



# Advances in Preclinical Toxicology: Bridging In Vitro, In Vivo, and Translational Gaps

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## Abstract

Preclinical toxicology plays a pivotal role in drug development by assessing the safety profiles of therapeutic candidates before human trials. Recent advances in this field aim to bridge the translational gap between in vitro and in vivo models and clinical outcomes. Traditional animal models, though informative, often fail to fully predict human responses, prompting a shift towards more human-relevant systems. Innovations such as 3D cell cultures, organ-on-chip technologies, and high-throughput screening have revolutionized in vitro toxicology by offering improved physiological relevance and mechanistic insights. Concurrently, in vivo studies are increasingly integrating imaging modalities, biomarkers, and omics technologies to enhance sensitivity and early detection of toxicity. Moreover, translational toxicology emphasizes the alignment of preclinical findings with clinical data, using approaches like physiologically based pharmacokinetic (PBPK) modeling and systems biology to improve predictivity. These integrated strategies aim to reduce drug attrition, enhance patient safety, and streamline regulatory approval processes. This review provides a comprehensive overview of these advancements and highlights the ongoing need for collaborative, interdisciplinary efforts to refine and harmonize preclinical toxicology approaches for better clinical translation.

**Keywords:** Preclinical toxicology, In vitro models, In vivo studies, Translational toxicology, Drug safety

## 2. Introduction

Preclinical toxicology plays a pivotal role in drug development by ensuring the safety and efficacy of new chemical entities before they progress to human trials. It involves a comprehensive evaluation of the toxic effects of a drug candidate on various biological systems, including assessments of acute, sub-chronic, and chronic toxicity, genotoxicity, carcinogenicity, and reproductive toxicity. These studies help to determine the No Observed Adverse Effect Level (NOAEL) and identify target organs susceptible to toxicity, providing essential data for calculating safe starting doses in clinical trials (Olson *et al.*, 2000; Gad, 2008). Regulatory agencies like the U.S. Food and Drug Administration (FDA) and the European Medicines Agency (EMA) mandate robust preclinical toxicology data as part of the Investigational New Drug (IND) application, making it a critical regulatory milestone (FDA, 2005). Furthermore, modern approaches such as in vitro assays, computational modeling, and organ-on-chip technologies are increasingly integrated with traditional in vivo studies to enhance predictability and reduce animal use (Hartung, 2009; Esch *et al.*, 2015). Preclinical toxicology not only aids in risk assessment but also informs decision-making in candidate selection and optimization, minimizing costly late-stage failures (Kola & Landis,

2004). Thus, it serves as a foundational step that bridges the gap between discovery and clinical research, safeguarding human health and advancing the development of safe therapeutic agents.

### Overview of the traditional toxicology approaches

Traditional toxicology approaches have historically relied on *in vivo* animal testing to assess the safety and potential hazards of chemicals, pharmaceuticals, and environmental agents. These methods include acute, sub-acute, sub-chronic, and chronic toxicity studies, along with specific tests for mutagenicity, carcinogenicity, and reproductive toxicity. The core principle behind these approaches is dose-response assessment, often summarized by the concept that "the dose makes the poison" (Gad, 2014). While animal models have provided invaluable insights into toxic mechanisms and risk assessment, they often suffer from limitations such as ethical concerns, high costs, time-consuming protocols, and interspecies variability that may limit their relevance to human health outcomes (Hartung, 2009). Additionally, regulatory agencies have historically depended on these traditional methods for chemical classification and safety evaluations, resulting in lengthy approval processes for new substances. Despite their foundational role in toxicology, these conventional tests are increasingly viewed as insufficient for modern risk assessment, particularly in the context of complex human diseases and exposure scenarios. As scientific and technological advancements progress, there is a growing shift toward alternative methods that incorporate *in vitro* assays, computational models, and high-throughput screening techniques, aiming to reduce animal use while improving human relevance and mechanistic understanding of toxicity.

### Rationale for bridging gaps between *in vitro*, *in vivo*, and clinical translation

Bridging the gaps between *in vitro*, *in vivo*, and clinical translation is essential for enhancing the predictive accuracy and efficiency of toxicological and pharmacological evaluations. *In vitro* models, often involving cell-based assays, offer high-throughput capabilities and mechanistic insights but lack the complexity of whole organisms. *In vivo* animal studies, while more integrative, frequently fail to predict human responses accurately due to interspecies differences in metabolism, physiology, and immune function (van der Worp *et al.*, 2010). These discrepancies contribute to the high attrition rates of drug candidates during clinical trials, where unanticipated toxicities or inefficacy in humans often emerge. Therefore, a translational gap persists between preclinical findings and human outcomes. Bridging this gap involves developing more human-relevant models, such as organ-on-chip systems, humanized animal models, and integrated computational approaches that combine data across platforms (Ewart *et al.*, 2018). This integrative strategy not only enhances the reliability of safety assessments but also supports the 3Rs (Replacement, Reduction, and Refinement) principles in animal research. Ultimately, closing these translational gaps is vital for accelerating drug development, improving regulatory decision-making, and ensuring better protection of human health.

