Bridging Animal and Human Nutrition Through INSIGHT: A Retrieved-Augmented Agentic Model

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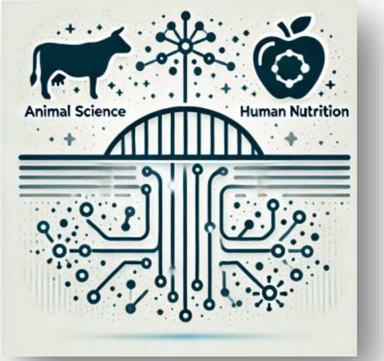
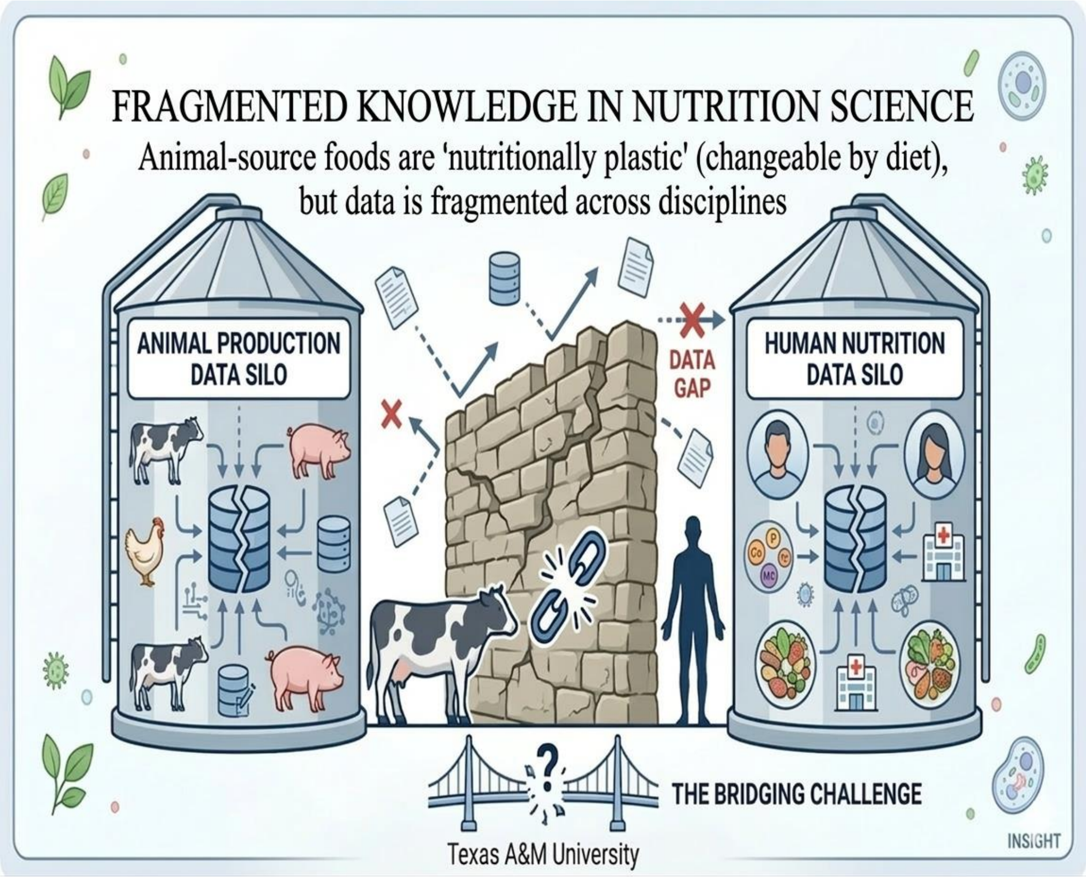
Why is the literature hard to use?



- Evidence is spread across animal science, feed composition, food science, and human nutrition
- Findings sit in different species, journals, vocabularies, and experimental contexts.
- That fragmentation limits translation into actionable guidance.



Why Retrieval-Augmented Generation rather than a generic chatbot?

