The Lab of the Future

What Leading R&D Organizations Are Building Now

A guide for R&D directors, heads of innovation, and lab operations leaders in chemicals, materials, pharma, and food.

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Introduction

The best R&D organizations in the world have something in common: **their scientists spend most of their time doing science**. They're not hunting for historical results, manually assembling reports, or re-running experiments because the data from the first time isn't findable. Their infrastructure handles the operational burden of data management so their people can focus on discovery.

That's not the reality in most labs today. In most R&D organizations, scientists spend a significant proportion of their working week on data-related tasks such as searching, reconciling, re-entering, and waiting, rather than experimenting. The constraint on R&D productivity isn't talent or investment, it's data infrastructure.

This guide describes what the lab of the future looks like in practice: the architecture that leading R&D teams are building, the capabilities it unlocks, and the decisions that determine whether you're ahead of the curve or falling behind it.

What's Changed

For most of the past twenty years, R&D technology investment followed a straightforward logic: deploy an ELN to replace paper notebooks, add a LIMS for sample management, and integrate them well enough to share data. The result was a more organized version of the same fragmented approach, with each system doing its job in isolation and the gaps between them filled with spreadsheets and institutional knowledge. That model is no longer adequate for what enterprise R&D is being asked to do.

AI only works if the underlying data is **structured, connected, and complete**.

R&D cycles are compressing. Customer requirements are changing faster. Supply chains are volatile. And AI, now genuinely capable of accelerating formulation, materials discovery, and process optimization, has moved from aspiration to operational reality. But AI only works if the underlying data is structured, connected, and complete. Most organizations' data isn't. The ELN-LIMS-spreadsheet stack wasn't designed to support what's now expected of it.

The organizations investing seriously in R&D are rebuilding their data infrastructure, not incrementally improving it. The lab of the future isn't the current lab with better software. It's a fundamentally different data architecture.

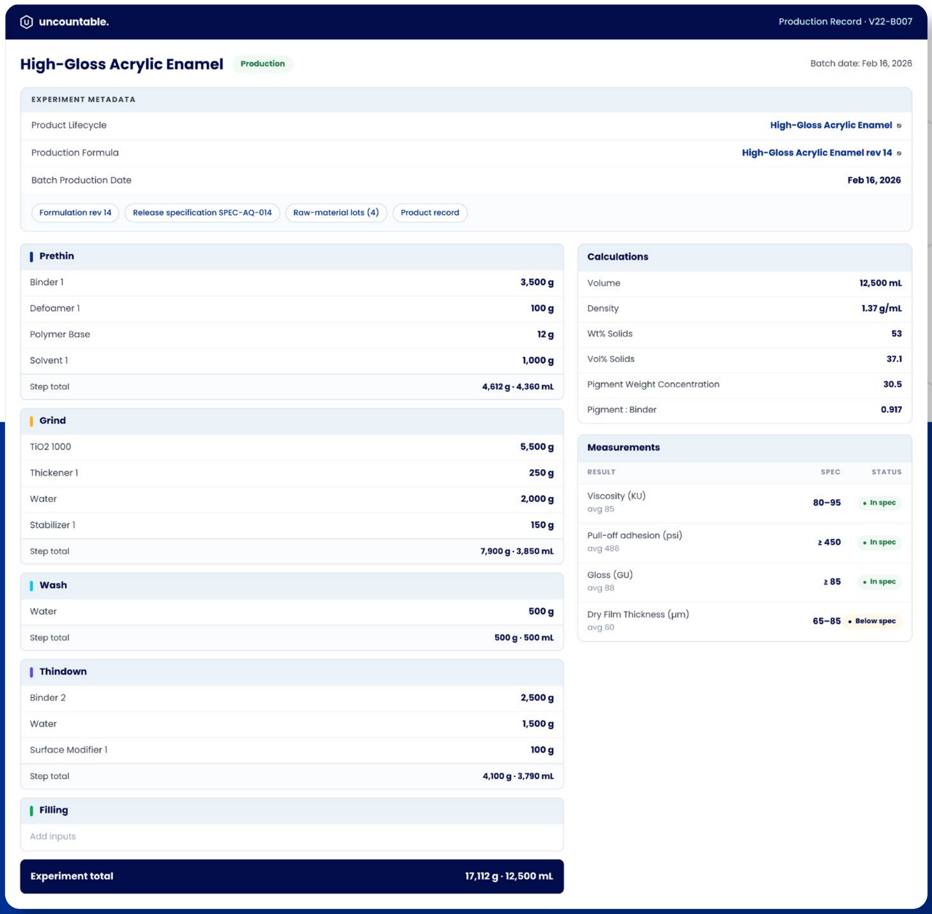
CHAPTER 2

What the Lab of the Future Looks Like

Connected Data Across the Full Product Lifecycle

In a modern R&D organization, data doesn't stop at the lab door. Experiment records, QC results, formulation history, manufacturing specifications, and production batch data are all part of the same connected record for a product, accessible to R&D, quality, and manufacturing from the same platform.