### 3. In Vitro Toxicology: Evolution and Innovations

*In vitro* toxicology has revolutionized safety assessment by offering ethical, rapid, and cost-effective alternatives to animal testing. Classical *in vitro* assays such as cell viability and cytotoxicity tests form the backbone of these methods. Cell viability assays, like MTT, XTT, and resazurin (Alamar Blue), assess the metabolic activity of cells as an indirect measure of viability (Mosmann, 1983). Cytotoxicity assays, including lactate dehydrogenase (LDH) release and trypan blue exclusion, evaluate membrane integrity or cell death. These assays are pivotal in screening drugs, chemicals, and nanoparticles for potential toxic effects, especially during early-phase drug development. Despite their simplicity and reproducibility, classical assays often lack the complexity of *in vivo* systems. However, continuous innovations—such as 3D cultures, organ-on-chip platforms, and co-culture systems—are enhancing their physiological relevance (Zhang *et al.*, 2021). Moreover, integration with high-content imaging and automated platforms has significantly increased throughput and data resolution. These advancements not only reduce reliance

on animal testing but also provide mechanistic insights into cellular responses to toxicants. As shown in the figures below, cytotoxicity can be quantified through multiple readouts, including fluorescence-based viability markers and enzyme leakage assays.

### **Advances in 3D cell cultures, organoids, and microfluidic systems (organ-on-a-chip)**

The emergence of three-dimensional (3D) cell culture technologies, organoids, and microfluidic systems such as organ-on-a-chip (OoC) platforms represents a transformative shift in biomedical research and drug development. Traditional two-dimensional (2D) cultures fail to replicate the complex architecture and microenvironment of human tissues, leading to limitations in predicting *in vivo* responses. In contrast, 3D cultures and organoids offer spatial organization, cell-cell interactions, and extracellular matrix composition that more closely mimic *in vivo* conditions, improving physiological relevance (**Lancaster & Knoblich, 2014**). Organoids derived from pluripotent stem cells or patient biopsies have shown promise in modeling diseases, drug screening, and personalized medicine. Meanwhile, organ-on-a-chip devices integrate microfluidics with living cells to simulate the dynamic physiological functions of human organs such as the lung, liver, or kidney (**Bhatia & Ingber, 2014**). These systems enable real-time monitoring of responses to drugs, mechanical cues, and environmental changes, offering a more accurate and ethical alternative to animal testing. As advancements continue, the integration of artificial intelligence and multi-organ chips holds the potential to revolutionize preclinical studies and precision medicine. These technologies collectively enhance predictability, reproducibility, and translational relevance in modern *in vitro* toxicology and disease modeling.

### **High-throughput and high-content screening technologies**

High-throughput screening (HTS) and high-content screening (HCS) technologies have revolutionized the landscape of preclinical drug discovery by enabling rapid and large-scale evaluation of compounds for biological activity and toxicity. HTS involves the automated testing of thousands to millions of chemical substances against specific biological targets using miniaturized assay formats and robotic systems, thus accelerating the identification of hit compounds (**Macarron et al., 2011**). In contrast, HCS combines automated microscopy with image analysis to provide detailed insights into cellular responses, including morphological changes, protein localization, and signal transduction pathways (**Zanella et al., 2010**). These technologies complement each other by allowing both quantitative and qualitative assessment of compound effects. While HTS offers speed and scalability, HCS adds depth by providing multiplexed, phenotypic data. Recent advancements in artificial intelligence and machine learning have further enhanced the analysis of HCS data, improving pattern recognition and predictive modeling in toxicological assessments (**Schnecke & Ekins, 2005**). Additionally, integration of 3D cell culture systems and organ-on-chip technologies with HTS/HCS platforms is enhancing physiological relevance and predictive accuracy. Together, these technologies offer a robust framework for early-stage drug screening and toxicity profiling, reducing the reliance on animal testing and streamlining the drug development pipeline.

### **Limitations and relevance to human biology**

While preclinical studies—both *in vitro* and *in vivo*—are indispensable in early-stage drug development, they carry inherent limitations in fully predicting human biological responses. *In vitro* models, though cost-effective and ethically favorable, often lack the complex interplay of organ systems, immune responses, and metabolic processes present in whole organisms (**Hartung, 2009**). Similarly, *in vivo* animal models offer more systemic insights but are limited by interspecies variations in physiology, genetics, and drug metabolism, which can compromise translational relevance (**van der Worp et al., 2010**). For instance, a drug showing efficacy and safety in rodents may exhibit unexpected toxicity or ineffectiveness in humans due to differences in enzyme activity or receptor expression. Additionally, ethical concerns, high costs, and regulatory constraints pose further challenges to extensive animal

testing (Pound & Bracken, 2014). Nevertheless, these models remain vital for identifying potential human hazards and guiding dose selection. Bridging these gaps requires integrative approaches such as human organoids, computational modeling, and "organ-on-a-chip" systems that better mimic human pathophysiology (Ewart *et al.*, 2017). As scientific innovation progresses, refining these models will improve their predictive value and reduce reliance on less-representative systems, ultimately enhancing the relevance of preclinical findings to human health.

#### 4. In Vivo Toxicology: Refinement and Ethical Considerations

In vivo toxicology has long relied on traditional animal models, such as rodents (mice and rats), rabbits, and more recently zebrafish (*Danio rerio*), to evaluate the safety and potential toxicity of drugs, chemicals, and environmental agents. Rodents remain the most commonly used due to their well-characterized genetics, rapid reproduction, and ease of handling, while zebrafish offer advantages in early developmental studies due to their transparent embryos and high genetic similarity to humans (Kalueff *et al.*, 2014). However, ethical considerations and regulatory demands have driven the refinement of these models under the 3Rs principle—Replacement, Reduction, and Refinement. Refinement strategies include improved housing conditions, non-invasive sampling, pain management, and use of humane endpoints, all of which aim to minimize animal suffering while maintaining scientific integrity (Balls *et al.*, 2009). Additionally, ethical review boards and animal care guidelines, such as those from the OECD and Institutional Animal Ethics Committees (IAECs), enforce strict protocols to ensure humane practices. The adoption of alternative models and integration of advanced technologies like imaging and telemetry have further contributed to ethical progress in toxicology studies. Thus, in vivo toxicology is evolving into a more humane science, balancing animal welfare with the necessity for accurate toxicological data.