Problem with parametric only LLM

- hallucinations and fabricated citations
- knowledge boundaries from training data
- weak traceability for scientific claims

What RAG adds

- retrieved evidence from external documents
- better factual grounding and provenance
- freshness without relying only on model memory

INSIGHT goal

domain-specific, evidence-grounded synthesis


INTRODUCING INSIGHT: Intelligent System for Integrating Global Human & Animal Health Technology
GOAL: Domain-specialized synthesis of evidence with explict provenance (citations)
INSIGHT AI CORE
Tedeschi 2023
INSIGHT EVIDENCE BRIDGE
PROVENANCE SHIELD
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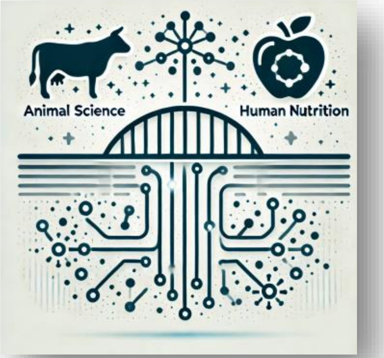
ANIMAL PRODUCTION & HEALTH DATA SILO
SYNTESIZED EVIDENCE (e.g., Reports, Models)
DOMAIN-SPECIFIC KNOWLEDGE GRAPHS
HUMAN NUTRITION & HEALTH DATA SILO
Texas A&M University
INSIGHT



Why is AI is needed?

~4,000

papers in the INSIGHT knowledge base

5

researchers on average

67.3

weeks for one systematic review

$141k–$180k

estimated labor cost per review

What is INSIGHT?

