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# Building Trust in AI for Pharma Library and Medical Information Teams

Artificial intelligence is changing how pharmaceutical library and medical information teams do their work. Jill M. Shuman, a science writer and pharmaceutical library director with more than three decades of experience, calls AI “the biggest paradigm shift in library technology since the advent of the Internet.” AI tools are shifting the focus of teams from static information providers to active investigators and experimenters. Information specialists are no longer limited to developing workflows that incorporate static information. Instead, they are leveraging AI to expedite how teams access, sort, and summarize scientific literature.

The potential benefits of AI adoption are huge: faster insights, streamlined workflows and freeing up human experts for higher-level data analysis. However, the excitement is tempered by risk and uncertainty. AI systems make mistakes, and they typically lack the conceptual depth needed to make good clinical or business decisions.

In areas where decisions must stand up to rigorous regulatory scrutiny and scientific review, incomplete or biased outcomes can have serious consequences. In a field where every decision must be transparent, defensible, reproducible, and accurate—trust in AI can’t be assumed.
**It must be built.**

This paper explores the requirements for building trust in AI, including structured human oversight, strong governance and AI ethics, as well as an understanding of the limitations of artificial intelligence.

## The Promise and Risks of AI in Pharma Knowledge Centers

AI is no longer just experimental in pharma knowledge centers and medical information teams. While some workflows are in their infancy, many AI tools are already embedded in daily operations—automating tasks that were once time-consuming and repetitive for human experts.

Common ways AI is driving efficiency include:

- **Summarizing complex scientific literature.**
  AI can parse anywhere from hundreds to more than 1000 pages of literature per second, extracting key findings, benchmarks, or main ideas for faster review.

- **Searching and organizing databases.**
  Intelligent automated systems can search through large internal and external databases, surfacing relevant studies or documents for human review.

- **Assisting in scientific writing.**
  Large language models (LLMs) and other types of AI can operate within documentation and writing processes. This is a particularly valuable use case for individuals writing in a non-native language or who require clarity regarding a document's structure or syntax.

- **Identifying emerging research trends.**
  AI can analyze enormous amounts of published data, leveraging pattern recognition to call out potential trends.

While these capabilities are certainly valuable in driving efficiencies and supporting more comprehensive research, Shuman cautions that AI is often misunderstood as "thinking." These tools don't approach thought processes like a human; instead, they produce results based on historical data without true understanding or context.

That distinction is critical to building trust in AI-powered research workflows. Shuman offers an example to demonstrate the risks of AI in such workflows: In an internal test that involved sourcing results for a specific bibliographic search request, AI returned 47 results. But 21 of them—almost half—were inaccurate. "Aside from these types of search inaccuracies, AI can fabricate or misinterpret information, fail to recognize retracted papers, rely on outdated resources or amplify existing biases that exist in some of the literature," Shuman notes.

To mitigate these concerns, library teams and researchers must understand where AI tools source their information. Many LLMs draw from the open internet—or massive databases built from the same sources. That's a landscape riddled with unverified, outdated, subjective, and non-peer-reviewed content. While the approach can be helpful for general knowledge research, it's risky in regulated industries like pharma. Some platforms, like ReadCube, limit model access to content in research databases. By linking AI-generated summaries directly back to peer-reviewed source materials, such systems support faster validation and reduce error risks.

**Even with safeguards, thoughtful human engagement and oversight of AI is critical in supporting accurate, compliant outcomes.**

## Human-in-the-Loop: Building Explainability, Accuracy, and Trust

**Human-in-the-loop (HITL)** systems combine the efficiency of AI with critical thinking and contextual awareness from human experts. In a typical HITL workflow, AI performs an initial task, such as summarizing literature or extracting data. Human experts, such as medical writers, librarians or information scientists, verify the accuracy of outputs, correct misinterpretations if needed and flag discrepancies, biases, or ethical concerns.

Feedback from human experts provides a two-fold benefit. First, it improves the compliance and quality of the immediate output. Second, it can help train the AI tool to support better performance in the future.

Advantages of HITL in AI-powered pharma library and medical information workflows include:

- **Greater rationale.**
  Human review adds logical rationale and critical thinking to the process, making it easier to trace AI-assisted decision-making to relevant inputs. This level of explainability supports transparency and more positive outcomes in cross-functional review and audit processes.
- **Enhanced accuracy.**
  Human experts can catch contextual errors, false positives, and outdated references that automated systems might overlook.
- **Better compliance.**
  Human-annotated outputs and revision histories that demonstrate expert approval and context create a more defensible record that aligns with regulatory expectations.
- **Support for reproducing efforts.**
  Human validation helps ensure results are verified so they can be replicated later.
- **Ethical assurance.**
  Human oversight helps ensure that data use and outcomes align with regulatory and organizational guidelines.

