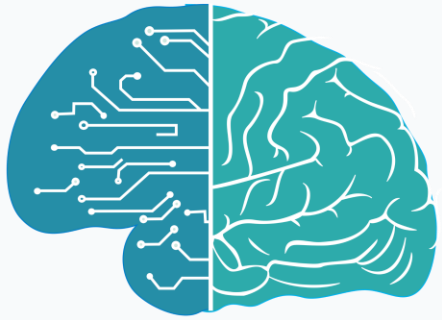


# OncoTrialMind

Oncology Clinical Trial Intelligent Decision-Making Center

# From Data to Insight at Speed: Optimizing Data-Driven Decision-Making

Zhiping Yan, Dizal Pharmaceutical Co., Ltd.

# Disclaimer

The contents represent solely the personal views of the presenter and do not necessarily reflect the stance of the employer

# Our Needs in Early Oncology Clinical Trials

01

## Phase I Dose Escalation Designs

*BOIN · 3+3 · mTPI*

02

## Dose Selection & Optimization

*PK/PD · E-R · ANN*

03

## Go / No-Go Decision

*Bayesian Posterior Prob.*

04

## Aggregate Safety Analysis

*AE · Co-occurrence Network*

05

## Phase II Study Designs

*Simon · Bayesian TTE*

06

## mPFS Prediction

*ORR-informed · PFS Trajectory Projection*

# The Problem We Were Solving

Decision Analysis Are Fragmented Across Dozens of Scripts

- Clinical data analysis is often scattered across multiple independent systems, and statistical programming and medical review tools lack interoperability, leading to discontinuous information transfer. Manual export/import collaboration is error-prone and time-consuming.
- The traditional process takes several days or more from data release to report generation, making it difficult to respond quickly to safety signals or strategy changes. Such delays in dynamic decision-making can jeopardize patient safety and clinical development progress.
- Statistics, medical, clinical pharmacology, and programming teams work on different platforms, resulting in high communication costs and frequent version inconsistency issues. The lack of a unified environment hinders real-time feedback and rapid iterative analysis.

*Can one platform replace this patchwork and produce audit-ready evidence in real time?*

▼ *See the answer on the next slide*

# OncoTrialMind — One Platform, Complete Solution

## OncoTrialMind™

Oncology Clinical Trial Intelligent Decision-Making Center

Integrated platform empowering medical, statistical, and clinical pharmacology teams — from data ingestion to Go/No-Go decisions. Seamless Bayesian inference, adaptive trial simulation, and real-time risk intelligence.

### Phase I/II Intelligent Decision Platform

BAYESIAN · DOSE ESCALATION · GO/NO-GO

- Dose escalation designs (3+3, BOIN, etc.)
- Bayesian statistical inference
- Safety monitoring & AE analytics
- Efficacy assessment & early signals
- Exposure–response analysis (E-R)
- ML risk prediction (toxicity/response)
- RP2D Planning-Multi-Discipline team (MDT) assessment
- Go/No-Go decision framework
- Competitive benchmark intelligence

Integrated for early-phase oncology trials

Launch Decision Platform

### Oncology Study Simulator

ADAPTIVE DESIGNS · POWER · PPOS · SSR

- Parametric survival simulation + empirical power
- Sample size & event target optimisation
- Group sequential boundaries (GSB)
- Multiplicity control (PFS, OS, ORR)
- Target event count prediction
- Non-proportional hazards (delayed, crossing)
- Bayesian predictive probability of success (PPoS)
- Frequentist conditional power & OC curves
- Adaptive SSR: Promising Zone / Unconditional Power

Integrated for late-phase oncology trials

Launch Study Simulator

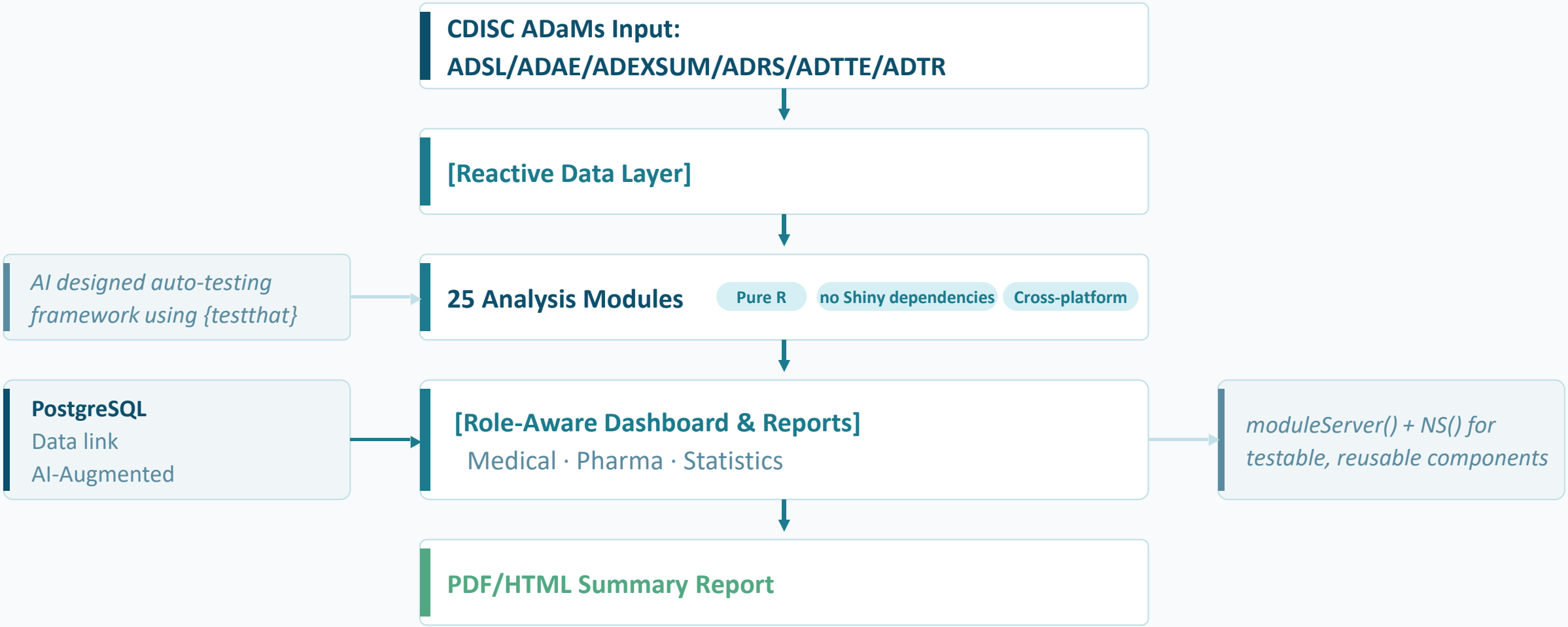
Enterprise R Shiny Server · Role-based access enabled | Click to launch respective decision tool