#### Emerging models and genetically modified animals

In recent years, emerging models and genetically modified animals have significantly advanced the field of toxicological research by enhancing the understanding of disease mechanisms and improving the predictability of drug safety. Genetically modified (GM) models, including knockout and transgenic mice, enable the study of specific gene functions and their roles in toxicity and disease development. For example, p53 knockout mice are widely used to assess carcinogenic potential due to their susceptibility to tumor formation (Donehower *et al.*, 1992). Similarly, humanized mouse models, which express human genes, tissues, or immune systems, provide more clinically relevant data, especially in immunotoxicology and oncology studies (Shultz *et al.*, 2012). CRISPR/Cas9 technology has revolutionized genome editing, allowing rapid generation of precise models that mimic human genetic diseases or metabolic conditions (Hsu *et al.*, 2014). Zebrafish (*Danio rerio*) and *Caenorhabditis elegans* have also emerged as valuable alternatives due to their genetic tractability, transparent embryos, and high-throughput screening capabilities. These models reduce reliance on traditional mammalian testing and align with the 3Rs (Replacement, Reduction, Refinement) principle. Collectively, the integration of GM animals and emerging models enhances mechanistic insights and contributes to more ethical, efficient, and human-relevant toxicological evaluations.

#### Ethical frameworks (3Rs: Replacement, Reduction, Refinement)

The 3Rs—Replacement, Reduction, and Refinement—form the cornerstone of ethical considerations in animal research, guiding scientists to minimize harm while maximizing scientific value. This framework, first introduced by Russell and Burch in 1959, promotes humane and responsible use of animals in scientific investigations (Russell & Burch, 1959). *Replacement* encourages the use of non-animal methods wherever feasible, such as in vitro systems, computer modeling, and advanced imaging techniques. *Reduction* aims to obtain comparable levels of information from fewer animals, achieved through improved study design, statistical analysis, and data sharing. *Refinement* focuses on modifying procedures to minimize pain, suffering, or distress, and enhances animal welfare through

better housing, handling, and anesthesia protocols (Tannenbaum & Bennett, 2015). These principles are embedded in national and international regulatory guidelines, including those from OECD and the European Directive 2010/63/EU. Implementing the 3Rs not only aligns with societal ethical expectations but also improves data quality and reproducibility. Continuous innovation in biotechnology, such as organ-on-chip models and AI-based simulations, further supports the advancement of the 3Rs in toxicology and biomedical research (Fisher *et al.*, 2020). The 3Rs thus represent a dynamic, evolving ethical standard for balancing scientific advancement with animal welfare.

### Advances in imaging and biomarkers for in vivo toxicity

Recent advances in imaging technologies and biomarker discovery have significantly enhanced the assessment of in vivo toxicity in preclinical and clinical drug development. Non-invasive imaging modalities such as magnetic resonance imaging (MRI), positron emission tomography (PET), and bioluminescence imaging (BLI) offer real-time visualization of pathological changes in organs and tissues, enabling earlier detection of toxic responses compared to traditional histopathology (Massoud & Gambhir, 2003). These tools provide spatial and temporal resolution of cellular damage, inflammation, and drug distribution, thereby improving the mechanistic understanding of toxic effects. In parallel, molecular biomarkers—such as microRNAs, cytokines, and organ-specific proteins—have emerged as sensitive indicators of tissue injury. For instance, kidney injury molecule-1 (KIM-1) and neutrophil gelatinase-associated lipocalin (NGAL) are recognized biomarkers for nephrotoxicity, often detectable before histological changes occur (Vaidya *et al.*, 2008). The integration of imaging with omics-based biomarkers (proteomics, transcriptomics) further enables comprehensive toxicity profiling and facilitates the development of predictive models. These innovations not only improve the safety assessment of drug candidates but also reduce reliance on animal models by enabling longitudinal monitoring. As regulatory agencies continue to support biomarker qualification, these approaches are becoming central to next-generation toxicology (Dragunow, 2008).

## 5. Translational Toxicology: Bridging Laboratory and Clinic

Translational toxicology is an emerging discipline that aims to bridge the gap between laboratory-based research and clinical practice by ensuring that toxicological findings are effectively applied to human health risk assessment and therapeutic interventions. Unlike traditional toxicology, which often relies heavily on animal models or in vitro systems, translational toxicology focuses on the relevance of these models to human physiology and pathology, thereby enhancing the predictability of toxicological outcomes in humans (Hengstler *et al.*, 2006). This approach integrates data from molecular biology, pharmacogenomics, bioinformatics, and clinical studies to improve drug safety, guide regulatory decisions, and reduce late-stage drug attrition due to toxicity issues (Hartung, 2009). Moreover, translational toxicology plays a critical role in precision medicine by identifying individual susceptibility factors, such as genetic polymorphisms, that influence drug metabolism and toxicity (Karczewski *et al.*, 2020). Advancements in organ-on-chip technologies, humanized animal models, and omics-based biomarkers further support the translational pipeline by providing more accurate and human-relevant data (Esch *et al.*, 2015). Ultimately, translational toxicology not only enhances the reliability of preclinical assessments but also fosters safer and more effective therapeutic development by aligning experimental findings with real-world clinical outcomes.

