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WHITE PAPER

Production RAG Governance: A Practical Playbook for Enterprises

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> *RAG can make LLM outputs auditable and grounded, but only if retrieval quality, policy controls, and monitoring are treated as first-class production concerns. This playbook outlines a governance pattern teams can adopt in weeks, not quarters.*

TL;DR

- Treat retrieval like data infrastructure: versioned sources, ownership, and clear provenance.
- Enforce permissions at retrieval time so restricted text never enters the model context.
- Measure citation accuracy and freshness weekly, not just “does the answer sound right”.
- Ship changes behind evaluation gates and keep audit-ready logs for incidents.

Executive Summary

Retrieval-Augmented Generation (RAG) is often sold as the safe way to use large language models in the enterprise. In practice, teams still get surprises: answers that cite the wrong document version, quotes that do not exist, and sensitive snippets leaking into prompts. You also see dashboards that look fine while users quietly stop trusting the tool. The root issue is rarely the model. It is the lack of governance around retrieval, permissions, and feedback loops. This paper proposes a pragmatic approach we have used with enterprise teams: treat retrieval as critical data infrastructure, define a slim set of production policies, and measure what users actually experience.

Why It Matters

In regulated or high-stakes environments, RAG is only defensible when you can explain what sources were allowed, what sources were used, why those sources were selected, and how answer quality

behaves over time. Without that, you are running a system that sounds confident but cannot be audited. Governance does not have to be heavy. A small set of controls such as document lineage, access enforcement, release gates, and incident-ready logs raises reliability quickly and keeps costs predictable.

What We Built

- A content pipeline that assigns stable document IDs, captures version history, and records provenance (source system, owner, and retention policy).
- Permission-aware retrieval using per-document ACLs synchronized from enterprise identity (e.g., Azure AD/Okta groups) so the model never sees content a user can't access.
- A retrieval quality scorecard (coverage, freshness, precision@k, and citation slip rate) tracked weekly, alongside end-user satisfaction signals.
- A "prompt firewall" layer that redacts sensitive fields before embedding and before generation, with allowlists for sensitive-data-safe fields.
- An evaluation gate for releases: golden queries, adversarial queries, and regression checks before shipping changes to indexing, chunking, or prompts.

Observed Outcomes

- Fewer incorrect citations by enforcing versioned sources and rejecting stale content at retrieval time.
- More consistent answers after standardizing chunk size rules by document type (policy, FAQ, runbook, contract).
- Lower incident risk by logging retrieval context and policy decisions for audit and post-mortems.
- Faster iteration because teams can change chunking and ranking with measurable impact, not guesswork.

Implementation Notes

- Don't start with "the best" embeddings model. Start with stable document identifiers and clean text extraction. Retrieval quality depends more on content hygiene than the last 2% of embedding accuracy.
- If your source-of-truth is SharePoint/Confluence/Drive, plan for duplicates. Use canonical URLs and content hashing to avoid indexing the same doc 5 times.
- Maintain a clear separation between: index-time enrichment (metadata, ACL, redaction) and query-time controls (policy checks, reranking, citation formatting).

- Adopt a simple tracing schema early: query_id, user_id (hashed), retrieved_doc_ids, retrieved_doc_versions, prompt_template_version, model_version, latency, and cost.

Governance & Risk

- Access control: enforce permissions in retrieval, not in the UI. If the model receives restricted text, it can leak it.
- Data retention: store embeddings and caches with the same retention and deletion behavior as the source document.
- Human-in-the-loop: define escalation paths for “I don’t know” or policy conflicts, instead of forcing an answer.
- Security review: threat model prompt injection and malicious documents; treat external content as untrusted input.

Release Checklist

- Can we trace every answer to versioned source documents with stable IDs?
- Do retrieval results respect the user’s permissions at query time?
- Do we measure citation accuracy, not just model accuracy?
- Do we have release gates (golden set + regression) before changing indexing or prompts?
- Do we have incident logs that a security or compliance team can use without reverse-engineering the system?

Conclusion

The fastest path to trustworthy RAG is to stop treating it as a demo and start treating it as production data infrastructure. If you build versioned sources, permission-aware retrieval, and a measurable quality loop, the model becomes the easy part. Governance is what makes RAG usable at scale.

Keywords

retrieval-augmented generation | RAG governance | LLM observability | AI risk management | enterprise AI | model monitoring | data lineage