# New Features in OncoTrialMind

- AI-Augmented R Shiny Platform for Oncology Clinical Trial Decision Intelligence
- Role-Based Dashboard & Automated Regulatory-Ready Reporting
- Unified Evidence Synthesis Under One Reactive Data Layer
- Comprehensive Bayesian Decision Suite
- AI Signal Intelligence Engine
- Competitive Benchmark Intelligence + ClinicalTrials.gov Integration

Architecture

# OncoTrialMind-Architecture at a Glance




✓ Designed for a Regulated Environment

# Technology Stack

| Component | Technology | Rationale |
|---|---|---|
| Web framework | R Shiny + bslib | Reactive UI without JavaScript expertise |
| Data link | PostgreSQL | Open-source; Data connection and share |
| Interactive plots | plotly, ggplot2, visNetwork | Client-side interactivity |
| MCMC | Custom Metropolis-Hastings (base R) | No JAGS/Stan dependency |
| Bayesian computation | Base R (dbeta, pbeta, qbeta) | Conjugate closed-form posteriors |
| ML | stats::glm, stats::kmeans | Zero external ML dependencies |
| Parallelism | furrr | Parallel OC simulations |
| Report generation | rmarkdown / flextable | Automated Word/HTML output |
| Data wrangling | dplyr, tidyr, purrr | Tidyverse consistency |

# Data Infrastructure: CDISC-Native + PostgreSQL Persistence

### 📂 Input Formats

- ADSL — Subject-level demographics
- ADAE — Adverse events
- ADEXSUM — Exposure summary
- ADRS — Response endpoints
- ADTTE — Time-to-event
- ADTR — Tumor response
- PK exposure data (CSV)

In-app upload with automatic CDISC column normalization

### 🗄️ PostgreSQL Persistence

- All results serialised as JSONB
  ↳ → analysis_results table
- Decision audit log:
  ↳ timestamp · user role · parameters
- Evidence score history
  ↳ trend tracking over interim analyses
- Multi-project support
  ↳ per-project PostgreSQL connection pools

# AI-Designed Validation Cases for Key Results

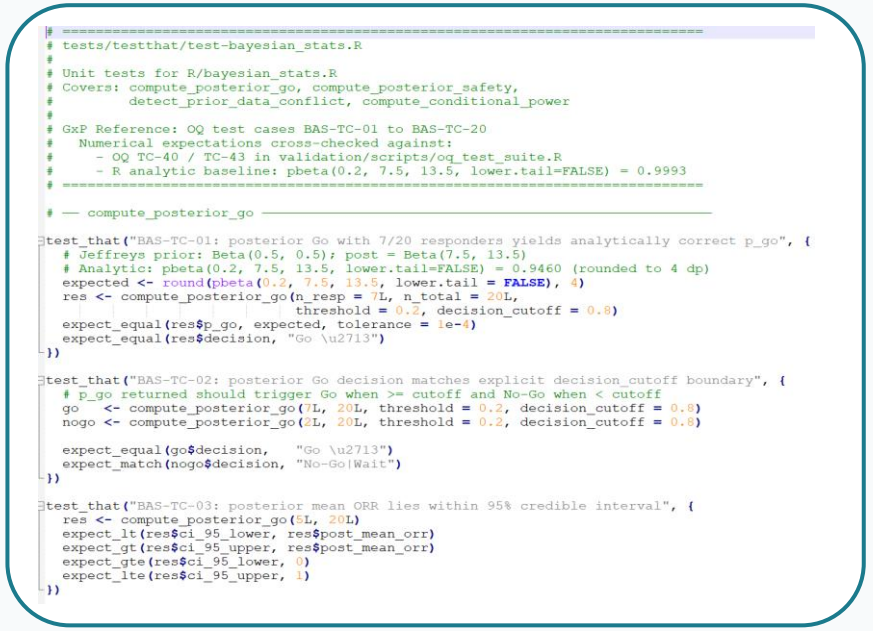
| Test case | Expected | Platform output | Status |
|---|---|---|---|
| Simon Optimal (p0=0.2, p1=0.4, α=0.05, power=80) | N1=13, r1=3, N=43, EN(p0)=20.6 | ✓ Exact match | ✅ |
| BOIN boundaries (ϕ=0.25) | λ1=0.197, λ2=0.298 | ✓ Exact match | ✅ |
| Jeffreys posterior r=15, n=60 | P(π>0.20) ≈ 82% | 82.1% | ✅ |
| CRM MCMC R-hat | ≤ 1.05 on all runs | Displayed live | ✅ |
| Bootstrap CI coverage (simulation) | Nominal 95% | 94.2–95.8% across scenarios | ✅ |

## Does It Work?

*Benchmark Against Published Results*

✓ Statistical results verified by multiple AI coding agents

✓ AI-designed auto-testing framework using {testthat}



```
# ================================================================================
# tests/testthat/test-bayesian_stats.R
#
# Unit tests for R/bayesian_stats.R
# Covers: compute_posterior_go, compute_posterior_safety,
#         detect_prior_data_conflict, compute_conditional_power
#
# GxP Reference: OQ test cases BAS-TC-01 to BAS-TC-20
#   Numerical expectations cross-checked against:
#     - OQ TC-40 / TC-43 in validation/scripts/oq_test_suite.R
#     - R analytic baseline: pbeta(0.2, 7.5, 13.5, lower.tail=FALSE) = 0.9993
# ================================================================================

# ── compute_posterior_go ──────────────────────────────────────────────────────

test_that("BAS-TC-01: posterior Go with 7/20 responders yields analytically correct p_go", {
  # Jeffreys prior: Beta(0.5, 0.5); post = Beta(7.5, 13.5)
  # Analytic: pbeta(0.2, 7.5, 13.5, lower.tail=FALSE) = 0.9460 (rounded to 4 dp)
  expected <- round(pbeta(0.2, 7.5, 13.5, lower.tail = FALSE), 4)
  res <- compute_posterior_go(n_resp = 7L, n_total = 20L,
                              threshold = 0.2, decision_cutoff = 0.8)
  expect_equal(res$p_go, expected, tolerance = 1e-4)
  expect_equal(res$decision, "Go \u2713")
})

test_that("BAS-TC-02: posterior Go decision matches explicit decision_cutoff boundary", {
  # p_go returned should trigger Go when >= cutoff and No-Go when < cutoff
  go   <- compute_posterior_go(7L, 20L, threshold = 0.2, decision_cutoff = 0.8)
  nogo <- compute_posterior_go(2L, 20L, threshold = 0.2, decision_cutoff = 0.8)

  expect_equal(go$decision,   "Go \u2713")
  expect_match(nogo$decision, "No-Go|Wait")
})

test_that("BAS-TC-03: posterior mean ORR lies within 95% credible interval", {
  res <- compute_posterior_go(5L, 20L)
  expect_lt(res$ci_95_lower, res$post_mean_orr)
  expect_gt(res$ci_95_upper, res$post_mean_orr)
  expect_gte(res$ci_95_lower, 0)
  expect_lte(res$ci_95_upper, 1)
})
```