Truthful synthesis with provenance

- Cites source passages and exposes retrieval context

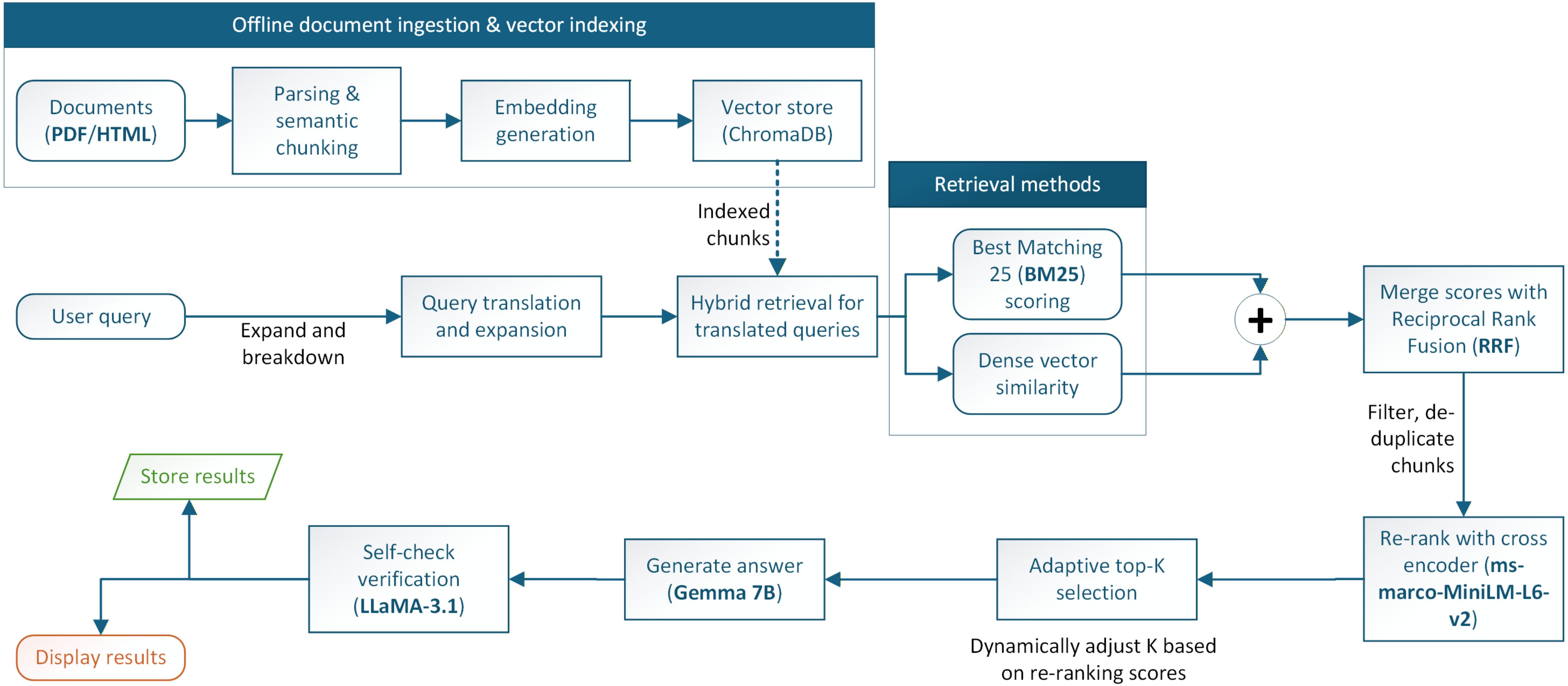
Agentic workflow

- Decides when to search, which tools to use, and when to escalate

Interoperability across domains

- Bridges animal science and human nutrition language

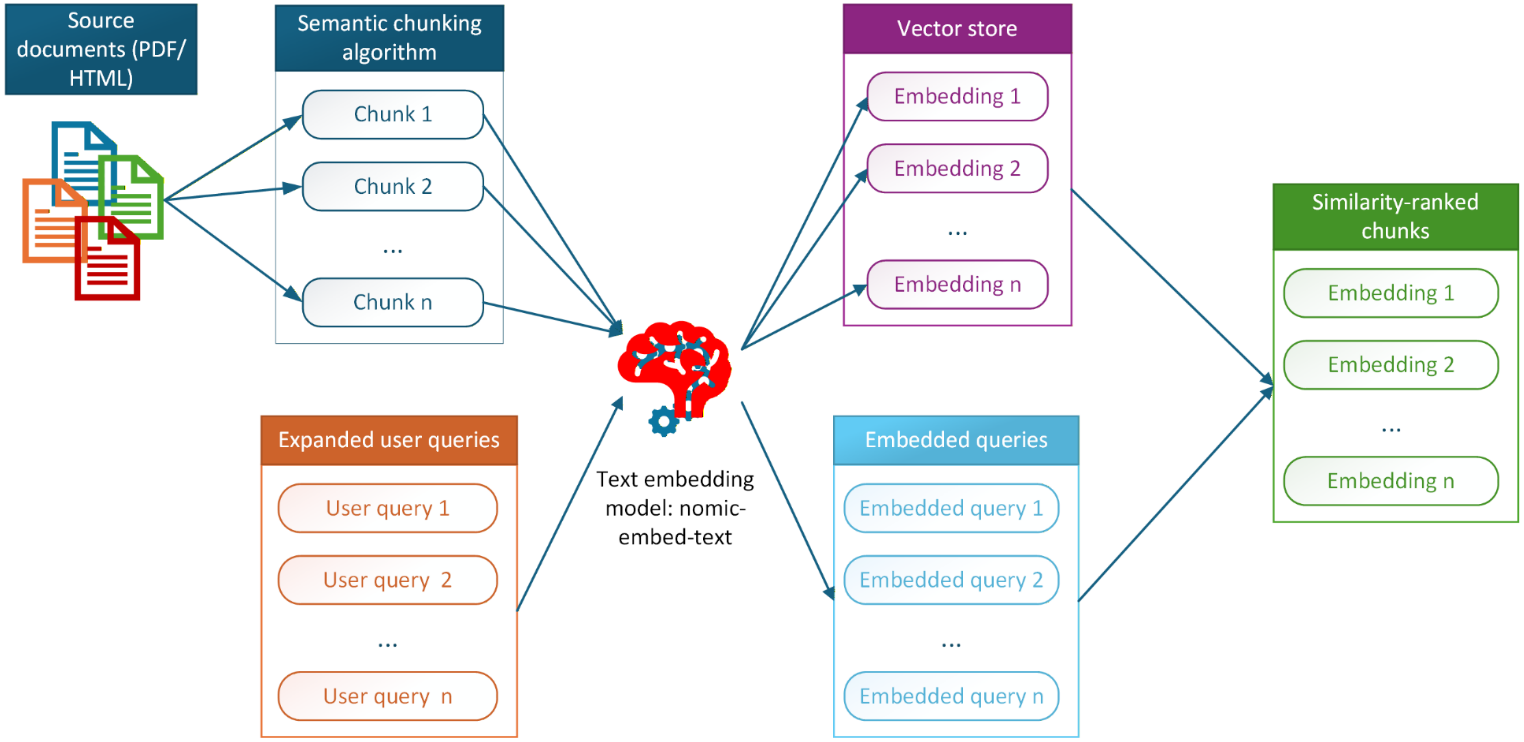
How the system works



Tedeschi et al. (2026; Frontiers in Nutr.)

Retrieval and indexing details

INSIGHT is engineered to improve recall without giving up evidence traceability