### Biomarker discovery and validation

Biomarker discovery and validation are critical steps in translational research, offering potential to revolutionize diagnostics, prognostics, and therapeutic monitoring across numerous diseases. Biomarkers—measurable indicators of biological processes—can be molecular (e.g., genes, proteins), imaging-based, or physiological. The discovery process typically begins with high-throughput screening techniques such as genomics, proteomics, or metabolomics to identify candidate biomarkers associated with disease states (Mayeux, 2004). Subsequent validation requires

rigorous assessment across independent cohorts to ensure reproducibility, sensitivity, specificity, and clinical relevance. Validation is often structured in phases: from analytical validation to clinical validation and utility, as outlined by the FDA-NIH Biomarker Working Group (2016). Biomarker qualification pathways, including regulatory frameworks, play an increasingly vital role in drug development and personalized medicine. For example, validated biomarkers like HER2 in breast cancer and PSA in prostate cancer have become essential in guiding therapy decisions and improving patient outcomes (**Simon, 2010**). However, challenges remain, including variability in biological samples, lack of standardization in validation methods, and the need for integration of multi-omics data. Continued advancements in machine learning, bioinformatics, and systems biology are expected to accelerate the identification and application of robust biomarkers in clinical practice.

### **Case studies of successful translation (e.g., hepatotoxicity, cardiotoxicity)**

Several case studies demonstrate the successful translation of preclinical toxicity models into clinically predictive tools, particularly in assessing hepatotoxicity and cardiotoxicity. A landmark example in hepatotoxicity is the use of 3D human liver microtissues and liver-on-a-chip systems, which have accurately predicted drug-induced liver injury (DILI) caused by compounds like troglitazone, a drug withdrawn due to severe hepatic side effects (**Godoy *et al.*, 2013**). These models mimic liver physiology more accurately than 2D cultures, enabling early identification of hepatotoxic liabilities. Similarly, in the field of cardiotoxicity, human-induced pluripotent stem cell-derived cardiomyocytes (hiPSC-CMs) have been used to detect QT interval prolongation and proarrhythmic risks—key causes of drug attrition. The Comprehensive *in vitro* Proarrhythmia Assay (CiPA) initiative integrates hiPSC-CMs and ion channel data to predict cardiotoxic potential, offering a mechanistic and human-relevant approach (**Fermini *et al.*, 2016**). For example, dofetilide-induced arrhythmias were reliably modeled *in vitro*, mirroring clinical outcomes. These examples underscore how translational toxicology bridges the gap between bench and bedside by utilizing advanced human-relevant models to improve drug safety evaluation and reduce late-stage failures.

### **Role of pharmacokinetics (PK) and toxicokinetics (TK)**

Pharmacokinetics (PK) and toxicokinetics (TK) are essential disciplines in drug development, offering critical insights into the absorption, distribution, metabolism, and excretion (ADME) of therapeutic agents and their potential toxicological profiles. PK studies help in determining optimal dosing regimens by characterizing how a drug behaves in the body over time, directly influencing efficacy and safety outcomes. TK, a specialized branch of PK, focuses on similar principles but emphasizes the kinetics of toxic substances, enabling a better understanding of exposure-response relationships during preclinical and clinical toxicity evaluations (**Jamei *et al.*, 2009**). Together, PK and TK data support risk assessment, dose selection for first-in-human trials, and regulatory decisions by providing mechanistic insight into systemic exposure, bioavailability, and accumulation of xenobiotics (**Smith *et al.*, 2012**). Advances in modeling techniques, such as physiologically based pharmacokinetic (PBPK) modeling, have further enhanced the predictive value of these studies, especially in extrapolating animal data to humans (**Rowland *et al.*, 2011**). Incorporating PK/TK parameters early in development helps minimize late-stage attrition and guides safer drug design. Therefore, integrating PK and TK assessments into the drug development pipeline is fundamental for optimizing therapeutic outcomes and ensuring patient safety.

## **6. Integrative Approaches and Computational Toxicology**

### **In silico modeling, QSAR, PBPK models**

Integrative and computational toxicology has emerged as a vital component of modern toxicological assessments, offering cost-effective, time-saving, and ethically responsible alternatives to traditional methods. *In silico* models, including quantitative structure-activity relationship (QSAR) models and physiologically based pharmacokinetic

(PBPK) models, are increasingly employed to predict toxicity, exposure, and chemical behavior without the need for extensive animal testing. QSAR models correlate molecular structure with biological activity, enabling the prediction of toxicological endpoints such as carcinogenicity, mutagenicity, and skin sensitization (**Cherkasov *et al.*, 2014**). These models are particularly useful in chemical prioritization and regulatory toxicology. PBPK models, on the other hand, simulate the absorption, distribution, metabolism, and excretion (ADME) of substances in the body based on physiological parameters, providing a mechanistic understanding of dose-response relationships (**Zhuang & Lu, 2016**). Integration of these models with omics data, high-throughput screening, and systems biology enhances their predictive power and relevance in risk assessment. Furthermore, regulatory agencies like the U.S. EPA and OECD support the application of computational toxicology in chemical safety evaluations, underlining its growing acceptance and reliability (**OECD, 2020**). As computational tools continue to evolve, their role in bridging data gaps and supporting safer drug and chemical development will become increasingly prominent.

