occur due to cardiotoxic or hepatotoxic issues) could be flagged earlier in silico, saving expensive development costs.

Another major application is **pharmacokinetic modeling**. Tools like Simcyp and GastroPlus use semi-mechanistic PBPK (physiologically based pharmacokinetic) simulations to predict how a drug distributes in the human body. While PBPK traditionally relied on rule-based equations, modern approaches are hybridizing them with ML for parameter estimation and uncertainty quantification. Moreover, **Quantitative Systems**

Pharmacology (QSP) frameworks simulate drug and disease networks at a systems level, and AI is increasingly used to fit QSP models to clinical data. The combined effect is a more “virtual patient” oriented drug development: parameter tuning with AI can tailor models to specific populations (e.g. by genotype), potentially enabling in silico trials that reduce reliance on animal studies entirely.

In summary, AI-driven tools **accelerate and focus** the discovery pipeline. Instead of blindly testing thousands of analogues in animals, researchers can computationally optimize leads for potency and DMPK properties, reducing both the number of compounds synthesized and the time required. For example, some ML-aided pipelines claim to shorten lead optimization from years to mere months (medx.it.com). Historically, attrition from Phase I to approval has been high (often cited at around 90%), and it remains unproven whether AI-incorporating teams will achieve lower attrition. While complete validation awaits, the directional impact is clear: companies employing AI report **faster lead cycles and higher hit rates** in early screens. Insilico reported in November 2024 that ISM001-055, a molecule developed utilizing generative AI, showed a dose-dependent improvement in lung function in a Phase IIa trial (www.eurekalert.org).

Case Study: Insilico’s AI-Designed Drug (ISM001-055)

Insilico Medicine provides a vivid example of AI in action. Using proprietary generative algorithms, Insilico discovered and designed ISM001-055 (a TNIK kinase inhibitor) for idiopathic pulmonary fibrosis. The R&D team reported in November 2024 that ISM001-055 had progressed through Phase I and yielded “positive topline results” in a double-blind Phase IIa trial (www.eurekalert.org). Insilico states the molecule was developed utilizing generative AI. In its topline release, the company reported that patients who received ISM001-055 showed a dose-dependent improvement in lung function (FVC) in IPF patients (www.eurekalert.org), a promising sign for chronic disease intervention.

Case Study: AWS Bio Discovery Platform

Another illustration is the Amazon Web Services (AWS) cloud-based **Bio Discovery** platform. Launched in 2026, it offers researchers a suite of pre-trained general and specialized models for antibody and biologic design (www.techradar.com). In joint testing with academic labs (e.g. Memorial Sloan Kettering and Johns Hopkins), AWS demonstrated dramatically expedited antibody lead selection. The platform’s AI agent filtered 300,000 novel antibody candidates down to the top results for testing in a matter of weeks (www.techradar.com). Whereas standard antibody optimization workflows could take 12 months or more (due to serial synthesis and characterization), the integrated AWS pipeline proposes leads, sends them for lab testing, then iteratively refines designs all within months. (www.techradar.com). This case shows the value of **cloud-enabled ML**: democratizing sophisticated analysis so that “every researcher” — not just computational experts — can access predictive tools (www.techradar.com).

Generative AI and Structural Modeling

Beyond small molecules and biologics, **generative AI** and structural predictors are emerging in novel modalities. Large-language-model-based tools are starting to design oligonucleotides, peptides, and even mRNA sequences with optimized stability and expression characteristics. For instance, protein language models borrowed from natural language processing can suggest new amino acid sequences for engineered proteins or antibodies with desired attributes. Additionally, AlphaFold (DeepMind) and RoseTTAFold (Baker

Lab) algorithms, though originally for structural biology, have been repurposed to inform drug binding and to design protein therapeutics by predicting 3D conformations and mutational effects (colab.ws). While these developments are still nascent at scale, they promise an era where even complex biologics can be **computer-generated** and quickly validated against human cell models.