This changes what's possible at every stage. R&D can design experiments informed by production data. Quality can investigate deviations against the full development history rather than just the production QC record. Manufacturing can access the context behind a specification rather than just the specification itself. And when regulatory submissions require a complete development history, it can be assembled from one system rather than gathered manually from several. The technical requirement is a single data model spanning what have historically been separate systems: ELN, LIMS, QC LIMS, PLM. Not integration between them, but a common architecture from the start.



A single production-batch record that carries the full picture (formulation, QC results, and links up to the product lineage and specification), so R&D, quality, and manufacturing all work from the same connected record instead of separate systems.

AI That Works on Real Data

AI is transforming R&D, but only in organizations with data structured well enough for models to learn from. The labs getting results from AI today aren't the ones with the most sophisticated models. They're the ones whose historical experimental data is connected, labeled, and queryable.

What that enables in practice: predictive models that suggest which experiments are most likely to meet a target, similarity search that surfaces relevant historical work before a new brief begins, and pattern detection across thousands of trials that no scientist could identify manually. Organizations like Clariant, Repsol, and Mitra Chem have built the connected data infrastructure that makes these capabilities possible. Repsol has applied machine learning on top of that infrastructure to reduce experimental workload and accelerate its R&D cycle. The path to AI in R&D runs through data infrastructure; building the infrastructure is the hard part, and once the data is structured and connected, the AI compounds from there.

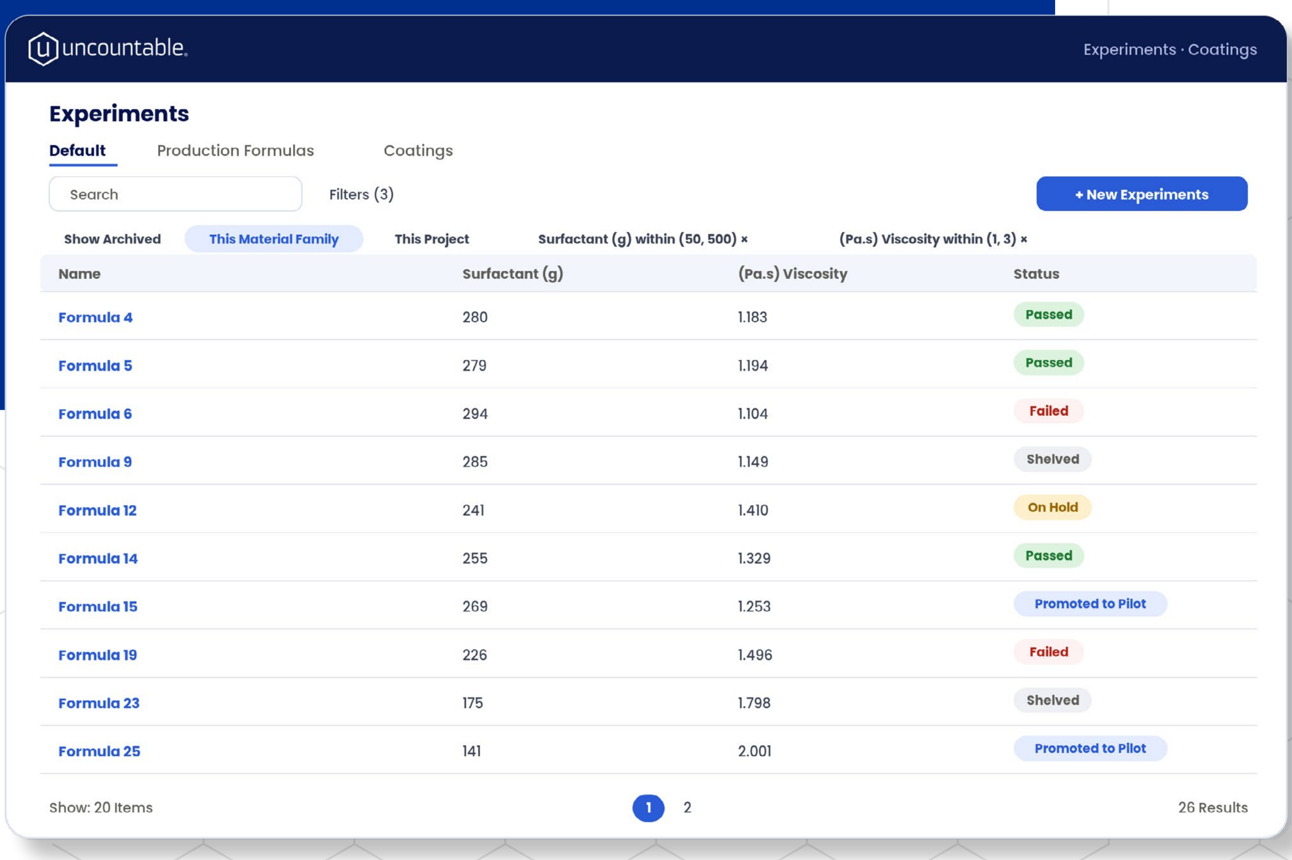
A predictive model built on the lab's own data: a response surface for gloss across binder and pigment levels, fitted to the real training formulations (shown as points). This is what becomes possible once the historical data is structured and connected.