# Regulatory & Validation Considerations

✓ Designed for Regulated Environment

- **AI-assistant documentation delivered with the system:**

| Document | GxP standard |
|---|---|
| Validation Plan (VP) | **GAMP 5** |
| User Requirements Specification (URS) | **21 CFR Part 11 / EU Annex 11** |
| Installation Qualification (IQ) | **GAMP 5** |
| Operational Qualification (OQ) | **GAMP 5** |
| Performance Qualification (PQ) | **GAMP 5** |
| Validation Summary Report (VSR) | **ICH Q10** |

📄 **Statistical methods:** Fully documented in STATISTICAL_METHODS.md (17 sections, 5 000+ words) — covers all formulas, prior choices, MCMC settings, convergence diagnostics, and references.

# Role-Aware Dashboard: One App, Three Perspectives

*The Right Information to the Right Person at the Right Time*

## Medical Monitor

- Patient-level Safety

KEY WIDGETS

**AE Summary**

**AE Co-occurrence Network**

**Patient ML Risk Table**

- Real-time AE surveillance
- Network graph: co-occurrence patterns
- ML individual patient risk scoring

## Pharmacometrician

- PK / PD Analysis

KEY WIDGETS

**E-R Scatter (Logistic/Emax/ANN)**

**Therapeutic Window**

**Quartile Analysis**

- Logistic / Emax / ANN model fitting
- Therapeutic window visualisation
- Exposure quartile response breakdown

## Statistician

- Decision Evidence

KEY WIDGETS

**Bayesian Go/No-Go**

**Simon 2-Stage**

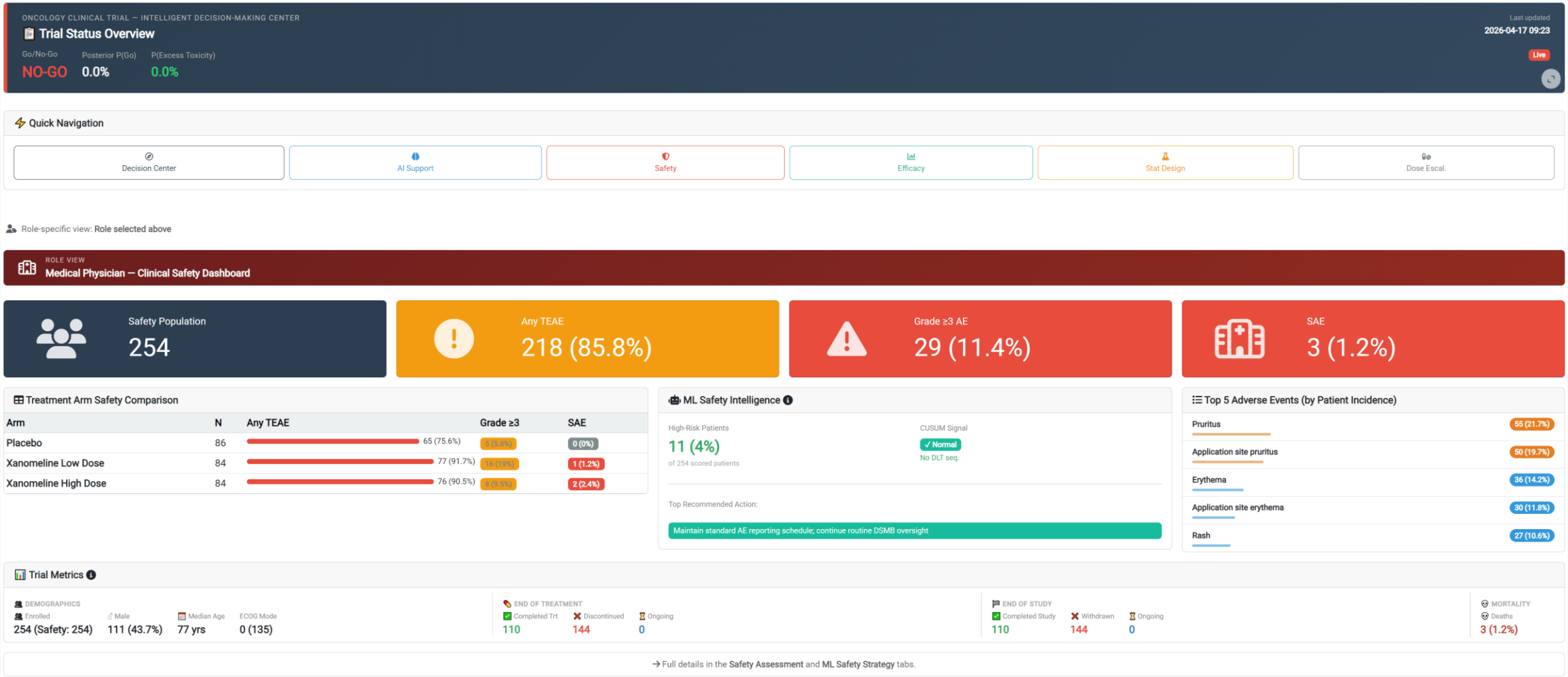
**BOIN Boundaries**

**Trajectory Projection**

- Posterior probability Go/No-Go engine
- Simon 2-stage interim decision rules
- BOIN dose escalation boundaries
- Response trajectory projection

Dashboard

# Role-Aware Dashboard




Multi-role View

Real-time Sync

ML-powered Risk

Decision

# Decision Center

**Integrated Decision Recommendation** Details

## REASSESS POPULATION

Based on synthesis of efficacy (Bayesian Go/No-Go), safety (posterior toxicity), PK/PD evidence, response data, and study design completeness.