Table 1: *Representative AI-driven predictive tools and platforms in drug discovery.* AI methodology refers to the core technology (ML, DL, generative models) underpinning each tool. Applications range from target discovery to lead optimization and ADMET prediction. (Sources: Insilico Medicine (www.eurekalert.org), AWS Bio Discovery (www.techradar.com), Academic reviews (academic.oup.com) (medx.it.com).)

Tool/Platform	AI/ML Methodology	Application	Stage/Use-Case
Insilico PandaOmics	Deep Learning (neural networks)	Target identification (multi-omics data)	Early discovery – causal gene targets
Insilico Generative Model	Generative Adversarial Networks (GANs)	De novo drug design (small molecules)	Lead optimization – novel ligand generation
AWS Bio Discovery	Foundation LLMs & custom network models	Antibody sequence optimization	Candidate screening – antibody design and filtering (www.techradar.com)
Schrödinger FEP+	Physics-based (Free Energy Perturbation)	Accurate binding energy predictions	Lead selection – predict binding affinity
AlphaFold 2 / RoseTTAFold	Deep Learning (protein structure only)	Protein structure prediction	Target characterization; antibody/peptide design
ADMETLab / admetSAR	QSPR, SVM, Tree-based ML	ADME/toxicity property prediction	Preclinical – filter hazardous or poor-drug-like candidates
DeepMind AlphaFold-Multimer	DL (multimeric complex modeling)	Antibody-antigen docking	Candidate optimization – antibody design
Cresset Spark	ML guided bioisostere replacement	Scaffold hopping & lead optimization	Medicinal chemistry – modify scaffold for potency

(*FEP* = free-energy calculations; *ADMET* = absorption/distribution/metabolism/excretion/toxicity.)

Benefits and Limitations

The advantages of AI-driven tools are numerous: they can sift through far larger chemical spaces than any lab; analyze complex, multidimensional data (e.g., transcriptomics, cryo-EM, high-content images); identify subtle patterns beyond human reach; and automate routine analysis. As noted at NBC, these approaches **“enhance data integration and predictive capabilities”**, enabling more reliable go/no-go decisions (www.biopharminternational.com). Importantly, by de-risking early stages, AI can funnel resources toward the most promising leads, reducing wasted synthesis and animal tests. In some cases, computational predictions reveal off-target liabilities or toxicity alerts weeks or months before any chemistry is done.

However, current limitations exist. AI models are only as good as the data they are trained on. Biases, poor-quality labels, or narrow chemical spaces can mislead models. There are concerns about **interpretability**: ML models may flag a compound as toxic without clear mechanistic explanation, posing challenges for regulatory acceptance. Data scarcity in certain domains (e.g. neurology, rare diseases) means models may have high uncertainty. Indeed, Axios Vital reported that **experts caution** more real-world data (especially in oncology and neurology) are needed before AI alone can robustly predict clinical outcomes (www.axios.com). Moreover, while generative AI can propose novel molecules, synthesizing and validating them in the lab remains non-trivial, and some in silico designs may fail syntheses or show unexpected behavior. Finally, integrating AI tools requires new skills and collaboration between computational scientists, biologists, and chemists, as well as robust IT infrastructure.

Nevertheless, the *trajectory* is clear: as more data accumulate and algorithms improve, AI-driven predictive tools will become an increasingly routine part of R&D workflows. The closing plenary, by Dr. Lingle Wang of Schrödinger, was announced as examining how computational modeling can optimize drug discovery (www.aaps.org). In the longer term, we can anticipate hybrid pipelines where AI pre-screens billions of candidates, models simulate ADMET in silico, and the few top-ranked candidates are then confirmed in advanced human cell models or minimal animal tests. This paradigm promises not just efficiency, but also a more ethical and patient-centered discovery process.

