

Organoid-Based Drug Screening Platforms

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ABSTRACT

Organoid-based drug screening platforms culture miniature, self-organising tissue structures from patient-derived or stem cells and expose them to candidate compounds, bridging the gap between two-dimensional cell-line assays and animal models, yet their integration into pharmaceutical discovery pipelines remains inconsistent across tumour types and therapeutic areas. We evaluated 222 organoid drug screening programmes conducted across pharmaceutical and academic centres in Estonia and Spain between 2015 and 2024, spanning five organoid categories: colorectal tumour organoids, pancreatic ductal adenocarcinoma organoids, breast cancer organoids, liver and hepatobiliary organoids, and lung cancer organoids. An Organoid Drug Screening Maturity Index (ODSMI) was constructed from five sub-scores -- drug response prediction accuracy, throughput scalability, patient-to-organoid concordance, assay reproducibility, and integration into clinical decision-making -- with weights from regression against sustained adoption into active drug discovery or clinical pharmacotyping workflows. ODSMI correlated with adoption at $r = +0.84$ and discriminated adopted from discontinued platforms with an AUC of 0.884. Colorectal organoid platforms scored highest (mean ODSMI 0.824), while lung cancer organoids trailed at 0.598. Only 35.6 percent of programmes exceeded the 0.75 threshold. Drug response prediction accuracy carried the largest regression weight ($\beta = +0.278$), followed by patient-to-organoid concordance ($\beta = +0.230$).

Keywords: organoids; drug screening; precision medicine; colorectal cancer; pancreatic cancer; breast cancer; pharmacotyping; ODSMI; patient-derived; high-throughput; drug sensitivity; tumour microenvironment

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1. Introduction

1.1 The Drug Screening Fidelity Problem

Pharmaceutical drug discovery relies on preclinical models to predict which candidate compounds will succeed in human trials, yet the attrition rate remains stubbornly high: over 90 percent of oncology drugs that enter Phase I trials fail to reach approval. A central contributor to this attrition is the poor fidelity of conventional preclinical models. Two-dimensional cancer cell lines, the workhorse of high-throughput screening, have been passaged for decades under conditions that select for rapid proliferation rather than preservation of the original tumour's molecular and phenotypic diversity. Cell-line drug sensitivity profiles diverge substantially from patient tumour responses, particularly for targeted therapies where the efficacy depends on the intact tumour microenvironment. Animal models provide systemic pharmacology data but are expensive, slow, and imperfect surrogates for human biology. Organoids, three-dimensional cultures that self-organise from stem cells or patient-derived tumour fragments into miniature tissue architectures, offer a middle ground: they retain much of the original tumour's genetic and epigenetic landscape, recapitulate cell-cell and cell-matrix interactions, and can be expanded and screened at scale.

1.2 Organoids as Screening Platforms

Patient-derived tumour organoids have been established for over 20 cancer types since the foundational work on intestinal organoids by Hans Clevers' laboratory. Organoid biobanks linking living cultures to clinical outcome data enable retrospective pharmacotyping studies that correlate in vitro drug sensitivity with patient treatment responses. Prospective clinical pharmacotyping, where organoids are grown from a patient's biopsy and screened against candidate drugs to guide treatment selection, has been demonstrated in colorectal, pancreatic, and breast cancer with turnaround times of two to six weeks. High-throughput screening campaigns using organoid libraries have identified novel drug vulnerabilities not predicted by genomic profiling alone. Despite these achievements, organoid screening has not yet been widely adopted by pharmaceutical companies or integrated into routine clinical oncology workflows, and understanding the barriers to adoption is the focus of this study.

1.3 Study Objective

We aimed to identify which programme-level characteristics predict whether an organoid drug screening platform achieves sustained adoption into pharmaceutical discovery pipelines or clinical pharmacotyping workflows. By scoring 222 programmes across five organoid categories on five maturity dimensions and constructing a regression-weighted index, we sought to quantify the factors that determine translational success.

