

Polymerize Materials R&D Insights 2026

The State of AI in Materials Development Challenges, Adoption Trends, and Future Opportunities

Introduction

Materials development is entering a new phase.

Organizations are under increasing pressure to shorten development cycles, respond more quickly to changing market demands, and deliver consistent innovation despite limited resources and expertise. Against this backdrop, interest in applying AI to materials development continues to grow.

For many organizations, a key challenge is no longer simply generating more research data, but connecting experimental results, scientific knowledge, and decision-making into a more productive and efficient R&D process.

To better understand the current landscape of AI adoption in materials development, Polymerize conducted original research among materials R&D professionals across Japan. This report presents the findings of that research, examining the key challenges facing materials development, the current state of AI adoption, barriers to implementation, the R&D data organizations rely on today, and the key considerations for successful AI adoption. Together, these findings provide a snapshot of where the industry stands today and where it is heading next.

Key finding

Accelerating Development Remains the Top Priority

65% Identified shorter development lead times as their top priority.

Research Data Infrastructure Is the Biggest Barrier

73% Cited fragmented and unstructured research data as a major challenge.

AI Adoption Is Moving from Exploration to Implementation

47% Currently evaluating AI adoption.

37% Already implementing or actively using AI.

Talent and Knowledge Management Remain Key Challenges

57% Reported a shortage of talent to drive AI initiatives.

54% Identified knowledge dependency as a key challenge.

Researchers Need More Time for Analysis and Interpretation

44% Reported insufficient time for data analysis and interpretation.

Practical Usability Matters Most

54% Prioritize ease of data preparation and processing.

Research Overview

Respondents	Materials R&D professionals in the Japanese manufacturing industry
Sample Size	200
Fieldwork Period	February–April 2026
Research Focus	The State of AI in Materials Development

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EXECUTIVE SUMMARY

Executive Summary

The findings reveal that AI adoption in materials development is steadily gaining momentum, driven by longstanding industry challenges such as accelerating development timelines, addressing talent shortages, and improving the continuity of research knowledge.

At the same time, the research indicates that the greatest barriers to AI adoption are not the AI technologies themselves. Instead, organizations continue to face challenges in managing fragmented research data and establishing an R&D data foundation that supports continuous use by researchers.

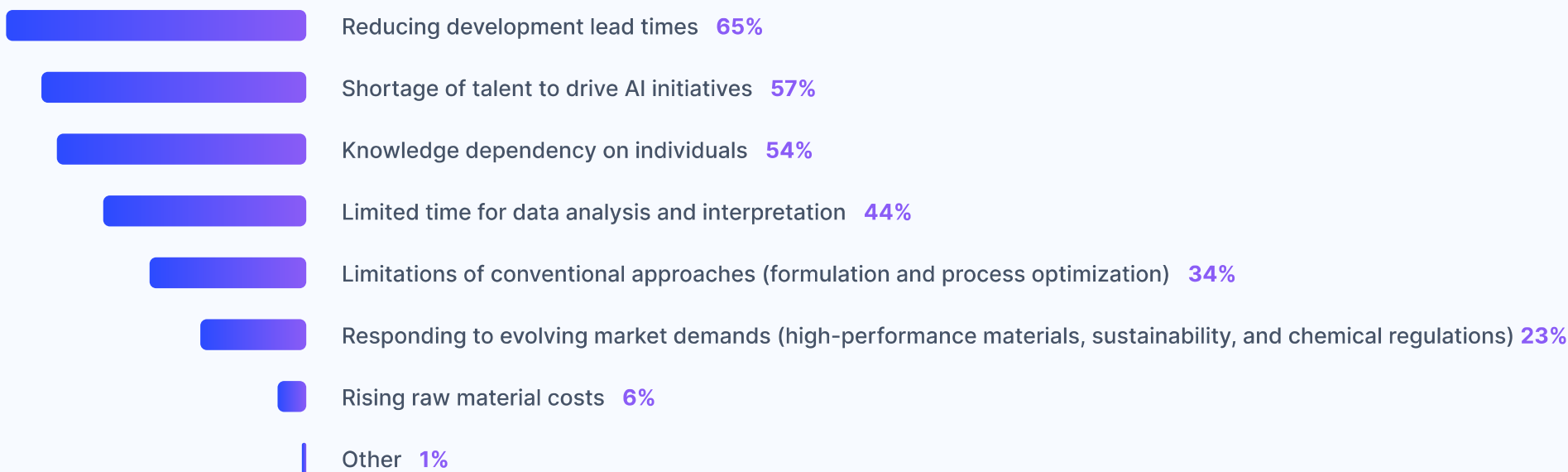
The results also suggest that the conversation is shifting from whether organizations should adopt AI to how AI can be effectively integrated into day-to-day R&D workflows and deliver long-term value.