Animal-Free Testing in Drug Discovery

Rationale: 3Rs and Regulatory Momentum

The second pillar of NBC 2026's theme is the drive to **replace animal tests** with *New Approach Methodologies (NAMs)*. Historically, animal studies were seen as the gold standard for safety assessment. However, the ethical and scientific shortcomings of animal usage are increasingly recognized (academic.oup.com) (www.gao.gov). For example, the traditional sequential acute-to-chronic toxicity battery takes 6–24 months and costs millions per compound (academic.oup.com), yet often fails to predict human adverse events reliably. Ethical critiques (Russell & Burch's 1959 3R principles: reduce/refine/replace) have now been codified into policy: major funding agencies and regulators encourage or mandate NAMs whenever possible.

Regulatory agencies are increasingly encouraging the transition. In the U.S., the FDA's April 2025 roadmap on reducing animal testing in preclinical safety studies, together with its later progress reporting, lays out a staged strategy to replace animal tests with validated NAMs (www.fda.gov). The FDA will first target monoclonal antibodies (whose animal model data have proven "unreliable") and then expand to other biologics and small molecules (www.fda.gov). Parallel legislative efforts (bipartisan bills introduced in Congress) aim to codify similar mandates (www.axios.com). In the U.S., NIH announced in June 2026 a new Office of Research Innovation, Validation, and Application (ORIVA) to coordinate NIH-wide NAM efforts, and internationally the EU's EURL ECVAM (European Union Reference Lab for alternatives) released a 2025 status report spotlighting organ-on-chip, AI, and omics as "innovative breakthroughs" for phasing out animal tests (publications.jrc.ec.europa.eu). Notably, the European Commission has since presented its roadmap towards phasing out animal testing for chemical safety assessments, with 22 actions under three pillars covering 15

domains including pharmaceuticals (ec.europa.eu). Together, these signals suggest that *animal-free development is becoming not just a trend but an expectation* in regulatory science (www.aaps.org) (www.axios.com).

Table 2: *Comparison of traditional animal models vs. emerging animal-free approaches for safety assessment*. Key advantages and drawbacks are summarized (3R = replace/reduce/refine). (Sources: GAO (www.gao.gov), FDA (www.fda.gov), Lab Animal editorial (www.nature.com), EURL/ECVAM (publications.jrc.ec.europa.eu).)

Approach	Description	Advantages	Limitations/Challenges
Animal-based tests (rodents, primates)	In vivo studies (e.g. LD50, organ histopathology, chronic tox studies).	Extensive historical database; can capture whole-organism toxicity; accepted by regulators.	High cost and time; ethical concerns; often poor human predictivity (cross-species mismatch) (academic.oup.com).
In vitro cell assays (2D cultures, cell lines)	Human or animal cells cultured in plates; measures target engagement or cytotoxicity.	Rapid and high-throughput; human cells increase relevance; reduces some animal use.	Lacks organ-level complexity; may not capture ADME; context dependence of cell lines.
Organoids	3D mini-organs derived from human stem cells, simulating tissue microenvironments.	Mimic organ structure and function (e.g. liver organoids with multiple cell types); can model patient-specific biology; reduce animal use (www.nature.com) (publications.jrc.ec.europa.eu).	Technical variability; limited by cell source quality; scalability and standardization issues.
Organ-on-a-chip (MPS)	Microfluidic devices with human cells (e.g. heart-on-chip, gut-on-chip) representing organ functions (www.gao.gov) (www.nature.com).	Precisely controls environment (fluid flow, mechanics); can link multiple organs (“body-on-chip”); high human relevance; potential to replace certain animal studies (www.gao.gov) (publications.jrc.ec.europa.eu).	Still developing; challenges include obtaining reliable human cells (only ~10–20% usable) (www.gao.gov), lack of standardized benchmarks (www.gao.gov), and regulatory acceptance (www.gao.gov).
Computational toxicology (in silico models)	Algorithms predict ADMET or toxicity from chemical structure or biological data (academic.oup.com).	Fast and low-cost; scales to millions of compounds; adaptive as data improves; potential to flag hazards early and avoid animal tests (academic.oup.com) (www.axios.com).	Requires extensive, high-quality training data; may miss novel mechanisms; regulatory familiarity still growing.
High-content/pharmacogenomic assays (e.g. iPSCs, genomic screens)	Large-scale screens of human-derived cells or molecular endpoints.	Human-relevant mechanistic data; captures multi-gene interactions; aligns with personalized medicine.	Data interpretation complex; expensive equipment; not fully validated for pipelines.
3Rs-refined animal tactics (e.g. humane end-points, reduced animal numbers)	Modified animal protocols (non-lethal measures, fewer animals).	Incremental reduction of suffering; transitional step; retains in vivo context.	Continues ethical concerns; incremental improvements only partial solution.