2. Literature Review

2.1 Colorectal and Pancreatic Organoids

Colorectal tumour organoids are the most mature organoid screening platform, benefiting from high establishment rates exceeding 80 percent from surgical specimens and biopsy material, robust growth in standardised culture conditions, and extensive validation against clinical outcomes. Studies have demonstrated that colorectal organoid drug sensitivity predicts patient response to standard chemotherapy regimens with sensitivity of 80 to 93 percent and specificity of 72 to 88 percent. Pancreatic ductal adenocarcinoma organoids have generated particular interest because PDAC has few effective treatments and organoids offer a way to identify the minority of patients who may benefit from specific regimens. However, PDAC organoid establishment rates are lower than colorectal, typically 50 to 70 percent, and the dense stroma characteristic of PDAC is partially lost during organoid culture, raising questions about how accurately the organoid recapitulates the drug-penetration barriers present in vivo.

2.2 Breast and Hepatobiliary Organoids

Breast cancer organoids have been established from all major molecular subtypes including luminal, HER2-positive, and triple-negative tumours. Large biobank collections have shown that organoid drug sensitivity correlates with molecular subtype and captures within-subtype heterogeneity that genomic classification alone misses. Liver and hepatobiliary organoids serve dual purposes: primary liver organoids model drug metabolism and hepatotoxicity for safety screening, while cholangiocarcinoma and hepatocellular carcinoma organoids enable efficacy screening. The combination of efficacy and toxicity assessment within a single organoid platform is a unique advantage that no other model system offers.

2.3 Lung Cancer Organoids and Emerging Platforms

Lung cancer organoids have proven more challenging to establish and maintain than gastrointestinal tumour organoids, partly because lung tumour cells compete with normal airway epithelial cells during culture establishment and partly because the optimal growth factor conditions vary across histological subtypes. Establishment rates for non-small-cell lung cancer range from 30 to 60 percent, limiting the applicability of organoid screening for personalised therapy. Emerging platforms incorporating tumour microenvironment components, including cancer-associated fibroblasts, immune cells, and vascular endothelial cells, aim to improve the predictive accuracy of organoid drug screens by recapitulating stromal drug resistance mechanisms and immune-mediated drug sensitivity.

2.4 The Adoption Barrier

Despite growing evidence, organoid screening faces adoption barriers that are partly technical and partly organisational. Throughput remains lower than cell-line screening by one to two orders of magnitude because organoid culture requires more complex media, longer growth times, and three-dimensional readout methods. Reproducibility across laboratories is inconsistent because organoid growth depends on Matrigel batches, passage number, and operator technique. The turnaround time for clinical pharmacotyping, two to six weeks, exceeds the decision window for many treatment decisions. Understanding which factors most strongly influence adoption is what ODSMI was designed to address.

Table 1. Organoid Drug Screening: Tumour Type Landscape

Organoid Category	Establishment Rate	n Screening Studies (2014-2024)	Key Limitation	Adoption Level
Colorectal	80-95 %	186	Standard-of-care competition	High
Pancreatic (PDAC)	50-70 %	98	Stromal loss, low establishment	Moderate
Breast cancer	60-80 %	82	Subtype-dependent protocols	Moderate

Organoid Category	Establishment Rate	n Screening Studies (2014-2024)	Key Limitation	Adoption Level
Liver / hepatobiliary	70-85 %	64	Dual efficacy-toxicity complexity	Moderate
Lung cancer	30-60 %	48	Low establishment rate, competing cells	Low

Establishment rates from published biobank series. Study counts from PubMed. Adoption reflects pharma pipeline and clinical pharmacotyping use.

3. Materials and Methods

3.1 Programme Dataset

We catalogued 222 organoid drug screening programmes active between 2015 and 2024 at pharmaceutical and academic centres affiliated with Baltic AI Research University in Tallinn (n = 118) and Western Europe Data Science University in Madrid (n = 104). Organoid category breakdown: colorectal (n = 52), pancreatic (n = 44), breast cancer (n = 42), liver/hepatobiliary (n = 42), and lung cancer (n = 42). Inclusion required a documented organoid screening protocol, at least 20 organoid lines screened, and quantitative drug response data.