When evaluating AI solutions, organizations are looking beyond model performance alone. Compatibility with existing research data, ease of use, long-term maintainability, and security have emerged as key factors in successful AI adoption.

This report provides insights into the current state of AI adoption in materials development and highlights the practical considerations for embedding AI into everyday R&D processes.

Key Challenges in Materials Development

● KEY CHALLENGES IN MATERIALS DEVELOPMENT (RESPONDENTS COULD SELECT MULTIPLE ANSWERS.)



1

Accelerating Development Speed Remains the Primary Focus

Shortening development lead times (65%) was identified as the single largest challenge in materials and product development. As market demands shift and product lifecycles compress, finding ways to accelerate development and reach targets with fewer trial-and-error iterations remains a critical priority for most enterprises. Rather than a simple preference for speed, this reflects a demanding R&D environment where researchers must make high-confidence decisions under strict resource constraints. The findings suggest **a strong mandate to transition from conventional, empirical exploration to more efficient, AI-enabled discovery methods.**

2

Strengthening the Talent Pool and the Organizational Knowledge Base

Closely following **lead-time reduction, shortages of AI-capable talent (57%)** and **the issue of knowledge dependency on specific individuals (54%)** emerged as prominent concerns. These statistics highlight that R&D bottlenecks are not merely administrative or logistical; **they stem from the fundamental way organizations store and utilize intellectual assets.**

Successfully adopting AI requires more than just hiring specialists. It demands institutional mechanisms to seamlessly preserve and transfer engineering expertise. Individual silos prevent the reuse of past trial-and-error insights, leading to redundant work. **R&D competitiveness in the AI era will increasingly depend on an organization's ability to digitize and systematically share internal knowledge, freeing R&D processes from dependency on individual experience.**

3 Researchers Face a Deficit of Time for Critical Analysis and Interpretation

A significant portion of respondents (**44%**) cited **insufficient time to analyze and interpret experimental results**. Although physical experimental data is often compiled, **researchers struggle to find the bandwidth to deeply analyze findings and translate them into next-step hypotheses or structured experimental designs**. In R&D, physical testing is only half the battle; the true value is unlocked when researchers synthesize insights to drive subsequent exploration. The data suggests that tedious data-preparation and preprocessing tasks consume too much of a researcher's day, leaving them with inadequate time for high-value decision-making. To accelerate R&D cycles and lift productivity, **organizations must build environments that deliberately free up researchers to focus on analysis and strategic interpretation.**