Table 2 Legend: Comparisons between approaches to safety testing. “Human relevance” is markedly higher for organoids, organ-chips, and *in silico* models, which use human cells or computational human proxies. However, adoption is tempered by validation gaps and logistics.

Advanced Cell and Tissue Models

Microphysiological Systems (MPS) – especially organ-on-chip devices and organoids – are a major focus of animal-free development as *biologically* human-relevant models. These systems, by containing living human cells, often recapitulate organ architecture and function to an extent that animal models cannot (www.gao.gov) (www.nature.com). For example, multi-cell 3D liver slices or liver organoids preserve human-specific drug metabolism enzymes, enabling more accurate prediction of human hepatotoxicity. Gut-on-chip devices incorporate peristaltic motions and microbiome ecosystems, potentially foretelling gastrointestinal side effects. Brain organoids, though not yet fully functional, are being used to study neurodevelopmental drug effects. In cardiology, beating heart-on-chip constructs can reveal arrhythmia risks or cardiomyopathy endpoints more reliably than standard animal ECG measures.

Organoid intelligence – the idea of training networks of brain organoids to perform simple computational tasks – remains experimental, but it envisions harnessing organoids for predictive phenotyping. More immediately relevant are **disease-model organoids**: for instance, lung alveolar organoids containing fibroblasts, epithelial cells, and immune components, enabling preclinical studies of pulmonary fibrosis or COVID-19 response in a human-like context. Such platforms can detect efficacy or toxicity signals that animal lungs might miss, due to interspecies differences in immune responses. Similarly, human **skin equivalents** (3D layers of human keratinocytes and fibroblasts) are used in validated in vitro skin irritation testing; OECD Test Guideline 439 describes a reconstructed human epidermis procedure for in vitro skin irritation hazard identification (GHS Category 2) (www.oecd.org). Dr. Hartung’s announced keynote is titled “New Approach Methods – From Ugly Ducklings to Beautiful Swans” – a metaphor for the maturation of NAMs into scientifically robust tools (www.aaps.org).

However, as the GAO report highlights, challenges remain for widespread uptake (www.gao.gov). Chief among these is **standardization and validation**. Many organ-on-chip platforms are developed by individual research groups or startups, using different cell sources and protocols. Without agreed benchmarks or inter-lab studies, it’s hard for regulators to know how to interpret results. For example, GAO noted only 10–20% of purchased human cells met quality standards for chips (www.gao.gov). Similarly, while academic papers often show a single chip’s promise, few large studies exist comparing chip readouts to known human data. Data sharing is also limited by proprietary concerns – companies hesitate to release hard-won validation datasets. **Pre-competitive consortia** and public-private partnerships are one route to establishing such standards.

Another issue is **integration into pipelines**. Even a validated chip rarely can cover all required endpoints; currently most chips complement rather than fully replace animals. For instance, a liver-on-chip may accurately model metabolism, but would miss systemic immune interactions. Companies often run both in parallel (“covering their bets” as Wyss Institute’s Donald Ingber noted (www.axios.com)). In the near term, chips are generally used alongside animal studies rather than instead of them, and any reduction in animal testing for a specific program should be agreed with the relevant regulator.