Scientists Who Search, Not Reconstruct

In the lab of the future, a scientist responding to a new formulation brief starts by querying what already exists: experiments run on similar materials, formulations that achieved comparable performance, failure modes already ruled out. The question "has anyone tried this?" takes seconds to answer, not hours to investigate.

This isn't about making scientists faster at their current jobs. It's about changing what the job is. When institutional knowledge is in the system rather than in people's heads, the organization learns continuously rather than losing expertise with every personnel change. Teams that can reuse prior work instead of recreating it save on the order of three months per recovered project, and up to seven or eight months when a shelved experiment becomes relevant again.

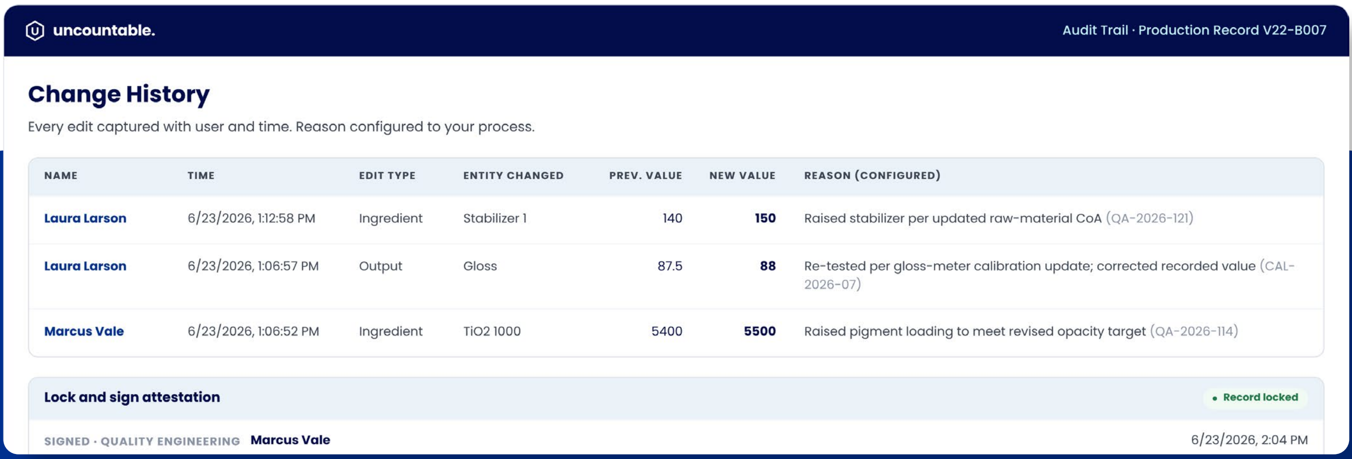
A search across prior work by chemistry, returning past experiments with their outcomes (passed, failed, shelved) before a new one is started, so a project builds on what the lab already knows, including the failures.



Name	Surfactant (g)	(Pa.s) Viscosity	Status
Formula 4	280	1.183	Passed
Formula 5	279	1.194	Passed
Formula 6	294	1.104	Failed
Formula 9	285	1.149	Shelved
Formula 12	241	1.410	On Hold
Formula 14	255	1.329	Passed
Formula 15	269	1.253	Promoted to Pilot
Formula 19	226	1.496	Failed
Formula 23	175	1.798	Shelved
Formula 25	141	2.001	Promoted to Pilot

Quality and Compliance Built In

In a modern R&D infrastructure, compliance isn't a layer added on top of the science. Audit trails, electronic signatures, version control, and access permissions are properties of how data is recorded and managed by default. Retrofitting compliance into a system that wasn't designed for it is costly: it takes time and validation effort, and it risks records that won't hold up under scrutiny. Leading regulated-industry labs choose systems where compliance is an inherent property of the data model.


uncountable.