4 Reaching the Limits of Conventional Empirical Development

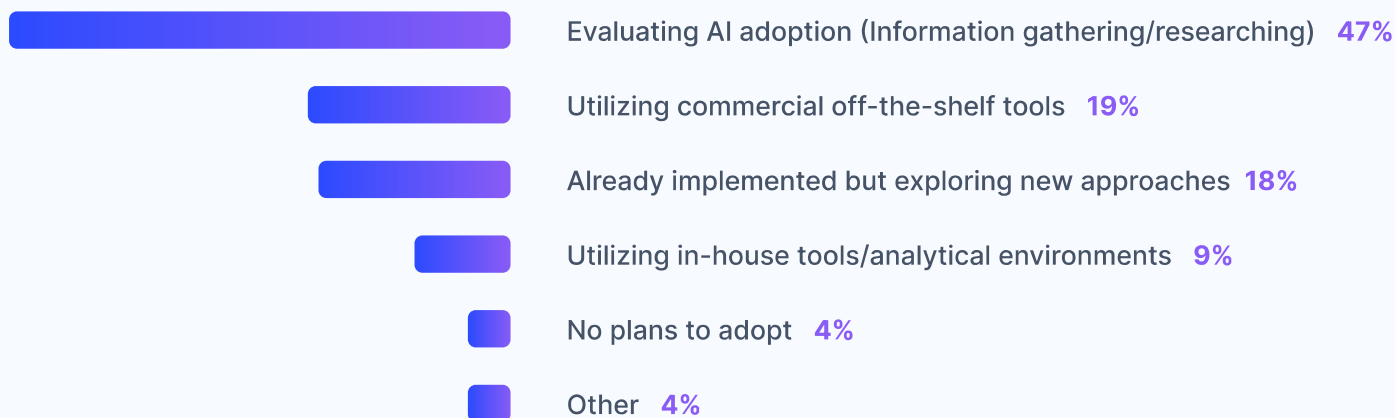
A noteworthy **34%** of respondents pointed to **the physical limitations of conventional development approaches (e.g., empirical formulation and process optimization) for performance improvements**. This indicator suggests that a growing number of organizations recognize that traditional, trial-and-error optimization is reaching its practical limit for discovering novel materials or driving breakthrough properties. As product requirements become more sophisticated, **R&D teams are increasingly looking for tools that leverage historical data and past intellectual capital to guide exploration and bolster scientific decision-making.**

Chapter Takeaways

While **accelerating development speed** is the ultimate objective, this chapter illustrates that the underlying bottlenecks are rooted in foundational R&D infrastructure, specifically, the availability of specialized talent, knowledge continuity, the accessibility of structured research data, and the cognitive bandwidth available to researchers. Resolving these challenges requires more than just installing AI software; it demands a comprehensive modernization of the R&D environment. **By centralizing research data and organizational knowledge, companies can empower their scientists to shift their focus from manual data management to high-impact analysis and accelerated decision-making.**

The Current State of AI Adoption

CURRENT R&D AI IMPLEMENTATION STATUS



1 AI Interests Continue to Intensify but remains in Evaluation for Many

Nearly half of all surveyed organizations (**47%**) are **actively evaluating AI adoption, currently positioned in the information-gathering and research phase**. This highlights a widespread, industry-wide focus on AI-driven materials development, as companies benchmark capabilities and run initial feasibility tests. Since this cohort represents the largest group, the broader market is currently in a critical assessment phase immediately preceding full-scale implementation. The question for modern R&D leaders is **no longer whether to bring AI into the laboratory, but how to apply it effectively to their specific material systems and product lines**.

2 Practical Application in R&D is Actively Expanding

Combining **those utilizing commercial off-the-shelf tools (19%)** and **those already running AI initiatives while exploring new approaches (18%)**, 37% of surveyed enterprises have successfully transitioned to active implementation. This indicates that AI is no longer a theoretical technology reserved for pioneering laboratories; **it has become a practical asset integrated into daily R&D workflows across a substantial portion of the industry**. The current market presents a dual landscape: a large group preparing and validating, alongside an active group successfully applying and refining AI in real-world development.