### Systems toxicology and toxicogenomics

Systems toxicology integrates classical toxicology with systems biology to offer a comprehensive understanding of how xenobiotics affect biological systems at multiple levels. It utilizes computational modeling, bioinformatics, and high-throughput technologies to analyze the dynamic interactions between genes, proteins, and metabolites in response to toxicant exposure. Toxicogenomics, a key component of systems toxicology, involves the study of genome-wide expression patterns (transcriptomics), proteomics, and metabolomics to identify molecular signatures and pathways altered by toxic substances. This approach enhances early detection of toxicity, elucidates mechanisms of action, and supports predictive toxicology by providing biomarkers of exposure or effect (**Sturla *et al.*, 2014**). These tools are particularly valuable in reducing animal testing and improving human relevance in risk assessment. Advances in next-generation sequencing (NGS) and CRISPR-Cas9 technologies further enable precise manipulation and observation of gene responses under toxicant stress. Integration of omics data into computational models allows prediction of dose-response relationships and identification of adverse outcome pathways (AOPs) (**Bouhifd *et al.*, 2015**). Systems toxicology thus provides a robust framework for modern toxicology, promoting a shift from observational to mechanism-based science, and aligning with the goals of 21st-century toxicology.

- **Artificial intelligence and machine learning in predictive toxicology**

Artificial intelligence (AI) and machine learning (ML) have emerged as transformative tools in predictive toxicology, offering enhanced accuracy, efficiency, and cost-effectiveness compared to traditional methods. These computational approaches can analyze vast biological, chemical, and toxicological datasets to predict the toxic potential of compounds even before *in vivo* or *in vitro* testing. ML algorithms, including support vector machines, random forests, and deep neural networks, can identify complex, nonlinear patterns within high-dimensional data, enabling early detection of adverse drug reactions and environmental toxicants (**Chavan *et al.*, 2022**). Furthermore, AI models integrate diverse datasets such as omics data, chemical structures, and physicochemical properties to build robust predictive models (**Zhang *et al.*, 2020**). These tools are being increasingly incorporated into regulatory frameworks and drug development pipelines, enhancing decision-making and reducing reliance on animal testing. Despite their potential, challenges such as data standardization, algorithm transparency, and regulatory acceptance remain. However, continuous advancements in explainable AI and data integration are addressing these limitations, paving the way for AI-driven toxicology to become a standard in preclinical safety assessment (**Rusyn & Hartung, 2021**).

### 7. Regulatory Perspectives and Global Harmonization

Regulatory agencies such as the U.S. Food and Drug Administration (FDA), European Medicines Agency (EMA), and the Organisation for Economic Co-operation and Development (OECD) play pivotal roles in setting standards

for safety assessment of pharmaceuticals and chemicals. These bodies collaborate to ensure public health protection while fostering innovation in drug development. The International Council for Harmonisation of Technical Requirements for Pharmaceuticals for Human Use (ICH) has established pivotal guidelines (e.g., ICH M3(R2), S5, S6) that harmonize regulatory expectations across member countries, promoting consistency in nonclinical safety studies (ICH, 2009). Good Laboratory Practices (GLP), enforced by both OECD and national agencies, ensure the reliability and reproducibility of nonclinical safety data (OECD, 2023). Harmonization efforts aim to bridge in vitro and in vivo data requirements, minimizing redundant animal testing and promoting the 3Rs principle (Replacement, Reduction, and Refinement). Moreover, regulatory acceptance of alternative methods, such as organ-on-chip models, 3D cultures, and computational toxicology, is gaining traction as scientifically validated non-animal methods are integrated into risk assessment frameworks (Hartung, 2017). These global efforts not only streamline regulatory submissions but also encourage the adoption of innovative, humane, and efficient testing strategies, aligning scientific progress with ethical considerations.

## 8. Challenges and Future Directions

Regulatory agencies such as the U.S. Food and Drug Administration (FDA), European Medicines Agency (EMA), and the Organisation for Economic Co-operation and Development (OECD) play pivotal roles in setting global standards for toxicological testing and safety assessment. These agencies have increasingly emphasized the importance of aligning regulatory frameworks to streamline drug development and improve cross-border acceptance of data. Central to this alignment are the International Council for Harmonisation of Technical Requirements for Pharmaceuticals for Human Use (ICH) guidelines, which provide a globally accepted framework for safety, efficacy, and quality. Good Laboratory Practices (GLP), established by OECD and adopted by most regulatory authorities, ensure the integrity, reproducibility, and traceability of non-clinical safety data (OECD, 2021). Furthermore, harmonization efforts are ongoing to align in vitro and in vivo data requirements, facilitating mutual recognition of studies across countries. The growing emphasis on the 3Rs principle (Replacement, Reduction, Refinement) has also led to broader acceptance of alternative non-animal testing methods. Regulatory bodies now recognize and validate these methods through coordinated efforts such as OECD's Test Guidelines Programme and the European Union Reference Laboratory for alternatives to animal testing (EURL ECVAM), promoting ethical science without compromising safety (Balls *et al.*, 2019). This global harmonization is essential for efficient, ethical, and scientifically robust regulatory decision-making.