Efficacy: No-Go | Safety: Acceptable at RP2D | — 0.0

19 / 100

Benefit-Risk Score

**Evidence Maturity** Dependencies

17%

1 / 6 analyses completed

- Clinical data (ADAE/ADSL) — Critical
- Response data (ADRS) — High
  Requires: Clinical data
- PK exposure data — High
- ✅ Bayesian Go/No-Go — Critical
- Dose escalation design — Medium
  Requires: Clinical data
- Simon's two-stage design — Medium
  Requires: Response data

**Benefit-Risk Radar**


**Integrated Findings** | Evidence Matrix | Decision Audit Log | Pattern Mining | Score Trend

Auto-generated cross-domain signals updated in real time as data and analyses change.

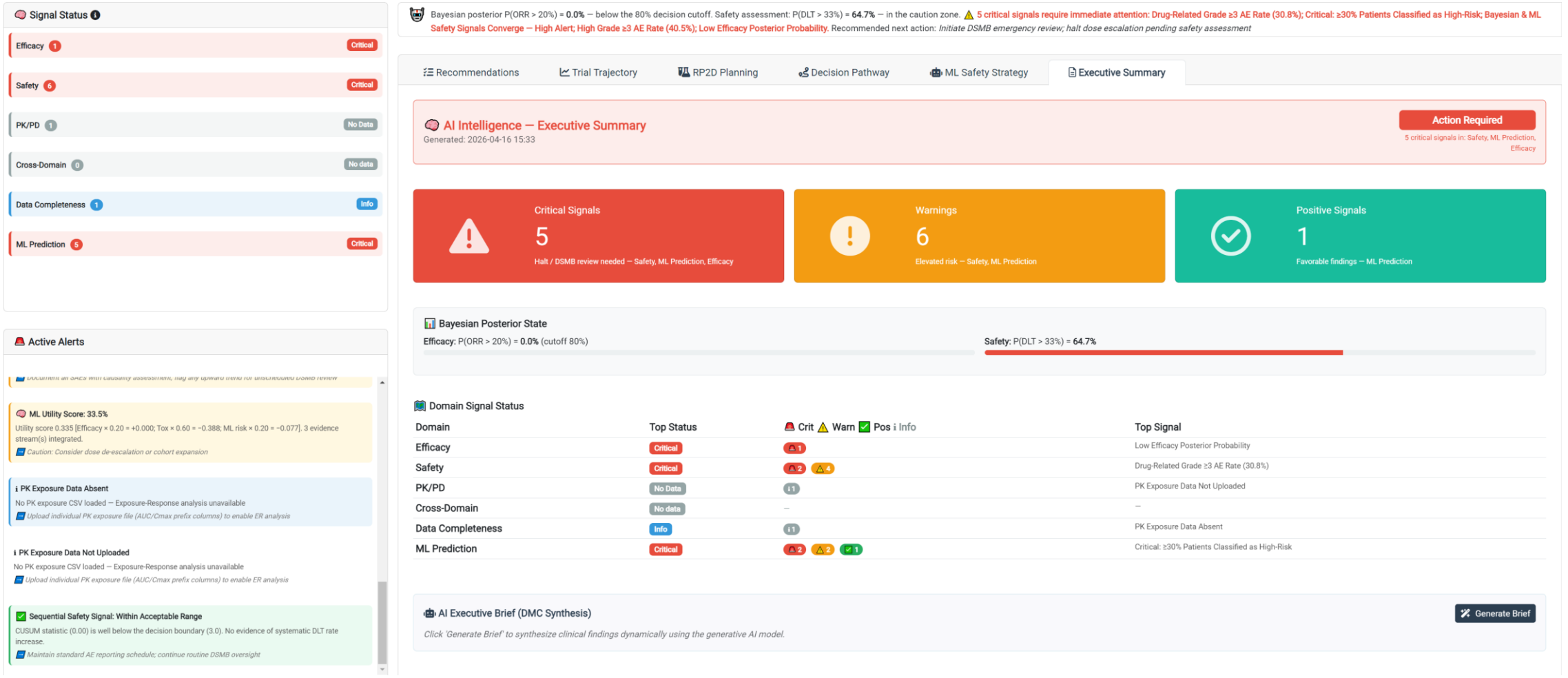
**Safety Population: Full (SAFFL = Y)** To analyze a sub-population, use the filter in Safety Assessment → Population Filter.

- ✗ Efficacy: Bayesian P(ORR > 20%) = **0.0%** < Go cutoff (80%) • Observed ORR = **8.1%** (15/185) < min. threshold (20%)
- ✅ Safety: P(DLT > 33%) = **64.7%** at evaluated doses — **Acceptable at RP2D** | EWOC constraint satisfied at RP2D (~200 mg) — safety confirmed at optimised dose | AE data: **DLT Summary Ready**
- ✅ MTD Estimate: **≈ 200 mg** (EWOC: satisfied)
- ⚠ SAE: **21.1%** of participants experienced ≥1 serious adverse event | Drug-related SAE: **11.4%** — safety score adjusted −7 pts
- ℹ PK/PD: No exposure data — upload CSV to enable ER analysis
- ℹ Response: No ADRS data — upload to compute ORR
- 🔍 **Cross-domain signal:** Acceptable safety at optimised dose but insufficient efficacy — consider dose escalation, population enrichment, or biomarker selection