3 Continuous Evolution: Searching for New Approaches Post-Adoption

Among organizations actively utilizing AI, a notable **18%** answered that they are **"already implementing AI but simultaneously exploring new approaches."** This reveals that AI-driven development is not a one-off "set-and-forget" software installation. Rather, as teams gain practical experience, **they uncover new bottlenecks, identify advanced use cases, and systematically seek to upgrade their modeling capabilities and methodologies to stay competitive.**

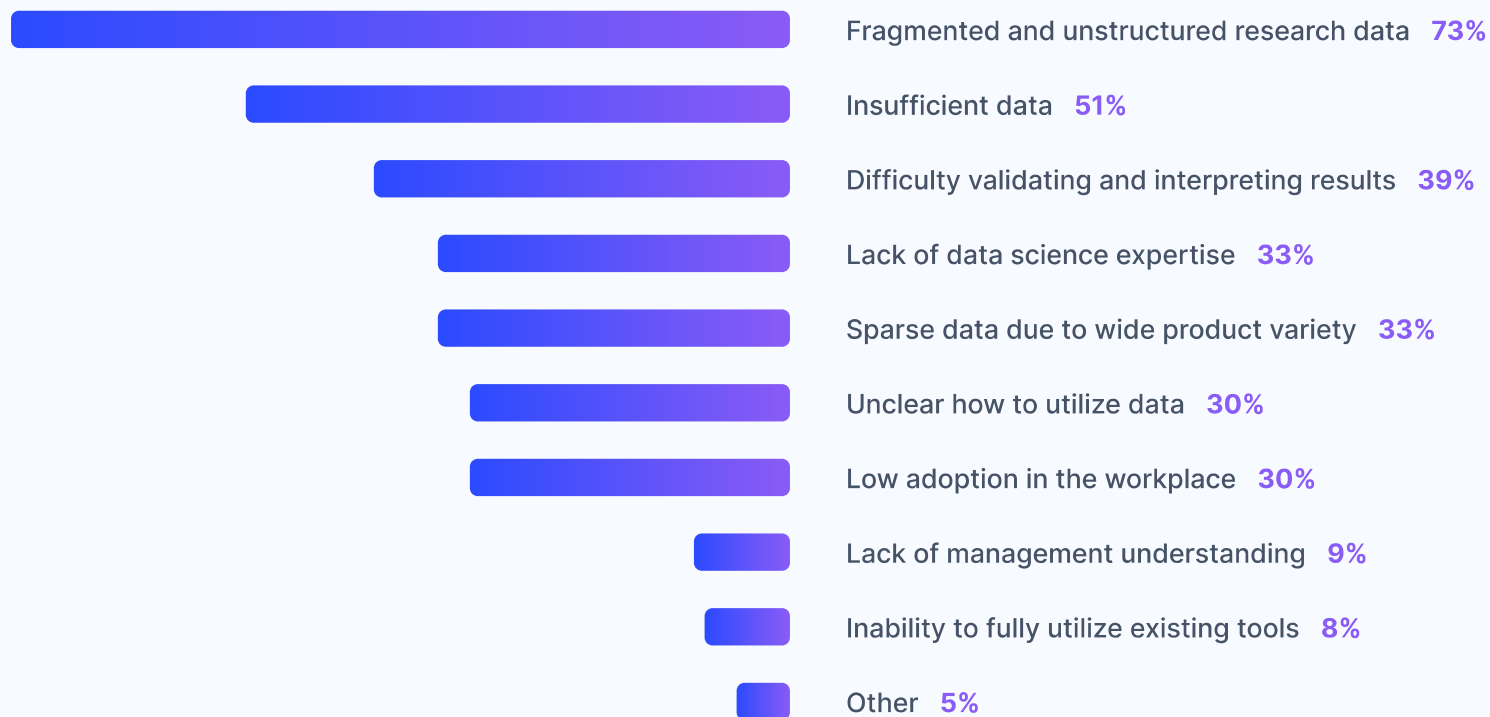
Chapter Takeaways

The survey highlights a diverse and mature landscape where high market interest is matched by expanding practical deployment. **Organizations are currently spread across multiple maturity levels**, ranging from initial technology scouting and proof-of-concept testing to steady-state operations and ongoing system optimization. Crucially, **AI-driven development is showing itself to be a continuous journey of operational refinement rather than a static IT project.** Consequently, the focus in the manufacturing sector is shifting rapidly from the entry-level question of "how do we buy AI" to the much more impactful strategic question of "how do we manage, sustain, and continuously extract compounding value from AI across our R&D lifecycle."