Audit Trail · Production Record V22-B007

Change History

Every edit captured with user and time. Reason configured to your process.

NAME	TIME	EDIT TYPE	ENTITY CHANGED	PREV. VALUE	NEW VALUE	REASON (CONFIGURED)
Laura Larson	6/23/2026, 1:12:58 PM	Ingredient	Stabilizer 1	140	150	Raised stabilizer per updated raw-material CoA (QA-2026-121)
Laura Larson	6/23/2026, 1:06:57 PM	Output	Gloss	87.5	88	Re-tested per gloss-meter calibration update; corrected recorded value (CAL-2026-07)
Marcus Vale	6/23/2026, 1:06:52 PM	Ingredient	TiO2 1000	5400	5500	Raised pigment loading to meet revised opacity target (QA-2026-114)

Lock and sign attestation — Record locked

SIGNED · QUALITY ENGINEERING Marcus Vale 6/23/2026, 2:04 PM

Compliance recorded by default: an audit trail capturing the original value, the new value, the time, the user, and the reason for change, with lock-and-sign attestation on the record.

Manufacturing That Doesn't Start From Scratch

The handoff from R&D to manufacturing is where most of the value created during development is at risk of being lost. In a connected lab, it doesn't happen as a document drop. The formulation, its development history, the QC data from trials, and the processing conditions that matter for scale-up are all available to manufacturing in the same system R&D used to build them. The result is faster scale-up, fewer deviations, and less back-and-forth between teams that previously worked from different information about the same product.

uncountable.

Manufacturing Record · V22-B007

High-Gloss Acrylic Enamel Production

Batch date: Feb 16, 2026

DEVELOPMENT LINEAGE

Trial T-4471 → Formulation rev 14 → Release spec SPEC-AQ-014 → **Batch V22-B007**

Prethin — 4,612 g · 4,360 mL

#	Charge, in order of addition	Amount
1	Binder 1	3,500 g
2	Defoamer 1	100 g
3	Polymer Base	12 g
4	Solvent 1	1,000 g

Dispersion speed	600 RPM
Temperature	22 °C
Hold time	15 min

Grind — 7,900 g · 3,850 mL

#	Charge, in order of addition	Amount
1	TiO2 1000	5,500 g
2	Thickener 1	250 g
3	Water	2,000 g
4	Stabilizer 1	150 g

Dispersion speed	3,500 RPM
Temperature	38 °C
Hold time	45 min

Wash — 500 g · 500 mL

#	Charge, in order of addition	Amount
1	Water	500 g

Dispersion speed	900 RPM
Temperature	30 °C
Hold time	10 min

Thindown — 4,100 g · 3,790 mL

#	Charge, in order of addition	Amount
1	Binder 2	2,500 g
2	Water	1,500 g
3	Surface Modifier 1	100 g

Dispersion speed	1,200 RPM
Temperature	25 °C
Hold time	20 min

Trial vs this batch

Result	Trial	Batch	Spec
Viscosity (KU)	87	85	80–95
Gloss (GU)	89	88	≥ 85
Pull-off adhesion (psi)	492	486	≥ 450
Dry film thickness (µm)	68	60	65–85

• Dry film thickness below spec

Scale-up context

Trial scale	2,500 mL
This batch	12,500 mL
Scale factor	5×
Grind dispersion, trial	3,500 RPM
Grind dispersion, batch	3,500 RPM

Batch totals

Total charge	17,112 g
Total volume	12,500 mL

The formulation charge, the per-step process conditions, the trial results behind them, and the development lineage on one record, so manufacturing starts from the context R&D built rather than a document drop.

The manufacturing-facing record: the formulation, the per-step process conditions (including dispersion speed), the QC results, and the development lineage, all in one place, so production starts from the full context R&D built, not a document drop.

CHAPTER 3

How Organizations Get There

The journey to a modern lab infrastructure follows a recognizable path. Most organizations start in a fragmented state: ELN plus LIMS plus spreadsheets, with integration overhead growing as the system scales. Cross-system queries take days. AI initiatives stall on data quality.

The shift begins when the cost of fragmentation becomes visible enough to justify change, typically at one of three trigger points: a major systems refresh, a significant quality or regulatory incident that exposes data gaps, or an AI investment that reveals the underlying data isn't fit for purpose.