🧠 Bayesian Engine | 📋 Audit Trail | 🔄 Real-time Sync | 👥 Multi-role View

AI Engine

# AI Signal Intelligence Engine

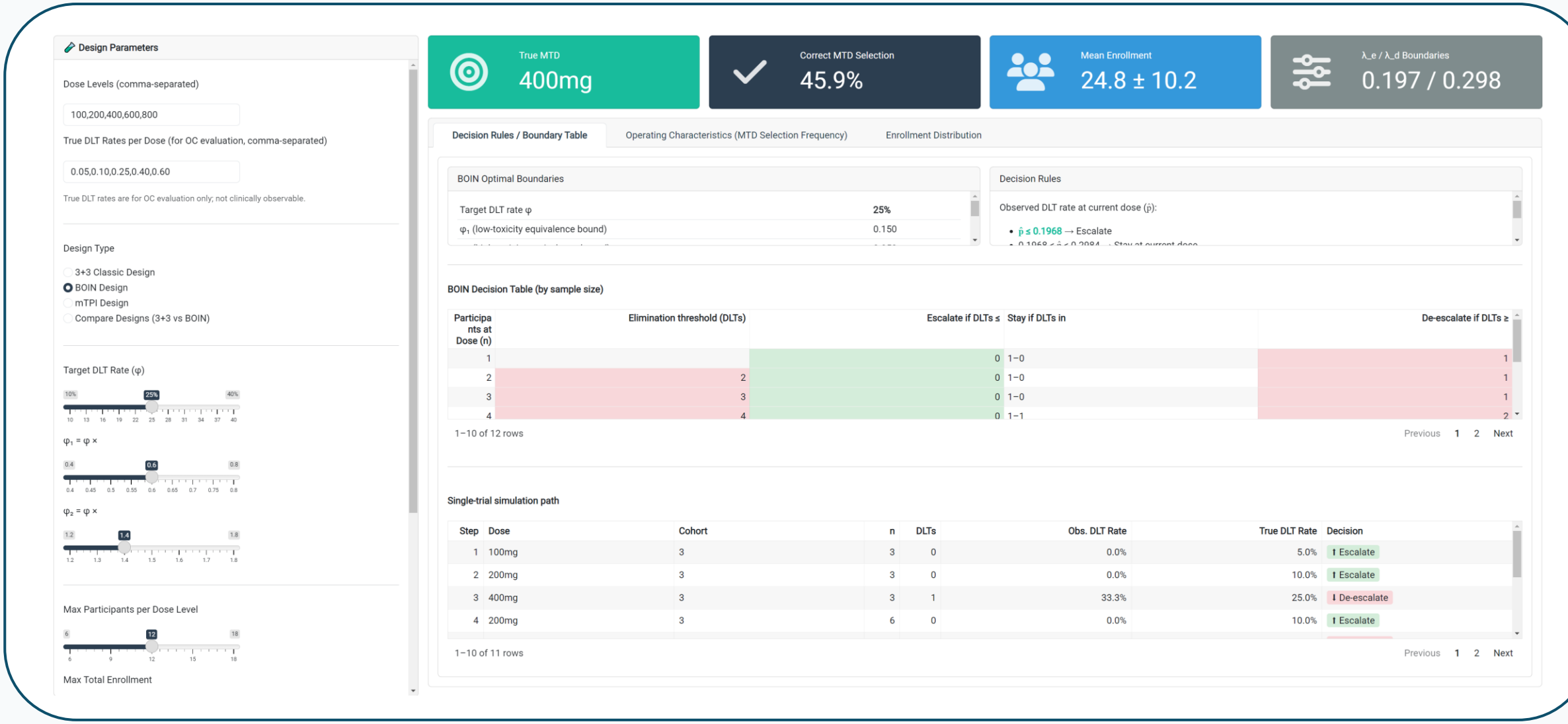



NLP Signal Parsing

Auto Signal Detection

Evidence Score

# Phase I Dose Escalation Designs




BOIN Design | 3+3 Rule-based | mTPI-2 Framework

# Comprehensive Bayesian Decision Suite

GO/NO-GO EFFICACY DECISION: BETA-BINOMIAL CONJUGATE MODEL

BAYESIAN PREDICTIVE PROBABILITY OF SUCCESS

JOINT EFFICACY–TOXICITY BAYESIAN PHASE II DESIGN

BAYESIAN TTE PHASE II DESIGN

🎯 Posterior Probability

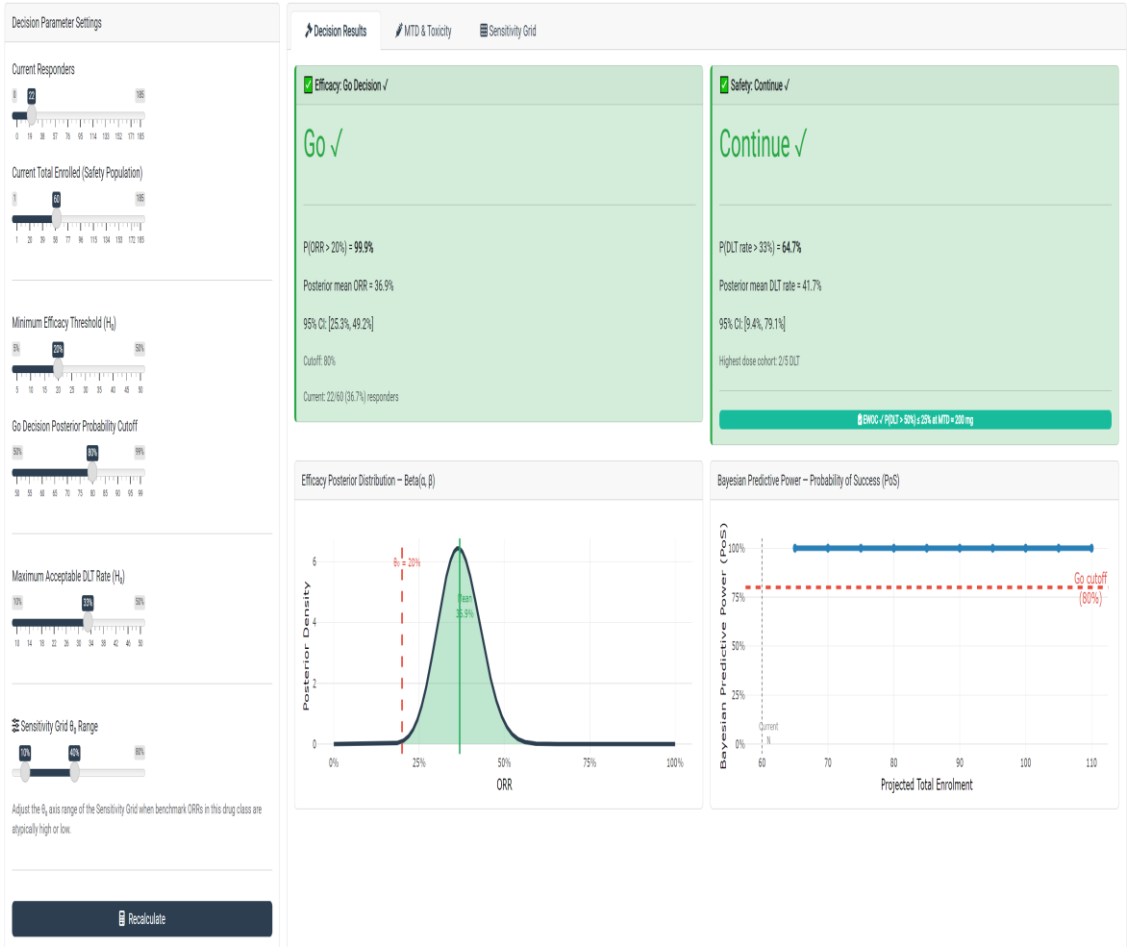
📊 Go/No-Go Framework

🔄 Interim Decision Rules

Bayesian

# Bayesian Go/No-Go with Real-Time Sensitivity Grid

## Go/No-Go Decision Panel




## Real-Time Sensitivity Grid

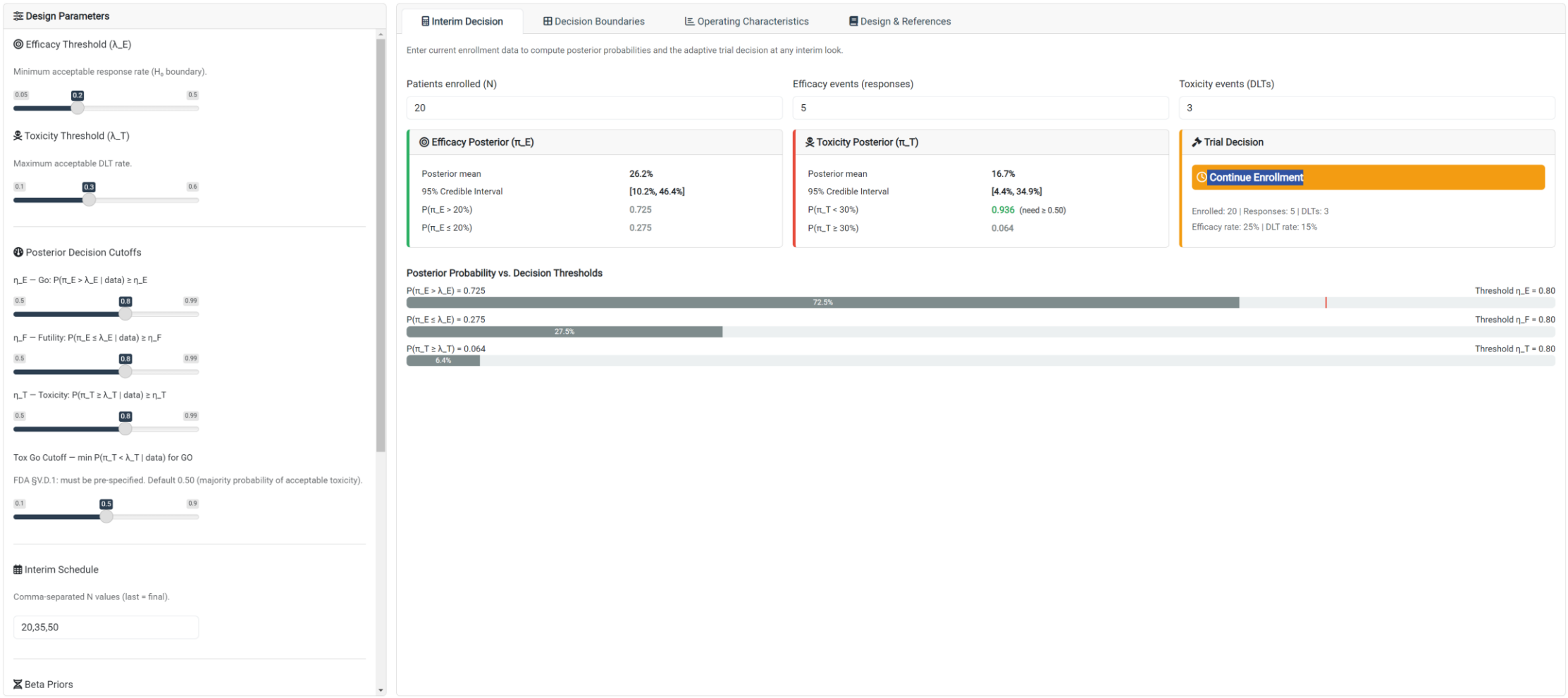

🎯 Posterior Probability

🔥 Sensitivity Grid

📋 Decision Audit Trail

Statistics

# Joint Efficacy–Toxicity Bayesian Phase II Design




🔲 Joint Efficacy–Toxicity