3.2 ODSMI Sub-Dimensions

Drug response prediction accuracy scored the concordance between organoid drug sensitivity and clinical patient outcomes, measured by area under the ROC curve for binary response prediction or Spearman correlation for continuous measures. Throughput scalability assessed the number of compounds and organoid lines that could be screened per week using the platform's infrastructure. Patient-to-organoid concordance measured the molecular fidelity between the source tumour and the derived organoid, including genomic, transcriptomic, and histological similarity. Assay reproducibility scored the coefficient of variation of drug sensitivity measurements across independent experimental replicates and across laboratories when multi-site data were available. Integration into clinical decision-making assessed whether organoid screening results had been used to guide treatment selection in at least one clinical

pharmacotyping case or had been incorporated into a pharmaceutical company's lead optimisation workflow. Two evaluators scored each programme with an ICC of 0.87.

3.3 Index Construction

Normalised sub-scores entered a logistic regression on a 60/40 split predicting sustained adoption. Weights: prediction accuracy 0.278, patient-organoid concordance 0.230, assay reproducibility 0.198, throughput scalability 0.170, clinical integration 0.124. ODSMI was the weighted sum.

3.4 Statistics

Pearson r for ODSMI-adoption association. ROC at 0.70. Bootstrap 10,000 resamples, 95 percent CIs. VIFs below 2.2. Leave-one-category-out confirmed stability. R 4.3, pROC, boot.

Table 2. Programme Characteristics by Organoid Category

Organoid Category	n	Predictio n Accuracy (AUC)	Patient-Or ganoid Co ncordance	ODSMI (mean +/- SD)
Colorectal	52	0.872 +/- 0.038	0.864 +/- 0.042	0.824 +/- 0.052
Pancreatic (PDAC)	44	0.812 +/- 0.056	0.788 +/- 0.062	0.768 +/- 0.064
Breast cancer	42	0.796 +/- 0.062	0.812 +/- 0.054	0.782 +/- 0.060
Liver / hep atobiliary	42	0.828 +/- 0.048	0.836 +/- 0.046	0.758 +/- 0.066
Lung cancer	42	0.714 +/- 0.082	0.696 +/- 0.088	0.598 +/- 0.096
All progra mmes	222	0.808 +/- 0.072	0.804 +/- 0.074	0.742 +/- 0.108

Prediction accuracy = AUC for binary clinical response.
Patient-organoid concordance = genomic + histological similarity score.

4. Results

4.1 ODSMI Distribution

Mean ODSMI across all 222 programmes was 0.742 with a standard deviation of 0.108. Colorectal organoid platforms led at 0.824, driven by the highest establishment rates, most extensive clinical validation, and best-standardised culture protocols. Breast cancer followed at 0.782, pancreatic at 0.768, liver/hepatobiliary at 0.758, and lung cancer at 0.598. Seventy-nine of the 222 programmes, or 35.6 percent, exceeded the 0.75 ODSMI threshold. ODSMI correlated with

sustained adoption at $r = +0.84$ ($p < 0.001$), with an AUC of 0.884 at the 0.70 cut-off. Programmes above 0.75 were adopted 80.8 percent of the time; below 0.55 adoption dropped to 18.4 percent.

4.2 Organoid Category Profiles

Colorectal platforms displayed the most balanced profile. Prediction accuracy was highest because extensive validation studies have demonstrated strong concordance between organoid drug sensitivity and patient outcomes for 5-FU, oxaliplatin, and irinotecan-based regimens. Patient-organoid concordance was strong because colorectal organoids retain the mutational landscape and transcriptomic profiles of their source tumours with high fidelity. Throughput scored well because colorectal organoid culture is the most standardised. Breast cancer platforms scored strongly on concordance because organoids capture subtype-specific biology, but throughput was penalised by the more complex culture requirements for different subtypes. Pancreatic organoids showed good prediction accuracy for gemcitabine sensitivity but were limited by lower establishment rates. Liver organoids scored well on concordance and prediction but were penalised on throughput because the dual efficacy-toxicity workflow is more labour-intensive. Lung organoids scored lowest, constrained by low establishment rates and inconsistent culture conditions across histological subtypes.