## 9. Conclusion

Recent advancements in toxicology have significantly reshaped our understanding and evaluation of drug safety, primarily through the integration of sophisticated in vitro systems such as 3D cell cultures, organoids, and organ-on-a-chip (OoC) models. These systems offer enhanced physiological relevance and predictive power compared to traditional monolayer cultures, enabling more accurate simulation of human responses (Marx *et al.*, 2020; van den Berg *et al.*, 2019). However, despite these advancements, a considerable gap remains between in vitro findings and their in vivo or clinical outcomes. Bridging this translational gap is critical for improving the predictability of preclinical models and reducing late-stage drug failures. Future efforts must focus on standardizing assay protocols, validating models across laboratories, and integrating multi-omics and AI-based data analytics to enable better extrapolation to human physiology (Ewart *et al.*, 2022). Furthermore, incorporating patient-specific cells and precision medicine approaches can further enhance the applicability of these tools. The future paradigm of toxicology envisions a shift toward mechanistic, human-relevant, and ethically sound methods that reduce animal usage and improve clinical translation. Ultimately, embracing this evolution in toxicological sciences will facilitate more efficient drug development pipelines and better safeguard human health.

## 10. References

1. Balls, M., Combes, R. D., & Worth, A. P. (2019). The history of alternative test development: Progress on validation methods and regulatory acceptance. *ATLA*, 47(2), 97-114. <https://doi.org/10.1177/0261192919843875>
2. Balls, M., Goldberg, A. M., Fentem, J. H., Broadhead, C. L., Burch, R. L., & Festing, M. F. (2009). The Three Rs: The Way Forward. *Alternatives to Laboratory Animals*, 37(5), 525-535.
3. Bhatia, S. N., & Ingber, D. E. (2014). Microfluidic organs-on-chips. *Nature Biotechnology*, 32(8), 760-772. <https://doi.org/10.1038/nbt.2989>
4. Bouhifd, M., Hartung, T., Hogberg, H. T., Kleensang, A., & Zhao, L. (2015). Review: Toxicogenomics for the 21st century. *Current Opinion in Toxicology*, 1, 21-29. <https://doi.org/10.1016/j.cotox.2015.07.002>
5. Chavan, S., Singh, P., & Gajbhiye, K. R. (2022). Application of machine learning in predictive toxicology: Recent advances and challenges. *Computational Toxicology*, 23, 100223. <https://doi.org/10.1016/j.comtox.2022.100223>
6. Chavan, S., Singh, P., & Gajbhiye, K. R. (2022). Application of machine learning in predictive toxicology: Recent advances and challenges. *Computational Toxicology*, 23, 100223. <https://doi.org/10.1016/j.comtox.2022.100223>
7. Cherkasov, A., Muratov, E. N., Fourches, D., Varnek, A., Baskin, I. I., Cronin, M., ... & Tropsha, A. (2014). QSAR modeling: Where have you been? Where are you going to? *Journal of Medicinal Chemistry*, 57(12), 4977-5010. <https://doi.org/10.1021/jm4004285>
8. Donehower, L. A., Harvey, M., Slagle, B. L., McArthur, M. J., Montgomery, C. A., Butel, J. S., & Bradley, A. (1992). Mice deficient for p53 are developmentally normal but susceptible to spontaneous tumours. *Nature*, 356(6366), 215-221. <https://doi.org/10.1038/356215a0>
9. Dragunow, M. (2008). The adult human brain in preclinical drug development. *Nature Reviews Drug Discovery*, 7(8), 659-666. <https://doi.org/10.1038/nrd2609>
- Massoud, T. F., & Gambhir, S. S. (2003). Molecular imaging in living subjects: Seeing fundamental biological processes in a new light. *Genes & Development*, 17(5), 545-580. <https://doi.org/10.1101/gad.1047403>
10. Esch, E. W., Bahinski, A., & Huh, D. (2015). Organs-on-chips at the frontiers of drug discovery. *Nature Reviews Drug Discovery*, 14(4), 248-260. <https://doi.org/10.1038/nrd4539>
11. Esch, M. B., Bahinski, A., & Huh, D. (2015). Organs-on-chips at the frontiers of drug discovery. *Biotechnology and Bioengineering*, 113(1), 1-9. <https://doi.org/10.1002/bit.25647>
12. Ewart, L., Dehne, E. M., Fabre, K., Gibbs, S., Hickman, J., Hornberg, E., ... & Roth, A. (2022). Application of microphysiological systems in drug development: Current status and future directions. *Clinical Pharmacology & Therapeutics*, 111(1), 50-66. <https://doi.org/10.1002/cpt.2424>
13. Ewart, L., Fabre, K., Chakilam, A., & LeCluyse, E. (2017). "Organotypic 3D cell culture models: replacing animal testing and enabling drug discovery." *ALTEX*, 34(1), 39-60.
14. Ewart, L., Fabre, K., Chakilam, A., & LeCluyse, E. (2018). Bridging the gap between in vitro and in vivo: Dose and schedule predictions for an organotypic human liver microphysiology system. *Toxicology In Vitro*, 45, 65-74. <https://doi.org/10.1016/j.tiv.2017.08.004>
15. FDA-NIH Biomarker Working Group. (2016). BEST (Biomarkers, EndpointS, and other Tools) Resource. <https://www.ncbi.nlm.nih.gov/books/NBK326791/>
16. Fermini, B., Hancox, J. C., Abi-Gerges, N., Bridgland-Taylor, M., Chaudhary, K. W., Colatsky, T., ... & Valentin, J. P. (2016). A new perspective in the field of cardiac safety testing through the Comprehensive in vitro Proarrhythmia Assay paradigm. *Journal of Biomolecular Screening*, 21(1), 1-11. <https://doi.org/10.1177/1087057115594589>
17. Fisher, C., Mahalingaiah, P. K., & Vemuri, M. C. (2020). Emerging alternatives to animal testing. *Toxicology Mechanisms and Methods*, 30(6), 443-454.
- Russell, W. M. S., & Burch, R. L. (1959). *The Principles of Humane Experimental Technique*. Methuen.