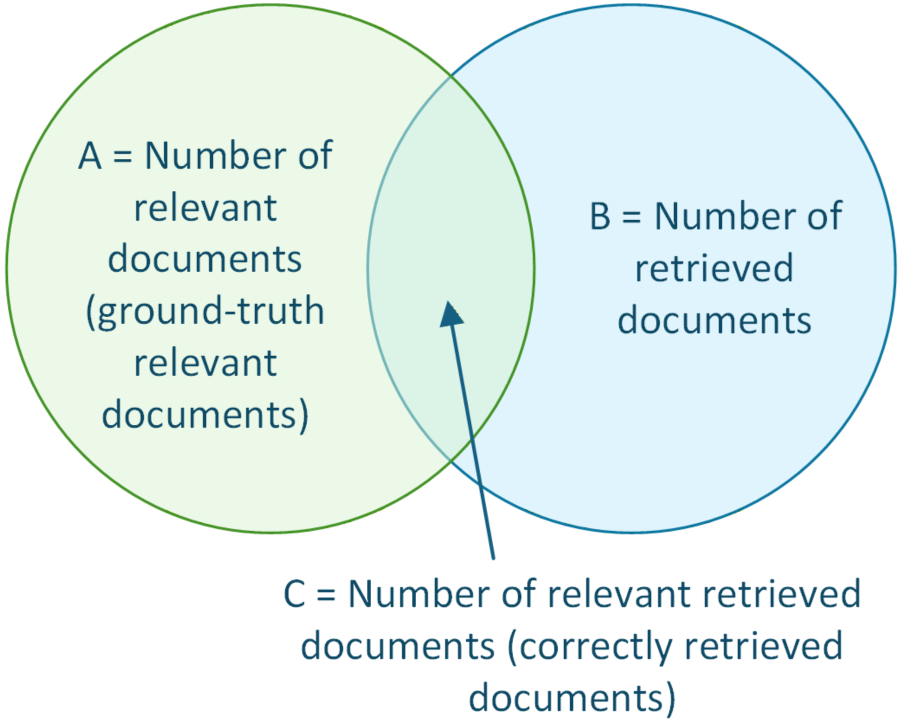
- Semantic chunking of extracted PDF/HTML content into 1024-token segments with 120-token overlap
- Text embeddings generated with Nomic Embed Text and stored in ChromaDB using Hierarchical Navigable Small World (HNSW) indexing
- Hybrid retrieval merges dense vector similarity with BM25 lexical matching via reciprocal rank fusion
- Cross-encoder reranking helps filter noisy candidates before final evidence selection

Tedeschi et al. (2026; Frontiers in Nutr.)