Barriers to AI Adoption



● CHALLENGES IN IMPLEMENTING AI-DRIVEN R&D (MULTIPLE CHOICES ALLOWED)



1

Data Preparation Remains the Preeminent R&D Bottleneck

At a staggering **73%**, the primary barrier to AI success is that **internal research data is fragmented and unstructured**, followed by a perceived **lack of sufficient data (51%)**. These metrics demonstrate that the core bottleneck of AI-driven materials science is not the mathematical capability of the AI models or the availability of software tools. Rather, it is the fundamental difficulty of **compiling, structuring, and standardizing historical R&D data into a machine-readable format**. Furthermore, the fact that over half of respondents struggle with "insufficient data" underscores the critical need for systems that systematically and continuously capture experimental data as it is generated, building a robust, compounding asset over time.

2

Bridging the Gap: Upstream Data Curation and Downstream Insight Action

The findings suggest a double-sided challenge in AI-driven R&D: **preparing data so AI can consume it** (upstream), and **interpreting AI outputs so researchers can act on them** (downstream). Upstream, laboratories require **data-cleaning structures, automated parsing, and specialized techniques to handle "sparse data"** a common issue in high-mix, low-volume materials R&D.

Downstream, R&D teams must possess the physical intuition and workflow processes to validate, interpret, and confidently apply AI-generated predictions to physical laboratory experiments. Successful AI adoption requires **an end-to-end framework that takes data from "raw and scattered," makes it "machine-ready," and ultimately translates AI outputs back into actionable R&D progress.**

3 The On-the-Ground Adoption Gap

A considerable share of organizations **(30%)** struggle with **low adoption rates among laboratory researchers**. This statistic serves as a vital reminder that purchasing software does not guarantee organizational capability. The true success of AI-driven materials development depends on whether **everyday bench scientists actively embrace and use these systems in their daily workflows**. To bridge the gap between software acquisition and daily utilization, enterprises must focus on creating intuitive, friction-free environments that organically align with the natural research and experimental cycles of the laboratory.

Chapter Takeaways

The journey toward AI-driven R&D is a multi-step process with potential bottlenecks at every turn. These range from original data ingestion and automated structural cleanup to model training, physical interpretation of results, and cultural adoption on the lab floor.

Consequently, a winning R&D strategy must address the entire lifecycle: **converting unstructured historical experiments into "model-ready" assets, establishing reliable pipelines to interpret predictions, and building an intuitive operational framework that integrates smoothly into a researcher's daily workflow to drive permanent, habit-based adoption.**

R&D Data Landscape

● TYPES OF DATA CURRENTLY UTILIZED IN MATERIALS R&D (MULTIPLE CHOICES ALLOWED)



To fully understand why **73%** of R&D organizations complain about "**fragmented and unstructured data**," we must analyze the specific types of data currently active in their modeling environments.

1 R&D Modeling is Dominated by "Input-Side" Data

The data sets currently used in modeling are heavily concentrated on **formulation/process recipes (78%)** and **raw material properties (75%)**. These represent the "**input variables**" of materials development. Because experimental formulations and raw material specifications are naturally recorded in numerical, structured tables, they present a much lower barrier to machine organization.

2 The Bottleneck: Under-utilization of "Output-Side" Performance Data

Conversely, "**output variables**", such as **final physical evaluation/performance data (34%)** and **microscopic/macro image data (31%)**, remain underutilized. In materials informatics, the ultimate goal of AI is to predict performance based on a given formulation. Therefore, output-side data is essential as the "target variables" for AI model training. The reality where inputs are organized but outputs remain neglected suggests that the "**unstructured data**" problem is concentrated heavily on the **performance and analytical measurement side of the R&D lifecycle**.