Major systems refresh

Quality/regulatory incident

AI investment into data quality

The organizations that make the shift successfully understand one thing clearly: this is not an integration project. It is a data architecture decision. They start with a clear view of what data needs to be connected and for whom, map their workflows across R&D, quality, and manufacturing before evaluating platforms, and choose a system based on data model architecture rather than feature lists. Implementation is more substantial than a point-tool replacement and requires organizational alignment across R&D, IT, quality, and manufacturing, but the organizations that have done it consistently report faster investigation times, reduced experiment duplication, improved scale-up success, and an AI capability that was impossible on the previous stack.

CHAPTER 4

What to Evaluate When Building the Lab of the Future

Data model first

The most important question isn't which features the system has; it's how its data model is structured. Ask vendors to show you, with live data, how a product can be traced from R&D experiment to QC result to production specification in a single workflow.

AI readiness

Ask what AI features are in production today, not on the roadmap; whether your historical data would be structured well enough to train models on; and which customers are actively using AI capabilities and what outcomes they've measured.

Lifecycle coverage

A platform that stops at the lab door creates a new silo. Evaluate how R&D data connects to QC, quality management, and manufacturing, and whether that connection is built into the architecture or dependent on custom integration.

Implementation approach

Understand the vendor's implementation methodology, the typical timeline for an organization your size, and the support model during and after go-live.

Validation and compliance

In regulated industries, the platform needs to meet compliance requirements by design. Ask how the system supports 21 CFR Part 11 (audit trails, electronic signatures, and access controls) and what validation documentation is provided as part of implementation.

CHAPTER 5

What Leading Organizations Have Built

CLARIANT

Clariant replaced a legacy ELN with Uncountable to build a structured scientific backbone connecting its synthesis and application teams, now relied on by more than 1,000 users across 35+ global facilities. At that scale, scientists can find prior work before they run new experiments, and institutional knowledge persists across personnel changes because it lives in the system.

1000
USERS

35+
GLOBAL FACILITIES

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repsol

Repsol used Uncountable to consolidate 10,000+ data points from twenty years of formulation work into a single structured database, then applied machine learning to reduce experimental workload and accelerate its R&D cycle. The value wasn't in the AI itself, but in the data infrastructure that made the AI viable.

10,000+
DATA POINTS

20
YEARS OF FORMULATION WORK

Mitra Chem

Mitra Chem, developing next-generation battery materials, uses Uncountable to unify lab workflows, streamline sample tracking, and accelerate discovery from early-stage experiments through to scale-up. In a field where iteration speed is the primary competitive variable, the data infrastructure is the competitive advantage.

UNIFY LAB WORKFLOWS

STREAMLINE SAMPLE TRACKING

ACCELERATE DISCOVERY

Customer Story: SCG Chemicals

SCG Chemicals, a leading chemical company in ASEAN, runs a complex product development landscape spanning the production of olefins through downstream plastics, resins, and polymers. The team set out to digitize its R&D data management and found that the way data was being captured and managed had become the constraint on how fast those projects could move.

Before Uncountable, R&D data lived across disconnected sources, and scientists spent a large share of their time assembling and mapping it rather than analyzing it. Choosak Kiwjaroen, Team Leader in Polymer Simulation at SCG Chemicals, describes data management as central to navigating a product development landscape of that complexity. The bottleneck wasn't the science, it was getting the data into a usable state.

Moving to Uncountable's all-in-one R&D platform put experiments, formulations, and results into a single structured system, and changed the economics of the lab. SCG Chemicals reports a 45% reduction in design-of-experiments workload, R&D accelerated by 10-20%, 50% less time spent mapping data from various sources, and up to 3X return on investment (contribution over investment). The infrastructure didn't just make the existing process faster: fewer experiments were needed to reach the same answers.

45%
REDUCTION IN DESIGN-OF-EXPERIMENTS WORKLOAD

10-20%
R&D ACCELERATION

50%
LESS TIME MAPPING DATA

3X
RETURN ON INVESTMENT

Full case study:
https://www.uncountable.com/case-studies/scg-chemicals-accelerates-research-development-20-percent-using-uncountable

Key Takeaways

1. The constraint on R&D productivity in most organizations isn't talent or investment: it's data infrastructure.

2. The ELN-LIMS-spreadsheet stack was designed for an era of slower R&D cycles and less data; it no longer supports what enterprise R&D is being asked to do.

3. AI in R&D is viable today, but only in organizations whose historical data is connected, structured, and queryable.

4. The lab of the future is defined by a single connected data model spanning R&D, quality, and manufacturing, not by the sophistication of any individual tool.

5. The organizations building this infrastructure now are compressing R&D cycles, reducing experiment duplication, and creating an institutional knowledge base that persists regardless of personnel changes.