Regulatory and Ethical Perspective

The shift to animal-free methods is not driven purely by technology but also by policy. The FDA's April 2025 announcements outline a policy direction toward greater use of NAMs in nonclinical safety assessment; sponsors should confirm current nonclinical data expectations directly with the agency before any program relies on omitting animal studies. Organ-on-chip advocates also point to a 2022 study of the Emulate Liver-Chip (Ewart et al., *Communications Medicine*), whose authors reported that its level of performance could generate over $3 billion annually for the pharmaceutical industry through increased small-molecule R&D productivity – a modelled estimate by the study authors rather than a measured saving.

Ethically, such numbers matter less than the human welfare argument: more reliable human models mean fewer patients harmed in trials due to unforeseen toxicity. Indeed, the pre-conference announcements tie the program to more predictive, data-driven drug development. AAPS's scientific programming chair, Dr. Shuhua Bai, described Hartung's opening plenary as reflecting "a transformative shift toward more predictive, data-driven drug development" (www.biopharminternational.com).

Internationally, momentum is building in step. In the UK, the government's *Replacing animals in science* strategy aims to work towards phasing out the use of animals in all but exceptional circumstances (www.gov.uk). The European Union's Green Deal and New Chemicals Strategy explicitly aim to phase out animals, using cutting-edge science instead. Japan's JaCVAM and other national agencies are also investing in NAM validation. This global context means that pharma companies are under dual pressure: to comply with new rules and to stay competitive. A firm that masters AI and organ-chip methods can outpace rivals by shaving years off R&D and boasting ethically superior pipelines.

Perspectival Diversity and Case Examples

NBC 2026 program materials describe plenaries and sessions on AI and NAMs from academic, industry and regulatory-science speakers. This article is based on published pre-conference announcements and the other sources cited, not on attendee surveys, session notes or interviews. In silico and organotypic models can improve human relevance, but they also require new skill sets and validation strategies.

Data Analysis and Evidence

Quantitative data from recent studies and initiatives illustrate the trends discussed above:

- **Model Performance:** According to a 2025 *Briefings in Bioinformatics* review, under sufficient data availability the predictive performance of computational toxicology methods for hepatotoxicity and cardiotoxicity has approached or even surpassed that of traditional animal-based assays (academic.oup.com); performance varies by model, endpoint and dataset.
- **Timeline and Cost Reduction:** Industry case examples illustrate AI-enabled discovery efforts. Insilico reported positive topline Phase IIa results for its generative-AI-developed IPF candidate in November 2024, including a dose-dependent improvement in lung function (www.eurekalert.org). In AWS's

demonstration, antibody design time shrank from “up to a year” to mere weeks (www.techradar.com). Even more conservatively, computational docking can score compound libraries in hours that would take wet labs months or years.

- **Animal Use Trends:** Though full global data for 2025 are not yet released, proxy indicators are striking. The UK Home Office reported about 2.64 million scientific procedures on living animals in Great Britain in 2024 (www.gov.uk). With the FDA and legislators actively eliminating certain requirements, that number may decline sharply in the US over the next 5–10 years. The GAO’s 2025 study specifically highlights organ-chips as a complement that “may be used alongside animals” for now (www.gao.gov), reflecting an interim mixed approach. In June 2026, NIH announced a new Office of Research Innovation, Validation, and Application (ORIVA) to coordinate NIH-wide efforts to develop, validate and scale NAMs.
- **Case Study Outcomes:** The phase IIa results for ISM001-055 gave quantifiable endpoints: a dose-dependent FVC (forced vital capacity) improvement in IPF patients was observed over 12 weeks (www.eurekalert.org). In a collaboration with MSK, AWS describes using Bio Discovery to design nearly 300,000 novel antibody candidates and filter them for wet-lab testing within weeks (www.techradar.com), versus up to a year using traditional design methods, according to AWS's own description of the workflow.
- **Economic Impact:** A 2022 *Communications Medicine* study of the Emulate Liver-Chip (Ewart et al.) modelled that routine use for drug-induced liver injury prediction could generate roughly $3 billion annually for the pharmaceutical industry through increased small-molecule R&D productivity (www.nature.com). While such figures are projections, they underscore the scale of potential gains: even a single megapharma avoiding a single phase III trial failure (costing $100–300M) by using a better model would validate the investment in these technologies.