Evaluation of INSIGHT

- Documents were organized into ~10-paper topical groups so each question could be answered within a focused literature set
- Perplexity Deep Research generated 25 Q&A pairs per group and identified the ground-truth relevant papers
- Each question was run through INSIGHT, and document-level precision, recall, and F1 were computed

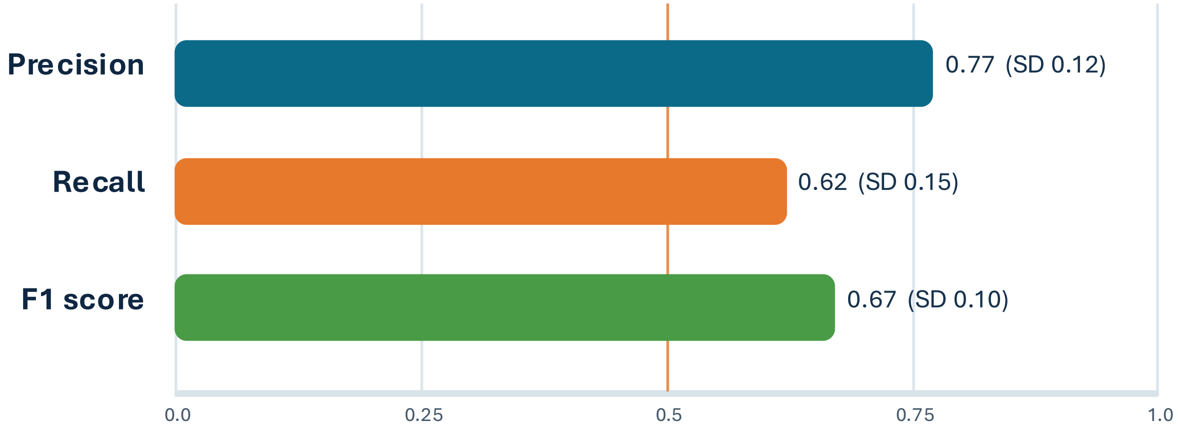
~4,000 papers in corpus → **282** papers sampled → **26** semantic groups → **614** total queries



Evaluation metrics: Precision (P) = C/B, Recall (R) = C/A, and F1 score (F1) = 2·P·R/(P + R)