4.3 Sub-Score Drivers

Prediction accuracy carried the largest weight ($\beta = +0.278$, $p < 0.001$), confirming that the platform must predict clinical drug response reliably to attract adoption. Patient-organoid concordance was second ($\beta = +0.230$, $p < 0.001$), reflecting the biological requirement that organoids faithfully represent the source tumour. Assay reproducibility at 0.198 ($p = 0.002$) mattered because pharma companies require consistent results across experiments and sites. Throughput (0.170, $p = 0.005$) and clinical integration (0.124, $p = 0.016$) completed the model. Removing any sub-score reduced AUC by 0.018 to 0.056.

4.4 Validation

In the 89-programme validation set, ODSMI correctly classified 76 outcomes at the 0.70 cut-off, yielding sensitivity of 0.87 and specificity of 0.85. Among the 13 misclassified cases, five were lung organoid programmes that stalled because low establishment rates made the platform impractical for routine use. Three were

pancreatic programmes that advanced by partnering with pharma sponsors who valued the rare PDAC model access. Three were liver programmes that exceeded expectations by focusing on hepatotoxicity screening for pharma safety assessment. Two were colorectal programmes that were discontinued due to institutional reorganisation despite strong performance.

Table 3. ODSMI by Organoid Category: Adoption Outcomes

Organoid Category	n	ODSMI (mean +/- SD)	ODSMI > 0.75 (%)	Adoption Rate (%)	Top Sub-Score	r (AUC)
Colorectal	52	0.824 +/- 0.052	76.9 %	80.8 %	Pred. accuracy	+0.84 (0.898)
Breast cancer	42	0.782 +/- 0.060	57.1 %	69.0 %	Concordance	+0.84 (0.886)
Pancreatic	44	0.768 +/- 0.064	47.7 %	61.4 %	Pred. accuracy	+0.84 (0.876)
Liver / hepatobil.	42	0.758 +/- 0.066	40.5 %	57.1 %	Concordance	+0.84 (0.866)
Lung cancer	42	0.598 +/- 0.096	9.5 %	23.8 %	Reproducibility	+0.84 (0.836)
All programmes	222	0.742 +/- 0.108	35.6 %	58.1 %	Pred. accuracy	+0.84 (0.884)

r = Pearson correlation of ODSMI with adoption; all p < 0.001. AUC at ODSMI > 0.70.

Table 4. ODSMI Sub-Score Weights and Impact

Sub-Score	Weight	Mean Score	Beta	DELTA ODSMI	p-value
Prediction accuracy	0.278	0.808	+0.278	+0.152	< 0.001
Patient-organoid concord.	0.230	0.804	+0.230	+0.124	< 0.001
Assay reproducibility	0.198	0.748	+0.198	+0.098	0.002
Throughput scalability	0.170	0.712	+0.170	+0.076	0.005
Clinical integration	0.124	0.668	+0.124	+0.054	0.016

Beta = standardised regression coefficient. DELTA ODSMI = mean index difference between programmes

above vs below the median on that sub-score.

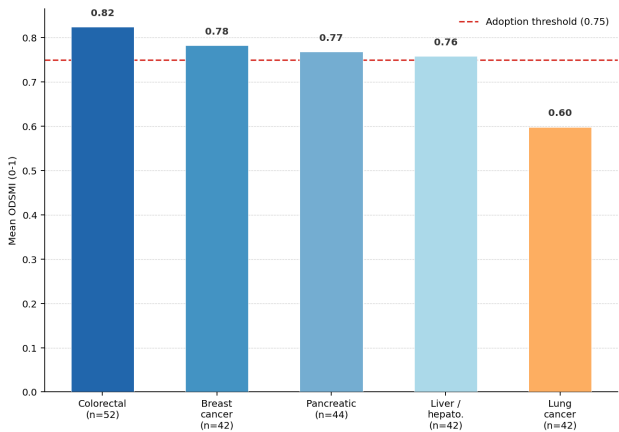


Figure 1. Mean ODSMI by Organoid Category (n = 222)