3 The "Structuring Wall" Facing Image and Performance Data

Performance data often exists in mixed, complex formats: some are direct tabular metrics, while others are stored as raw analytical curves or physical images (such as microscopy, spectroscopy, or fracturing scans) that traditionally require human inspection to quantify. Unlocking the power of image and complex wave data requires robust preprocessing, automated feature extraction, and specialized image-processing pipelines to convert raw visuals into structured, machine-learnable numerical vectors. The underutilization of output data is not due to a lack of physical experiments, but rather **a lack of established protocols for structuring complex analytical outcomes.**

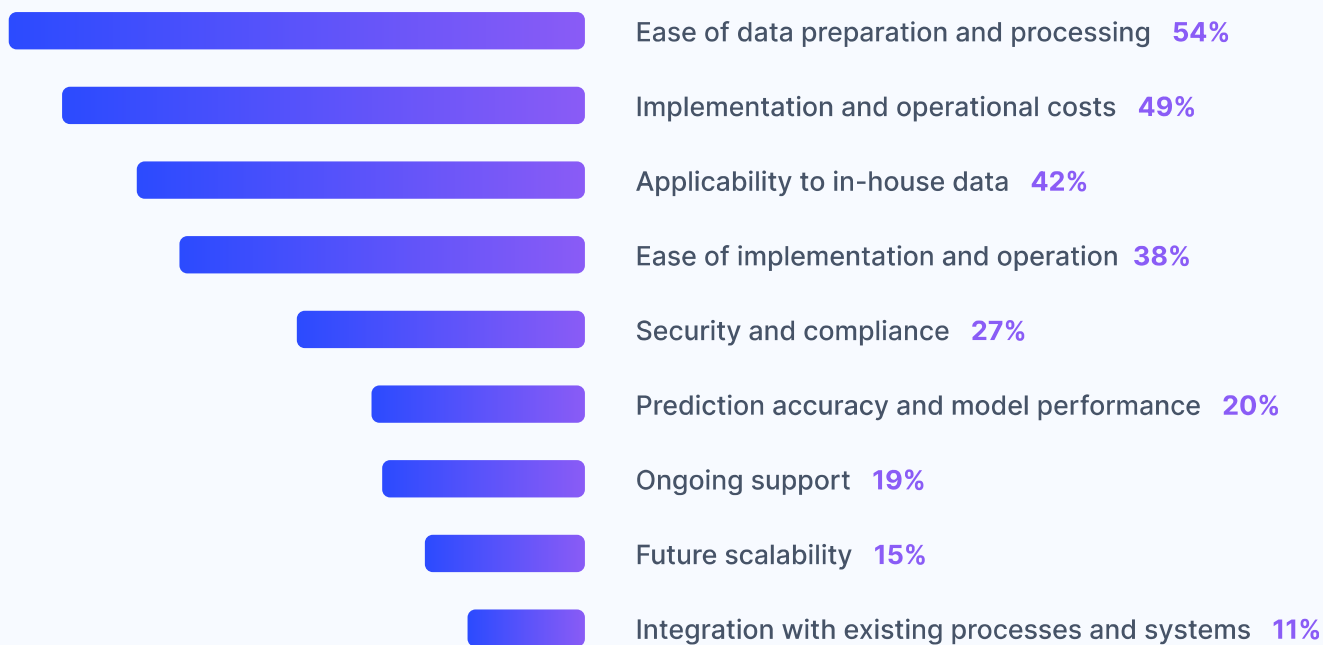
Chapter Takeaways

The current state of Materials Informatics shows a clear imbalance: **R&D departments have successfully digitized their input parameters (formulation and recipe sheets) but continue to struggle with their output metrics (performance profiles and structural imaging).**

To achieve high-accuracy predictive modeling, **organizations must design end-to-end data pipelines that systematically structure complex, multi-modal output data. Standardizing these analytical results and linking them directly back to their original formulations is the critical next step required to unlock advanced machine learning capabilities in materials development.**

Key Considerations for AI Adoption

WHAT ORGANIZATIONS PRIORITIZE WHEN SELECTING AI SOLUTIONS (MULTIPLE CHOICES ALLOWED)



1

Practical Utility and Data Preparation Take Center Stage

"**Ease of data preparation and processing**" (54%) emerged as the top priority, with "**applicability to in-house data**" (42%) also ranking high. These results show that R&D decision-makers prioritize day-to-day usability over theoretical AI capabilities. In light of the fact that "fragmented and unstructured research data" is the number-one challenge, it is natural that buyers seek solutions that help them **easily structure and ingest their unique materials data**. An AI system's value is directly tied to its practical integration, meaning **how smoothly it connects with and structures the diverse experimental data generated on the laboratory floor**.