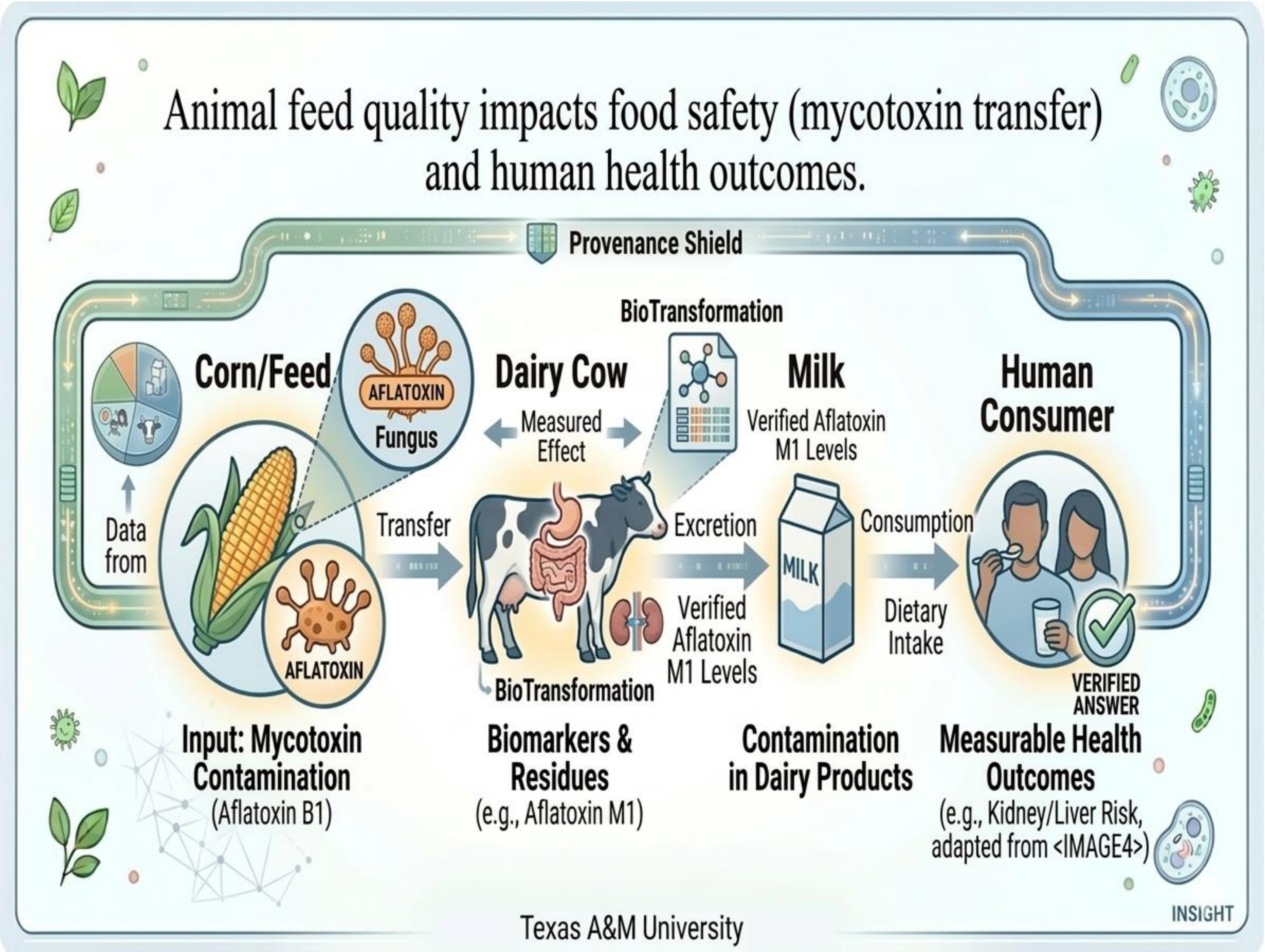
Evaluation results

- Strong precision means the retrieved evidence is usually relevant
- Lower recall means some relevant papers are still missed
- Performance changes across semantic domains, so hard topics remain hard topics



Case Study 1: The mycotoxin connection

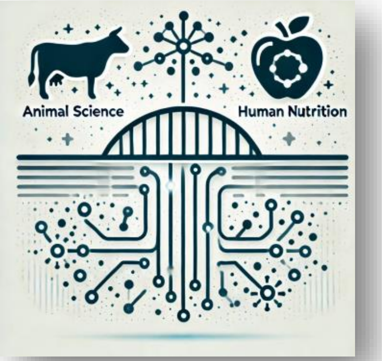
- Contaminated corn/feed (aflatoxin b1) is ingested by the animal
- INSIGHT tracks this flow to provide verified evidence on measurable health outcomes, such as kidney and liver risks



Case Study 2: Chromium supplementation

- Highlights how chromium propionate supplementation in feed leads to improved lean tissue deposition and higher growth efficiency, resulting in enriched beef for human consumption
- INSIGHT provides domain synthesis to verify how these specific animal feed interventions directly enhance the nutritional value of human food

Future Directions



What INSIGHT does well

- Gives transparent, document-grounded synthesis rather than unsupported narrative generation
- Performs reliably above baseline across a diverse, multi-group nutrition benchmark
- Supports cross-disciplinary discovery at the animal–human nutrition interface

What still needs improvement

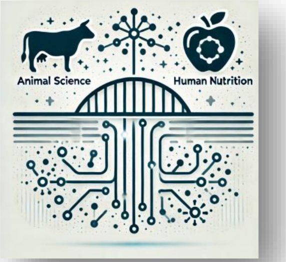
- Improve recall in semantically complex domains and with terminology variation
- Agentic AI-Knowledge Graph
- Expand corpus coverage and add broader expert evaluation beyond the current proof-of-concept benchmark

INSIGHT looks most valuable as an evidence-grounded assistant for researchers, practitioners, and policy work — not as a substitute for expert appraisal

Agentic AI + Knowledge Graphics

- **What it is**
  - AI agents using structured knowledge networks
- **Why it matters**
  - Reasoning, explainability, and multi-step tasks
- **Example flow**
  - Agent + KG ➔ Plans➔LLM➔Actions