Nonetheless, rigorous **head-to-head validations** remain scarce. Notably, the NIH’s Tox21 program and the EPA’s ToxCast have generated massive public screening datasets (e.g. thousands of pesticides and chemicals tested in hundreds of cell-based assays) to underpin model building. Validated replacement of individual animal tests proceeds test by test through formal validation and regulatory acceptance, so broad percentage estimates of how many animal tests could be replaced should be treated cautiously.

In summary, while exact figures vary, the weight of evidence from trials, papers, and pilot programs strongly supports the efficacy of AI and NAMs. These conclusions rest on the published studies and announcements cited above; direct, independently validated comparisons remain limited. Taken together, this evidence-based picture justifies the conference’s optimistic framing that these innovations will become “central to future drug development” (www.biopharminternational.com).

Case Studies

Case Study: Organs-on-Chips in Action

Organ-on-chip systems are being evaluated in research and drug-development settings. The U.S. Government Accountability Office has described both their potential benefits over animal testing and the challenges that limit wider adoption, including the supply of quality human cells and the lack of standardized benchmarks. At present, chips generally complement rather than replace animal studies.

Case Study: AI-Integrated Screening (Example from BioTech)

The following is a hypothetical illustration of a hybrid workflow, not a reported case study. An AI model trained on public kinase-inhibitor data could be used to screen a proprietary library for off-target cardiotoxicity, for example by predicting hERG channel blockade. A compound flagged as high-risk could then be tested in a targeted human iPSC-cardiomyocyte assay (an NAM) before any rodent QT study is considered, and interpretable-ML tools such as SHAP values could help chemists see which structural features drive the model's concern. This hybrid **AI + NAM** pattern illustrates a key theme: AI and experimental alternatives often work best when paired, with each de-risking the other's blind spots.

Discussion: Implications and Future Directions

The convergence of AI-driven tools and animal-free methods has profound implications for the future of drug discovery:

- **Acceleration of R&D:** Computational models and human-based assays promise to drastically shorten the development timeline. Predictive algorithms will triage poor candidates rapidly, focusing laboratory resources on high-probability leads. AWS has described one such workflow, in a collaboration with Memorial Sloan Kettering Cancer Center, in which candidates were sent to the wet lab for testing in weeks versus up to a year using traditional design methods (aws.amazon.com). In the longer term, fully simulated clinical trials and disease models are envisioned, where AI predicts patient responses to a candidate before any human is enrolled, enabling rational go/no-go decisions.
- **Improved Success Rates:** By pivoting away from animal models with limited human relevance, attrition due to late-stage toxicity or lack of efficacy should decline. Early case studies (Insilico, etc.) hint that truly first-in-class drugs – especially in challenging areas like fibrosis or neurological disease – may become more achievable. Safety margins may widen as compounds are vetted in more human-like systems. The cumulative effect would be more drugs reaching patients and fewer wasted compounds in the pipeline.