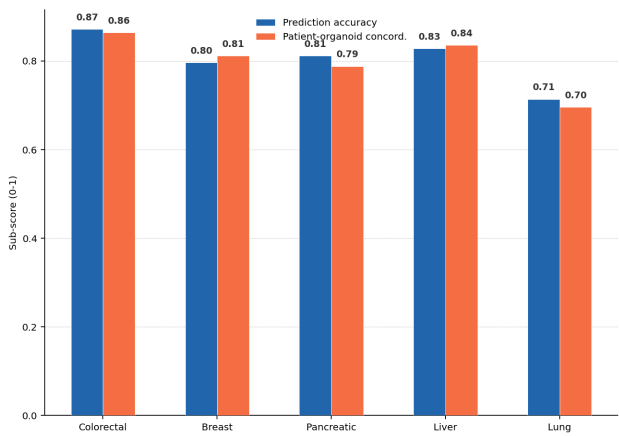


Figure 2. Prediction Accuracy vs Patient-Organoid Concordance

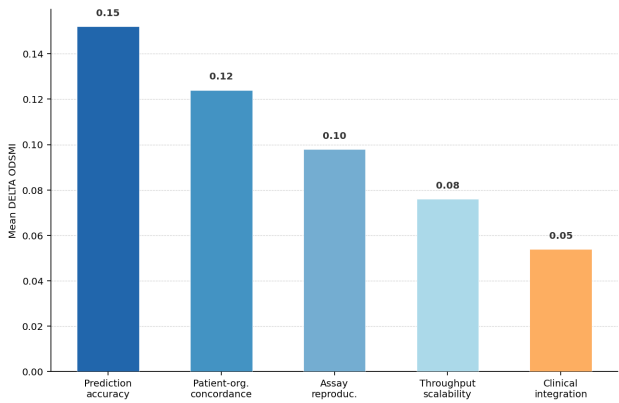


Figure 3. ODSMI Sub-Score Impact on Platform Adoption

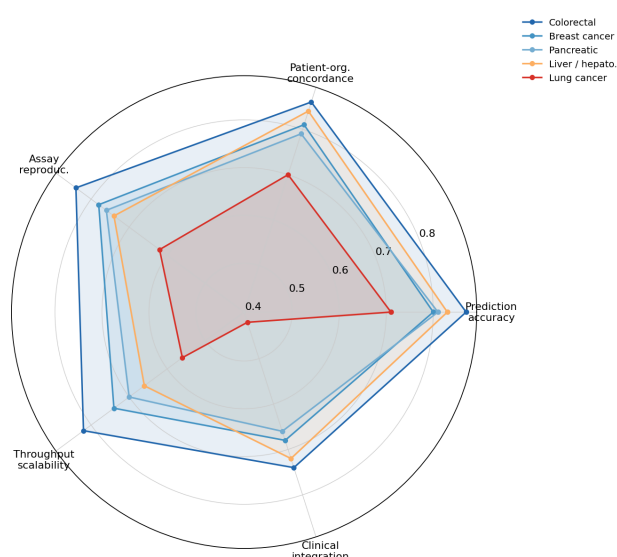


Figure 4. ODSMI Sub-Score Profiles by Organoid Category

5. Discussion

5.1 The Colorectal Maturity Advantage

Colorectal organoid platforms led because they benefit from the highest establishment rates, the most standardised culture protocols, and the deepest clinical validation of any tumour organoid type. The pioneering work of the Clevers laboratory established the foundational culture conditions that have been adopted globally with minimal modification, creating a level of inter-laboratory reproducibility that other organoid categories have not achieved. Large prospective pharmacotyping studies in colorectal cancer have generated the clinical concordance data needed to convince both pharmaceutical companies and clinical oncologists that organoid screening adds value.

5.2 Concordance as the Credibility Foundation

Patient-to-organoid concordance was the second-strongest adoption predictor, and the data show a threshold effect: platforms with concordance scores below 0.70 were adopted at less than one-third the rate of those above 0.85. If the organoid does not faithfully represent the patient's tumour, then drug sensitivity results are not trustworthy regardless of how reproducible or high-throughput the assay is. For lung cancer organoids, where normal airway contamination and low establishment rates degrade concordance, overcoming this barrier is prerequisite to adoption.