Acknowledgments



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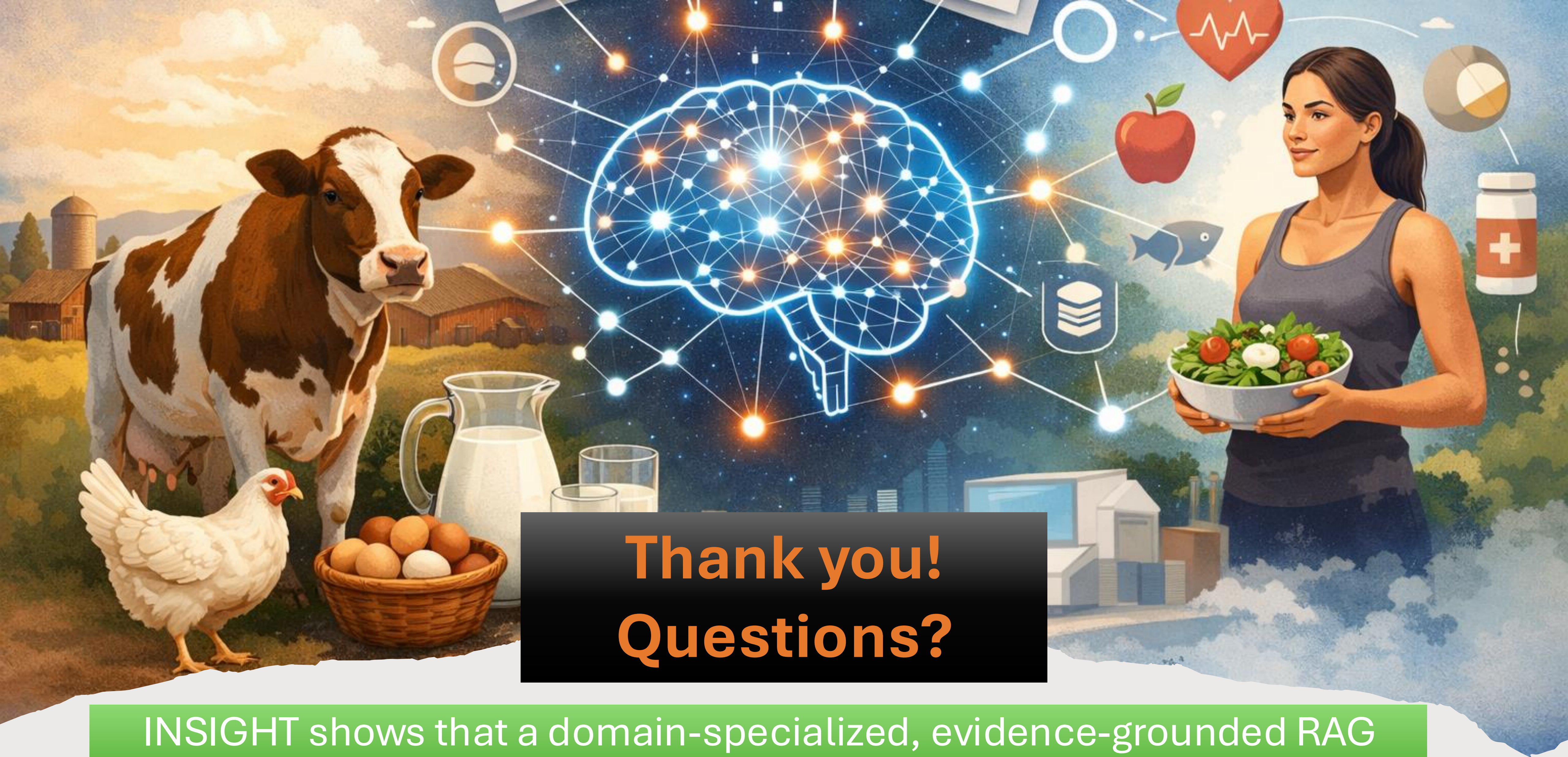

Thank you!
Questions?

INSIGHT shows that a domain-specialized, evidence-grounded RAG system can reliably retrieve relevant literature across animal and human nutrition while making its reasoning more transparent and traceable