2

Maximizing Usability to Drive Stable Habituation on the Lab Floor

A strong preference was voiced for "**ease of implementation and operation**" (38%). R&D managers recognize that software only delivers returns if **bench scientists use it continuously**. Given that 30% of companies identify "low adoption on the lab floor" as a barrier, selecting an AI solution with an intuitive user interface, one that **seamlessly embeds into the physical R&D workflow without adding administrative burdens**, is critical to transforming AI from an IT mandate into a daily habit.

3 Balancing Total Cost of Ownership (TCO) with Long-Term ROI

Almost half of the respondents (**49%**) highlighted "**implementation and operational costs**" as a major factor. AI-driven R&D is a long-term strategy; its predictive accuracy and business value grow as experimental data and internal knowledge accumulate. R&D leaders look beyond initial licensing costs, **evaluating the long-term operational costs and cost-to-benefit ratio to ensure the platform remains financially sustainable and continues to deliver compounding returns over multiple years.**

4 Protecting Intellectual Property: Uncompromising Security and Compliance

For **27%** of organizations, **security and compliance** are paramount. In materials science, experimental formulations, synthesis parameters, and performance profiles represent the core intellectual property (IP) and competitive edge of a chemical or manufacturing enterprise. Particularly in high-tech or advanced materials divisions, **secure data environments are mandatory.** AI solutions must demonstrate top-tier security standards, **ensuring that sensitive proprietary research data remains protected.**

Chapter Takeaways

The selection of an R&D AI solution is heavily driven by practical considerations: **ease of data processing, TCO, usability, and data security.** R&D divisions prioritize holistic R&D integration over stand-alone AI capabilities.

To drive a successful R&D transformation, **organizations must deploy platforms that combine strong predictive models with intuitive data curation, manageable cost structures, enterprise-grade security, and a user experience that aligns naturally with a chemist's day-to-day work.**

Key Takeaways & Conclusion

The findings from this survey confirm that R&D divisions are actively adopting AI to **accelerate development speed, preserve technical knowledge, and navigate talent shortages**. However, the true bottleneck in this digital transformation is not the AI algorithm itself. Instead, success hinges on an organization's ability to **systematically structure fragmented research data and build R&D environments that support continuous, frictionless utilization by laboratory scientists**.

Currently, modeling efforts are heavily skewed toward input data (formulations and raw material specifications), leaving significant untapped potential in output data (complex performance metrics and analytical image data). Unlocking advanced materials informatics requires bridging this data gap.

Ultimately, competitiveness in the AI era is not defined by the simple acquisition of AI tools. Rather, it is determined by **whether an organization can convert its daily experimental findings and historical tribal knowledge into a structured, centralized digital asset**. By establishing a robust data foundation, companies can liberate their scientists from routine data management, allowing them to **focus their cognitive bandwidth on high-value analysis, deep scientific interpretation, and breakthrough decision-making**.

Advancing AI-Driven Materials R&D with Polymerize

Our research reveals a clear reality: while the desire to accelerate materials development using AI is strong, the primary barrier lies in managing fragmented research data and creating an environment where scientists can thrive.