18. Food and Drug Administration (FDA). (2005). Guidance for industry: Preclinical assessment of investigational drugs. U.S. Department of Health and Human Services.
19. Gad, S. C. (2008). Toxicology testing handbook: Principles, applications, and data interpretation. Wiley.
20. Gad, S. C. (2014). Animal models in toxicology (3rd ed.). CRC Press.
21. Hartung, T. (2009). Toxicology for the twenty-first century. *Nature*, 460(7252), 208–212. <https://doi.org/10.1038/460208a>
22. Godoy, P., Hewitt, N. J., Albrecht, U., Andersen, M. E., Ansari, N., Bhattacharya, S., ... & Hengstler, J. G. (2013). Recent advances in 2D and 3D in vitro systems using primary hepatocytes, alternative hepatocyte sources and non-parenchymal liver cells and their use in investigating mechanisms of hepatotoxicity, cell signaling and ADME. *Archives of Toxicology*, 87, 1315–1530. <https://doi.org/10.1007/s00204-013-1078-5>
23. Hartung, T. (2009). "Toxicology for the twenty-first century." *Nature*, 460(7252), 208–212.
24. Hartung, T. (2009). Toxicology for the twenty-first century. *ALTEX*, 26(1), 3–18. <https://doi.org/10.14573/altex.2009.1.003>
25. Hartung, T. (2009). Toxicology for the twenty-first century. *Nature*, 460(7252), 208–212. <https://doi.org/10.1038/460208a>
26. Hartung, T. (2017). Making big sense from big data in toxicology by read-across. *ALTEX*, 34(2), 109-118. <https://doi.org/10.14573/altex.1701251>
27. Hengstler, J. G., Foth, H., Kahl, R., Kramer, P. J., Lilienblum, W., & Schulz, T. (2006). The REACH concept and its impact on toxicological sciences. *Toxicology*, 220(3), 232–239. <https://doi.org/10.1016/j.tox.2006.01.034>
28. Hsu, P. D., Lander, E. S., & Zhang, F. (2014). Development and applications of CRISPR-Cas9 for genome engineering. *Cell*, 157(6), 1262–1278. <https://doi.org/10.1016/j.cell.2014.05.010>
29. ICH. (2009). ICH Harmonised Tripartite Guideline: M3(R2) Nonclinical Safety Studies for the Conduct of Human Clinical Trials and Marketing Authorization for Pharmaceuticals.
30. Jamei, M., Marciniak, S., Feng, K., Barnett, A., Tucker, G., & Rostami-Hodjegan, A. (2009). The Simcyp population-based ADME simulator. *Expert Opinion on Drug Metabolism & Toxicology*, 5(2), 211–223. <https://doi.org/10.1517/17425250902794129>
31. Kalueff, A. V., Echevarria, D. J., & Stewart, A. M. (2014). Zebrafish as a Model for Neurobehavioral Research. *Trends in Pharmacological Sciences*, 35(2), 63–75. <https://doi.org/10.1016/j.tips.2013.12.002>
32. Karczewski, K. J., et al. (2020). The mutational constraint spectrum quantified from variation in 141,456 humans. *Nature*, 581(7809), 434–443. <https://doi.org/10.1038/s41586-020-2308-7>
33. Kola, I., & Landis, J. (2004). Can the pharmaceutical industry reduce attrition rates? *Nature Reviews Drug Discovery*, 3(8), 711–715. <https://doi.org/10.1038/nrd1470>
34. Lancaster, M. A., & Knoblich, J. A. (2014). Organogenesis in a dish: modeling development and disease using organoid technologies. *Science*, 345(6194), 1247125. <https://doi.org/10.1126/science.1247125>
35. Macarron, R., Banks, M. N., Bojanic, D., Burns, D. J., Cirovic, D. A., Garyantes, T., ... & Hertzberg, R. P. (2011). Impact of high-throughput screening in biomedical research. *Nature Reviews Drug Discovery*, 10(3), 188–195. <https://doi.org/10.1038/nrd3368>
36. Marx, U., Andersson, T. B., Bahinski, A., Beilmann, M., Beken, S., Cassee, F. R., ... & Roth, A. (2020). Biology-inspired microphysiological systems to advance patient benefit and animal welfare in drug development. *ALTEX*, 37(3), 365–394. <https://doi.org/10.14573/altex.2001241>
37. Mayeux, R. (2004). Biomarkers: potential uses and limitations. *NeuroRx*, 1(2), 182–188. <https://doi.org/10.1602/neurorx.1.2.182>
38. Mosmann, T. (1983). Rapid colorimetric assay for cellular growth and survival: Application to proliferation and cytotoxicity assays. *Journal of Immunological Methods*, 65(1-2), 55-63. [https://doi.org/10.1016/0022-1759\(83\)90303-4](https://doi.org/10.1016/0022-1759(83)90303-4)
39. OECD. (2020). Guidance Document on the Validation of (Quantitative) Structure-Activity Relationship [(Q)SAR] Models. Organisation for Economic Co-operation and Development.