As Shuman says:

> **“ AI can misinterpret context, especially in nuanced regulatory language and scientific terminology.”**

It’s important to see HITL not as a barrier to automation but as a guardrail for trust. She notes that expert oversight enhances credibility because every human interaction provides reasoning and accountability. Over time, these practices safeguard data and create a valuable cycle. Human insights support model refinement, building a more trustworthy AI partner for literature review and other work.

## Governance and Safeguards for Responsible AI Adoption

Structure is critical to the responsible use of AI in pharma. Shuman points out that governance is more than a compliance checklist; it requires a cultural shift that embeds oversight into every stage. As teams begin to integrate AI into their workflows, they should include colleagues with expertise in ethics, compliance and legal issues; library and information management; and technical implementation.

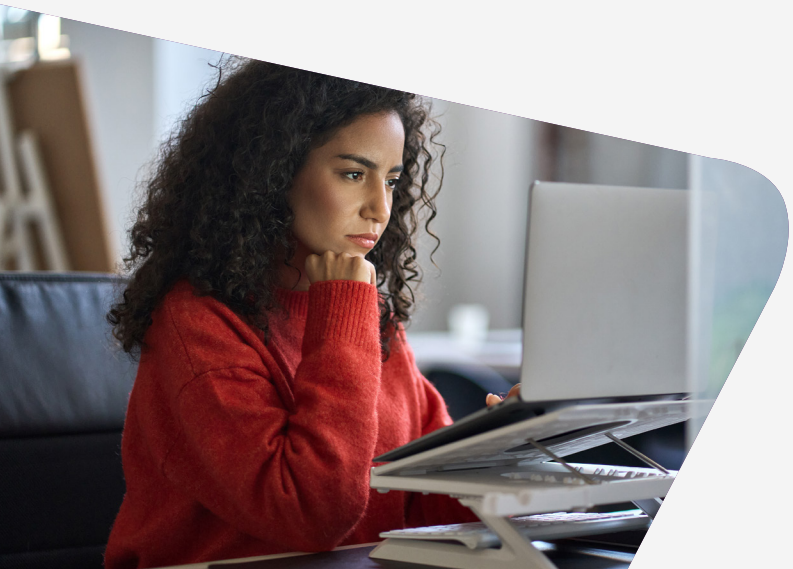
By including the pillars listed below, organizations that formalize frameworks can meet regulatory and compliance expectations and enjoy competitive advantages as AI use and regulations evolve.

### Data Provenance

In highly regulated environments, every data set used to train, inform, or validate AI must be documented with details such as source, date, license, and intended use. Validation processes must confirm complete, accurate and representative data, and audit trails should include immutable records of data inputs, model versions, and outputs.

### Human Oversight

Human oversight ensures accountability even in the accelerated workflows supported by automation. Designated reviewers must monitor model performance, validate key outputs, and intervene when outliers occur. Shuman reiterates that human annotations and version control help establish a traceable record of decisions, supporting transparency and reproducibility.