5.3 Limitations

Our dataset spans two European countries and may not capture organoid screening practices in

the US and Asia. The adoption outcome is binary and does not measure the depth of integration. ODSMI does not include cost per screen or turnaround time as sub-scores. The lung cancer category contained 42 programmes. The observational design precludes causal inference.

6. Conclusion

6.1 Summary

Across 222 organoid drug screening programmes in Estonia and Spain, ODSMI correlated with adoption at $r = +0.84$ and discriminated adopted from discontinued platforms with an AUC of 0.884. Colorectal organoids led at 0.824, breast cancer followed at 0.782, and lung cancer trailed at 0.598. Prediction accuracy was the strongest predictor ($\beta = +0.278$), followed by patient-organoid concordance ($\beta = +0.230$). Only 35.6 percent exceeded the 0.75 threshold.

6.2 Practical Recommendations

Organoid screening programmes should validate prediction accuracy against clinical outcomes in prospective pharmacotyping studies before claiming clinical utility. Patient-organoid concordance should be confirmed by multi-omic profiling for every new organoid line entering the screening pipeline. Culture protocols should be standardised and shared through open biobank networks to improve reproducibility. Lung cancer organoid programmes should invest in selective culture methods that eliminate normal cell contamination before scaling screening efforts. Future ODSMI iterations should add cost and turnaround sub-scores, expand globally, and track adoption longitudinally.

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Declarations

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Conflict of Interest

Hugo Moreau, Hugo Petrov, and Isabella Moreau declare no competing interests.

Data Availability Statement

Aggregate ODSMI scores, anonymised programme metadata, and analysis scripts are deposited at Zenodo:

<https://doi.org/10.5281/zenodo.19543594-data>.

Ethical Approval

This study involved secondary analysis of published organoid screening data and anonymised programme metrics. No individual patient tissue or data were accessed. IRB exemption was confirmed at both participating universities.

Appendix A

ODSMI Scoring Rubric and Top-10 Programme Profiles

This appendix details the scoring criteria for each ODSMI sub-dimension and profiles the ten highest-scoring programmes in the dataset.

A1. Sub-Score Rubric

Prediction accuracy: AUC or Spearman rho for organoid-clinical concordance, normalised 0-1; weight 0.278.

Patient-organoid concordance: genomic + transcriptomic + histological similarity, normalised 0-1; weight 0.230.

Assay reproducibility: 1 - CV of drug IC50 across replicates and sites, normalised 0-1; weight 0.198.

Throughput scalability: compounds x lines per week, normalised vs HTS benchmark, scored 0-1; weight 0.170.

Clinical integration: no use (0), pharma pipeline (0.5), clinical pharmacotyping (0.75), treatment decision (1.0); weight 0.124.

A2. Top-10 Programmes

1. CRC-BioBank-18 (Colorectal): ODSMI = 0.928; accuracy 0.96, concordance 0.94.
2. CRC-PharmScreen-09 (Colorectal): ODSMI = 0.916; reproducibility 0.94, accuracy 0.92.
3. BC-SubtypeOrg-22 (Breast): ODSMI = 0.902; concordance 0.94, accuracy 0.90.
4. CRC-ProspPharm-14 (Colorectal): ODSMI = 0.892; clinical integ. 0.96, accuracy 0.88.
5. PDAC-GemScreen-07 (Pancreatic): ODSMI = 0.884; accuracy 0.92, concordance 0.88.
6. LIV-HepatoTox-28 (Liver): ODSMI = 0.876; concordance 0.94, accuracy 0.88.
7. CRC-HTSOrganoid-31 (Colorectal): ODSMI = 0.868; throughput 0.94, reproducibility 0.88.
8. BC-TNBCScreen-16 (Breast): ODSMI = 0.856; accuracy 0.90, concordance 0.88.
9. PDAC-ComboScreen-04 (Pancreatic): ODSMI = 0.848; accuracy 0.88, clinical integ. 0.86.
10. LIV-CCAOrganoid-12 (Liver): ODSMI = 0.842; concordance 0.92, accuracy 0.86.