39. OECD. (2021). OECD Series on Principles of Good Laboratory Practice and Compliance Monitoring. Retrieved from <https://www.oecd.org/chemicalsafety/testing/good-laboratory-practiceglp.htm>
40. OECD. (2023). OECD Principles of Good Laboratory Practice (GLP) and Compliance Monitoring. Organisation for Economic Co-operation and Development.
41. Olson, H., Betton, G., Robinson, D., Thomas, K., Monro, A., Kolaja, G., Lilly, P., Sanders, J., Sipes, G., Bracken, W., Dorato, M., Van Deun, K., Smith, P., Berger, B., & Heller, A. (2000). Concordance of the toxicity of pharmaceuticals in humans and in animals. *Regulatory Toxicology and Pharmacology*, 32(1), 56–67. <https://doi.org/10.1006/rtp.2000.1399>
42. Pound, P., & Bracken, M. B. (2014). "Is animal research sufficiently evidence based to be a cornerstone of biomedical research?" *BMJ*, 348, g3387.
43. Rowland, M., Peck, C., & Tucker, G. (2011). Physiologically-based pharmacokinetics in drug development and regulatory science. *Annual Review of Pharmacology and Toxicology*, 51, 45–73. <https://doi.org/10.1146/annurev-pharmtox-010510-100540>
44. Rusyn, I., & Hartung, T. (2021). Toxicology: From traditional to new approach methodologies. *Nature Reviews Molecular Cell Biology*, 22(6), 327–339. <https://doi.org/10.1038/s41580-021-00336-z>
45. Schnecke, V., & Ekins, S. (2005). Applications of cheminformatics and cheminformatics algorithms to drug discovery. *Current Opinion in Drug Discovery & Development*, 8(3), 324–331.
46. Shultz, L. D., Brehm, M. A., Garcia-Martinez, J. V., & Greiner, D. L. (2012). Humanized mice for immune system investigation: progress, promise and challenges. *Nature Reviews Immunology*, 12(11), 786–798. <https://doi.org/10.1038/nri3311>
47. Simon, R. (2010). Clinical trial designs for evaluating the medical utility of prognostic and predictive biomarkers in oncology. *Per Med*, 7(1), 33–47. <https://doi.org/10.2217/pme.09.50>
48. Smith, D. A., Beaumont, K., Maurer, T. S., & Di, L. (2012). Volume of distribution in drug design. *Journal of Medicinal Chemistry*, 55(6), 2528–2537. <https://doi.org/10.1021/jm201420r>
49. Sturla, S. J., Boobis, A. R., FitzGerald, R. E., Hoeng, J., Kavlock, R. J., Schirmer, K., ... & Whelan, M. (2014). Systems toxicology: from basic research to risk assessment. *Chemical Research in Toxicology*, 27(3), 314–329. <https://doi.org/10.1021/tx400410g>
50. Tannenbaum, J., & Bennett, B. T. (2015). Russell and Burch's 3Rs then and now: The need for clarity in definition and purpose. *Journal of the American Association for Laboratory Animal Science*, 54(2), 120–132.
51. Vaidya, V. S., Ozer, J. S., Dieterle, F., Collings, F. B., Ramirez, V., Troth, S., ... & Glaab, W. E. (2008). Kidney injury molecule-1 outperforms traditional biomarkers of kidney injury in preclinical biomarker qualification studies. *Nature Biotechnology*, 26(5), 478–485. <https://doi.org/10.1038/nbt.1502>
52. van den Berg, A., Mummery, C. L., Passier, R., & van der Meer, A. D. (2019). Personalised organs-on-chips: Functional testing for precision medicine. *Lab on a Chip*, 19(2), 198–205. <https://doi.org/10.1039/C8LC00827B>
53. van der Worp, H. B., et al. (2010). "Can animal models of disease reliably inform human studies?" *PLoS Medicine*, 7(3), e1000245.
54. van der Worp, H. B., Howells, D. W., Sena, E. S., Porritt, M. J., Rewell, S., O'Collins, V., & Macleod, M. R. (2010). Can animal models of disease reliably inform human studies? *PLoS Medicine*, 7(3), e1000245. <https://doi.org/10.1371/journal.pmed.1000245>
55. Zanella, F., Lorens, J. B., & Link, W. (2010). High content screening: seeing is believing. *Trends in Biotechnology*, 28(5), 237–245. <https://doi.org/10.1016/j.tibtech.2010.02.001>
56. Zhang, B., Korolj, A., Lai, B. F. L., & Radisic, M. (2021). Advances in organ-on-a-chip engineering. *Nature Reviews Materials*, 6(5), 402–420. <https://doi.org/10.1038/s41578-021-00279-z>
57. Zhang, M., Wilkinson, J., & Sayre, R. R. (2020). The promise of machine learning in predicting chemical toxicity. *Frontiers in Artificial Intelligence*, 3, 15. <https://doi.org/10.3389/frai.2020.00015>
58. Zhuang, X., & Lu, C. (2016). PBPK modeling and simulation in drug research and development. *Acta Pharmaceutica Sinica B*, 6(5), 430–440. <https://doi.org/10.1016/j.apsb.2016.05>