📉 Toxicity Boundary

✅ Efficacy Gate

Statistics

# Bayesian optimal phase II design with TTE endpoint

Design Parameters

Decision Thresholds

$\eta_{go}$ 0.8 $\eta_{fut}$ 0.8

Gamma Prior on λ = log(2)/Median

Default Gamma(0.001, 0.001) is non-informative.

Shape $a_0$ 0.001 Rate $b_0$ 0.001

Prior Elicitation Helper

Historical median (mo) 3 Prior strength (events) 1

Apply Elicited Prior

Trial Design (for OC)

Max patients (N) 50

Accrual duration (mo) 24

Additional FU (mo) 12

Interim events (comma-separated) 15, 25, 40

Current Interim Data

Interim Monitor | Predictive Probability | Decision Boundaries | Operating Characteristics | Design & References

Interim Decision

Continue Enrollment

P(M > 5.0 mo) = 0.669 | GO threshold = 0.80
P(M ≤ 3.0 mo) = 0.012 | Fut threshold = 0.80

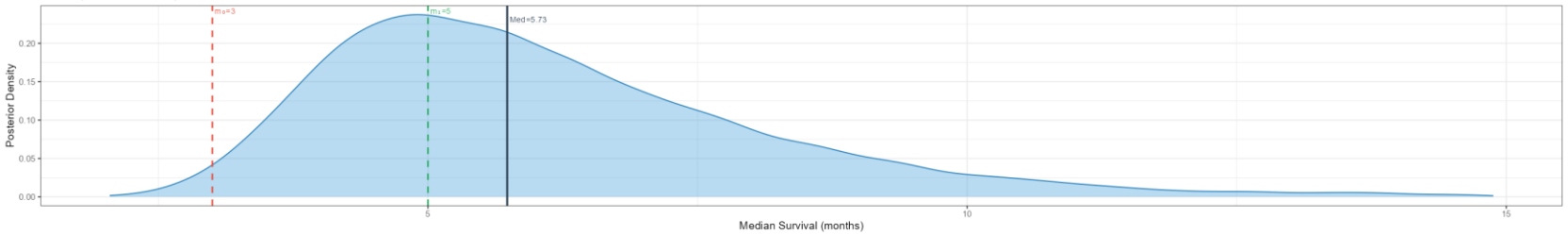
Posterior Median (months)
5.73
95% CI: [3.25, 11.56]