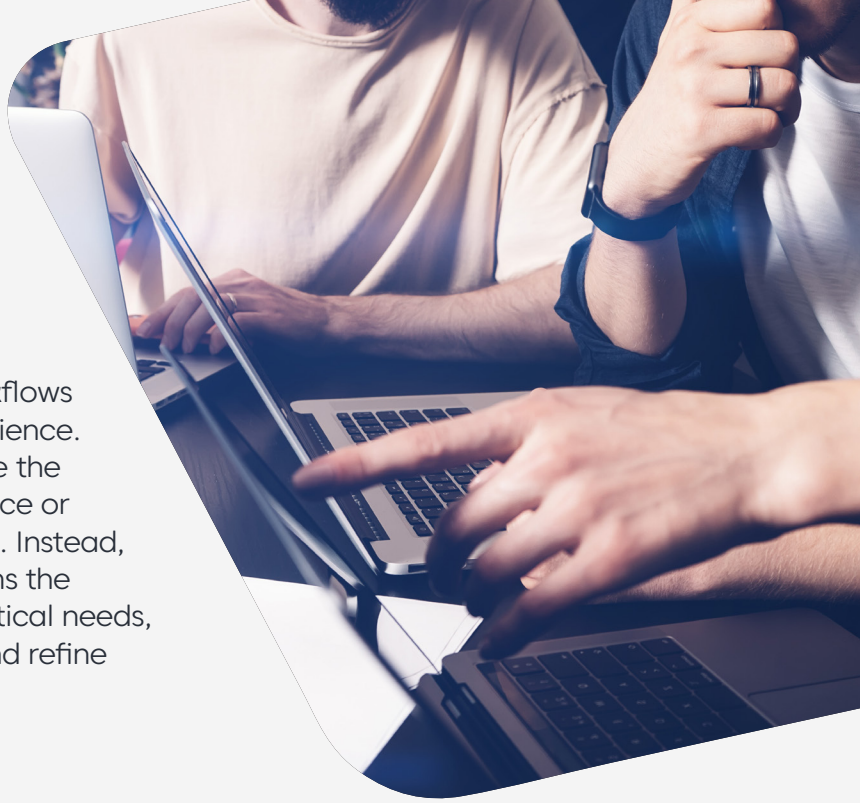


### Regulatory Compliance

AI models must align with established quality principles such as Good Machine Learning Practice (GMLP) and Good Automated Manufacturing Practice (GAMP 5). Each model update should follow documented change-control procedures, with testing and approval processes similar to those required for validated systems. Governance frameworks should reference global standards issued by agencies such as the U.S. Food and Drug Administration (FDA), European Medicines Agency (EMA), and International Council for Harmonisation (ICH) to support compliance with current expectations.

### Access Control and Security

Strict access control protects data integrity and confidentiality. Role-based permissions should define who can train, modify or deploy AI models, ensuring datasets are safeguarded against unauthorized use, breaches, and cyber threats. Continuous cybersecurity monitoring helps create confidence in AI-assisted processes.



## Strategic Implementation: From Pilot Testing to Full Integration

Moving from AI experimentation within workflows to sustainable use requires structure and patience. Shuman notes that many organizations make the mistake of purchasing tools before governance or change management processes are in place. Instead, a thoughtful, multi-phased rollout gives teams the opportunity to align AI capabilities with practical needs, test assumptions in low-risk environments, and refine oversight protocols before scaling up.

### Phase 1: Define Goals and Run Limited Pilots

In highly regulated environments, every data set used to train, inform, or validate AI must be documented with details such as source, date, license, and intended use. Validation processes must confirm complete, accurate and representative data, and audit trails should include immutable records of data inputs, model versions, and outputs.

### Phase 2: Evaluate Outcomes and Refine Approaches

Next, teams should evaluate the accuracy and efficiency of the pilot processes. They should measure error types, time savings, and the cost and time burden of reviewing AI-generated outputs. Shuman advises using any time saved in this phase to reinvest in evaluation and training, ensuring continuous improvement.

The second phase should also include team documentation of the lessons learned during the pilot. What worked and what didn't? What governance adjustments are needed before the process can scale?

### Phase 3: Integrate AI Tools at Scale

Once tools are validated, teams can integrate them into existing systems, including document management platforms and medical information workflows. Cross-functional teams with representation from IT, compliance, and the library/information center help to ensure that Standard Operating Procedures (SOPs), technology integrations, and workflows evolve together for a more seamless shift in mindset and practical application.

## Misunderstood Capabilities and the Risks of Over-Reliance

Misplaced confidence is one of the biggest risks in AI adoption. The ability of AI to produce fluent, well-structured text can lead users to mistakenly believe it truly understands and communicates with them—when in fact, no such comprehension is taking place. "This misunderstanding is common and dangerous. When professionals assume AI can accurately analyze or fact-check, they risk relying on outputs that might be incomplete, biased, or even entirely fabricated", warns Shuman.

Advanced systems can "hallucinate" citations and misrepresent facts. In one publicized case, two lawyers leveraged ChatGPT to conduct legal research. Without a rigorous HITL process in place, the output produced fictitious quotes and research that were submitted to the courts resulting in a fine and an apology from the lawyers.

In the pharma library and medical information context, such errors can lead to flawed regulatory submissions, unsupported scientific claims and decisions that put patients or others at risk. Building trust in AI processes requires treating the technology as a collaborative tool, never a replacement for human expertise.

## Trusted AI Comes From the Right Tools, Guided by the Right Oversight

AI might be transforming how pharmaceutical libraries and medical information teams work, but its value depends heavily on how thoughtfully the technology is implemented. Trustworthy systems don't emerge from technology silos—no matter how robust they are. Trust is built through governance, human oversight, and a culture that values accuracy and accountability across all workflows, whether AI- or human-powered.

Step-wise AI augmentation—rather than full automation—is likely the future of pharma information processes. Teams that invest in structured pilots, cross-functional collaboration, and continuous feedback can gain efficiencies without sacrificing the integrity of their work.

ReadCube's suite of AI-powered literature management and systematic review solutions make it possible for organizations to organize, discover, understand, and synthesize research materials. Curious as to how ReadCube supports the next generation of AI-informed pharma workflows?

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