- **Ethical and Economic Benefits:** Reducing animal use aligns with ethical imperatives and public sentiment. Economically, the estimated multi-billion-dollar savings could translate into higher industry sustainability and possibly lower drug prices. The U.S. GAO and European bodies stress that these new methods not only advance science but also promote “sustainable growth” and competitiveness (publications.jrc.ec.europa.eu). For societies struggling with drug access, faster and cheaper development could improve supply of essential medicines and foster innovation in neglected disease areas.
- **Regulatory Evolution:** The 2025–2030 policy landscape is likely to further enshrine NAMs. Further regulatory guidance on AI and NAMs may clarify evidence requirements, but its timing and content cannot be assumed, and sponsors should follow current FDA, ICH and OECD guidance. A challenge for regulators will be to remain science-driven while validating novel endpoints (e.g. organ-chip biomarkers).
- **Challenges and Risks:** Widespread adoption is not automatic. Investment in infrastructure, training, and data is necessary. Smaller biotech may lack resources to develop proprietary AI; this could widen gaps between large and small companies. Data sharing remains a bottleneck, as highlighted by GAO; until pharmaceutical companies and chip makers collaborate on open validation studies, uncertainty will persist. There is also the risk of hype-outpacing reality: overreliance on “AI hype” without proper controls could lead to costly failures. Ethical considerations arise with human-derived models too (e.g. consent and use of human cells for organoids, data privacy in AI). These issues require broad discussion and guidelines.
- **Equity and Global View:** The “democratization” of AI (cloud services, open-source tools) could help smaller labs partake in advanced modeling. However, there is a concern about equitable access – similar to how not all nations have equal high-throughput lab capacities. Possible approaches to equity include centralized NAM testing hubs in lower-income countries and open data platforms shared across consortia.
- **Scientific Perspectives:** Enthusiasm for these methods is tempered by caution: *in silico* models can fail to account for emergent biological phenomena, and **experimental validation remains crucial**. In practice, aspects like ADME are already reliably predicted by integrated in vitro/in silico ADMET pipelines, but complex immunogenic responses or idiosyncratic effects are still difficult to foresee without some in vivo context. Future R&D will thus likely stratify research: use NAMs for common safety flags but reserve narrow, well-justified animal tests for the toughest issues.

Conclusion

The sources reviewed here, including the NBC 2026 pre-conference announcements, point to a cautiously optimistic picture: drug discovery is moving toward a hybrid model where **AI-driven predictive models and advanced human-based assays** form the backbone of preclinical research. This transition is not just technological but philosophical. As Dr. Shuhua Bai, the AAPS NBC chair, emphasized, it represents “a transformative shift toward more predictive, data-driven drug development” (www.aaps.org). AAPS said its

plenaries “showcase the scientific forces reshaping biotechnology,” with AI and human-relevant models among the announced themes in the push toward safer, smarter therapeutics (www.aaps.org) (www.biopharminternational.com).

Our analysis – grounded in current case studies and scientific literature – finds that the evidence supports this shift. With sufficient data, computational toxicology models have approached or even surpassed animal-based assays for some endpoints, notably hepatotoxicity and cardiotoxicity (academic.oup.com); pioneering companies have drug candidates in trials based on AI design (www.eurekalert.org); and regulators are explicitly opening doors to NAMs (www.axios.com) (publications.jrc.ec.europa.eu). Remaining obstacles (validation, data gaps, integration) are real but tractable through concerted efforts by industry consortia and international agencies. Importantly, the ultimate goal of these approaches is patient benefit: reducing uncertainty and the time needed to bring effective medicines to people in need.

Looking ahead, the next few years should see iterative improvements as the field gathers momentum. Over time, we would expect more **metrics** to enter the public domain – e.g. validated case studies with quantitative performance numbers – as firms and regulators gain confidence. Artificial intelligence models will become more explainable and better regulated; NAM technologies will mature into validated standards. Note that this article draws on pre-conference announcements and does not report the proceedings of the May 2026 meeting.

In summary, the sources reviewed here, including the NBC 2026 pre-conference announcements, point to a clear message: AI-driven and animal-free methods are reshaping drug R&D toward a more efficient, ethical, and human-centered paradigm. As these approaches solidify, they carry the promise not only of faster cures but of a fundamentally improved innovation ecosystem where science, technology, and compassion converge.

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(The above references are used illustratively to support the analysis; citation numbers correspond to the bracketed markers in the text.)

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