P(Efficacious | data)
66.9%
Need ≥ 80% for GO

P(Futility | data)
1.2%
Need ≥ 80% to stop

**Posterior Distribution of Median Survival**

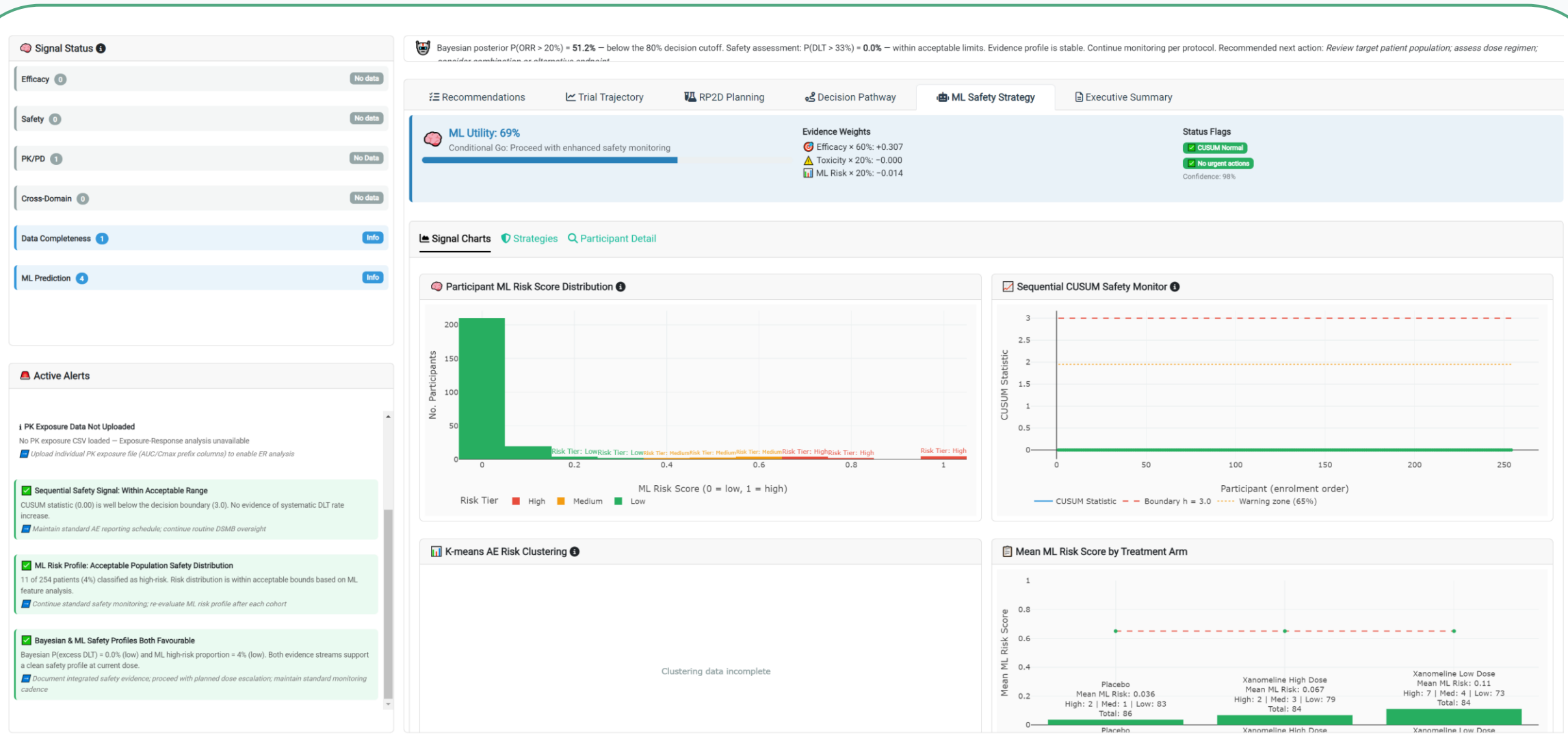
Gamma($a_0$ + 10, $b_0$ + 80.0) ⟹ d = 10 events, T = 80.0 mo