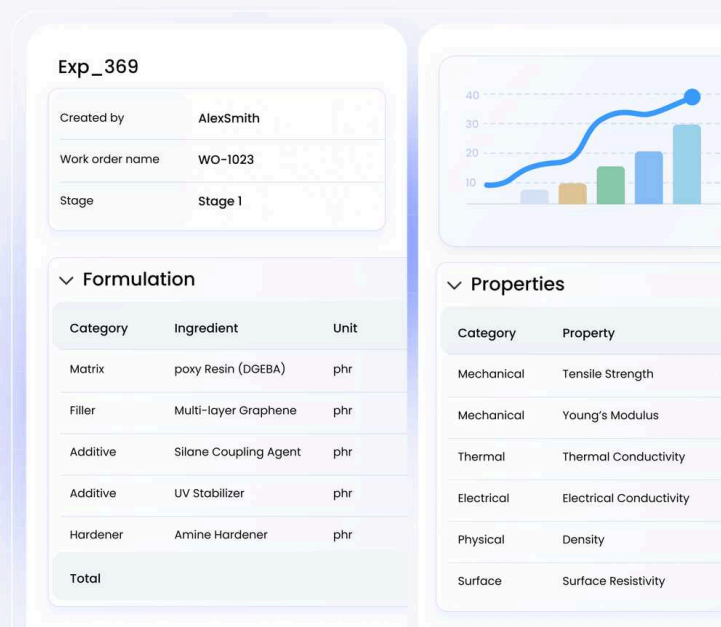
Polymerize is built specifically to address these fundamental challenges. By seamlessly centralizing raw lab data, standardizing complex experimental results, and providing intuitive AI capabilities, we enable research teams to move from friction to faster, data-driven innovation.

THE SYSTEM OF RECORD

Polymerize **Connect**

The foundational data architecture that standardizes your historical and ongoing R&D.

A comprehensive **data management solution** that offers a suite of customizable tools that make managing, storing, analyzing, and sharing your research data simpler.

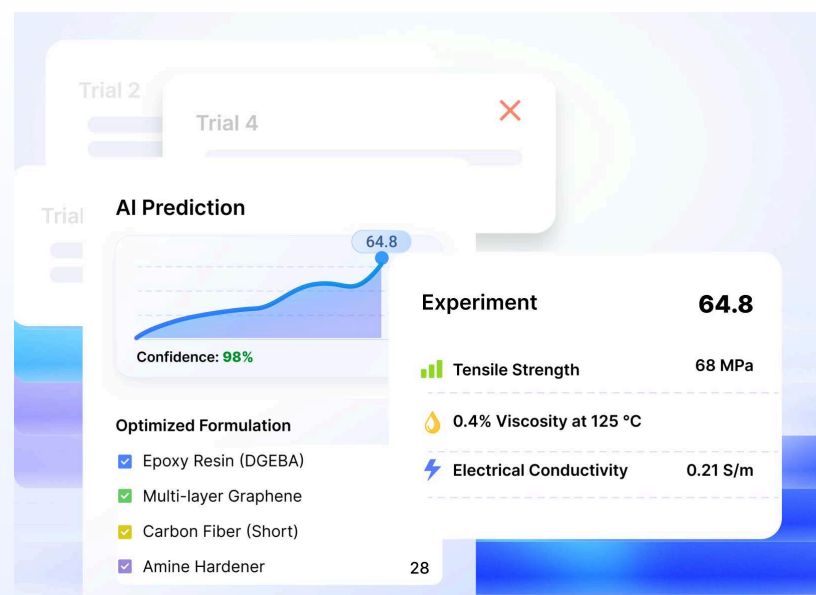


THE SYSTEM OF INTELLIGENCE

Polymerize **Labs**

The predictive engine that transforms your standardized data into formulation breakthroughs.

A **cloud-based material informatics platform** that provides AI-recommended formulations based on desired properties of high performing materials. Starting with as little as **25 data points**, Polymerize Labs can provide desired results with **95% accuracy**.



Polymerize One

Extends data-driven R&D into real-world validation and execution:

An **all-in-one materials innovation service** to drive material innovation that integrates its material informatics platform, outsourcing prototyping and testing, and expert domain support.



Ready to take the next step in materials innovation?

Learn more about how your organization can centralize lab data and unlock predictive AI with Polymerize.

[Request a Demo →](#)

Or contact us at [✉ marketing@polymerize.io](mailto:marketing@polymerize.io)