TTE Endpoint | Survival Curve | Interim Analysis

ML / AI

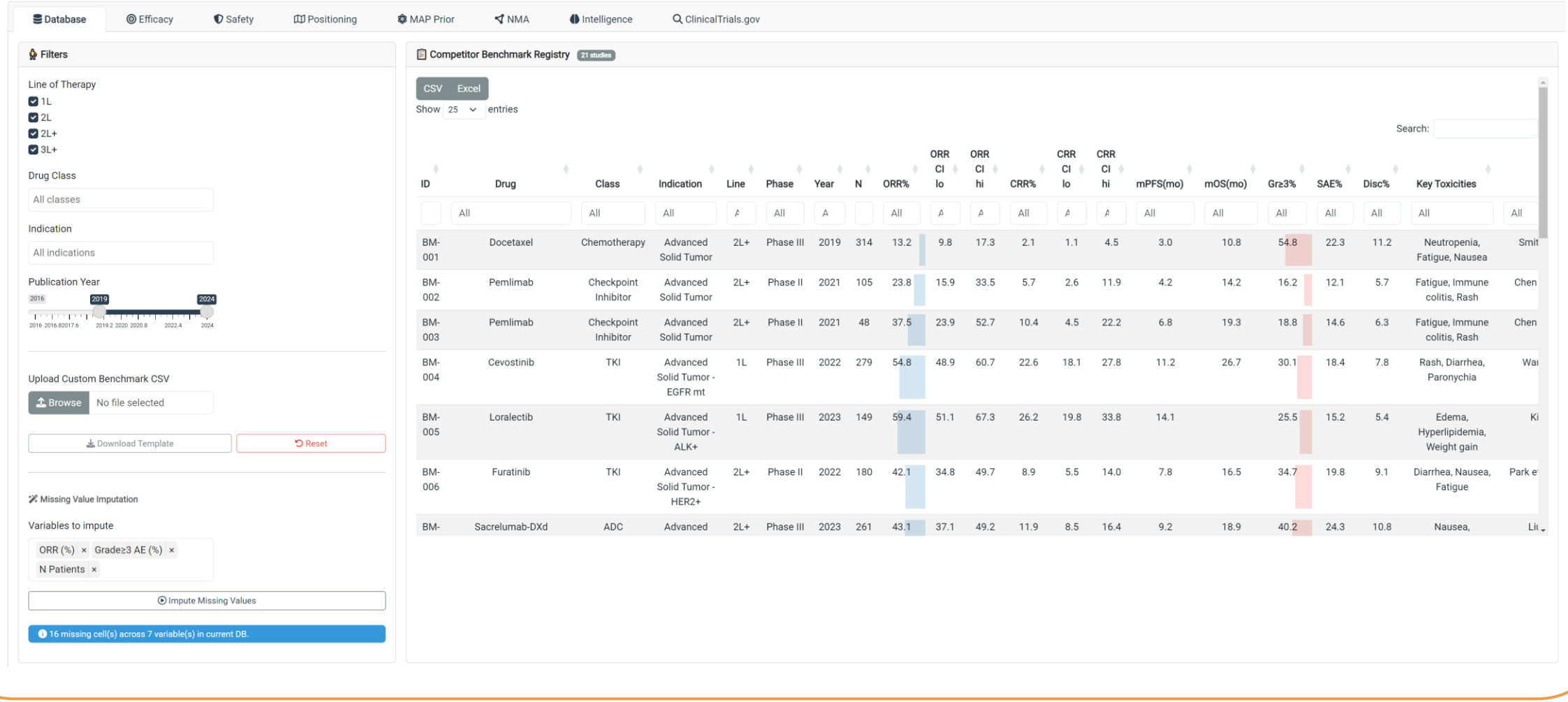
# ML Safety Monitoring




AE Early Detection | Patient Risk Scoring | Real-time Alert

Intel

# Competitive Benchmark Intelligence + ClinicalTrials.gov Integration



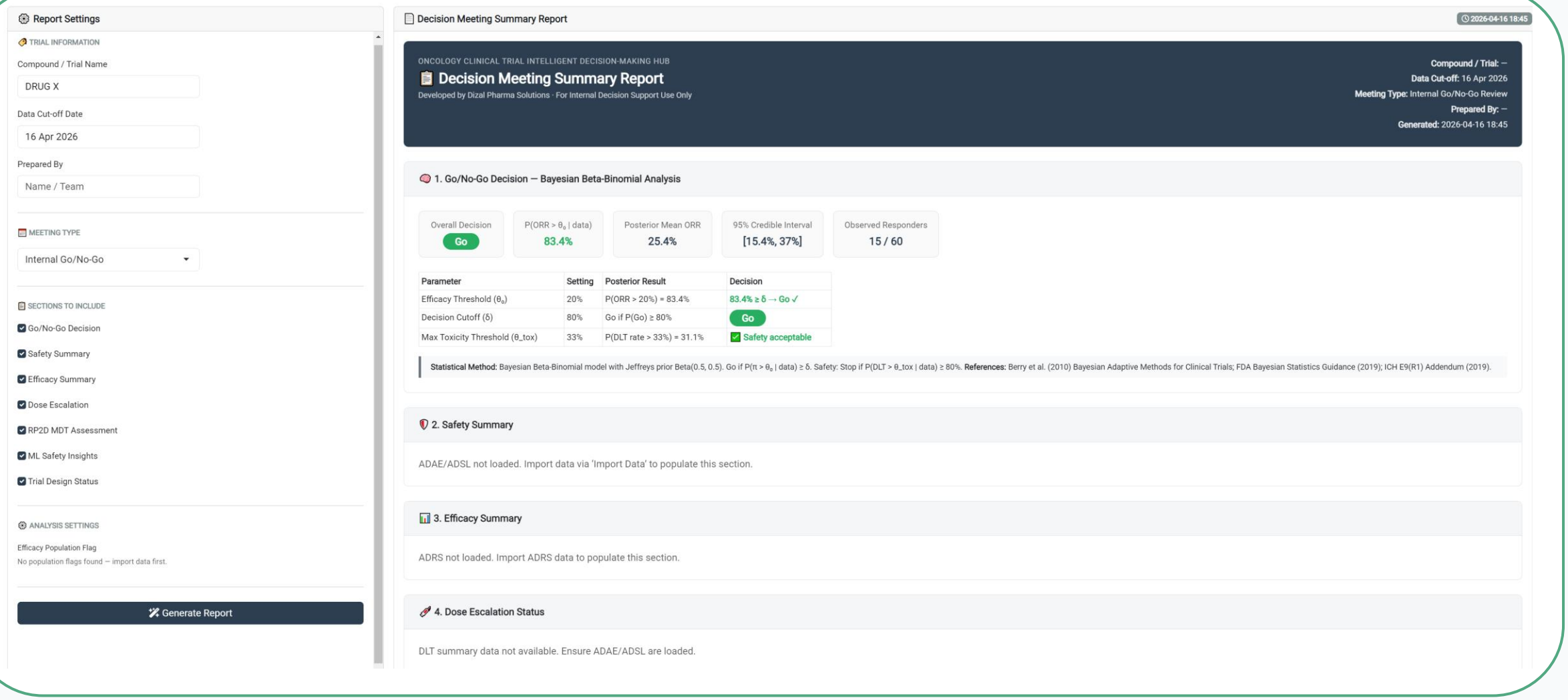

🌐 ClinicalTrials.gov

📊 Competitor Benchmark

🔍 Gap Analysis

AI Report

# AI-Augmented Summary Report




✍️ Auto Narrative

📑 Evidence Package

🔒 Audit-ready

Positioning

# How Does OncoTrialMind Differ from What's Already Out There?

### CDISC Data Ingestion

*Auto column normalisation*

### Real-time Bayesian Go/No-Go

*Posterior probability engine*

### Role-aware Dashboards

*Monitor · PK · Statistician*

### ML Safety Monitoring

*Patient risk scoring · AE alert*

### NMA + Competitor Benchmarking

*ClinicalTrials.gov · Gap analysis*

### PostgreSQL Audit Persistence

*JSONB · Audit trail · Multi-project*

### AI-Augmented Summary Report

*Auto-narrative · Evidence pack*

### Open Source R-native

*Shiny · Reproducible · Auditable*

ClinicalTrials.gov | Competitor Benchmark | Unique Differentiators

# Transformation from Passive Response to Proactive Insight

### Built-in statistical models

Integrate Bayesian methods, multiple hypothesis tests with safety signal analysis, support one-click execution, and enhance the efficiency and consistency of the analysis

### Rapid iterative analysis

It empowers statisticians to expeditiously experiment with diverse analysis strategies, thereby substantially reducing the validation and optimization cycle

### Visual drag-and-drop operation

Through an intuitive interface, hierarchical analysis and subgroup exploration can be accomplished, which reduces the technical threshold and improves usability

### Real-time sharing of results

Support the prompt sharing of statistical results with the medical team to facilitate cross-functional collaboration

### Accelerate the feedback loop

Compress the medical verification feedback cycle from a weekly basis to a daily basis to expedite the decision- making process.

### Efficient collaborative works

Achieve a close interaction between data analysis and medical judgment to improve the overall research efficiency.

🔁 Passive → Proactive

⚡ Real-time Insight

🧠 Decision Intelligence

# Conclusions

**Integration wins over specialization** — a unified platform reduces decision latency from days to minutes

**Bayesian methods + real-time UI = better risk communication** — sensitivity grids and trajectory projections let teams explore “what if” interactively, not post-hoc

**Regulatory readiness is a design choice, not an afterthought** — validation documentation, audit logging, and explicit limitation statements were built in from day one

**Future Directions: LLM-assisted natural language query:** “Show me all patients with Grade 3 rash on Arm B” → reactive filter via LLM API (prototype in R/nlq_engine.R)

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# Thank You — Questions Welcome